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Modeling Coronavirus Conspiracy Theories

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1 Introduction

In November of 2019, early cases of Covid-19 began to be observed in China [5]. The initial infection grew to become newsworthy on a global scale as months passed and the virus crossed borders. By late March, most of the world had instated lockdown and masking policies as countermeasures to lower the virus's rate of transmission. After the countermeasures were introduced, rates of infection generally lowered [4] because people were able to both avoid being infected and recover more quickly if they were infected.

While the coronavirus spread through the world, another disease began proliferating online. Coronavirus conspiracies began their spread around the same time as the virus itself in late November. Like the virus, conspiratorial thinking reached a peak in early April before beginning a decline [3]. Because the spread of conspiracy theories surrounding the coronavirus spreads similarly to the disease, it can be modeled in the same way that infectious diseases are modeled. The basic model can then be modified with countermeasures that could slow the transmission of conspiracy theories to test their effectiveness.

2 The Model

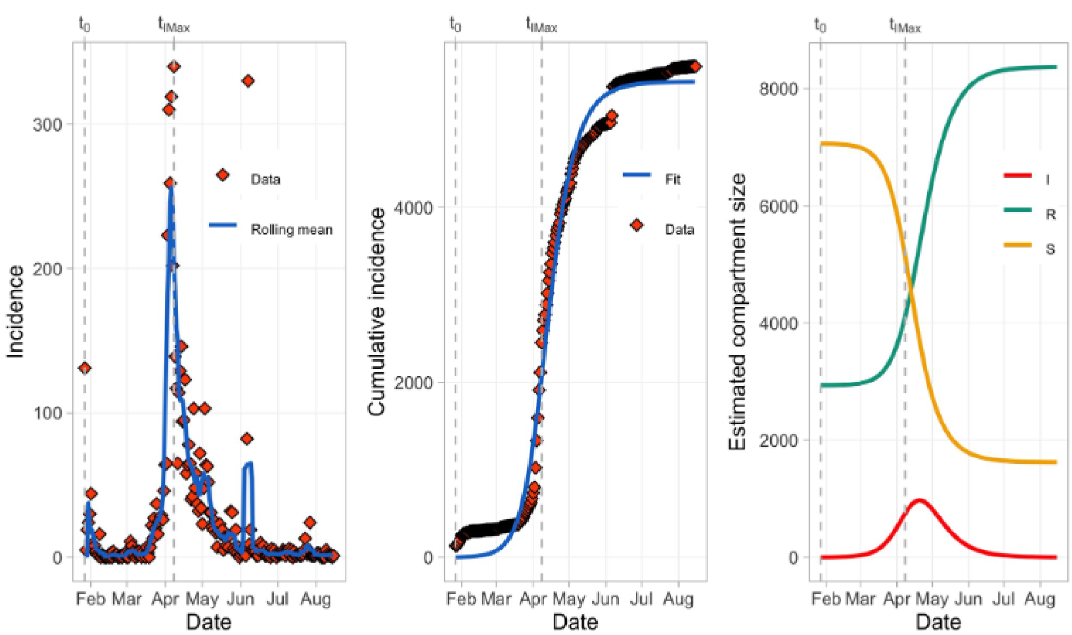
The model that will be used is based on a study done by Julian Kauk that created a model based on the rate conspiracy hashtags were used on twitter. As a base, Kauk used a SIR model that is commonly used to model the spread of infectious diseases [3]. Modified SIR models have been used to model the spread of rumors and information since an article was published in 1964 supporting the idea that the three groups in the model could be redefined to fit this case [2]. The SIR model contains three groups, Susceptible, Infected, and Recovered. In this scenario, Susceptible people are those who have not posted a tweet supporting conspiracy theories, Infected people have tweeted using conspiracy hashtags, and Recovered people have previously tweeted using a hashtag but do not anymore. The unmodified SIR model is as follows,

$$\begin{aligned}\frac{dS}{dt} &= \frac{-\beta SI}{N} \\ \frac{dI}{dt} &= \frac{\beta SI}{N} - \alpha I \\ \frac{dR}{dt} &= \alpha I\end{aligned} \tag{1}$$

In the model, α is the recovery rate in $\frac{1}{days}$, or how long it takes an individual to stop tweeting using conspiracy hashtags. The parameter β is the infection rate in $\frac{1}{days}$, or how likely it is for a susceptible individual to begin using conspiracy hashtags if they are exposed to someone else using the hashtags. Lastly, N is the total population from each of the three groups. To find values for these parameters and initial conditions, Kauk used twitter data and fit that to the model.

3 Finding Parameter Values

Accumulation of Twitter usage data surrounding coronavirus conspiracies has been ongoing since January first, 2020 [1]. Kauk used data from January 27, 2020 to August 15, 2020 that recorded 5611 uses of the top ten most popular coronavirus conspiracy hashtags. Each use of a hashtag was plotted on the day it happened as follows in the first plot,



The second plot shows the cumulative usage of the hashtags through the time data was collected. Assuming everyone that everyone in the SIR model who is infected will eventually recover, this cumulative incidence was fit to the recovered part of the SIR model, and initial conditions to reach that recovered curve were produced by R's Epimodel package. The initial conditions Kauk produced are $S(0) = 7060.94$, $I(0) = 1.1$, and $R(0) = 2936.53$. Values for the parameters will be $\alpha = 0.11$ and $\beta = 0.3$. The parameter values mean that it will take about 9 days for someone to stop using conspiracy hashtags, and the conspiracy 'virus' has an infection rate of 0.3 [3]. With parameter values from the unmodified SIR model, Kauk then made alterations to simulate how countermeasures would affect the growth of conspiracies.

4 Modifications to the Basic SIR

The first alteration models how deleting tweets would impact the change in the system by adding the parameter ζ with units $\frac{1}{days}$. Deleting tweets would increase the rate at which people stop using the hashtags, and in the model allow people to become recovered faster. The new model is,

$$\begin{aligned}\frac{dS}{dt} &= \frac{-\beta SI}{N}\\ \frac{dI}{dt} &= \frac{\beta SI}{N} - (\alpha + \zeta)I\\ \frac{dR}{dt} &= (\alpha + \zeta)I\end{aligned} \tag{2}$$

Where ζ is a function of time defined as,

$$\zeta(t) = \left\{ \begin{array}{cc} 0 & \text{if } t > \delta \\ \zeta_o & \text{otherwise} \end{array} \right\} \tag{3}$$

Defining ζ as a function, allows the impact of fact checking to have a time delay, δ and remain constant, ζ_o after that time delay.

The second modification to the model adds a fact checking parameter, γ with units $\frac{1}{days}$ to the simulation. Fact checking would cause people who are skeptical or not aware of the conspiracies to not believe them if they were to make contact. This moves people from the susceptible population to the removed population in the model as follows,

$$\begin{aligned}\frac{dS}{dt} &= \frac{-\beta SI}{N} - \gamma S\\ \frac{dI}{dt} &= \frac{\beta SI}{N} - \alpha I\\ \frac{dR}{dt} &= \alpha I + \gamma S\end{aligned} \tag{4}$$

Where gamma is defined by the function,

$$\gamma(t) = \left\{ \begin{array}{cc} 0 & \text{if } t > \delta \\ \gamma_o & \text{otherwise} \end{array} \right\} \tag{5}$$

Combining the two modifications, we get the final model,

$$\begin{aligned}\frac{dS}{dt} &= \frac{-\beta SI}{N} - \gamma S \\ \frac{dI}{dt} &= \frac{\beta SI}{N} - (\alpha+\zeta)I \\ \frac{dR}{dt} &= (\alpha+\zeta)I + \gamma S\end{aligned} \tag{6}$$

5 Analysis

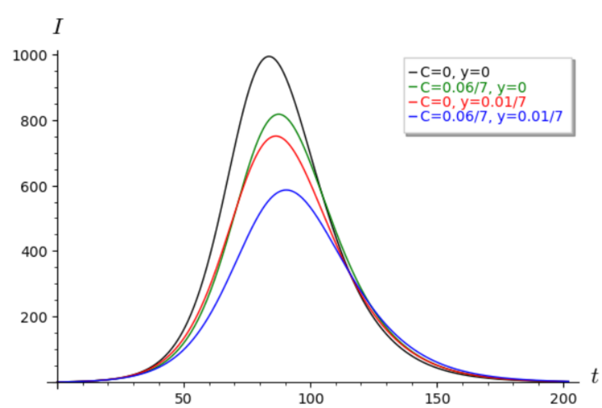
This model has three dependent variables, one for each equation. All three equations are first order because they only use the first derivative and they are all autonomous because they do not rely on the independent variable, time. The equations for the susceptible and infected populations are non linear because they have dependent variables being multiplied by each other, and the recovered equation is linear.

In the unmodified system, the infected population is at equilibrium when $S = \frac{N\alpha}{\beta}$. This is the point at which the number of infected people begins to decline. In the modified model, this occurs around $S = \frac{N(\alpha+\zeta_o)}{\beta}$, but not exactly because of the time delay in $\zeta(t)$. This nullcline was found as follows by first setting $\frac{dI}{dt} = 0$ and assuming $I \neq 0$,

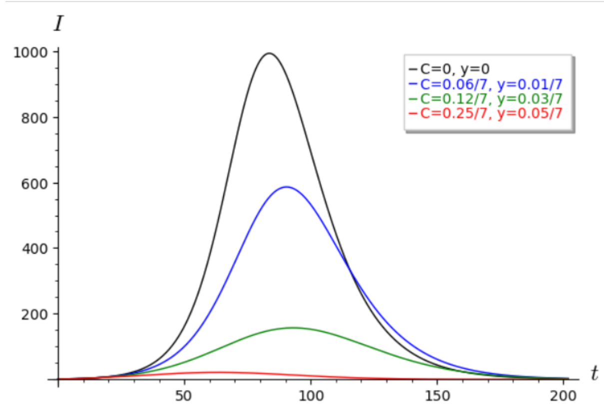
$$\begin{aligned}0 &= \frac{\beta SI}{N} - (\alpha+\zeta)I \\ (\alpha+\zeta) &= \frac{\beta S}{N} \\ \frac{N(\alpha+\zeta)}{\beta} &= S\end{aligned} \tag{7}$$

Other Equilibrium points and nullclines are at 0 or require a parameter or population to be negative and do not affect the model.

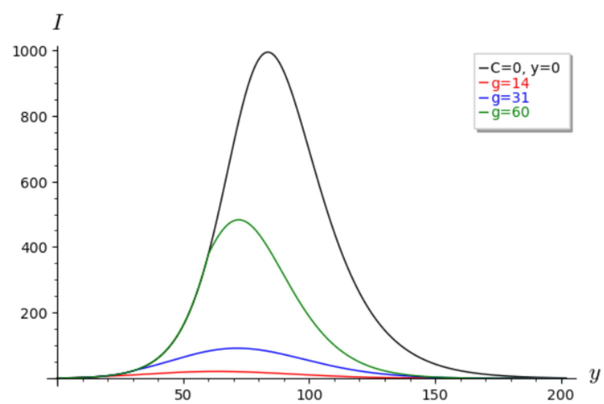
5.1 Simulations



This simulation shows the individual affects of fact checking and deleting tweets. For parameters, δ is 14 days for every curve, and ζ and γ change. These parameters were used by Kauk and change the basic SIR model reasonably [3]. In the simulation, having fact checking has a larger effect on reducing the spread of conspiratorial beliefs than deleting tweets. Tweet deletion, on the other hand, is better for delaying the peak of infected individuals than fact checking. Using both counter measures simultaneously clearly has a greater effect than either of them individually, reducing the unmodified SIR's peak of 993 infected by about half to 586 people.



The next model displays how larger values for the fact checking and tweet deletion parameters affect the spread of conspiracy theories. For all of these simulations, $\delta = 14$ was used. This plot shows that by multiplying the rate at which these countermeasures are used by 5, the amount of people spreading conspiracy theories drops massively from about 586 to only 22 infected.



Lastly, this model shows how delaying the countermeasures affects how conspiracies are able to spread. This model uses the largest values for fact checking and tweet deletion, $\gamma = \frac{0.05}{7}$ and $\zeta = \frac{0.25}{7}$. While lowering the delay has a smaller impact, increasing the delay from 14 days to 60 days allowed the maximum infected to rise from just 22 to 483.

6 Conclusions

From the models it is clear that both fact checking and deleting tweets will have a positive effect on reducing the spread of coronavirus conspiracy theories over twitter. Implementing these countermeasures quickly is also incredibly important in stopping misinformation. More broadly, this model shows the importance of moderation in online spaces. Though the study focused on twitter, other websites like facebook and instagram operate similarly by providing fact checks on flagged posts and deleting content that breaks platform rules on spreading misinformation. Fact checking is more effective generally and is what these sites should focus on, but more important is implementing these countermeasures as soon as possible.

One part of this model that may seem unrealistic at first is that initially about 70% of people are susceptible to the conspiracy theories. While people may not themselves believe in a conspiracy, just the act of spreading it, even if as a joke or to debunk it, will mark you as 'infected,' or someone who is spreading the misinformation. Framing the infected class as just spreaders of misinformation rather than true believers could help to explain why so many are considered susceptible initially. Rather than just focusing on countermeasures that organizations should implement, it is important for individuals to be aware of what they are spreading and how their audience might interpret their words. To adjust the model, the infection rate β could be lowered, or a new population could be introduced to signify spreaders. The model also makes the assumption that people can recover from these thoughts and do so relatively quickly. Kauk notes this by pointing out that the process of reeducating people is not the same for everyone, and some people can fall back into conspiratorial beliefs.[3] Overall, this model displays how easily misinformation can spread unchecked and the importance of online moderation to stop it.

References

[1] Banda, Juan M., et al. "A Large-Scale COVID-19 Twitter Chatter Dataset for Open Scientific Research—An International Collaboration." Epidemiologia, vol. 2, no. 3, Aug. 2021, pp. 315–24.

[2] Daley, D. J., and D. G. Kendall. "Epidemics and Rumours." Nature, vol. 204, no. 4963, 4963, Dec. 1964, pp. 1118–1118.

[3] Kauk, Julian, Helene Kreysa, and Stefan R. Schweinberger. "Understanding and Countering the Spread of Conspiracy Theories in Social Networks: Evidence from Epidemiological Models of Twitter Data." PLoS One 16.8 (2021)ProQuest.

[4] Mathieu, Edouard, et al. "Coronavirus Pandemic (COVID-19)." Our World in Data, Mar. 2020.

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