Modeling the Spread of Fake News

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Introduction:

With multiple and unrestricted access to information in the modern world, it is not surprising that collecting and diffusing information becomes easier and more manageable than ever. However, this leads to the emergence of invalid and unfounded information which can be difficult to distinguish from accurate and verified news. The following paper discusses the investigation of the patterns of rumors and fake news using explorative mathematical models. The goal of this project is to model the spread of fake news and explore possible ways to deter distributing misinformation.

In order to understand the diffusion of fake news, we would use the SIR model. This type of model divides the population into three different groups which reflect the behavior of each of the individuals in the population as they move from one group to another:

S: the number of susceptible, the people who are not sick but can become sick
I: the number of infected, the people who are currently sick
R: the number of recovered or removed, the people who are already sick and can no longer infect

The SIR model consists of a system of differential equations as the following:

$$\frac{dS}{dt} = -aSI$$
$$\frac{dI}{dt} = aSI - bI$$
$$\frac{dR}{dt} = bI$$

$$S(0) = S_0,\ I(0) = I_0,\ R(0) = R_0$$

The SIR model is usually applied to predict diseases and epidemics, but it can also be used in the context of information distribution. In this situation, the susceptible would be those who are likely to believe in fake news once they are exposed to it and the infected would be those who currently believe in fake news. There are also the recovereds, which can also be referred to as the resistant in this specific case, would be those who are not willing to believe in fake news, which can result from people learning that the news is a hoax. Using the SIR model and data gathered from previous studies, we hope to gain more insight into how fast fake news is diffused and possibly ways that we can employ in order to stop the spread of fake news.

Interpretation of Differential Equations:
In order to model the spread of fake news, we would employ the system of differential equations mentioned above with the initial data. Differential equations are equations such that they include a function and its derivative, also known as its rate of change. Each differential equation is associated with each of the three groups (susceptible, infected, and recovered) accordingly.

Firstly, for the susceptible group in which people are likely to believe in fake news, the function $S(t)$ would be the function which indicates the number of susceptible population S at any given time t. We are interested in the derivative of $S(t)$, also denoted as $\frac{dS}{dt}$, which is the rate of change of the number of susceptible people over time. We assume that the rate of change of the susceptibles is proportional to the number of interactions between the susceptibles (S) and the infected (I). Furthermore, we assume that the number of interactions is proportional to the number of susceptibles (S) and the number of infected individuals (I). This means that if there are more people who are likely to believe in fake news, the number of interactions will increase, and similarly, having more people currently believing in fake news will increase the number of interactions. Therefore, we can say that the number of interactions is proportional to the product of the number of susceptibles and the infected, SI. Thus, we get the following equation:

$$\frac{dS}{dt} = -aSI$$

where a is the infection rate constant and $a > 0$. There is a negative sign in the equation because the number of susceptible people (S) decreases with time as they start to believe in fake news.

Secondly, for the recovered or resistant group in which people are not willing to believe in fake news, the function $R(t)$ is the function that indicates the number of recovered people at any given time t. We are also interested in the rate of change of this population over time, $\frac{dR}{dt}$. We assume that the recovered people are those who already believed the hoax and will not believe it again once they realize it is fake. Thus, in this case, the rate of change of the number of recovered individuals is proportional to the number of infected individuals. This means that as the number of infected people increases, the number of recovered or resistant individuals increases. Therefore, we get the following equation:

$$\frac{dR}{dt} = bI$$

where b is the recovery rate constant and $b > 0$.

Finally, for the infected group in which people currently believe in fake news, the function $I(t)$ is the function that shows the number of infected people at any given time t. The number of the infected population is determined by both the number of people who start to believe in fake news and the number of people who either realize that the news is a hoax or are not willing to believe in fake news. Those starting to believe in fake news are added to the infected group and those who stop believing in fake news are removed from the infected group. Accordingly, the rate of change of the number of infected individuals over time, $\frac{dI}{dt}$, is determined by the rate at which susceptible people begin to believe the hoax minus the rate at which infected people stop believing in the hoax. The newly infected people are also the ones who leave the susceptible group, therefore the number of susceptible people beginning to believe the hoax increases at a rate of aSI. The number of people who stop believing in the hoax is removed from the infected group at a rate proportional to the number of people who currently believe in fake news, bI. Hence, we get the following equation:

$$\frac{dI}{dt} = aSI - bI$$

We also determine the initial data points for the SIR models. The number of people who are susceptible to fake news at time $t = 0$, $S(0)$, is equivalent to the initial number of susceptible people, S_0. Similarly, the number of people who currently believe in fake news at time $t = 0$, $I(0)$, is equivalent to the initial number of infected people, I_0, and the number of people who are not willing to believe in fake news at time $t = 0$, $R(0)$, is equivalent to the initial number of recovered people, R_0.

Effect of Parameters:

The constant a measures how quickly fake news spreads between individuals in the population over time. As a increases, the maximum number of the infecteds increases while the number of the susceptibles decreases, which accelerates the rate at which the fake news spreads. On the other hand, the constant b represents the rate at which people who currently believe in fake news decide to no longer believe in fake news. As b increases, the rate at which people "recover", or stop to believe in fake news also increases.

Spread of Fake News Tweets Model:
To obtain specific values that would allow us to model the spread of fake news on a social media platform, we appealed to a few outside sources. An MIT study on the spread of false news on Twitter [1], revealed that false news stories are 70 percent more likely to be retweeted than true stories. Thus, given by [2] that the average user has approximately 707 followers, we reasoned that if one individual retweets a false news story, 707 would see it and 70 percent of them would believe it and be compelled to retweet it. From this information, we obtain our initial number of infected people ($I_0 = 1$), our initial number of recovered people ($R_0 = 0$), our initial number of susceptible people ($S_0 = 707$), and our rate of change of susceptible people over time ($\frac{dS}{dt} = 0.7$), using hours for t. Plugging these new values into our equation, $\frac{dS}{dt}$, to solve for a, we get our desired infection rate constant of 0.0009901. Moreover, to obtain a value for b, we referred to [3], which claims that it takes anywhere from 15-20 hours for a false rumor to be solved. For the purposes of our investigation, we assume thus that it takes approximately 20 hours for those infected to realize the news story is fake. With this information, we obtain that 707/20 = 35.35 people recover per hour, and since 35.35 is 5 percent of 707, our rate of change of recovered people over time ($\frac{dR}{dt} = 0.05$). Plugging this value into our equation , $\frac{dR}{dt}$, with $I_0 = 1$, to solve for b, we get our desired recovery rate constant of 0.05. Our new values, thus yield the following particular model for the spread of fake news on Twitter:

$$\frac{dS}{dt} = -(0.0009901)SI$$
$$\frac{dI}{dt} = (0.0009901)SI - (0.05)I$$
$$\frac{dR}{dt} = (0.05)I$$

$$S_0 = 707, \;\; I_0 = 1, \;\; R_0 = 0$$

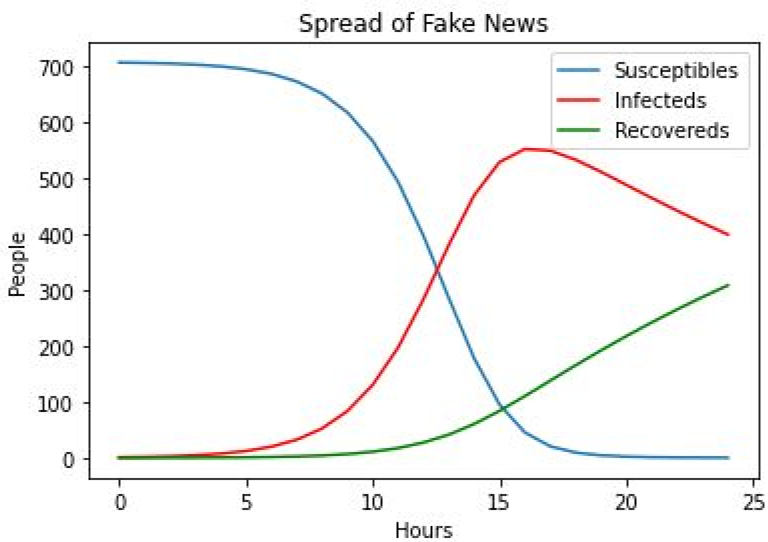
Using Python, we derive the following code to solve the system of differential equations:

```
DT = 1
simLength = 24
numIterations = int(simLength/DT) + 1
t = 0

susceptibles = 707
infecteds = 1
recovereds = 0

infection_rate = 0.0009901
recovery_rate = 0.05

get_sick = infection_rate * susceptibles * infecteds
recover = recovery_rate * infecteds

tLst = [t]
SLst = [susceptibles]
ILst = [infecteds]
RLst = [recovereds]

for i in range(1, numIterations):
    t = i * DT
    susceptibles = susceptibles + (-get_sick) * DT
    infecteds = infecteds + (get_sick - recover) * DT
    recovereds = recovereds + (recover) * DT

    get_sick = infection_rate * susceptibles * infecteds
    recover = recovery_rate * infecteds
```

From this, we gather the following data to show what happens to the population of Susceptibles, Infecteds, and Recovereds over the course of 24 hours (in 1-hour increments):

	Hours	Susceptibles	Infecteds	Recovereds
0	0	707.000000	1.000000	0.000000
1	1	706.299999	1.650001	0.050000
2	2	705.146141	2.721359	0.132500
3	3	703.246183	4.485249	0.268568
4	4	700.123176	7.383993	0.492830
5	5	695.004651	12.133319	0.862030
6	6	686.655422	19.875882	1.468696
7	7	673.142654	32.394856	2.462490
8	8	651.552178	52.365589	4.082233
9	9	617.771042	83.528446	6.700512
10	10	566.680441	130.442625	10.876935
11	11	493.492958	197.107976	17.399066
12	12	397.184546	283.560989	27.254465
13	13	285.673501	380.893984	41.432514
14	14	177.939415	469.583371	60.477213
15	15	95.209243	528.834375	83.956382
16	16	45.357787	552.244113	110.398101
17	17	20.557197	549.432497	138.010306
18	18	9.374223	533.143846	165.481931
19	19	4.425892	511.434984	192.139123
20	20	2.184745	488.104382	217.710873
21	21	1.128919	464.754989	242.116092
22	22	0.609442	442.036716	265.353841
23	23	0.342713	420.201609	287.455677
24	24	0.200130	399.334112	308.465758

To better visualize the change in our populations of interest in 24 hours, we generated the following graph:

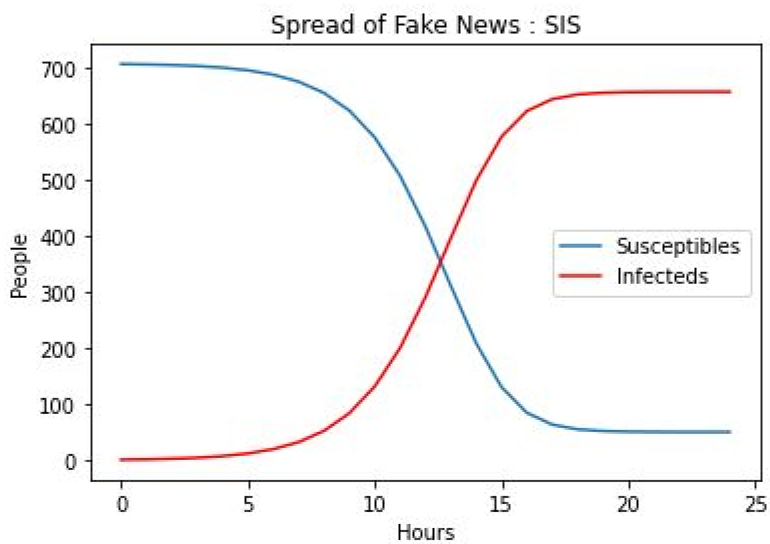


Analysis:
From the graphed solution above, we are able to analyze certain characteristics about this model. We can see that the model runs slower than a typical SIR model, and leaves several individuals still in the dark about the truth of the hoax. We can also see that, at some point, everyone exposed to the hoax believed it was real, since the number of susceptible individuals approaches 0. At around hour 15, roughly 600 people believe this hoax and then the population of infecteds slowly starts to decline. It looks like the graph will continue, and the number of recovered individuals will overcome the number of infected individuals.

SIS Model:
What if after people realized something was a hoax, they were once again susceptible to being convinced that it was true? This kind of situation would be represented by a SIS model. Using the following differential equations, we can get an idea of what this model will look like.

$$\frac{dS}{dt} = -\frac{aSI}{N} + bI$$
$$\frac{dI}{dt} = \frac{aSI}{N} - bI$$

Recovered individuals are no longer part of this model, since people can return to being susceptible (they don't have very good memories). So our graph should show the number of susceptibles decreasing when the infecteds increase.



Based on how misinformation works, we'd say the SIR model is more accurate in this situation. Since we are analyzing a hoax that lasts roughly 24 hours, it's logical to assume that people won't become susceptible again after realizing it's a hoax. There won't be any new information after the 24 hours to potentially reinfect the population. If the model lasted for several days with new information coming out every day to reinforce the hoax, we think the SIS model would become more logical.

Conclusion/Memo:
This project allowed for the study of a simulation of the spread of fake news using a SIR model and the constraints mentioned in previous sections. Using an SIR model helped us predict the number of individuals who could potentially be affected by fake news. To conclude this paper, we would like to leave a memo to anyone who comes across our findings and would like to use them to make changes regarding their social media platform or news outlet.

To Whom It May Concern,

After researching the spread of fake news and using an SIR model to illustrate it, we've concluded that the drastic way in which individuals become exposed to and share misinformation calls for some form of intervention. If you would like to decrease the number of individuals affected by fake news on your social media platform, we recommend implementing the following methods.

First, decrease the number of people that will see the fake news. If the tweet, article, or any other form of information was flagged soon after it was posted, then the number of people who saw the post would decrease. This decreases the number of people who could potentially believe the misinformation is true. This method decreases the number of susceptible people, ultimately decreasing the number of infected people.

Second, let your audience know that the misinformation isn't fact checked. Including some sort of automated disclaimer on posts containing news would let people know that the information before them could potentially be false and encourage them to reference other sources before sharing it. In this way, people that come across fake news are less likely to repost them and more apt to consider the content they share.

By adopting these (or similar) preventative measures, your company may significantly reduce the spread of fake news and begin to foster a healthier, more veracious environment.

Sincerely,

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References:

- [1] Dizikes , Peter. “Study: On Twitter, False News Travels Faster than True Stories.” *MIT News | Massachusetts Institute of Technology*, 8 Mar. 2018, news.mit.edu/2018/study-twitter-false-news-travels-faster-true-stories-0308.
- [2] Smith, Kit. “60 Incredible and Interesting Twitter Stats and Statistics.” *Brandwatch*, 2 Jan. 2020, www.brandwatch.com/blog/twitter-stats-and-statistics/.
- [3] Turenne, Nicolas. “The Rumour Spectrum.” *PloS One*, Public Library of Science, 19 Jan. 2018, www.ncbi.nlm.nih.gov/pmc/articles/PMC5774683/.