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Extrapolation of Online News Spread on Social Media

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Abstract

Social media's influence on news dissemination has grown as it has gained in popularity. The news spreads more quickly on social media than it does on conventional media because it is so accessible and provides easy interaction. This study envisions the ongoing dialogue between experienced and ignorant users. As more people use social media, they are more likely to receive news that affects their views. Despite this, social media makes it simple for people to get a range of news stories from many sources. It is true that utilising social media to distribute news has its pros and cons, but it is important to take into account how things function there. Six hypotheses are used in the study's mathematical derivation of the rate of change of news diffusion. It has been discovered that when an 'informed' user shares or likes the news, the rate at which it spreads on social media may be mathematically extrapolated. The difficult part is figuring out how long it will take to reach the maximum populace. The research runs a thorough simulation analysis to determine when news will reach the people. The findings could provide some insightful information about how news spreads on social media.

Keywords: Informed Users, Non-Informed Users, Pandemic Model, Social Media, Mathematical Modelling

Introduction

We cannot ignore the datum that social media has become a dominant tool for online news distribution and consumption (Shearer & Matsa, 2018). Astonishingly, even newspapers are now using social media to spread the news faster (Kümpel et al., 2015). One of the main reasons for the news spreading on social media is that users can segment and share it simultaneously (Pourghomi et al., 2017). Therefore, it is not surprising that approximately 64.5% of people get their news through social media (Lee & Ma, 2012; Martin, 2018). In addition, the impression that negative news travels faster on social media (Kumar & Shah, 2018; Shin et al., 2018) was found irrelevant, as Berger & Milkman (2013), Kümpel et al. (2015), and Lee & Ma (2012) researched that the critical reason for news spread on social media is informativeness.

There are several studies performed on news spread on social media through different mathematical models. Dhar et al. (2016) and Jin et al. (2013) researched, identifying the rumors through epidemic models. The first categorised the news as original or a rumor and then evaluated the news spread rate. Davoudi and Chatterjee (2016) performed the research on identifying the quality of information spread through ordinary differential equations. More and Lingam (2019) used two parameters, structural characteristics, content analysis, greedy algorithm, and an SI (Suspected and Infected) epidemic model to analyse the news spread. Campan et al. (2017) deliberated that news spread depends on three factors – influence maximisation, information diffusion, and epidemiological modelling. Budak et al. (2011) discovered that the news spread through the NP-hard problem through a greedy algorithm.

In our study, we performed the news spread considering the continuous interaction between the informed, $I(t)$ and the uninformed, $NI(t)$, users. As this interaction is dynamic, it is paramount to identify the rate of change of interactions $\frac{dI(t)}{dt}$ to reach the maximum population, n, $n \varepsilon N$. The interaction is defined in Fig. 1.

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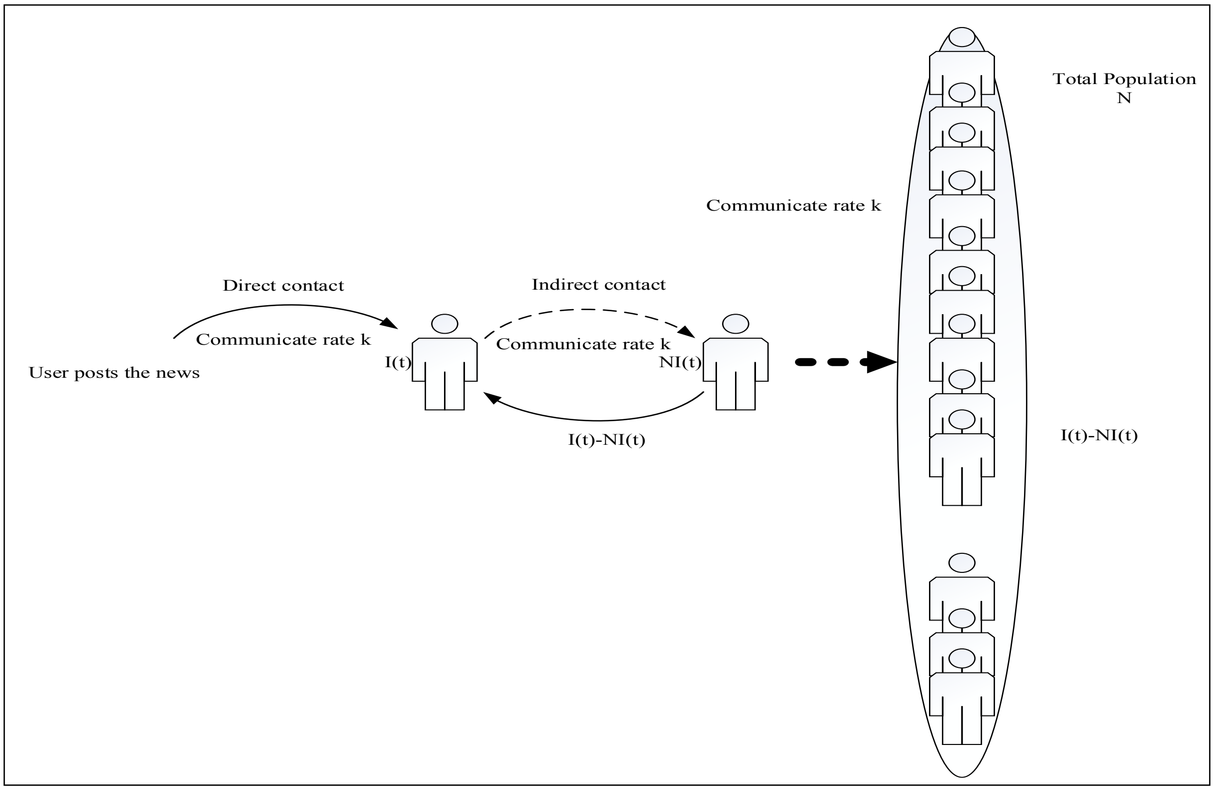

Fig. 1: Social Media News Spread

As mentioned in Fig. 1, the news first reaches the direct contact users. If they open the information, they are called informed users. These direct contact users contact other users, whom we call uninformed users. The aim of the research is thus to identify the rate of change of and to identify the time it reaches maximum.

The paper is divided into three sections. Section 2 illustrates the mathematical model of news spread on social media. Based on the derivations from section 2, section 3 gives the probable outcomes. Finally, section 4 mentions recommendations and results.

Mathematical Model of News Spread in Social Media

News in social media is not limited to spread and dilution. News spreads before becoming trending news to friends (who are part of the population), then spreads through the population. News gets distributed when it reaches the maximum number of people.

To develop the mathematical framework, six assumptions were formulated for the mathematical derivation.

Assumption 1: Either the news on social media is known to the user (called informed), or the user is not aware of the news (called uninformed).

Assumption 2: Nobody in the population can be both informed and uninformed.

Assumption 3: Once the user views or reads the news, he is informed and will always be in that state.

Assumption 4: The total population is assumed to be constant over time.

Assumption 5: News spread is only through interaction between the informed and uninformed. There is no meaning of interaction between the informed and informed, or between the uninformed.

Assumption 6: The interactions between informed and uninformed are purely random.

To derive the mathematical equations for the assumptions mentioned above, we assume the following symbolic representation:

Table 1: Symbolic Notation for the Mathematical Derivation of News Spread

Symbol	*Meaning*
t	Time (in minutes)
I(t)	Informed population in social media
NI(t)	Uninformed population in social media
N	The total population in social media
k	Communication rate

Assumptions 1-4 can be summarised together as:

[*rate at which informed population increases*]

= [*rate at which uninformed population decreases*] (1)

Equation (1) can be further restated as:

[rate at which informed population increases]

= – [*rate at which uninformed population increases*] (2)

Assumptions 5 and 6 can be stated together as:

[*rate at which informed population increases*]
= [*communication rate*]*[*rate of interaction between informed and uniformed population in social media*] (3)

From equation (3), it is observed that chances of interaction between informed and uninformed are random and independent events. We can state that:

[*rate of interaction between informed and uninformed population in social media*] =

[*rate of social media user being informed*]*[*rate of social media users being uninformed*] (4)

We can represent the values of equation (4) as follows:

rate of social media user being informed = $\frac{I(t)}{N}$

rate of social media user being uninformed = $\frac{NI(t)}{N}$

From equation (4), we get:

$$\frac{dI(t)}{dt} = k.\frac{I(t)}{N}.\frac{(N-I(t))}{N} \quad (5)$$

Also, the total population of social media is:

$$N = I(t) + NI(t) \quad (6)$$

$$NI(t) = N - I(t) \quad (7)$$

Placing equation (7) in equation (5), we get:

$$\frac{dI(t)}{dt} = k.\frac{I(t)}{N}.\frac{(N-I(t))}{N} \quad (8)$$

$$= \frac{k}{N^2}[I(t)(N-I(t))] \quad (9)$$

There are three observations from equation (9), as mentioned below:

Observation 1:

When $I = N$, it means all of N becomes informed user.

$$\frac{dI(t)}{dt} = \frac{k}{N^2}[I(t)(N-I(t))] \approx \frac{k}{N^2}[I(t) * 0] = 0 \quad (10)$$

Thus, equation (10) indicates that there will be no further spreading of the news since everyone is informed.

Observation 2:

When $I = 0$, it means the user posts the news, but none of the friends view it.

$$\frac{dI(t)}{dt} = \frac{k}{N^2}[I(t)(N-I(t))] \approx \frac{k}{N^2}[0 * (N-0)] = 0 \quad (11)$$

Thus, equation (11) indicates that since everyone is uninformed, maybe the news is not exciting or the reshared information is one in which no one is interested.

Observation 3:

When $0 < I < N$, it indicates that the people are reading the news. In this case, the news spread from the initial condition, $I(0)$, as:

$$\frac{dI(t)}{dt} = \frac{N.I(0)}{\left(e^{-\frac{kt}{N}} - e^{-\frac{kt}{N}}.I(0)\right)+I(0)} = \frac{N}{e^{-\frac{kt}{N}\left(\frac{1}{I(0)}-1\right)}+1} \quad (12)$$

Equation (12) mentions that the rate of change of informed users is directly proportional to the total sample. The outcomes of the result are described in the next section.

Research Outcomes

Table 2 shows the outcomes of news spread. Seven different outcomes from equation (12) use the news spread for sample size, with the communication rate of respectively.

Table 2: Research Outcomes for the News Spread through the Proposed Model

	N = 1000	*N = 2000*	*N = 3000*	*N = 4000*	*N = 5000*	*N = 6000*	*N = 7000*
k = 0.5	**6669.67**	**26672.67**	**60009**	106678.7	166681.7	**240018**	**326687.7**
k = 0.6	**5819.47**	**23266.85**	**52342.13**	93045.32	145376.4	**209335.4**	**284922.3**
k = 0.7	**4730.32**	**18907.33**	**42531.03**	75601.42	118118.5	**170082.3**	**231492.8**
k = 0.8	**3753**	**14996.63**	**33730.9**	59955.8	93671.34	**134877.5**	**183574.3**
k = 0.9	**2978.31**	**11897.21**	**26756.7**	47556.79	74297.47	106978.7	145600.6

The outcomes can be shown in Fig. 2; it was quickly established that the news's spread increases with the number of people who reads the news first.

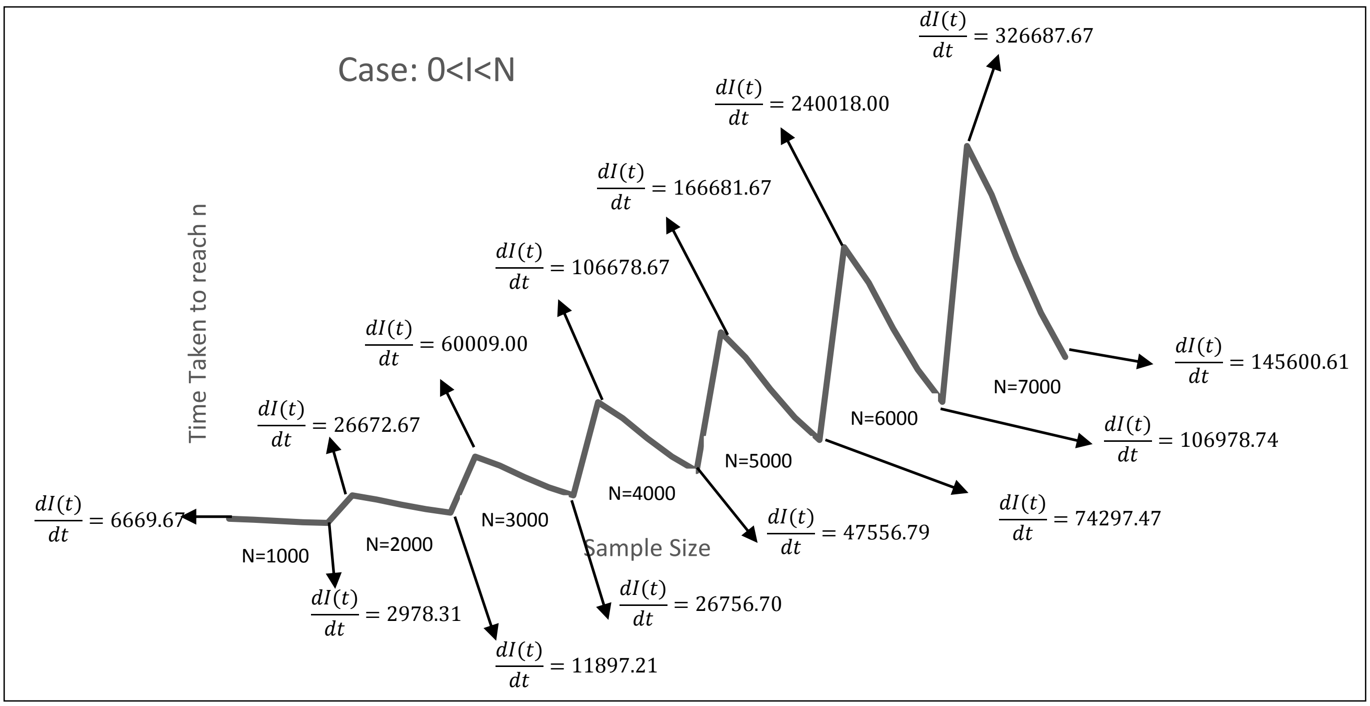

Fig. 2: News Spread on Social Media

Conclusion

The present study contributes to research in several ways. First, to our knowledge, this is one of the first studies that draws from diverse literature to investigate the time it takes to reach the maximum population. The outcomes are from n, the equation derived from continuous interaction between informed and uninformed users. It was observed that the rate of change of news spread is proportional to the total sample space. The results are for condition, where was the size of users' total population on social media.

The model makes several assumptions and approximations under some presumed conditions:

- The sample space was limited to 7,000 users only, which be extrapolated for a larger population.
- It was assumed that news spread happens when we share or like the news without considering news sharing.
- We also assumed that the user would open the news only once, and interaction increases when they share it. The condition of liking the information and again sharing it needs to be considered.

We will consider the three limitations in the research to follow; however, the present study will find its suitability in several ways:

- It will guide the organisation to identify its time to spread the news, advertisements, or social media campaigns.
- The research provides a guideline to monitor the rate of change of news spread on social media.

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