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Fake News and Post-truth: Numerical Simulations of Information Diffusion in Social Networks

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Abstract

The year 2016 was crucial in terms of the use of social networks as tools for disseminating information for political purposes. The election of candidate Donald Trump for the presidency of the United States of America lit a warning signal about the influence that the information disseminated through social networks exerted in the choice of candidates by the American people. Since then, researchers from different areas have focused on the topic, which involves different aspects: computing, social sciences, mathematics, among others. Therefore, the object of study of this work is the phenomenon of behavioral changes brought about by the new social relationships established by digital social networks, under the scope of the spread of fake news through them. To guarantee the intended study, the general objective was to adapt mathematical models consisting of ordinary differential equations for the dissemination of information on social networks for the spread of fake news. As specific objectives, the contribution of the mathematical models proposed in the mitigation, through algorithms, of the spread of false or distorted information was discussed, as well as the discussion on the concepts of fake news and post-truth from a social point of view, in a way that individuals can also distinguish true information from disinformation through individual interpretation tools. As a research methodology, bibliographic research was chosen and a systematic literature review was carried out, to consider published works on the proposed research object. For the numerical simulations, a numerical code was developed in MATLAB, which was able to carry out the desirable experiments. It is concluded that innovation diffusion models can adapt to fake news dissemination models. However, such models are not able to robustly simulate the mitigation of fake news.

Keywords: Logistic Models of Ordinary Differential Equations; Numerical Simulations; Fake News; Post-Truth; Dissemination of Information.

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1. Introduction

The understanding of the current social scenario permeates, without questioning, the influences that digital information and communication technologies exert on people's daily lives. In fact, it is difficult to think about today's society without the services available through technological-digital artifacts with internet access. The COVID-19 pandemic was an immersive experience in this intimately digital landscape [1,2].

Several authors carry out robust studies on the social transformations triggered by the internet [3–5]. In Manuel Castells' view, the technological advance represented, above all, by Big Techs has been leading to paradigmatic changes from an economic and social point of view.

In an optimistic view, the authors Pierre Lévy and André Lemos [6] considered that the expansion of access to communication between individuals and the creation of an interplanetary space such as cyberspace would be enough to create a wide public square for debates, including and, in this way, expand the concept of democracy also in the virtual space. For the authors, the possibility of a greater number of people having a common space for exchanging ideas would foster a more plural space, in which divergent voices would have the chance to dialogue and, consequently, more “people” would be exercising their political rights. People are understood to be the set of citizens of a given territory who participate in the political and legal processes of the State [7]. However, what was seen after the election of President Donald Trump in the United States of America and Brexit in the United Kingdom, both in 2016, was the incorporation of digital social networks as tools for political manipulation of a certain population. Such facts sparked an alert to social researchers: how can the algorithms of social networking platforms, in fact, manipulate information and communication, worldwide? [8]

It is in this context of insecurity and uncertainty that two similar concepts are coined: fake news and post-truth. According to Rodrigo Santos [9, p.124] ‘A fake news is a lie told to obtain some gain on the part of its perpetrator’, that is, when talking about fake news in the political scenario, it refers to lies that are deliberately disclosed with the objective of obtaining some gain, mainly about electoral issues.

The concept of post-truth is a little more complex. For Santaella [8], there are two possible interpretations for the concept. One, related to the meaning of the expression itself, that is, it would be a concept after the fact that the truth was already known. The other, more recent, means that the truth is no longer relevant. For this work, the second perspective is adopted: the non-relevant truth in the context of generalized disinformation generated by digital social networks.

Considering the current scenario of influence of quick information on society, including political decisions based on inaccurate information, this work is situated. Therefore, this research intends to answer the following research question: ‘Is it possible to simulate the propagation of disinformation from ordinary differential equations, in order to predict the impact of fake news in the communicational scope?’ In order to answer the previous research question, the general objective is the study of models generated from ordinary differential equations which, in fact, reflect simulations of information propagation. As specific objectives, we intend to analyze such models from the perspective of fake news, observing the social impact of disinformation on a certain population of individuals. Finally, it is intended to propose strategies from a computational and educational point of view that can, in fact, mitigate the effects of linking fake news today.

2. Modeling the spread of information

Digital social networks such as Facebook, Twitter or YouTube, managed by algorithms based on artificial intelligence, have gained extreme relevance in the social life of individuals, especially since the 2010s. Such importance is largely due to the increase in internet coverage worldwide, driven by internet access by individual devices such as smartphones and tablets [10]. From these advances, several researchers, in different areas, became interested in modeling the phenomenon, in an attempt to observe the virtual behavior of individuals from their actions through digital social networks.

According to Wang and his colleagues [11], digital social networks emerge as ‘model organisms’ of Big Data and, for the most part, are dynamic models based on information diffusion through Ordinary Differential Equations (ODE). However, in more recent models, the inclusion of Partial Differential Equations (PDE) is perceived as integral parts of the mathematical models which describe the problem in question.

Studies on the dissemination of information through digital social networks have gained extreme relevance in the academic and research environment. The interdisciplinary character of such studies is observed, since the phenomenon in focus can be analyzed from a mathematical point of view, from computer science, from social communication, from sociology, marketing, among others [11].

It is observed that the first models for the dissemination of information were thought of by the academic Rogers [12] and his theory of the diffusion of innovation gained strength in areas such as marketing and administration, culminating in the dialogicity between digital social networks and information dissemination. Therefore, as a pioneering theory on the issue of information diffusion, the mathematical models derived from this theory were considered in this work.

Diffusion of innovation is then defined as the theory that seeks to explain how new ideas and technologies spread across different cultures. [11]. For Rogers [12] there are four elements that influence the diffusion of a new idea: innovation itself, communication channels, time, and the social system. For the same author, innovation is conceptualized as a new idea, practice, or object if it is perceived as new by individuals or other adoption units (companies, institutions, among others).

From the definitions by Rogers [12] it is intended, under the ordinary differential equations, to identify factors that influence the spread of information from a mathematical point of view and how such models adapt to the process of diffusion of false information.

For this work, the classification in levels of adoption of innovations defined by Rogers [12] is considered: innovators, representing 2.5% of the total; early adopters, representing 13.5%; initial majority, representing 34%; late majority, representing 34% and, finally, latecomers, representing 16%. In addition to the definitions by Rogers [12], mathematical curves were observed which would adequately model the phenomenon of information scattering. Among the possible models, those that adopted the logistic curve were chosen, which is characterized by an inflection point where the curve changes its concavity downwards to concavity upwards. After the change of inflection, few individuals would adopt the innovation.

It is important to note that the influence of characters on social networks is not identical for each profile. There are individuals who exert greater influence on the population, who are usually more experienced and have a higher social status. To better understand this process, in the context of mass communications, the two-step flow theory of Katz and Lazarsfeld [13] is considered. First, opinion leaders should be willing to accept the information. Next, opinion leaders pass on their own interpretations or opinions to others, as illustrated in Figure 1.

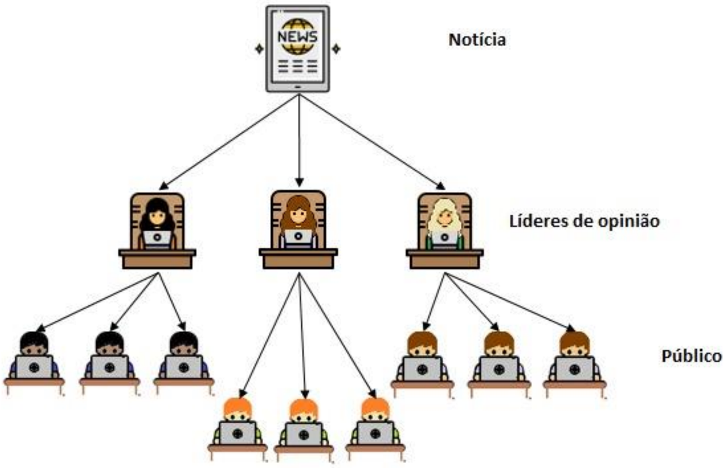


Figure 1: Mass Communication Flow.

From the theory of the flow of mass communication in two steps, it is possible to observe the fundamental role of opinion leaders in the dissemination of information. Considering the context of social networks, we have the so-called digital influencers: people who gather a significant number of followers on their social networks and, therefore, gain relevance in their posts, driven, above all, by the algorithms of social networks. Therefore, the post on a certain subject by a digital influencer is much more relevant than posts by the public, that is, it is the digital version of the opinion leader. However, the dynamics of social networks is quite different from the dynamics of mass media and, in this sense, the study of robust mathematical models that translate this phenomenon is of paramount importance.

3. Research Methodology

From the two-step mass communication flow theory [13] and the definitions for the different profiles of innovation adoption [12] we tried to adopt mathematical models that reflected the logistic behavior, which is the most suitable for the phenomenon. Therefore, the present work is outlined as exploratory research, with a quantitative character. The research is characterized as exploratory because the mathematical models studied have not been used, so far, to model the dissemination of fake news in social networks [14].

The research problem in question arises from the need, on the part of researchers, to understand the social phenomenon of fake news. The post-positivist perspective was chosen, which defends a deterministic philosophy in which causes determine effects [15]. By hypothesis, it is believed that the dissemination of fake news occurs through a process like the dissemination of information, that is, it is intended to validate the models of information diffusion, under the cut of ordinary differential equations, as descriptors, also, of the phenomenon of spreading fake news.

First, a literature review on the subject was carried out, observing the existence of publications by Brazilian researchers involving mathematical models for the dissemination of information in social networks. As these works were not found, we searched for works published in English that addressed the research object. The works of Wang [16], [17], Xu [18] and Wang [11] presented several approaches involving differential equations, both ordinary and partial, to which they modeled the diffusion of information from known phenomena, epidemiological problems.

4. Results and discussions

The mathematical model of innovation diffusion chosen was represented by the following equation [11]

$$\frac{dN}{dt} = g(N,t)[\bar{N} - N(t)],\ N(0) = N_0, \qquad (1)$$

where the function N is the cumulative number of adopters at time t in a network. $\bar{N}$ denotes the total number of potential adopters. $g(N,t)$ represents the diffusion coefficient, that is, the way in which the innovation spreads. Therefore, the information dissemination rate as a function of time is proportional to the difference between the total number of potential adopters and the total number of adopters at any instant of time t.

The diffusion coefficient $g(N,t)$ depends on several aspects, namely: the nature of the information; the available communication channels and attributes of the social system. Considering the cut in the dissemination of fake news, the influence of the nature of information occurs in several ways. Information can be purposely biased, with the aim of causing controversy, or misinformation with the aim of ensuring relevance on social networks (the more clicks, the greater relevance). About communication channels, it is observed that digital social networks are an efficient channel due to the speed with which information is disseminated. Facebook, Twitter, Whatsapp are tools used ostensibly by Brazilians and, in this sense, they are important communication channels. Regarding the attributes of the social system, there is information on who are, in fact, the social actors that are acting in cyberspace, that is, who are the people who have access to fake news, who work for its dissemination and who are the individuals influenced for them. At this point, the so-called bots stand out, which are fake profiles created on digital social networks with the aim of generating relevance to certain information through clicks and views. Twitter is one of the platforms that houses this type of profile. Contrary to this discussion, there are real individuals who are not part of the universe of digital social networks, either by choice or by lack of digital ability to communicate through the platform. Therefore, the attributes of the social system under study in the proposed research problem are not simple.

Despite the difficulties described, we considered, like Wang [18], three cases of innovation diffusion.

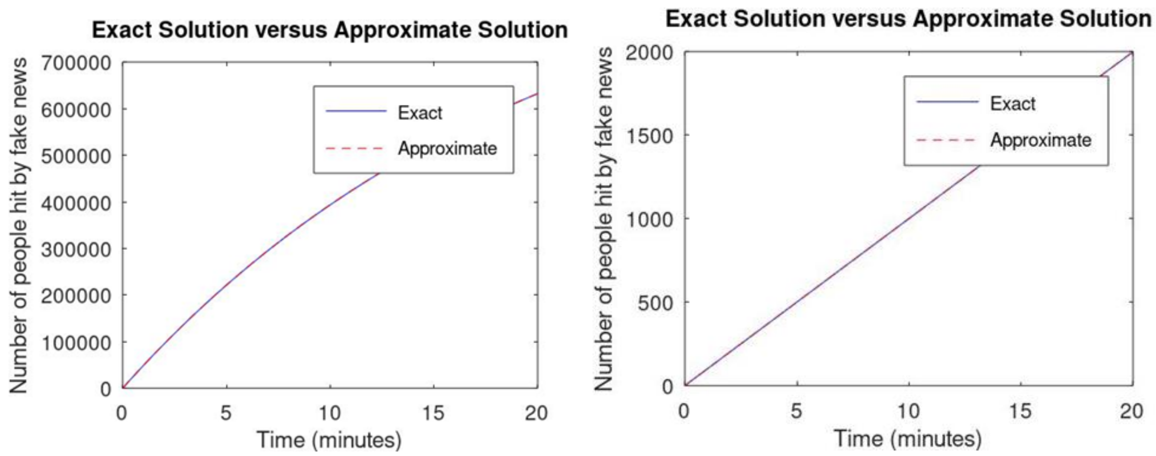
Case I: $\boldsymbol{g(N,t)=\alpha}$

Considering the diffusion of information as a constant, a diffusion coefficient independent of the number of adopters is being represented, that is, a model of strictly external influence. The function that represents the number of innovation adopters as a function of time t is given by

$$N(t) = \bar{N} - (\bar{N} - N_0)e^{-\alpha t} \qquad (2)$$

Considering the analytical solution (2) and a numerical approximation to equation (1) from $g(N,t) = \alpha$ given by Euler's method, the following comparisons between the analytical and numerical graphs are presented. Numerical simulations and the analytical graph were generated from MATLAB. The h for Euler's method was 0.05 for both experiments.

In the first experiment, $N_0 = 1$, $\alpha = 0.05$ and $\bar{N} = 1000000$ were considered as initial parameters, that is, if it starts with just one individual who adopts the innovation and if it intends to reach 1 million adepts. In the second experiment, the same initial parameters were considered, with a different value for α, that is, $\alpha = 0.0001$. Figure 2 presents the exact and approximate solutions for the parameters described above.



(a) (b)

Figure 2: Spreading fake news by strictly external influence.

(a) Diffusion coefficient α=0.05; **(b)** Diffusion coefficient α=0.0001.

In Figure 2 (a) it is observed that, in 20 minutes, a little more than 600000 people are reached by fake news while in Figure 2 (b) 2000 people are reached by fake news in 20 minutes. It should be noted that, with this diffusion coefficient, an individual affected by fake news does not become a multiplier, that is, he does not influence other people. This is the main criticism of this model: it is not realistic, as the network influences the propagation of fake news.

Case II: $g(N,t) = \beta N(t)$

For this model, it is assumed that the diffusion coefficient is linearly proportional to the current number of adopters. The crucial difference of this model in relation to Case I is the influence of innovation adopters in obtaining new adopters. In the context of the dissemination of fake news, everyone affected by the fake news can become a replicator of it, depending, of course, on the value of the β coefficient. The function that represents the solution to equation (1) considering the function $g(N,t)$ described above is

$$N(t) = \frac{\bar{N}}{\frac{\bar{N}-N_0}{N_0}e^{-\beta\bar{N}t}+1} \quad (3)$$

Again, experiments were carried out using two different values for β, considering again the parameters $N_0 = 1$,N $\bar{N} = 1000000$ and β=0.0001 using the analytical solution (3) and the numerical approximation via Euler's method with h =0, 05. Figure 3 presents the simulations for the parameters described above through MATLAB.

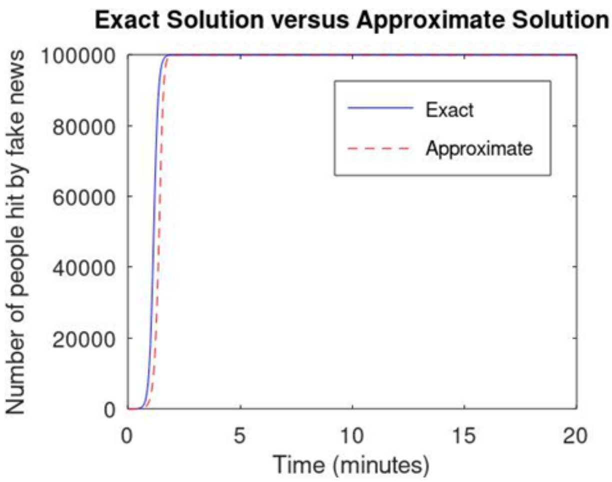


Figure 3: Spreading fake news by internal linear spreading.

It is possible to observe that, in this case, the total number of adopters of fake news is reached in approximately 2.35 minutes, that is, much faster than the previous case. It can be deduced that if a part of the adopters of fake news becomes a multiplier of the same, the fake news is quickly disseminated.

Case III: $g(N,t) = \alpha + \beta N(t)$

This model admits a mixed diffusion coefficient, that is, composed of a part referring to external influence and another part referring to internal influence. In this way, the diffusion of innovation takes place through external factors in the same way that adopters become multipliers of it.

The analytical solution for this model is given by

$$N(t) = \frac{\bar{N}-\frac{\alpha(\bar{N}-N_0)}{\alpha+\beta N_0}e^{-(\alpha+\beta\bar{N})t}}{1+\frac{\beta(\bar{N}-N_0)}{\alpha+\beta N_0}e^{-(\alpha+\beta\bar{N})t}}, \quad (4)$$

In order to carry out the experiments with the analytical solution (4) and the numerical solution by Euler's method for h=0.05 for the previous function $g(N,t)$, we used as input data $\alpha = 0.001$, β =0.0001, $\bar{N} = 100000$ and $N_0 = 1$. Figure 4 is the exact and approximate solution for the above data.

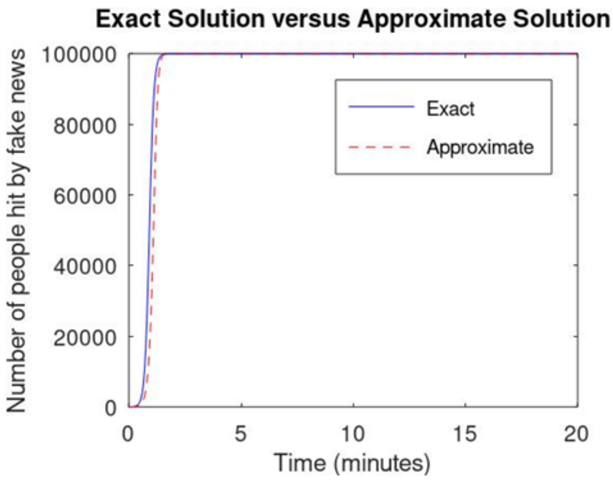


Figure 4: Spreading fake news by mixed spread.

It is possible to observe that in 2.05 minutes the dissemination of fake news reaches the total number of people intended, that is, when there is a mixed mechanism for the dissemination of fake news. It is concluded, therefore, that the most efficient mechanism of dissemination is the one that uses internal and external influences.

5. Final Considerations

The present work aimed to analyze the mathematical models of innovation diffusion as a modeling proposal for the dissemination of fake news.

Based on a model of innovation diffusion, in which individuals are divided between innovators and laggards, totaling 100% of the population, the relevance of innovation diffusion was observed in three scenarios: only by external influence, only by the influence of those that adopted the innovation and in a mixed way, that is, by external or internal influence.

Translating the model of diffusion of innovation to the dissemination of fake news, it is possible to observe that, not always, the models presented in this work translate reality. The model that only contemplates external influence was the one that presented the lowest speed of propagation of innovation, that is, it would have the least impact on the dissemination of fake news. However, this model is not realistic since it does not consider the influence of the information network itself on disclosure. This model would simulate, for example, a post on Twitter that doesn't receive any likes or retweets, and users see it and don't comment to anyone else about it. In fact, this is an unrealistic situation.

Among the situations of internal influence and mixed influence, the simulation of mixed influence is the most realistic: individuals can be informed from comments, likes or retweets (due to the influence of someone's profile or someone's comments), by a posting an unknown profile or an ad. This case presents the highest speed of dissemination of fake news, reaching the total number of individuals that is estimated in the shortest period.

From the simulations presented, more refined mathematical models can be proposed in future works, to try to absorb the different profiles of people who are affected by fake news according to their profile of adoption of innovations, a fact that was not discussed in the model introduced. It is concluded, therefore, that the innovation diffusion model can be adapted for the dissemination of fake news. However, the model does not have characteristics that can mitigate the spread of fake news. It is still believed that an education for social networks is the most effective instrument in the fight against disinformation.

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