Detection of Fake News in Virtual Social Networks: a review of methods based on propagation data

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ABSTRACT: The popularization of virtual social media has significantly increased the intentional dissemination of false information, known as Fake News. This type of news can cause a wide range of negative impacts on society, reinforcing the need for developing computational methods that can detect this harmful type of news. Among the existing computational methods, those that use news propagation data have been highlighted given their relation with the disseminative nature of information on social media. Thus, this study describes a state-of-the-art review of Fake News detection methods based on news propagation data. By introducing the basic concepts related to these methods and describing and discussing their main characteristics, the authors intend to provide subsidies for the creation of new research in this area.

KEYWORDS: Virtual Social Networks. Disinformation. Fake News. Propagation data; Computational tools.

RESUMO: A popularização das redes sociais virtuais aumentou significativamente a divulgação intencional de informações falsas, as chamadas Fake News. Esse tipo de notícia pode causar uma grande variedade de impactos negativos à sociedade, o que reforça a necessidade do desenvolvimento de métodos computacionais que possam detectar esse tipo nocivo de notícia. Entre os métodos computacionais existentes, destacam-se aqueles que utilizam os dados de propagação da notícia, tendo em vista sua relação com a natureza disseminava das informações existentes nas redes sociais. Assim, este trabalho apresenta uma revisão do estado da arte dos métodos de detecção de Fake News baseados em dados de propagação da notícia. Ao introduzir os conceitos básicos relacionados a esses métodos, além de apresentar e discutir suas principais características, espera-se fornecer subsídios para a criação de novos trabalhos na área.

PALAVRAS-CHAVE: Redes Sociais Virtuais. Informações falsas. Fake News. Dados de propagação. Métodos computacionais.

1. Introdução

Although news dissemination has historically been linked to traditional means of communication, such as newspapers, magazines and television, recently virtual social networks (RSVs) have consolidated themselves as an important means of disseminating news to users [1]. Among the reasons for this change, we can highlight the relevance and popularity of RSVs today, as well as the existence of a simplified content publication process in these networks [2]. This process, combined with the wide variety of interaction mechanisms with the published content, ends up boosting the audience of the publications and consequently of the RSVs themselves.

In this context, in addition to the real news, based on the journalistic investigation of the facts and typically made by the press, one can also find several examples of false information intentionally disseminated, known as *Fake News* [2]. Several epi-sodes in recent years have attracted attention to this type of information in RSVs, among which we can highlight:

- During and shortly after the occurrence of Hurricane Katrina in 2005, several fake news were disseminated with themes ranging from the origin and explanation of the atmospheric phenomenon, to what were the affected areas and the impacts generated on people's lives[1];
- On the occasion of the terrorist attacks on the Boston Marathon, which took place in the United States in 2013, false information was disseminated, generating fear and apprehension about the fact[2];

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1 Cf.: https://www.theguardian.com/us-news/2015/aug/16/hurricane-katrina-new-orleans-looting-violence-misleading-reports

2 Cf.: https://www.bbc.com/news/world-us-canada-39930236

- In the 2016 American presidential elections, disputed by Republican candidate Donald Trump and Democratic candidate Hillary Clinton, *Fake News* was disseminated with the objective of distorting facts and opinions related to campaign themes in favor of one or another candidate[3]; - More recently, during the covid-19 pandemic, false information was disseminated with themes that covered the origin of the disease, the potential use and application of medicines, in addition to the effectiveness of vaccines[4].

Episodes like these can generate different impacts on society, such as discrediting the public image of people and institutions, problems involving public security, and even an eventual collective feeling of insecurity [3]. Its frequent occurrence attracts the attention of society, thus arousing the interest of academia and industry in understanding and analyzing the occurrence of this phenomenon.

Due to the large volume and speed of publications in RSVs, and also, given the difficulty of manually evaluating the veracity of the news, the use of computational methods to combat this type of content becomes increasingly common [2]. Among the main methods for detecting *Fake News*, those related to the use of news propagation data recently stand out for their intrinsic relationship with the dissemination nature of information in RSVs. These methods use data related to user interactions that occur from the publication of news, as in the case of sharing a post, a comment or other types of reaction to the published content [1].

Despite the promising results obtained by *Fake News* detection methods that use news propagation data, as far as it was possible to observe, there are still few state-of-the-art review works that explored [4] their main characteristics. Thus, this research intends to address some important aspects not addressed by previous works.

In addition to this introduction, the article contains three additional sections. *Section 2* presents a brief theoretical foundation of matters inherent to the theme of the review. *Section 3* presents the related works and the model used for their comparison. Finally, *Section 4* presents the conclusions of this review, in addition to some additional considerations.

2. Basic Concepts

2.1 Virtual Social Networks

In recent years, RSVs have become massively popular, causing millions of users to use them every day [5]. RSVs are composed of people, entities, companies, and organizations that connect and interact with each other, in a collaborative environment that offers several communication facilities for its users. Given the wide variety of existing RSVs, there was a segmentation of these networks according to the published content and the audience they intend to reach. For example, while TikTok's content[5] consists mainly of videos and is aimed at young audiences, Linkedin[6] is focused on the corporate world, being widely used by companies and professionals from the most varied industries.

Relationships in RSVs are established based on principles of social influence, similar to those existing in non-virtual social networks [6]. When people are connected in an RSV, it becomes possible to influence other people's behavior and decisions. This influence can be observed in several situations, such as, for example, in the opinions issued regarding products purchased, in the demonstration of political positions, in the information about activities carried out by a particular user, or even in a place visited by him. In the context of RSVs, people typically make decisions based on their inferences from what other

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3 Cf.: https://www.washingtonpost.com/news/the-fix/wp/2018/01/03/how-hillary-clinton-might-have-inspired--trumps-fake-news-attacks/

4 Cf.: https://edition.cnn.com/2021/11/09/media/kaiser--covid-misinformation/index.html

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5 Cf.: https://www.tiktok.com/

6 Cf.: www.linkedin.com

people have done. This behavior is known as *herding behavior* [6] and occurs in the form of a sequential decision-making process of the users of a network. The popularity of RSVs, added to the social influence among their users, reinforce the need to study *Fake News* on these networks.

2.2 False Information

The state of the art characterizes the different types of false information such as *Misinformation* and *Disinformation* [2]. The first type includes information that is accidentally false as a result of errors. In the second type, there is the information known to be false, intentionally disclosed. That is, intentionality is established as a fundamental criterion used to distinguish the two types of false information. In this context, for a news to be considered a *Fake News*, one must confirm its dissemination was intention.

It is worth mentioning that the *Fake News* found in the RSVs are part of a system composed of several participants, and which goes beyond these networks. Among the most relevant participants are the press, fact-checking agencies, publicly exposed people, the legislative and judicial branches, as well as the users of RSVs themselves [2]. Although not all types of false information are necessarily news, as previously mentioned, the press plays an important role in the system of spreading false information. In some situations, the traditional process of journalistic work is mischaracterized by false information, replacing the careful investigation of the facts and the impossibility of the parties involved to express their opinions (often of a contradictory nature). To complement the work of the press in the context of *Fake News*, fact-checking agencies emerged. These agencies also monitor the information disseminated in traditional media, but focus on those circulating in RSVs [1]. The information analyzed is typically in the form of articles, news or even speeches and statements coming mostly from public people, giving preference to matters of general interest that have recently gained prominen-

ce. As a result of their work, an evaluation of the information analyzed is obtained, based on the fact--checking process that is carried out by their teams.

Publicly exposed people, such as celebrities, politicians, social influencers and other prominent personalities, are commonly both targets and disseminators of false information, since information related to these people usually obtain greater reach, as they are more shared and discussed [7]. The legislative and judicial branches play a central role in this system. With the increase in the dissemination of false information in RSVs, the need has arisen to study and propose laws that can punish those responsible for its dissemination, especially when they cause some kind of damage to the parties involved. Both in the Brazilian judiciary and in other countries, there are currently discussions in this regard. In the absence of specific laws, the judiciary today uses general laws, such as, for example, the laws of material and moral damages arising from the possible aggression to the honor of victims of false information [8].

2.3 Automatic Fight against Fake News

In addition to the manual treatment that can be carried out by a fact-checking agency, another possibility has been widely explored recently, namely the use of computational resources to automatically detect *Fake News*, thus avoiding the need for manual detection or complementing it when necessary [1]. This alternative has been widely feasible, especially due to the advance in the use of computational methods through the application of data mining and machine learning techniques [9], in addition to the increase in the processing capacity of the computers that support its execution.

In the context of the automatic fight against *Fake News*, two main features are consolidated: the detection and intervention of *Fake News* [4]. In detection we have, in short, a binary classification problem. Considering the evaluation of a given news, the result will be true if it is *Fake News*, or false otherwise. In order to

avoid the harmful effects of the dissemination of *Fake News*, we have the intervention functionality, in which it becomes possible to interrupt the propagation of a particular news.

3 State of the Art

3.1 Selection of works

To analyze the state of the art of methods for detecting *Fake News* that use news propagation data, a set of criteria was defined for the selection of related works. Initially, the bases of articles to be consulted were defined. Due to its popularity in topics related to computing, the following were selected: Institute of Electrical and Electronics Engineers (IEEE)[7], *Association for Computing Machinery* (ACM)[8], and Science Direct[9]. Once the article bases were defined, an initial search question was identified consisting of the keywords related to the theme of propagating intentionally disseminated false information, resulting in *"Fake News"+ propagation*. In addition to the search question, the criterion of identifying the system of "qualis" classification of articles was used, privileging, whenever possible, those in the upper stratum. Papers written after 2015 were considered due to the lack of papers published before this cut-off date.

3.2 Related Works

This section will present the works selected for review in which computational methods were developed for the detection of Fake News based on news propagation data. Each work is briefly described, including the data used, the type of learning, datasets and best results obtained in the experiments carried

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7 Cf.: https://ieeexplore.ieee.org/

8 Cf.: http://dl.acm.org

9 Cf.: https://www.sciencedirect.com

out by these works. Additional details of these works can be found through their references:

- *News credibility evaluation on microblog with a hierarchical propagation model* [10]: the authors rely on the triad of news, user and community to detect *Fake News*, proposing, as part of their study, the creation of a hierarchical model that identifies sub-events within the news, to describe their details. The automatic detection problem is treated as a graph optimization problem, in which an optimal solution is proposed. Text content data, *hashtag* topics, links, among others, were used. This work is based on supervised learning. The *datasets* used are SW-2013 and SW-MH370. The best result obtained was 0.889 (Accuracy).

- *CSI: A hybrid deep model for Fake News detection* [11]: the detection process is divided into three parts: *Capture, Score and Integrate* (CSI). The first module is based on the response and text, through a recurrent neural network, *long short-term memory* (LSTM), to capture a temporal pattern of user activities on the article and the *doc2vec* representation of the text generated in this activity. The second uses a neural network to learn the characteristics of the source based on the behavior of users according to their interactions, generating a score through a graph. The two modules are integrated with the third to characterize, or not, the article as *Fake News*. User data was used, without specifying exactly which ones. This work is based on supervised learning. The *datasets* used are Twitter and Weibo. The best result obtained was 0.892 (Accuracy).

- *Tracing fake-news footprints: Characterizing social media messages by how they propagate* [12]: this method uses the proximity of the nodes and the social dimensions to infer a representation of the users of the social network to subsequently represent and classify the propagation paths of messages propagated by said users. Data from the news propagation structure were used. This work is

based on supervised learning. The *dataset* used is an adaptation of Twitter. The best result obtained was 0.9380 (F-Measure).

- *Fake news detection on social media using geometric deep learning* [13]: this explores patterns of propagation of Fake News using *Geometric Deep Learning* (generalization of *deep learning* techniques to non-Euclidean data such as graphs that use convolutional neural networks), using four types of information: user profile, user activity, network, and content. Profile settings data, language, profile description, geolocation, verified user, social connections between users, and others were used. This work is based on supervised learning. The *datasets* used are adaptations of Twitter15 and Twitter16. The best result obtained was 92.7% (ROC AUC).

- *Hierarchical propagation networks for Fake News detection: Investigation and exploitation* [14]: developed the concept of hierarchical network propagation for the detection of Fake News. To build this hierarchical structure, it is based on two levels: 1. Macro-level (topological and temporal analysis of the network) and 2. Micro-level (topological, temporal and linguistic analysis of the network). Data from the news propagation structure were used. This work is based on supervised learning. The *datasets* used are Politifact and GossipCop. The best result obtained was 0.863 (Accuracy).

- *Network-based Fake News detection: A pattern-driven approach* [15]: proposes to investigate the patterns of dissemination of Fake News. In general, these patterns can be classified into three groups: 1. News-related patterns, 2. Patterns related to news publishers and 3. Patterns of relationship between the disseminators of the news. Data from the news propagation structure were used.This work is based on supervised learning. The *datasets* used are Politifact and BuzzFeed. The best result obtained was 0.929 (Accuracy).

- *GCAN: Graph-aware co-attention networks for explainable Fake News detection on social media* [16]: uses the content of the original *tweet* and the

sequence of corresponding *re-tweets* to detect the news as "*fake*" or "*not fake*". First, it extracts user information from their profiles and interactions, learning how to *embed* original content. It then uses convolutional (CNN) and recurrent (RNN) neural networks to learn the representation of the spread of *re-tweets*, building a graph that models the possible interactions between users. Finally, it establishes the correlation between the original tweet and its propagation, generating a binary prediction based on this correlation. Geolocation data, verified user, among others, were used. This work is based on supervised learning. The *datasets* used are Twitter15 and Twitter 16. The best result obtained was 0.9084 (Accuracy).

- *Graph neural networks with continuous learning for Fake News detection from social media* [17]: the authors consider that false and true information propagate differently on the internet. In addition to the flow information, they use eight attributes of the posts (verified Twitter user, user creation *timestamp*, number of followers, number of friends, number of lists, number of favorites, number of status and *timestamp* of tweets). It uses graph neural networks (GNN) to differentiate *fake* and *non-fake* news patterns. Verified user data, profile creation date, among others, were used. This work is based on supervised learning. The *datasets* used are from FakeNewsNet (Politifact and GossipCop). The best result obtained was 0.853 (Accuracy).

- Unsupervised Fake News Detection: A Graph-based Approach [18]: Method consisting of three steps: 1. Bi-click mining, based on news shared synchronously, generating a *Seed* set (heterogeneous graph – user and article vertices); 2. Bi-click mining of the remaining articles (without the restriction of synchronous sharing), using similarity of publication text and user information; and 3. Mining of the remaining articles (outside the bi-clicks), using similarity of the publication text and user information. Data from the news propagation structure were

used. This study was based on unsupervised learning. The *datasets* used are from FakeNews-Net (Politifact and GossipCop). The best result obtained was 0.800 (Accuracy).

- *Fake news detection in social networks via crowd signals* [19]: Motivated by a tool at the time, recently introduced in the Facebook social network, in this work the so-called *crowd signals* were used to detect *Fake News*. These signals are the explicit opinion of users indicating that certain content is *Fake News*. Its authors developed an algorithm that performs Bayesian inference capable of learning over time about the ability of users to opine on this type of content. User opinion data was used. This is based on semi--supervised learning. The *dataset* used is Facebook. The best result obtained was 0.9967 (Accuracy).

- *Fake news detection based on explicit and implicit signals of a hybrid crowd: An approach inspired in* meta--learning [20]: inspired by [19], this work also uses so-called *crowd signals* to detect *Fake News*. However, in contrast to the initial work, which uses the so-called explicit opinion of users, issued through a tool aimed at this purpose –, its authors explored the use of the implicit opinion of users, obtained through their behavior when interacting with this type of content. This work also combines the implicit opinion of users with that of machines (algorithms), forming the so-called hybrid crowd. Data on the implicit opinion of users, in addition to the number of interactions and the text of the news were used. This work is based on supervised learning. The *datasets* used are Gossip, Politifact, Gossip2, FakeNewsSet and FakeBR. The best result obtained was 0.9989 (Accuracy).

- *Early detection of Fake News on social media through propagation path classification with recurrent and convolutional networks* [21]: this work uses the classification of the propagation flow created by the news to perform early detection. This classification is carried out from the modeling of the news dissemination flow as a multivariate time series, in which each pair of values is a numerical vector representing the characteristics

of the user who participated in the propagation process. User data such as their friendships and followers were used, as well as the age and geolocation characteristics of these users, among others. This work is based on supervised learning. The *datasets* used are Twitter 15, Twitter16 and Weibo. The best result obtained was 0.921 (Accuracy).

- *Propagation2vec: Embedding partial propagation networks for explainable Fake News early detection* [22]: the authors attribute different levels of importance to the elements of news propagation, reconstructing knowledge about the complete flow of this news based on partial flows of the propagation. The method uses hierarchical attention mechanisms to emphasize the most important information in these flows. User data such as: whether they are verified, their followers, friends, lists, favorites, *tweets*, among others, were used. This work is based on supervised learning. The *datasets* used are Politifact, Gossipcop. The best result obtained was 0.897 (Accuracy).

- *Detect rumors in microblog posts using propagation structure via kernel learning* [23]: initially creates a representation of propagation through trees to subsequently capture patterns that differentiate the types of rumors by evaluating the similarity of their structure (kernel-based method). Although it describes the detection of rumors, the output of this method also points out a news as *"fake"* or *"not fake" (non-rumor, false rumor, true rumor or unverified rumor)*. User data such as their followers and friendships, account verification status, post history, among others, were used. This work is based on supervised learning. The *datasets* used are adaptations of Twitter15 and Twitter16. The best result obtained was 0.750 (Accuracy).

3.2 Comparative model

To proceed with the analysis of the state of the art, three criteria for comparison between the selec-

ted works were defined. These are: the propagation data used, the indication of the use of restricted access data, and whether they perform early detection of *Fake News*. The choice of these criteria aims to deepen the understanding of the main characteristics and limitations existing in the selected works.

There is a wide variety of propagation data used by the state of the art. In [4]'s work, a classification of these data was established considering the following categories: contribution, user, subject, temporality, and network. User's contribution concerns the different types of media (e.g., text, audio, or images) used during propagation. In relation to the user who propagates the news, their profile data and reputation are obtained, which may be linked to their ability to identify or publish *Fake News*. Another relevant aspect is the subject of the news, which aims to explore the relationship of the news in question with popular and controversial issues. Regarding the temporality criterion, data on the time of each of the news propagations are used, an important criterion from the point of view of the automatic detection of *Fake News*. Finally, we also have the network criterion, in which we intend to identify whether data from the relationships of each user who interacted with a given news item were used.

Based on the exposed classification, Table 1 summarizes the relationship of the selected works with the types of propagation data used. It is possible to observe that the most frequently used types are user data and their network of relationships, in addition to the temporality related to the interactions that occurred during the propagation of the news. The contribution data were also used, albeit in smaller numbers.

Although several propagation data are used by the state of the art, their practical application can be made unfeasible in the face of restrictions on access to these data. These restrictions are mainly due to the consolidation of the legal framework of data privacy [24], especially due to laws such as the *General Data Protection Regulation* (GDPR) and the General Data Protection Law (LGPD). Considering the large number of security incidents and the popularization of internet use around the world, there was a great debate about the need for laws to help combat cybercrime, which culminated in the creation of these laws. In response to this move, RSVs created their data privacy policies, ensuring proper handling and restriction of data access. These policies focus primarily on personal data (e.g., name, surname, photograph, and geographic location) and sensitive data (religion, racial origin, among other examples). Personal data can be used to identify a user, while sensitive data has the potential to discriminate against people. Thus, studies that depend on restricted access data to detect *Fake News* have a significant disadvantage compared to those that do not depend on this data.

Table 1 - Use of propagation data: C (Contribution), U (User), A (Network), T (Temporality) and R (Network).

Study	C	U	A	T	R
[10]		X	X		
[11]		X		X	X
[12]		X		X	X
[13]		X		X	X
[14]	X	X		X	X
[15]	X	X			X
[16]	X	X		X	X
[17]	X	X		X	X
[18]	X	X		X	X
[19]		X			
[20]	X	X		X	X
[21]	X	X		X	X
[22]		X		X	X
[23]		X		X	X

Table 2 presents a summary of the studies related to the use of restricted access data, and it is possible to observe that there is an equivalent distribution between the studies that depend on these data and those that do not.

A challenge posed to automatic *Fake News* detection methods, both for those using the propagation data or possibly other types of data, is the fact that the propagation of the news can take hours, days, weeks and even years to complete. From the moment the news is published, it can be permanently available. That is, users who may have access to this content can still interact with it and thus can create new cycles of news propagation. Considering that waiting longer makes it difficult to implement intervention actions aimed at avoiding the impacts of *Fake News*, some detection methods based on propagation data seek to perform detection in advance [1]. In these works, detection must be carried out in the early stages of propagation, that is, before this news has been widely disseminated. This criterion was also considered as part of the analysis of the state of the art.

Looking at Table 3, one can verify that the use of early detection by *Fake News* detection methods is still uncommon.

Table 2 - Use of restricted access data.

Study	Does it use Restricted Access Data?
[10]	Yes
[11]	Could not be determined.
[12]	No
[13]	Yes
[14]	No
[15]	No
[16]	Yes
[17]	Yes
[18]	No
[19]	No
[20]	No
[21]	Yes
[22]	Yes
[23]	Yes

Table 3 - Use of Early Detection.

Study	Does it perform Early Detection?
[10]	No
[11]	No
[12]	No
[13]	No
[14]	No
[15]	No
[16]	No
[17]	No
[18]	No
[19]	No
[20]	No
[21]	Yes
[22]	Yes
[23]	Yes

4 Final considerations

In recent years, the use of virtual social networks to disseminate news has become increasingly frequent. However, these networks are also used for the dissemination of Fake News, which are intentionally false information. In this article, a review of the state of the art was performed, focusing on works that use a particular type of data related to the propagation of news. Although popular, few reviews [4] have been made to specifically evaluate this particular type of data. In this context, this article updated the previous review work [4], highlighting the Fake News detection works that use propagation data. The result of this review points out some relevant observations that deserve to be highlighted. First, the spectrum of propagation data types used by the state of the art is broad. Regarding the use of restricted access data, the work is divided in a balanced way among those who depend on this data or not. Finally, the early detection of Fake News, which seeks to enable intervention actions after news detection, is still little explored.

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