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The Rumor Categorizer: An open-source software for analyzing rumor posts on Twitter

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ABSTRACT

The Rumor Categorizer Software (RCS), an open-source software, categorizes Twitter posts based on their stance towards a given rumor into six categories; rumor tweet, anti-rumor tweet, rumor retweet, anti-rumor retweet, rumor-related tweet, and rumor-related retweet. Then for the publishers of those tweets/retweets, analyze the user dynamics. Furthermore, the software calculates the number of users belonging to any combination of the sextuple categories and plots the number of tweets/retweets in each hour for rumor and anti-rumor. The software aids researchers and practitioners in analyzing rumors effectively.

Code metadata

Current code version	v1
Permanent link to code/repository used for this code version	https://github.com/SoftwareImpacts/SIMPAC-2021-185
Permanent link to Reproducible Capsule	https://codeocean.com/capsule/5652628/tree/v1
Legal Code License	MIT License
Code versioning system used	GIT
Software code languages, tools, and services used	Python
Python Compilation requirements, operating environments & dependencies	Python packages: matplotlib, nltk, numpy, xlrd, xlsxwriter
If available Link to developer documentation/manual	Not provided
Support email for questions	abodaghi@cityu.edu.hk

1. Introduction

The introduction proceeds with the three main aspects of this open software which are; (1) Considering the competitive nature of rumors on social media, (2) Characterizing the spreaders based on the stance of rumor posts, (3) Extracting the macro patterns of diffusion. Finally, the uniqueness and generalizability of the software will be discussed.

1.1. Competitive nature of rumors on social media

Nowadays, with the inclusive use of mobile computing devices [1] and the pervasiveness of social media [2], rumors are part of our daily lives whose impacts could not be dismissed. Rumor, as social psychology literature defines, is a story or a statement in general circulation without confirmation or certainty to facts [3]. Due to the definition, the very nature of rumors is uncertainty that means rumors come along with anti-rumors. The confrontations of these two on social media impact their spreading through the network [4]. For instance, in the case of the Zika Virus Outbreak, the researchers [5] analyzed rumor and anti-rumor and noticed the differences between their diffusion networks which has a direct impact on the spreading process in general. In fact, the competitive nature of rumor spreading demands inclusive models to consider both contagions simultaneously [6]. The RCS takes into account this fundamental feature in rumor analysis.

1.2. Characterizing the spreaders

Broadly speaking, the rumor analysis can be summarized as rumor detection, rumor veracity, rumor tracking, and rumor stance [7]. Rumor detection deals with the classification of social media posts as

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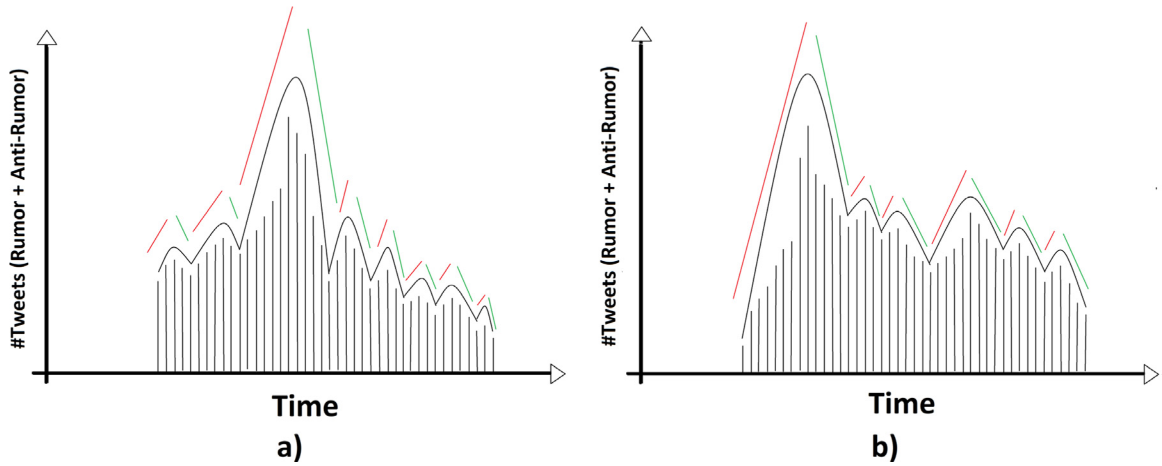

Fig. 1. The wavelike patterns of rumor spreading on social media. (a) The Shipstern wave with the peak appeared after a couple of minor spikes. (b) The Teahupoo wave, which bursts out most of its power at the beginning with the highest peak, followed by moderate spikes after.

either rumor or non-rumor [8]. For a given detected rumor, rumor veracity classifies the rumor as true or false, while in the case of rumor tracking, the task is to clarify social media posts as either related or unrelated to a given rumor. Stance classification focuses on the identification of opinions in social media posts or stance of their publishers with respect to a given rumor and has been performed early as a 2-class problem (support and deny) [9] or more recently as a 4-class problem (support, deny, question and comment) [10]. Therefore, based on the context and the tweet's type, rumors on Twitter could be divided into six categories; rumor tweet, anti-rumor tweet, rumor retweet, anti-rumor retweet, rumor-related tweet, and rumor-related retweet. The identification of spreaders based on their characteristics is one of the crucial steps in rumor analysis [11]. In this vein, some researchers [12] have tried to characterize Twitter users involved with the discussions of "fake news" based on different characteristics such as type of user, gender, and political affiliation; however, their study was limited to political context. Also, there have been some efforts to do the characterization based on the retweeting behavior of their publishers [13]. The RCS first categorizes the rumors into the mentioned sextuple categories and then extracts the characteristics of their spreaders.

1.3. Extraction of macro patterns

A variety of variables impact the form of rumor diffusion on social media. Even though these variables and the way they influence diffusion have not been discovered entirely yet, but any pattern resulting from their impact at the aggregate level would be of interest. One of these patterns is the wavelike form of spreading, which has been proved to have a direct influence on the lifespan of rumors on social media [14]. Indeed, the investigation of rumor spreading on Twitter in a competitive process has shown that rumors last longer if the delay in their detection increase [15]. This proven relationship between the time of detection, the wavelike pattern, and the lifespan of rumors indicates the importance of real-time monitoring of wavelike patterns when the early detections fall short. Moreover, some studies have shown that the original source of rumor has an impact on the temporal patterns of diffusion [16]. This means the study of wavelike patterns of diffusion aids the identification of the origins. In [14], two general forms of these wavelike patterns in rumor spreading are presented. These patterns, which are named after two oceanic waves with similar shapes; Shipstern, and Teahupoo, are illustrated in Fig. 1. Early detection of the pattern paves the way for devising better strategies to mitigate the devastating effects of rumors by the advent of crisis events. The RCS plots the frequency of rumor and anti-rumor tweets per hour which aids the monitoring process of rumor spreading and extraction of wavelike patterns of diffusion in early times.

1.4. Uniqueness and generalizability

To the best of our knowledge, there is no open-source software that enables micro and macro level analysis on rumors while considering the competitive nature of diffusion in which rumor and anti-rumor spread simultaneously. RCS provides user characterization based on the stance of rumor posts at the micro level and extracts wavelike patterns of diffusion at the macro level. Even though RCS is created for rumor analysis on social media, but it is applicable to the diffusion of any contagion which has a competitive nature. It means the network and the type of contagion which spreads through it impose no barrier for the use of RCS, as long as there is another contagion that spreads against the first one.

2. Description

The RCS is written in python and uses libraries such as NLTK, Numpy, and Matplotlib. The input is an excel file containing all the crawled tweets for a rumor story. Each tweet is presented in a separate row in the excel file and includes information related to both tweet and user. The tweet part covers data such as the date and time of publishing, #favorite, type of tweet (retweet, quote, reply, or original), the tweet and user IDs of the referred tweet in case the tweet be a retweet, quote, or reply, frequency of tweet occurrence in the dataset. Finally, the last feature is the nature of the tweet which can be a rumor (marked as 'r'), anti-rumor (marked as 'a'), not related (marked as 'n'), or just questioning about the rumor (marked as 'q'). The user part includes data of the user who published the tweet such as ID, #tweets, #followings, #followers, data and time of the account creation, language, and description sentence. After reading the input, the software first divides the users into different categories based on their stance towards the rumor;

- Origin Spreaders of Rumor Tweet (Category 1)
- Origin Spreaders of Anti-Rumor Tweet (Category 2)
- Rumor Retweeter (Category 3)
- Anti-Rumor Retweeter (Category 4)
- Origin Spreaders of Rumor Related Tweet (Category 5)
- Retweeter of Rumor Related Tweet (Category 6)

Then based on the above categories, the following calculations will be done for each user:

- The number of the published tweet in each category
- The ratio of following to follower
- Membership period (#days)
- The average daily rate of tweeting

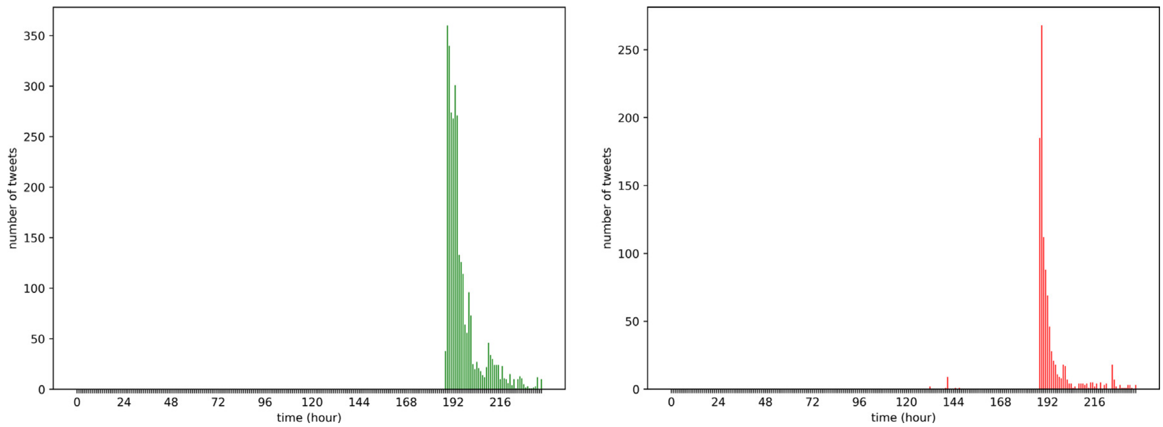

Fig. 2. The number of tweets per hour for a sample rumor dataset. The green plot represents the anti-rumor tweets, while the red plot represents rumor tweets. The plots reveal the Teahupoo nature of the sample rumor. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

- The sentiment score for the description sentence (negative, positive, and compound)

Furthermore, the mean value of the above features will be calculated for all users in each category and also for pure users in each category (i.e., users whose tweets in the dataset all belong to only one of the sextuple categories). Finally, the RCS plots hourly plots of rumor and anti-rumor, which enables detection of macro patterns such as wavelike forms of diffusion (Fig. 2).

2.1. Functionality and scalability

As earlier mentioned in the introduction, RCS is capable of doing the above analyses on any rumor or contagion in different networks as long as the counter contagion is spreading also. To utilize RCS on different data sources, the only task that needs to be done is the annotation of contagions with at least two labels that refer to the main contagion and its counterpart. Other labels (if any) could be those whose stances are not clear enough to support or deny the two contagions but somehow are related to them. This would be the only input to RCS whose accuracy has a direct impact on the credibility of output results. Therefore, researchers need to make sure the annotations are accurate and also the required data (the five mentioned bullets in the description) for each piece of contagion exist in text format because most parts in RCS are based on text analysis. Also, the calculations are integrated in a way to free the users from any handling during the process and also to minimize the runtime that is most welcome in case of large datasets.

In terms of the user characteristics, even though RCS is designed for Twitter data, but it supports other major social media like Instagram and Facebook. However, it should be noted that the characteristic of the ratio of following to follower is not applicable to undirected networks such as Facebook, where mutual agreement between two users is a must for link creation. Moreover, even though the wavelike patterns of diffusion can be seen in almost every social media, but their interpretations may differ. The introduced macro patterns in this manuscript are based on proven results from Twitter-based research [14] and may not have the same interpretations in other social media.

3. Impact

The efficiency of RCS in rumor analysis is proven in recent research [14]. Indeed, the software facilitates a series of calculations for rumor analysis at micro and macro levels. The former level of analysis provides the categorization and extraction of user data with respect to each category, while the latter aids in the detection of wavelike forms of diffusion. Also, recently a similar approach has been taken into account for fake news analysis but with a focus on the underlying graphs [17]. The latter level of analysis helps with the extraction of wavelike forms of diffusions. Based on the recent research [14], the two distinctive wavelike patterns, Teahupoo and Shipstern, leave different impacts at the aggregate level, and early detection of them may lead to better strategies against rumor spreading on social media. RCS could be implemented in real-time systems of rumor monitoring to enable the selection of such patterns at the early stages of rumor spreading. In fact, the data-driven approach toward rumors on social media promises a bright future that may lead to a better understanding of different cyber behaviors. Moreover, a variety of features such as gender, race, geography, and educational level could be considered in the analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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