The Impact of a Crisis Event on Predicting Social Media Virality

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Abstract. Understanding why specific information pieces become viral in online social networks is a fundamental step in governing social media platforms. While previous studies explored which user and network properties enable information virality, little is known about how offline crisis events impact these features. Here we investigate to what extent a crisis event impacts virality prediction models. We analyze Twitter data before and after the 2022 Russian invasion of Ukraine as a case study. We train and test statistical learning models on data before and after the invasion, evaluating which features related to content (e.g., existence of an URL), the user (e.g., number of previous tweets), or the network (e.g., degree centrality) are most relevant to predict virality. Tweets with more than 100 retweets are considered viral. We observe that the crisis event affects virality prediction: predictive accuracy is reduced when a model trained on data before the invasion is evaluated on data after the invasion—instead of being evaluated on data before the invasion. We observe that the crisis event leads to an increased fraction of viral tweets by users with fewer followers after the invasion. Moreover, we observe that, after the invasion, tweets containing URLs are more likely to become viral, implying an increased interest in website links, photos, and videos. Overall, our study reveals a shift in the importance of features underlying virality as a result of an offline crisis event.

Keywords: Social networks · Social media · Information diffusion

1 Introduction

Social media platforms are nowadays places where users can express themselves at an unprecedented scale [21]. The opportunity for sharing content on social media allows users to be exposed to a great amount of information, making social media platforms like Twitter, Instagram, and Facebook important assets when it comes to accessing real-time data [11]. More specifically, during crisis events like natural disasters [19], pandemics [17], or armed conflicts [29], information is often shared by people and authorities on social media platforms [22, 25, 26]. Not all of these messages become viral and are widely shared, though. Which user, content, or network features enable information to become viral? And how is the

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importance of such features impacted by crisis events? These are questions we approach in this paper.

Online viral information during crisis events has serious societal effects. Social media platforms provide a fast and effective manner to disseminate important information, which improves awareness and can offer safety information on how to react during and after a crisis event. On the downside, misinformation is often spread (un)intentionally by individuals or organizations during crisis events [17]. The spread of misinformation can lead to the lack of trust in reliable news sources and authorities, even facilitating conspiracy beliefs [3,9]. Machine learning models that predict when information spreads widely in an online social network can aid in tackling the spread of misinformation during crisis events and can be used to understand the drivers of information sharing by humans.

While prior studies investigated which features contribute to information going viral within an online social network [13,20], it remains unclear to what extent the influence of these features is impacted by real-life crisis events. As the online and offline worlds are blended in today's society, the relation between the underlying features and the possibility of a viral spread of information on social media is likely to be impacted by real-world events. In a broader context, machine learning prediction models can be affected by concept drift [6]: the relationship between input features underlying machine learning models and an output of interest can change over time. Therefore, some features underlying virality might become more or less important for model prediction during and/or after a crisis event, or the type of the relationship between a feature and virality might change. For example, the indegree (followers) of a user is often considered to be the most predictive feature for virality on Twitter [8,13,30], however, it is uncertain whether its relationship with virality might change due to a real-world event. As a result, this may impact virality prediction models' accuracy.

To study the effect of a crisis event on the virality prediction model in online social networks, we focus on Twitter as a social media platform, together with the invasion of Russia in Ukraine (24-02-2022) as a crisis event. Twitter is chosen because it is a widely used platform, often used to study information spread [7,8,13,15,17,19,20,29,30]. We retrieved tweets posted before the invasion (February 21 to 24, 2022) and right after the invasion (February 24 to 25, 2022).

We believe this is a unique dataset as it allows to study the influence of real-world events on feature dynamics underlying virality on Twitter, while still analyzing tweets about the same broader topic. Contrarily, in prior literature, only tweets posted during or right after the crisis event [19], or users that tweeted about the event [7], are investigated. The latter is achieved by investigating tweets about another topic prior to the event. Furthermore, the dataset provides a timeserving perspective of how a real-life crisis event impacts the influences of content, network, and user features underlying the virality of tweets.

We perform a descriptive analysis to investigate to what extent content, network, and user features underlying a tweet virality prediction model are impacted by a real-world crisis event. The characteristics and performance of three binary virality classification models are analyzed. One model is trained on data before the invasion (before model), one model on data after the invasion (after model), and one context-ignorant control model on before and after data (ignorant model). Using these models, we explore (i) whether the model performances are context-dependent, (ii) how important and what type of relationship content, network, and user features have within the model, and (iii) whether the relationships between the features and virality differ before and after the event.

2 Related Work

2.1 Defining Virality

Providing a proper definition for virality is difficult as this concept can be context-specific, depending on specific datasets or topics. One simple way to define virality is to consider the number of retweets and define a threshold for the minimum number of retweets to classify a tweet as viral [13]. Another common measure is structural virality [10,31], which also considers the pattern of retweet cascades. Given the difficulty of building a retweet cascade from the functionality provided by Twitter's current API, we use the number of retweets as a measure of virality. We consider that a tweet is viral if it is retweeted a number of times above a certain threshold. This is a similar approach to the method of Jenders et al. and Neppalli et al. [13,19] (see Sect. 3.1 for details).

2.2 Crisis Events on Twitter

During crisis events, social media is often used as a source of information about the event [22,25,26]. The existing literature is often focused on the dynamics of features during or after the crisis event, without taking into account the state before the event [17,19,29].

The study by Neppalli et al. considers a model that predicts how likely a tweet is to be retweeted more than a specific threshold (with 20 as the best-performing threshold), using 7.5M initial tweets about hurricane Sandy [19]. Both user and network features were found to be important predictors of virality. However, there was no distinction made between which user features were the most meaningful. Another study found the number of followers (indegree) to be the most important predictor when predicting retweet chain size using data from the Japanese Earthquake and Tsunami [24]. Unsurprisingly, also within non-crisis events, the number of followers (indegree) is often found to be the strongest predictor for viral information diffusion [8,13,30]. Therefore, we expect the number of followers and the number of listed users (a related network feature) to be among the most important predictors.

While the study by Buntain et al. did include a comparison between before and after crisis event data [7], the tweets did not include a similar context. The study analyzed the effect of three crisis-event Twitter datasets on activity and social interactions on Twitter: the 2013 Boston Marathon Bombing, the 2014 Sydney Hostage Crisis, and the 2015 Charlie Hebdo Shooting.

Tweets were scraped two weeks before and after the events, using the keywords *Boston, Sydney, Paris*, and *Hebdo*. The work of Buntain et al. differs from ours in several dimensions: Buntain et al. do not focus on any predictive task; moreover, the study focuses on understanding how different topics, containing similar keywords, are discussed by the same users (one crisis and one non-crisis), rather than studying the influence of an event on an already discussed topic. For instance, tweets containing the word 'Boston' could describe the weather when posted before the event, but after the event, the same keyword mainly addresses the bombing. In the current study, the tweets from the before invasion dataset already address the situation between Russia and Ukraine.

The results of Buntain et al. are interesting with respect to our expectations of what features underlying virality are important within a crisis context. Their study notes that the number of relevant tweets, retweets, hashtags, and URLs increases significantly after the events; the topic itself goes viral on Twitter. Moreover, accounts from the police, government, and news organizations become an important means to obtain prompt information. The latter result suggests that the influence of some user features might be impacted by crisis events.

Another interesting study about the war in Gaza between Palestine and Israel highlights that, next to the usual users of interest (e.g. politicians, journalists, and activists), a new group of users get an important role in the dissemination of information on Twitter: witnesses [29]. This group of users is becoming an interesting and important source of information during crises, such as wars, because they tweet about their first-hand experiences. Importantly, this class of users is not necessarily central in the network according to degree centrality, i.e., the number of followers or the number of listed users (how many users have added you to their list). Therefore, we expect in our current study that the network features are impacted by the crisis event.

3 Methodology

3.1 Datasets

Crisis Event Data Extraction. Twitter data was extracted using the historical Twitter API and Tweepy [27], between the 14th and the 16th of March 2022. All scraped tweets were written in English because it is the most used language on Twitter [12], and the most convenient for sentiment analysis. To avoid duplicate tweets, all collected tweets were originally written tweets and did not contain any replies, retweets, or quoted tweets. Keywords used to scrape tweets related to the invasion of Russia in Ukraine were: *Ukraine*, *#Ukraine*, *Russia*, *#Russia*, *Putin*, *#Putin*, *Zelensky*, *#Zelensky*, and *#UkraineRussianWar*. This means that all collected tweets, posted by publicly available user accounts on Twitter, contained one or more of these keywords. These keywords are chosen because of their likelihood to represent content related to the tensions/invasion between Russia and Ukraine and/or because they were trending.

On February 24 2022, Putin announced the invasion of Ukraine on national television a little before 03:00 UTC, after which explosions were reported in

Kyiv, Kharkiv, Odesa, and the Donbas region [1,28]. Therefore, tweets posted before the invasion were scraped using a historical time frame from 02:30 UTC on 21-02-2022 up to 02:30 UTC on 24-02-2022: the before data set. Tweets posted after the invasion were scraped using a historical time frame from 03:00 UTC on 24-02-2022 up to 02:30 UTC on 25-02-2022: the after data set. As 73% of all retweets already occur within 2 h after posting the original tweet [32], the time gap of 18-23 days between posting and scraping the tweets should be enough to capture an accurate retweet number for each tweet. The Ukraine before data consisted of the tweet and user features of 697,498 initial tweets, written by 276,612 unique users. For the Ukraine after data 1,365,732 initial tweets were scraped, written by 783,812 unique users.

Table 1. Description of all content/tweet, network, and user features, and the target feature of the before invasion data (21-02-22 to 24-02-22) and after invasion data (24-02-22 to 25-02-22). The author refers to the user that originally posted the tweet.

Type	Feature	Description
Content/ Tweet	emoji_count	Number of emojis used in the tweet
	sentiment	Compound sentiment score between 1 (positive) and -1 (negative) (NLTK's Vader Sentiment analysis [5])
	urls_count	Number of URLs in the tweet
	mention_count	Number of mentions in the tweet
	hashtag_count	Number of hashtags in the tweet
	tweet_char_length	Number of characters in the tweet
Network	log_followers	Logarithm of the number of users that follow the author
	log_following	Logarithm of the number of users that the author follows
	log_listed	Logarithm of the number of lists the author is part of (listed by other users)
User	log_tweetcount	Logarithm of the number of historical tweets of the author
	account_age_y	Number of years that the account of the author exists
	verified	1 if the user is verified
	sex_generalized	1 if a male, -1 if female, and 0 if unknown (gender-guesser [14])
	organization	1 if most likely an organization (if $verified = 1$ and $sex\_generalized = 0$)
Target	viral	1 if the number of retweets is more than 100

Data Description. All content, network, and user features can be found in Table 1 together with their descriptions. Logarithmic transformations were applied to some network and user features to make them suitable for linear models. The number of followers and the number of listed users are both metrics of the users' indegree, and the number of following of the outdegree. On Twitter, lists are used to prioritize and organize your timeline. The listed feature describes the number of users that put the author of the tweet in their list.

The binary target variable $viral = \{0, 1\}$ is created using the number of retweets of the tweet provided by the Twitter API. A tweet is marked as viral if the number of retweets is higher than 100. This threshold of 100 retweets is based on two different considerations: on one hand, the threshold should be high enough to capture true viral tweets. More retweets of a tweet mainly mean a higher virality and usually result in a better distinction from non-viral tweets [13]. On the other hand, a higher threshold for virality results in a smaller sample of viral tweets, and therefore a larger class imbalance. These two aspects led to the decision to have a threshold of 100 retweets. We assume that this number is still high enough to be considered viral while not impacting the model performance too drastically by creating a large class imbalance.

Splitting the Data. All datasets are randomly split into a train and test set (respectively 85% and 15%). The goal of the study is to analyze the effect of the invasion. Therefore, the three train and test datasets need to be equally sized with an equal class distribution to make the models and their performance comparable. The train and test datasets from the after data and combined data (for the ignorant model) are randomly down-sampled using *Imbalanced-learn* [16] to fit the dataset size and class balance of the smallest dataset: the before dataset. This resulted in a final train set of 592,873 tweets (6376 viral tweets) and a final test set of 104,625 tweets (1109 viral tweets) for all datasets.

3.2 Experimental Setup

To study the impact of the invasion on the dynamics of the features underlying tweet virality, three final binary classification models are trained to predict tweet virality. The before model is trained on the Ukraine before data. The after model is trained on the Ukraine after data. The ignorant model serves as a control model that is trained on both before and after data. Therefore, the ignorant model is not aware of the crisis event. If the invasion impacts the virality prediction model, it is expected that the performance of the before model is better when tested on the before test set, compared to the after test set. Likewise, it is expected that the performance of the after model is better when tested on the after test set, compared to the before test set. Moreover, it is expected that the ignorant model performs worse than the two specified models because it ignores the period when data was created.

Model Training. To come up with the final models, four different supervised machine learning classification models are trained: a logistic regression model (LG), a random forest classifier (RF), an extreme gradient boosting classifier (XGB), and a multi-layer perceptron classifier (MLP). The first fit of these models, without hyperparameter tuning or taking class imbalance into account, served as the baseline models. The LG model is chosen because it is relatively simple to interpret the relationships between the features and the target variable. However, the LG model is not able to capture non-linear relationships, unlike the MLP, RF, and XGB classifiers. The MLP classification is based on a neural network and the RF and XGB are both based on an ensemble of decision trees, which makes them more robust to outliers and less prone to overfitting.

To reduce the risk of overfitting, the models were trained using 5-fold cross-validation using Scikit-learn version 1.0.2 [23]. Class balances were taken into account when making the splits. Throughout the entire process of model training, the macro averaged F1 score is used to measure model performance. For the LG and MLP classifiers, predictive features of the data were first scaled using a standard scaler fitted on the train data (to prevent data leakage to the validation set). The RF model turned out to be the best model for the before and after model. Therefore, the results (Sect. 4) describe only the RF classifier models.

As the class distribution is highly imbalanced, multiple resampling techniques were tried to improve model performance. The sampling strategies include random oversampling, random undersampling, SMOTE, and a bound method (setting a maximum number of retweets for the non-viral class). The bound method was found to be the best resampling method for our data. Afterward, hyperparameters were tuned for the models using a cross-validated grid search (see Table 2 for the final settings). Moreover, the same type of final model and resampling strategy is chosen for the ignorant model to save some computational time, as the type of train data is the same as the before and after train data. Afterward, the best ratio/bound method was searched for the ignorant model and its hyperparameters were tuned as well (see Table 2).

Model Evaluation. The performance of the final models is evaluated using the averaged macro F1 score because the accuracy of both classes is equally important. To make a statistical comparison of the hypotheses, the test sets are bootstrapped. For each original test set, 1000 bootstrapped samples of the size of the original test set are created by taking random instances from the original test set with replacement. For each bootstrapped sample, the macro F1-score is calculated, resulting in a macro F1 probability distribution. The before and after model are both tested on the before and after test set. The ignorant model is only tested on the combination test set.

The bootstrapped confidence intervals of the differences in the macro F1 distributions are used to decide whether the observed differences are significant. The significance level used is $\alpha = 0.05$. However, because the F1 distributions are tested twice (e.g. for the before model: 1) if accuracy is different for before and after test data, and 2) the difference between the before model and ignorant model with corresponding test data), a correction for multiple testing is done using a Bonferroni correction, resulting in a new significance level of $\alpha' = \frac{0.05}{2} = 0.025$ (a confidence interval of 97.5 %). If the confidence interval of the difference in the macro F1 distribution overlaps zero, the difference is not significant.

Feature Importance and Relationships. To investigate the changes in feature importance, we looked at the permutation importance for each feature for

Table 2. Final hyperparameters, resampling bound, and F1 train scores for the random forest models. All models outperformed a majority baseline model (always predicting non-viral, $F1 = 0.50$).

	n estimators	Min samples_split	Max depth	Max features	Criterion	bound (ratio)	F1 train (SD)
Before model	150	5	40	sqrt	Entropy	25 (0.0111)	0.752 (0.004)
After model	150	2	20	sqrt	gini	10 (0.0114)	0.736 (0.005)
Ignorant model	150	5	40	sqrt	entropy	25 (0.0111)	0.736 (0.004)

both before and after models [2,18], using the implementation in Scikit-learn 1.0.2 [23]. The permutation importance describes the average drop in macro F1 score as a result of permuting the feature with random values. Because the aim of using the permutation importance in this study is to get a better understanding of how the models work and on what features the predictions are based, the permutation importance is computed on the train set [18]. The permuted importances ($n = 30$ per feature) are divided by the total macro F1 score of the trained fit of the model and multiplied by 100 to get the percentage of macro F1 drop.

Furthermore, visualizations are made to explain the relationship of a feature with virality and its change after the event. Based on prior research, we focused in this paper on the number of followers [7,29] and the number of URLs [7].

4 Results

4.1 Model Evaluation

The F1 scores of the final random forest classifier model trained with before/after event data and tested with before/after test data can be found in Table 3, together with the F1 score of the ignorant model. For the ignorant model, we trained and tested the model on the whole dataset, ignoring the period during which the tweets were produced. For the before model, the 97.5% confidence interval of the difference in F1 score when tested on the before and after test set does not overlap zero ($BB - BA = [0.0111, 0.0590]$). For the after model, the 97.5% confidence interval of the difference in F1 score when tested on the before and after test set also does not overlap zero ($AA - AB = [0.0144, 0.0530]$). Therefore, both models perform significantly better on their

Table 3. Macro F1 scores (SD) on the bootstrapped test sets. It can be seen that the RF models perform better when trained and tested in data produced in the same period.

	Before test	After test	Combined test
Before model	0.7503 (0.0066)	0.7139 (0.0076)	-
After model	0.6962 (0.0055)	0.7290 (0.0065)	-
Ignorant model	-	-	0.7378 (0.0071)

corresponding test set: the crisis event affects the possibility that information virality in an online social network is accurately predicted. In contrast, the ignorant model does not perform significantly worse than both specified models ($BB - CC = [-0.0099, 0.0338]; AA - CC = [-0.0288, 0.0135]$).

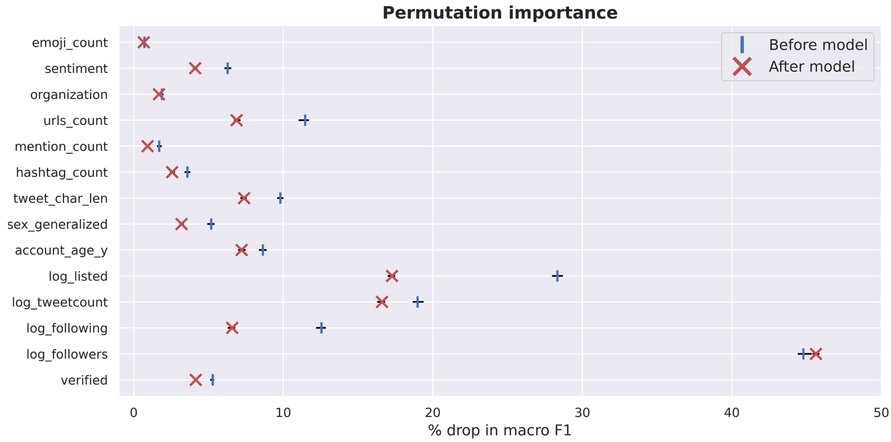

Fig. 1. The mean permutation importance for each feature of the before model (blue stripe) and after model (red cross). The permutation importance is measured by the percentage of macro F1 drop after randomly permuting the feature, compared to the total macro F1 score of the model. A bigger drop means higher importance. The spread of the minimum and maximum values for each importance are shown with a black line. If the line is (almost) unnoticeable, the extreme values are close to the mean. (Color figure online)

4.2 Feature Importance and Relationships

The distributions of the relative permutation importance are visualized in Fig. 1. The feature with the highest mean permutation importance (i) for the before (b) and after (a) model is the number of followers ($i_b = 44.7837 \pm 0.0337, i_a = 45.6161 \pm 0.0205$). The second most important feature is the number of listed users ($i_b = 28.3316 \pm 0.0394, i_a = 17.2663 \pm 0.0214$), this feature also shows the biggest difference in importance. The third most important feature is the number of tweets from the user ($i_b = 18.9824 \pm 0.0311, i_a = 16.5600 \pm 0.0206$), followed by the number of following ($i_b = 12.5535 \pm 0.0277, i_a = 6.5795 \pm 0.0172$) and the URLs count ($i_b = 11.4582 \pm 0.0327, i_a = 6.8701 \pm 0.0197$). Except for the number of followers, we see a slight reduction in permutation importance in the after model. Taken together, this shows that the indegree network features (number of followers and listed users) are overall important predictors for virality.

While the importance of the number of followers is relatively similar for both models, its relationship with virality looks different before and after the invasion. The fraction of viral tweets per number of followers is shown in Fig. 2, the peak

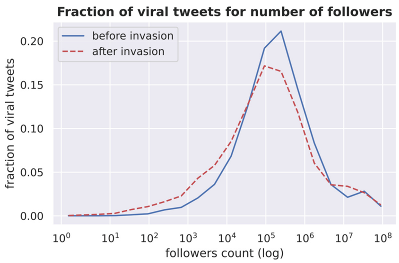

Fig. 2. The fraction of viral tweets within 20 logarithmic bins for followers counts, compared to all viral tweets.

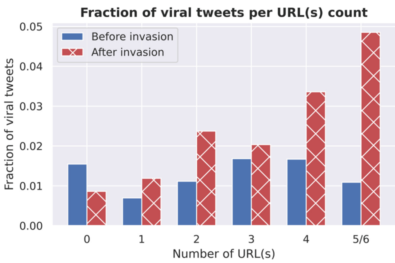

Fig. 3. Per URLs count the fraction of viral tweets compared to all tweets for that number of URLs count.

in viral tweets from 100,000 to 1,000,000 followers decreased after the invasion. Furthermore, the fraction of viral tweets from users with fewer followers (10 up to around 1000) increased after the invasion. The listed and tweetcount features show a similar pattern (not visualized).

Fig. 3 visualizes the fraction of viral tweets for each possible number of URLs (as there are no tweets containing 6 URLs for the before data, tweets with 5 or 6 URLs are taken together). After the invasion, the fraction of viral tweets having at least one URL increased compared to before the invasion.

5 Discussion and Conclusion

The aim of this study was to investigate to what extent content, network, and user features underlying a tweet virality prediction model are impacted by a real-world crisis event: the Russian invasion of Ukraine. The performance of the random forest classifier model trained on data before the invasion (before model) significantly decreased when tested with data after the invasion, compared to test data from before the invasion. Likewise, the after model performed significantly better on the after test data, compared to the before test data. The change in model predictive capabilities was expressed by an overall reduction of the feature permutation importance, except for the number of followers. Taken together, we can conclude that the features underlying a virality prediction model can be affected by a crisis event, impacting model accuracy.

As expected based on prior studies [7,24,29], the most important and most impacted features were mainly the network centrality features. The number of followers and the number of listed users were both key features in virality prediction. While we see that the number of followers preserves its predictive power (feature importance) before and after the invasion (Fig. 1), its relationship with virality is changed: we see an increased fraction of viral tweets after the invasion for users with fewer followers (Fig. 2). This effect can possibly be explained by a shift in the importance and relevance of specific users: information posted by witnesses (not necessarily with a high indegree) who first-hand experienced the crisis event is an important source of information [29]. Another user feature, the number of previous tweets, was also an important predictor for virality, representing prior user engagement on Twitter.

While the feature importance for the number of URLs decreases after the invasion, there are some interesting changes seen in the visualization of the number of URLs before and after the invasion (see Fig. 3). After the invasion, the fraction of viral tweets increases when the number of URLs increases. As an example, from all tweets containing 4 URLs, a higher fraction is viral after the invasion. The increased fraction of viral tweets for tweets containing more URLs after the invasion may represent a stronger interest in information coming from websites, photos, and videos after a crisis event, in line with prior research [7].

Unexpectedly, the specified models did not outperform the ignorant combined model, probably as the ignorant model is trained to generalize well over two different contexts (before and after the invasion). Therefore, future research could address how to decide on the best trade-off for data inclusion to adapt a prediction model to quick and abrupt changes caused by a crisis event (e.g. by assigning weights to more recent data).

There are some limitations that could have impacted the generalizability of our results. Firstly, as all tweets were in English, our results should be interpreted from an international level of communication. Possibly, results could yield different conclusions when only Ukrainian/Russian tweets are used. Furthermore, more research is required to investigate whether the current conclusions hold for other crisis events (e.g. a natural disaster or pandemics). Our results show that a social media virality prediction model can be impacted by a specific crisis event, suggesting future research to evaluate how these observations generalize to events of a different scale and nature.

As the indegree network features (number of followers and listed users) were key predictors for virality, we suggest that future works investigate the impact of a crisis event on the network structure of virality itself. This can eventually consider higher-order networks: the Twitter lists of users can be considered hyperedges, i.e., a generalization of (pairwise) edges as the connection between larger sets of nodes [4]; in this regard, features such as order or hyperdegree might be relevant features to infer virality. Future research could also analyze whether viral tweets frequently remain within clusters of similar users and whether the observed level of inter-community outreach is impacted after a crisis event.

Data and Code Availability. The data and code used for this study are available on Github[1]. Due to Twitter's limitations, only tweet ids are shared.

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[1] https://github.com/sudegroot/CompleNet_virality_social_network.

References

1. Full text: Putin's declaration of war on Ukraine. The Spectator, February 2022. https://www.spectator.co.uk/article/full-text-putin-s-declaration-of-war-on-ukraine/. Accessed 13 Mar 2022
2. Altmann, A., Toloşi, L., Sander, O., Lengauer, T.: Permutation importance: A corrected feature importance measure. Bioinformatics. **26**(10), 1340–1347 (2010). https://doi.org/10.1093/bioinformatics/btq134
3. Ball, P., Maxmen, A.: The epic battle against coronavirus misinformation and conspiracy theories. Nature. **581**(7809), 371–374 (2020)
4. Battiston, F., et al.: Networks beyond pairwise interactions: structure and dynamics. Phys. Rep. **874**, 1–92 (2020)
5. Bird, S., Klein, E., Loper, E.: Natural Language Processing with Python: Analyzing Text with The Natural Language Toolkit. O'Reilly Media, Inc., Sebastopol (2009)
6. Brzezinski, D., Stefanowski, J.: Reacting to different types of concept drift: the accuracy updated ensemble algorithm. IEEE Trans. Neural Netw. Learn. Syst. **25**(1), 81–94 (2014). https://doi.org/10.1109/TNNLS.2013.2251352
7. Buntain, C., Golbeck, J., Liu, B., Lafree, G.: Evaluating public response to the Boston marathon bombing and other acts of terrorism through Twitter. In: Proceedings of the Tenth International AAAI Conference on Web and Social Media (2016)
8. Bunyamin, H., Tunys, T.: A comparison of retweet prediction approaches: the superiority of random forest learning method. Telecommun. Comput. Electron. Control. **14**(3), 1052 (2016). https://doi.org/10.12928/telkomnika.v14i3.3150
9. Enders, A.M., et al.: The relationship between social media use and beliefs in conspiracy theories and misinformation. Polit. Behav. 1–24 (2021). https://doi.org/10.1007/s11109-021-09734-6
10. Goel, S., Anderson, A., Hofman, J., Watts, D.J.: The structural virality of online diffusion. Manage. Sci. **62**(1), 180–196 (2016). https://doi.org/10.1287/mnsc.2015.2158
11. Haewoon, K., Changhyun, L., Hosung, P., Sue, M.: What is Twitter, a Social Network or a News Media? In: Proceedings of the 19th International Conference on World Wide Web, p. 1365 (2010)
12. Hong, L., Convertino, G., Chi, E.: Language matters in Twitter: a large scale study. In: Proceedings of the International AAAI Conference on Web and Social Media, vol. 5, pp. 518–521 (2011)
13. Jenders, M., Kasneci, G., Naumann, F.: Analyzing and predicting viral tweets. In: WWW 2013 Companion - Proceedings of the 22nd International Conference on World Wide Web, pp. 657–664. Association for Computing Machinery (2013). https://doi.org/10.1145/2487788.2488017
14. Michael, J.: 40000 names (2017)
15. Kupavskii, A., et al.: Prediction of retweet cascade size over time. In: Proceedings of the 21st ACM International Conference on Information and Knowledge Management, pp. 2335–2338 (10 2012)
16. Lemaître, G., Nogueira, F., Aridas char, C.K.: Imbalanced-learn: a python toolbox to tackle the curse of imbalanced datasets in machine learning. J. Mach. Learn. Res. **18**, 1–5 (2017). http://jmlr.org/papers/v18/16-365.html.
17. Mirbabaie, M., Bunker, D., Stieglitz, S., Marx, J., Ehnis, C.: Social media in times of crisis: learning from Hurricane Harvey for the coronavirus disease 2019 pandemic response. J. Inf. Technol. **35**(3), 195–213 (2020). https://doi.org/10.1177/0268396220929258

18. Molnar, C.: 8.5 Permutation Feature Importance. In: Interpretable Machine Learning. A guide for Making Black Box Models Explainable, pp. 193–203 (2019)
19. Neppalli, V.K., et al.: Retweetability Analysis and Prediction during Hurricane Sandy. ISCRAM (2016)
20. Nesi, P., Pantaleo, G., Paoli, I., Zaza, I.: Assessing the reTweet proneness of tweets: predictive models for retweeting. Multimed. Tools Appl. **77**(20), 26371–26396 (2018). https://doi.org/10.1007/s11042-018-5865-0
21. Neubaum, G., Krämer, N.C.: Opinion climates in social media: blending mass and interpersonal communication. Human Commun. Res. **43**(4), 464–476 (2017). https://doi.org/10.1111/hcre.12118
22. Oh, O., Agrawal, M., Rao, H.R.: Community intelligence and social media services: a rumor theoretic analysis of tweets during social crises. Technical Report. 2 (2013)
23. Pedregosa, F., et al.: Scikit-learn: machine learning in python. J. Mach. Learn. Res. **12**, 2825–2830 (2011). http://scikit-learn.sourceforge.net
24. Remy, C., Pervin, N., Toriumi, F., Takeda, H.: Information diffusion on twitter: everyone has its chance, but all chances are not equal. In: Proceedings - 2013 International Conference on Signal-Image Technology and Internet-Based Systems, SITIS 2013, pp. 483–490 (2013). https://doi.org/10.1109/SITIS.2013.84
25. Reuter, C., Hughes, A.L., Kaufhold, M.A.: Social media in crisis management: an evaluation and analysis of crisis informatics research. Int. J. Human-Comput. Interact. **34**(4), 280–294 (2018). https://doi.org/10.1080/10447318.2018.1427832
26. Reuter, C., Kaufhold, M.A., Schmid, S., Spielhofer, T., Hahne, A.S.: The impact of risk cultures: citizens' perception of social media use in emergencies across Europe. Technol. Forecast. Soc. Change. **148**, 1–7 (2019). https://doi.org/10.1016/j.techfore.2019.119724
27. Roesslein, J.: Tweepy: Twitter for Python! (2020). https://Github.com/Tweepy/Tweepy
28. Sheftalovich, Z.: Battles flare across Ukraine after Putin declares war, February 2022
29. Siapera, E., Hunt, G., Lynn, T.: #GazaUnderAttack: Twitter, Palestine and diffused war. Inf. Commun. Soc. **18**(11), 1297–1319 (2015). https://doi.org/10.1080/1369118X.2015.1070188
30. Suh, B., Hong, L., Pirolli, P., Chi, E.H.: Want to be retweeted? Large scale analytics on factors impacting retweet in Twitter network. In: Proceedings - SocialCom 2010: 2nd IEEE International Conference on Social Computing, pp. 177–184 (2010). https://doi.org/10.1109/SocialCom.2010.33
31. Vosoughi, S., Roy, D., Aral, S.: The spread of true and false news online. Science. **359**(6380), 1146–1151 (2018). https://doi.org/10.1126/science.aap9559
32. Yin, H., Yang, S., Song, X., Liu, W., Li, J.: Deep fusion of multimodal features for social media retweet time prediction. World Wide Web **24**(4), 1027–1044 (2020). https://doi.org/10.1007/s11280-020-00850-7