Analysis of the COVID-19 Communication on Twitter via Multilayer Network

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Abstract: In this paper we describe a multilayer network based framework for the representation of online communication in social media. More precisely, we define the formalism that captures knowledge about the users, actions and messages in social networks such as Twitter. We present a possible application of the proposed framework for the analysis of COVID-19-related communications on Twitter in the Croatian language during the third wave of the pandemic. Given the multilayer network of six layers, we first calculate and analyse set global and local network measures. In the second step, we perform the grouping of the tweets by using community detection algorithm and k-means clustering of tweets represented as vectors composed of centrality measures across the layers. As a result, the proposed multilayer framework provides an insight into the crisis communication in terms of quantifying users' actions and the amount of tweeting and retweeting about the specific topics related to COVID-19.

1 INTRODUCTION

Social media plays a significant role in global crises, such as the COVID-19 pandemic. It serves as a key communication platform, and it is a potential source of valuable information (Cuello-Garcia et al., 2020). It affects the public perception and may influence political communication and policy-making activities (Cinelli et al., 2020). During the last two decades, social media has amplified the spread of information, as well as misinformation and disinformation which may cause an infodemic as a negative side effect (Eysenbach, 2002). Recent studies confirm that (social) media influences human behavior in the context of disease transmission and thus may affect the spread and control of infectious diseases (Bedson et al., 2021; Xiaet al., 2019). Hence, for both reasons (positive and negative effects of social media), social media monitoring is important for a better understanding of crisis communication.

Modelling social media via networks is a powerful tool to analyse relationships and communication between individuals. This representation is highly useful in modelling various social phenomena and has been widely studied in numerous research papers. Lately there has been a great deal of network-based research related to COVID-19 communication in social media (Ahmed et al. 2020; Caldarelli et al., 2021; Mattei et al., 2021). However, a single network can represent only one type of relationship among users and thus might not capture all the important properties of the communication. The more appropriate approach is to use a multilayer network that can represent different layers of relationships in social networks. The main goal of this study is to define a framework based on multilayer network and to apply this framework in the task of COVID-19 related communications on Twitter.

The analysis of multilayer networks is an emerging field that can capture various sorts of relationships over heterogeneous data (Boccaletti et al., 2014; Kivelä et al., 2014). We have already shown that a multilayer network structure is fundamentally

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more expressive than individual layers in the examples of modelling a multilayer language network (Martinčić-Ipšić et al., 2016) and multidimensional knowledge network (Vukić et al., 2020).
Social networks have already been modelled as multilayer networks in different ways and for various tasks in some previous studies, such as (Singh et al., 2020; Sheikh et al., 2020; Zhang et al., 2020). Some of these approaches modelled Twitter as a multilayer network based on retweet, quote, mention and reply layer as, for example, in the task of disinformation detection (Pierri et al., 2020). Solé et al. examined Twitter and Instagram as a multilayer network of two layers and proposed centrality measures for ranking the users (Solé et al., 2020). Fewer studies consider multilayer networks of tweets and even fewer research combine heterogeneous sources of social networks. Some examples of such approaches include the analysis of the two layers based on hashtags (Türker and Sulak, 2018) and the construction of the two layers of Twitter based on followers and tweets (Bindu et al., 2020), used for community detection.

There is still a lack of research that applies multilayer networks to model social network communications as multiple layers of heterogeneous data that include both, users and messages. To overcome this gap, we propose a framework that uses a multilayer network to represent messages as nodes in one layer and users as nodes in other layers. This way it is possible to capture more details of the communication on social networks such as the users' activities and properties of posted messages. More precisely, we model this communication by defining five layers of users' activities and one more layer representing messages. In the case of Twitter these aspects include various users' actions such as retweet, reply, quote, mention and follow plus one additional layer dedicated to tweets. It is also possible to include the metadata of tweets as an additional set of attributes.

The objective of this research is to define a general formalism that can capture different aspects of communication on Twitter and then to apply this formalism in analysis of COVID-19 related communications on Twitter. We formalised this model as a communication multilayer framework, and we applied this framework to the task of analysing COVID-19 communications on Twitter. For this purpose, we collect a representative sample of Twitter communication in the Croatian language during the third wave of the pandemic including a total number of 32,193 tweets. Within the proposed framework, we calculate global and local network measures and describe the structural properties of twitter communication. Next, we analysed the different subset of tweets in terms of structure, semantic and sharing properties. The proposed approach sheds light on users' actions and themes related to COVID-19 and may be used to advise the authorities how to better communicate during the healthcare crisis. In general, the proposed framework can be applied to other similar situations when better understanding of the crisis communication is needed.

2 METHODOLOGY

2.1 Multilayer Framework

According to (Boccaletti et al. 2014) a multilayer network is defined as a pair:

$$\mathcal{M} = (\mathrm{G}, \mathrm{C}) \tag{1}$$

where

$$\mathrm{G} = \{G^{\alpha};\ \alpha \epsilon \{1, \dots, m\}\} \tag{2}$$

is a family of networks (graphs) $G^{\alpha} = (V^{\alpha}, E^{\alpha})$ called *network layers* of $\mathcal{M}$ and $\mathrm{C} = \{E^{\alpha\beta} \subseteq V^{\alpha} \times V^{\beta}; \alpha, \beta \epsilon \{1, \dots, m\}, \alpha \neq \beta\}$ is the *set of interconnections* between nodes of different layers G^{α} and G^{β} where $\alpha \neq \beta$.

Layers are annotated as numbers from the set $\{1, \dots, m\}$, where m is the number of layers. Multilayer networks can be directed or undirected, weighted or unweighted. Communication in social networks is best captured with the weighted and directed multilayer network.

Additionally, we introduce and consider a set T of all metadata related to posted textual messages. The concrete metadata that is used may vary depending on the task. However, this set includes all messaging metadata that is available. In the case of Twitter, this metadata includes information such as the number of retweets, quotes, mentions, etc. Additionally, this set may contain text embedding provided by the language model that captures the semantic of the text message. All these data is represented as vectors and can be later used for detailed examinations of the messages. In the context of network analysis, these vectors are actually the attributes of nodes that represent messages.

Finally, the communication multilayer framework is defined as a tuple:

$$\mathcal{CMF} = (\mathcal{M}, T) \tag{3}$$

2.2 The Networks Construction and Analysis

For the network construction we first collected dataset of 32,193 COVID-19 related tweets. Data is collected using tweepy, a Python library for accessing the Twitter API. For the purpose of this preliminary study, we collected Twitter data posted in the period from February 15, 2021 to May 31, 2021 covering the time of the third pandemic wave in the Republic of Croatia.

Given the framework $\mathcal{CMF}$, we model Twitter data into five layers, thus $m = 6$. Each layer represent one aspect of communication on Twitter as follows. $G^1 = (V^1, E^1)$ is a **user retweet layer** where Twitter users are nodes. Two nodes i and j are connected with the directed link if user j retweets user i. The weight represents the number of retweets. $G^2 = (V^2, E^2)$ is a **user reply layer** where Twitter users are nodes and two nodes i and j are connected with the directed link if user j replies to user i. The weight represents the number of replies. $G^3 = (V^3, E^3)$ is a **user quote layer** where Twitter users are nodes and two nodes i and j are connected with the directed link if node j quotes user i. The weight represents the number of quotes. $G^4 = (V^4, E^4)$ is a **user mention layer** where Twitter users are nodes and two nodes i and j are connected with the directed link if user j mentions user i.The weight represents the number of mentions. $G^5 = (V^5, E^5)$ is a **user follow layer** where Twitter users are nodes and two nodes i and j are connected with the directed link if user j follows user i. All weights are set to 1 since this layer is an unweighted network. $G^6 = (V^6, E^6)$ is a **tweets layer** where Twitter messages are nodes and two nodes i and j are connected with the directed link if message i and j have at least one word and/or hashtag in common. The connection is established according to the timeline; from the first tweet to the second tweet. The weight represents the number of common words/hashtags. Illustration of this model is represented in Figure 1.

Interconnections between nodes of different layers are defined in the way that for the first five layers (which may be described as multiplex), links are connecting the same nodes. The weight of the interconnection links is set to 1 and the directions are set from the upper layer to the lower layer. However, in this case, the order of layers is arbitrary and directed links are necessary only because the rest of the multilayer network is directed. Additionally, we construct directed links from users represented as nodes on the fifth layer to the tweets represented as nodes on the sixth layer. Node i is connected with the node j if user i posted a tweet j. Analogously, we construct interlinks between the other layers and the sixth layer: we connect the user with the tweet according to the user's actions. In this case, the hierarchy of the layers is natural because it represents the direction of the relationship from the user to a certain tweet.

The first step of this approach is the analysis of the global properties for all layers. We pick a set of global network measures: average degree, average strength (in/out), network density, average path length, diameter, reach, global efficiency, average clustering coefficient (weighted/unweighted), average degree centrality, transitivity and modularity. The second step is the grouping of messages using two different approaches: (i) the Louvain algorithm (Blondel et al., 2008) and (ii) k-means clustering of tweets represented as vectors. Tweet vectors are constructed using local node measures: in/out-degree, in/out-strength, hubs and authorities. Hubs and authorities, also known as HITS (Hyperlink-Induced Topic Search) were initially introduced by Jon Kleinberg (Kleinberg, 1998) for ranking web pages. The idea behind applying these measures in the directed social networks is that authorities will highly rank nodes with many followers, replies, retweets, quotes or mentions, while hubs will highly rank nodes that retweet, reply, quote, mention or follow many other nodes. After calculating four measures for all six layers, a tweet is represented as a 24-dimensional vector. For the purpose of this second step, we need to combine heterogeneous data from $\mathcal{M}$, such as the number of interlinks from G^1 to G^6, with the texts from the set T. This approach provides knowledge about the possible similarities of messages, the quantity of messages in a group and how certain groups of messages are spreading.

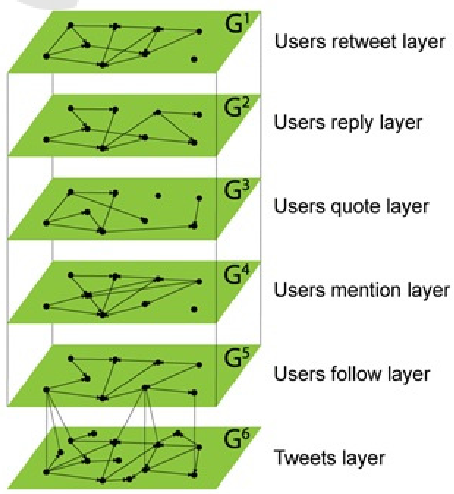

Figure 1: Multilayer network diagram.

3 RESULTS

3.1 Network Structure on the Global Level

The global network measures for all six layers are reported in Table 1. Although the first five layers represent users, each layer includes different number of nodes because we take into account only users that are involved in observed relationships. Thus, the Follow layer includes only nodes (users) that posted tweets from the Tweets layer; and Mention layer includes only nodes (users) that are mentioned in tweets from the Tweets layer. Furthermore, the relation of following is the most common and the number of links that represent following is always higher that number of links that represent replying, retweeting, mentioning and quoting. Consequently, the number of nodes and links across layers substantially varies. For example, the Follow layer has lower number of nodes, but the highest number of links comparing the first five layers. Next, if we compare only the first four layers that represent users' actions, it seems that mention is the most frequent action, while quote is very rare within COVID19 related communications on Twitter. Among these four layers, mention and reply layers have the highest values of average degree and in-strength measures. This means that the users involved in this communication replied and mentioned much more often than retweeted and quoted.

Furthermore, all four layers have similar diameters and low clustering coefficients, which may indicate that these are small world networks. The reply layer has the highest values of average path length and reach, which can mean that the users are not so closely connected in the case of replying. The differences between layers can also be noticed in the values of modularity measure. Retweet and quote layers have values of modularity higher than 0.5, which means that in these actions, users are better grouped into communities than in mention and reply layers.

On the other side, the layer that represents the action of following is somewhat different than the first four layers. In this sample of the dataset, we cannot include users with protected profiles, therefore the number of nodes is smaller than the real number of users involved in COVID-19 communications. However, even based on this data it is obvious that the follower layer has more connections, and it is much denser than the first four layers. Consequently, the diameter is lower, indicating that all users are relatively close which is the usual property of social networks. However, the average path length is higher than in the first two layers. This property is expected, because following somebody does not automatically imply actions of replying, retweeting, quoting and mentioning.

Table 1: Global network measures across layers.

Measure/Layer	Retweet	Reply	Quote	Mention	Follow	Tweets
total nodes	1543	2582	190	4963	1240	32,193
total edges	2141	6292	157	12,145	58,179	56,844,682
average degree	2 .7751	4.8737	1.6526	4.8942	93.837	3531.49
avg in-strength	0.8782	1.1311	0.6636	1.0993	-	1.0957
avg out-strength	0.7912	0.6818	0.5373	0.4636	-	1.0919
network density	0.0009	0.0009	0.0044	0.0005	0.0379	0.0548
avg. path length	0.0239	0.7214	0.0182	0.0007	2.2544	/
diameter	14	14	15	14	6	/
reach	0.1692	0.4073	0.0592	0.0299	0.021	/
global efficiency	0.1275	0.1807	0.0458	0.1641	0.4838	/
avg. clust. coeff. (uw)	0.016	0.0259	0.0037	0	0.3509	/
avg. clust. coeff. (w)	0.0001	0.0001	0.0003	0	-	/
avg. degree cent.	0.0018	0.0019	0.0087	0.001	0.0757	0.1097
transitivity	0.0096	0.0329	0.0036	0	0.2959	/
modularity	0.5413	0.1882	0.7724	0.145	0.0008	0.0004

Table 2. Communities detected in a tweet layer.

#	Number of tweets	Avg. no. of rt	10 most frequent terms
1	1,979	75.31	masks, mask, rt, wear, @usenname11, open, don't have, misinformation, know, man
2	3,298	23.26	pandemic, covid, rt, covid-19, #covid19, croatian, man, person, new, measure
3	5,806	18.56	infect, headquaters, new, newly-infected, measure, person, croatian, epidemiological, number, county
4	7,582	17.7	#koronavirus, #dnevnikhr, coronavirus, rt, new, person, @koronavirus_hr, croatian, infect, corona
5	3,287	11.66	vaccines, vaccine, rt, dose, croatian, pfizer, patient, new, respirator, other
6	3,383	5.29	@usenname1, @usenname2, @usenname3, @usenname4, @usenname5, @usenname6, @usenname7, @usenname8, @usenname9, @usenname10
7	3,495	4.47	hospital, doctor (\textit{male}), medical, therapy, rt, medicine, doctorate, doctor (\textit{female}), know, all
8	4,387	1.11	vaccination, vaccinate, vaccine, man, vaccines, rt, dose, all, person, other
9	66	0.49	#unizg, #mojesveuciliste, #ostanimoodgovoran, @sveucilistezg, project, student, attach, university, faculty, competition

The sixth layer introduces tweets as nodes and thus has a completely different structure. It captures the semantic aspect of communication. Due to the large number of links, distance measures are not calculated. This network is much larger than the network of other layers with a higher number of edges and consequently much higher average degree. However, the values of the average strength are not high in comparison to other layers. This can be explained in the sense that many tweets have only one word or a hashtag in common. This property of tweets' similarity is examined in more detail in the next subsection.

3.2 Communities and Clusters of Tweets

In the second step we analyse the properties of groups based on structure, semantics and the amount of tweeting and retweeting. As described in the Methodology section, we perform the grouping of tweets using two different approaches. The results are shown in Table 2 and 3 reporting the number of tweets, the average number of retweets (calculated based on the number of interlinks from G1 to G6) and the top ten most frequent terms (words) translated in English for each group (extracted from the set T). Note that the most frequent words may contain hashtags (indicated by the "#" character) and user mentions (indicated by the "@" character), the metadata for retweets (indicated by "rt") as these terms are essential parts of a tweet.

In Table 2 we show the results of grouping tweets from the layer G^6 into 9 communities sorted by the number of average retweets. We analyse the content of tweets and assign a topic to every community as follows: #1 - masks and misinformation, #2 - COVID-19 pandemic in general, #3 - headquarters and epidemiology, #4 - COVID-19 news, #5 - vaccines, #6 - user mentions, #7 - healthcare, #8 - vaccination, #9 - education. This set of topic covers some of the main themes related to COVID-19. Note that vaccines and vaccination are formed as two separate communities, however, we decided to analyse these two groups together. The most tweeted topics are related to the vaccination (7,674 tweets in #5 and #8), COVID-19 news (7,582 tweets in #4) and headquarters and epidemiology (5,806 tweets in #3). The highly retweeted (on average around 75 retweets of one tweet) is the group with the topic related to masks and misinformation. Very low sharing (less than 10 retweets on average) is detected for the groups of tweets related to #6 - user mentions, #7 - healthcare, #9 - education.

In Table 3 we report the results of clustering the tweets into 10 clusters using k-means algorithm.

Table 3. Clusters of tweets constructed using k-means algorithm.

#	Number of tweets	Avg. No. of rt	10 most frequent terms
1	3,980	38.85	coronavirus, person, @koronavirus_hr, new, infect, corona, #koronavirus, croatian, hour, rt
2	15,661	24.68	rt, vaccination, @usenname1, vaccine, croatian, new, man, hospital, person, pandemic
3	180	10.1	rt, @koronavirus_hr, @usenname12, vaccination, know, croatian, masks, get, vaccine, measure
4	5895	5.9	vaccination, person, rt, @usenname1, new, croatian, man, vaccine, #hrvatski, #vijesti
5	334	3.47	@andrejplenkovic, rt, vaccine, dose, vaccination, \#covid19, @viliberos, @astrazenec, @koronavirus_hr, minister
6	3,088	1.55	rt, vaccination, vaccine, croatian, new, man, pandemic, covid, need, person
7	437	0.86	@dnevnikhr, \#koronavirus, rt, \#dnevnikhr, \#novatv, person, new, croatian, measure, headquarters
8	782	0.64	\#dnevnikhr, \#koronavirus, rt, @novahr, cases, new, Croatian , #dnevniknovetv, number, @koronavirus_hr
9	319	0.12	@usenname1, @usenname4, @usenname3, @usenname5, @usenname9, @usenname2, @usenname7, @usenname10, @usenname13, @usenname14
10	1,517	0.02	@usenname1, @usenname2, @usenname4, @usenname8, @usenname3, @usenname5, @usenname6, @usenname15, @usenname7, @usenname14

Clusters are sorted by an average number of retweets. According to the top ten most frequent terms of each cluster, it is possible to recognise differences within the structure of these clusters: some clusters contain only mentions (#9, #10), some contain hashtags (#5, #7, #8) cluster #6 contains only words and metadata for a retweet. Some clusters are a combination of terms with marks for mentions and retweets (#1, #2, #3, #4). In the light of retweeting, it seems that the clusters with a mixed structure (#1, #2, #3, #4) have far more retweets than clusters with the structure in which mentions (#9, #10) or hashtags (#7, #8) are predominant. Tweets with a lot of mentions referred to private communication, and for such a cluster, it is expected to be less retweeted. The first two highly retweeted clusters contain the highest number of tweets as well. Furthermore, according to the most frequent terms, we assign a predominant theme for each cluster as follows: #1 - general terms, #2 - vaccination, #3 - measures, #4 - vaccination, #5 - politicians, #6 - vaccination, #7 - news and measures, #8 - number of new cases, #9 - mentions, #10 - mentions.

It turns out that the largest and the most retweeted clusters mention vaccination and pandemic measures. This consideration of topics related to vaccination is similar to the one based on the previous results with communities. However, the topic detection of tweets makes more sense in communities, while clusters provide information about users' actions.

4 CONCLUSIONS

In this paper we propose a multilayer network framework for the representation and analysis of communications in social media. We apply the proposed framework to the analysis of COVID-19 related tweets.

On the global level we detect some general properties of communication in social networks such as the intensity of the communication and how well these users are connected in terms of different possible actions. Overall, in the case of COVID-19 related communications on Twitter in the Croatian language, users are highly connected as followers, while there are lower connection realised through the actions of retweeting, replying, quoting and mentioning. The most intense communication is obtained via replies and mentions while the best grouping into communities is achieved for users that reply and quote.

Furthermore, by analysing local network measures we get a better insight into the online communication on Twitter related to COVID-19. Specifically, the communities formed on G^6 represent semantically similar groups of tweets pointing out the main COVID-19 related topics that were in focus during the third pandemic wave. According to our results the most tweeted topics are related to vaccination, COVID-19 news and headquarters and epidemiology, while the most retweeted topic is related to masks and misinformation. This approach can be further used as a step in the task of topic modelling. Clustering based on the data gathered from all six layers reveals the patterns of users' actions. In the case of COVID-19 communications on Twitter we recognise that the majority of tweets contain vaccination, masks and coronavirus as the most frequent terms. These are also clusters of the most retweeted tweets.

This study is preliminary research and the first step toward the modelling and understanding of the multilayer communication network. In this approach, we do not exploit the full potential of a defined multilayer framework. There are several possible directions of our future work, such as exploring other possibilities of combining and analysing all the layers and using more network measures, especially centrality measures of the multilayer network. Furthermore, we plan to extend this approach by representing the Twitter message using the multilayer network properties. This way, the message can be represented as a vector composed of different network features.

Moreover, the proposed approach can be applied in the analysis of any other domain of communication on Twitter.

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