IJICIS, Vol.22, No.3, 70-81
DOI: 10.21608/ijicis.2022.105691.1139

International Journal of Intelligent Computing and Information Sciences

https://ijicis.journals.ekb.eg/

The Identification of the Top Positive Influential Users of the Social Networks to Help in the Control of Covid-19 Spread

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Received 2021-11-12; Revised 2022-04-19; Accepted 2022-04-28

Abstract: *Covid-19 pandemic is considered the most worldwide problem, and causes horrible crises for all human being. Social networks can play a vital role in the prevention of the spread of the Covid-19 pandemic. The top influential users of social networks like Twitter can have positive or negative effect in the broadcast of useful and same time harmful information about how to deal with the virus, and encourage people to follow up the rules announced by World Health Organization (WHO). So the detection of the top positive and negative influential users can help in the control of the spread of the virus. The proposed approach is based on applying influence maximization solutions to identify the top influential users from Twitter social network graph, and to determine if the influence is positive or not. The proposed approach has four main phases, the first phase is collecting Covid-19 pandemic related tweets dataset and extract the related users and their followers. The second phase is creating a social network graph from the collected dataset. The third phase is using LKG influence maximization approach to identify the most effective users from the social network graph. The last phase is based on using hashtags frequency analysis to be able to identify the type of influence of each top influential user.*

Keywords: *Covid-19, Hashtags, Tweets, Top influential users, Social networks*

1. Introduction

The global spread of the coronavirus 2019 known as COVID-19 disease has resulted in a worldwide pandemic, and millions of people around the world are in danger. The number of confirmed COVID-19

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cases at August 23, 2021 was 211,730,035, including 4,430,697 deaths [1]. As a result, governments all over the world are fighting to find all possible ways to control and prevent the spread of epidemic. Social networks such as Tweeter can play a vital role to help the control of the spread of the COVID-19. As estimated about 2.95 billion people around the world use social networks [2]. The control of spread of positive and negative information within the social networks can help to reduce the number of new infected people. The misleading information like “no need to wear masks “ or “no need for social distances” can directly increase the possibility of more infected people .

Twitter is now a widely popular microblogging and social networking service, with more than 353 million of users [3]. Millions of people tweet or rewets others tweets on daily base. Several researchers from multidisciplinary fields are working to help the world to prevent the spread of COVID-19 disease. Due to the great importance of the social networks, so it can be considered one of the main directions for many researches. Al-Shargabi et al. [4] proposed a research study to explore the effects of the COVID-19 global epidemic by analyzing the tweets of Saudi Arabia Twitter users. They collected 8905 Arabic tweets to visualize the social network graph for the COVID-19 tweets of the people who live at Saudi Arabia. Also, they tried to identify the sources of knowledge that the users of Twitter employ with the COVID-19 pandemic to help of the identification of the top influencers. Gunduz et al. [5] provided Sentiment analysis study of tweets related to COVID-19 pandemic. The main target of the presented work is to analyze the effects of the worldwide epidemic problem of COVID-19 on crisis management, message, and language with the data of the social networks. Lang et al. [6] provided study to examine the temporal trends, themes, types and exchange patterns of the hashtags that are related to mask wearing posted by the users of Twitter who live in the United States. One of most important and helpful direction is the detection of the top positive and negative social networks influencers. As they have a great effect on their followers. The COVID-19 positive influential users are the social networks users that are more likely to share or post a useful and helpful information to help the others in protecting themselves and their families from the COVID-19 epidemic.

The detection of the top positive influential users can provide a great help for the governments and health organizations, as their influence effect can be used to spread accurate information from official sources. The top positive influential users can share and publish the official WHO and local health organizations updates about the COVID-19 virus, and the updated guidelines for personal and social safety. The proposed approach is based on applying the LKG influence maximization approach [19] to detect the top influential users from Twitter social network graph, and then apply hashtags frequency analysis to determine if the influence effect is positive or not, based on the frequency of appearing of the most common positive hashtags like #stayhome, #staysafe .The proposed approach has four main phases, the first phase is the collecting of Twitter social network datasets. The Twitter API is used to get most recent COVID-19 related tweets that contain certain hashtags like #COVID-19. Also, it used to extract the users of the collected tweets and their followers. The second phase is the creation of the social network graph from the collect dataset. The third phase is the detection of the top social network influencers by using LKG influence maximization approach. The last phase is the detection of the frequency of appearing of certain collected positive hashtags like #stayhome. It will help to detect the type of the influence for each top influencers and rank the detected top influential users based on the frequency analysis results.

The remaining of this paper is structured as follows: Section 2 provides a summarized survey of the related work, Section 3 shows the proposed approach on COVID-19 epidemic, and Section 4 presents the results of the presented work. Finally, Section 5 presents the conclusion of the proposed approach and the future work.

2. Related Work

There are many most recent approaches have been performed to analyze social networks data to help in preventing the spread of the COVID-19 pandemic, and provide more analytical knowledge about COVID-19 pandemic. Also, it can help in detecting the misleading information and fake news about the COVID-19 pandemic. Several studies are focused on analyzing the Twitter tweets, as mentioned at the introduction section. Twitter is a widely used microblogging and social networking service [3]. It can provide great daily updated information about the social effects of the COVID-19, and it can be used as indicator of the size of the COVID-19 spread. Park et al. [7] used content analysis and social network analysis to perform an analyical study on COVID-19 related Korean tweets. They implemented three approaches: content analysis, news channel classification and social network analysis. They found that the transmission of information in COVID-19 networks was faster than the other networks. Belso-Martínez et al. [8] studied COVID-19 pandemic in Spain using social network analysis techniques. The main target of their approach is to analyze the positions and the rules of the organizations that participate on the ecosystem. The archived results of the proposed study show that the social network analysis techniques is a practical and suitable tool to identify and analyze the relationship between organizations. Dubey et al. [9] collected related COVID-19 pandemic tweets from four different European countries for a period of 20 days. The collected tweets are used for analyzing the explosion of the new COVID-19 pandemic.

Alhajji et al. [10] implemented a sentiment analysis study for tweets related to COVID-19 in Saudi Arabia. Naïve Bayes model is applied to analyze the collected tweets of the Twitter users to predict their sentiment. Deng et al. [11] used data mining approaches and a set of predefined search terms related to COVID-19 to analyze Twitter data. Also, used Latent Dirichlet Allocation (LDA), as topic modeling approach to detect the most popular topics published by the different users to detect and identify the trending topics. According to the findings of the study, the economic situation is more important for Twitter users than the current status of COVID-19 pandemic. Also, according to COVID-19 stage, the online discourse in the United States and China reflects the crisis lifecycle.

Alsuias et al. [12] collected Arabic tweets related to COVID-19 pandemic, and performed an analytical study on the collected tweets. There are three different types of the performed analysis to explore the collected data: source type prediction, cluster and rumor detection. Medford et al. [13] used unsupervised machine learning approaches for the analysis of related COVID-19 pandemic collected tweets. Alqurashi et al. [14] used two ranking algorithms to identify the most effective users of the Twitter Arabic content: PageRank and hyperlink-induced topic search (HITS). The results of the study showed that PageRank and HITS detected a similar subset of influential accounts, where 50% of the detected top influential users live at Saudi Arabia, and 40% of them are verified as Twitter accounts.

Al-Shargabi et al. [4] proposed a research study to explore the spread and the effects of the COVID-19 pandemic by analyzing the tweets of Saudi Arabia Twitter users. They collected 8905 Arabic tweets to visualize the social network for COVID-19 pandemic tweets of Saudi users. Singh et al. [15] performed a sentiment analysis to analyze social opinions about the COVID-19 and to represent their opinions, using BERT model on two collected Twitter datasets. One of the collected datasets related to Indian tweets and another one for the rest of the world. Chintalapudi et al. [16] used the deep learning BERT model to analyze COVID-19 pandemic related tweets for Indian people. The analytical results of the Indian tweets during COVID-19 pandemic present high prevalence of keywords and the associated terms.

3. The Proposed Approach

The proposed approach of the detection of the top positive influential social networks users has four phases as shown on figure1. The first phase is the data collection of Twitter users, and the most popular positive hashtags. The second phase is the creation of the social network graph using the collected datasets. The third phase is based on using of the LKG influence maximization approach to select and detect the top influential users from the created social network graph. The fourth phase is the analyzing of the related tweets of the detected top influential users using the set of the collected positive hashtags to rank and select the top positive influential users.

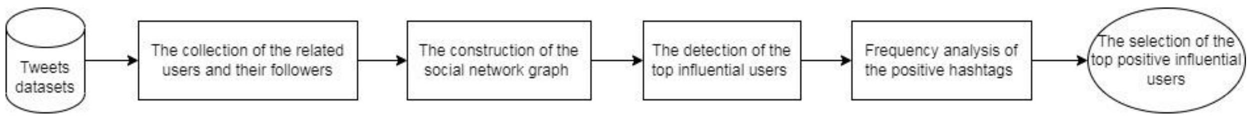

Figure. 1: The main stages of the presented approach to detect the top positive social networks influential users.

3.1. Data Collection

There are two types of datasets have been collected at this phase. The first one is the collection of a raw social network dataset. Twitter APIs is used to collect tweets contain hashtags related to COVID-19 pandemic like #Coronavirus, #Covid19 and #Covid-19. The collected tweets contain raw information, as each tweet has many parameter like “Twitter user ID” which is a unique value to identify each user, “Created_at” which means when the tweet has created, “Location” which refers to the place where this tweet is created, and “Followers_count” which refers to the number of the followers of the user who created this tweet. Figure 2 shows a sample of the collected tweets. Also, it shows the details of each collected tweet. The collected tweets can’t be used directly to create the social network graph. So the next step is extracting the unique users from the collected tweets followed by searching and extracting samples of the followers of each user (up to 5000 followers) using Twitter APIs. Table 1 shows the details of the collected dataset. The most popular positive hashtags is the second type of the collected datasets. The online sources are used for detecting and collecting the public and trending positive hashtags, used by local and national health organizations [17, 19]. Table 2 shows the collected positive hashtags. The positive hashtags are used at the last phase of the proposed approach to analyze the latest tweeted of the top influential users as the users that use positive hashtags on their tweets more frequently than the other are more likely to have positive influence effects than the other users.

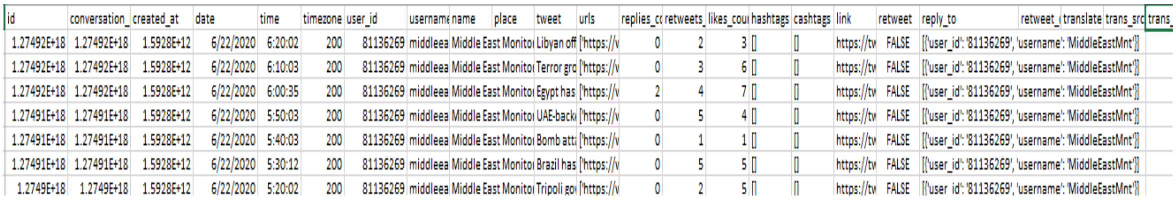

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Figure. 2: A sample of the collected tweets.

Table 1 The details of the collected dataset

Metrics	Value
No of tweets	52963
No of users	7422
Date of tweets	From 2020-3-15 to 2020-4-15
Place	England

Table 2 All the positive hashtags that are used to implement the proposed approach

Hashtag	Hashtag	Hashtag	Hashtag
#SlowTheSpread	#FlattenTheCurve	#GetVaccinatedNow	#WearAMask
#StaySafeStayHome	#DoYourPart	#TogetherWeCanDoIt	#Lockdown
#Maskathon	#StayHome	#StaySafe	#HealthcareHeroes
#stayathomechallenge	#TogetherAtHome	#VaccinesSaveLives	#trustscience
#StayHomeStaySafe	#COVIDIOTS	#covidvaccine	#StayHomeSaveLives
#SocialDistancing	#ViewFromMyWindow	#AtHomeWorkouts	#TogetherAtHome
#vaccines	#MaskOn	#vaccinated	#GetVaccinated

3.2. The Construction of the Social Network Graph

The graphs of the different social networks can be represented as an undirected graph or as a directed graph. The undirected graphs have edges between the different nodes, but without a direction. The edges represents a two-way relationship, where each edge can be traversed in both directions. Figure 3 shows a simple example for an undirected graph has three nodes and three edges between these nodes. The directed graphs have edges with direction. The edges represents a one-way relationship, where each edge can only be traversed in a single direction. Figure 4 shows a simple example for a directed graph has three nodes and two edges between the both nodes. Twitter social network can be represented by a directed graph G= (V, E), where V represents Twitter's users and E represents the following relationships between the different users. Figure 5 shows an illustrative example for the directed graph of Twitter following relationship. As shown user A follows users B, and C, while user B follows user C, and user C follows user A. The collected dataset at the previous phase is used here to construct the social network graph to be used in the next phase to select and detect the top social network influencers.

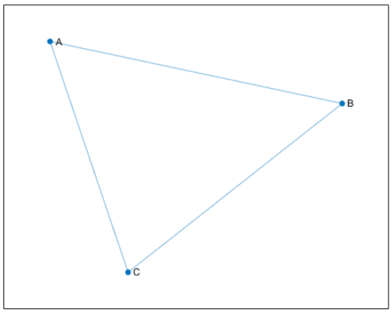

Figure. 3: A simple example for an undirected graph with three nodes and three edges.

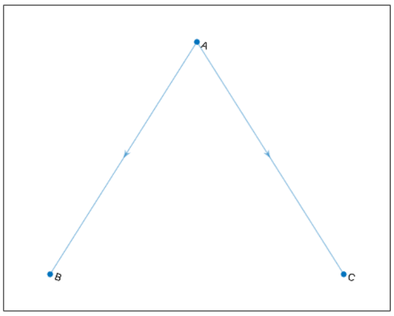

Figure. 4: A simple example for a directed graph with three nodes and two edges.

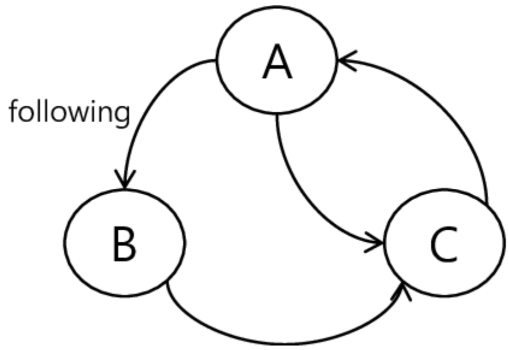

Figure. 5: An illustrative example for the directed graph of Twitter following relationship.

3.3. The Detection of the Top Influential Users

The detection of the top influential users of the social networks is a well-known as the influence maximization problem. There are several approaches and methods have been implemented for the detection of the top influential users [19-21]. The node degree is a one of the most popular centrality-based algorithms [21]. For Twitter directed follow graph there are two types of degree. The in-degree of each user refers to the number of users who follow him. Meanwhile out-degree of each user refers to the number of users who he follows [22]. The influence maximization approach LKG (Louvain K-Shell Generalization) which is proposed by Samir et al. [19] is used to detect the top influential users from the constructed social network graph. The LKG is a recently developed community based approach for influence maximization problem. It shows great performance on different size datasets of different social networks. LKG approach has three main phases: The first phase is the community detection, at this phase the different communities that represent the social network graph are detected using Louvain algorithm [23]. The second phase is based on applying the k-shell decomposition approach [24] on each of the generated communities to detect the k-core nodes of each one. The last phase is to generalize the selection of the top influential users of the whole social network graph by applying a generalization algorithm to select the top influential users that will represent the whole social network graph. The in-degree is used as the effective degree for the calculation and sorting of the top influential users. As the tweets that have been created by the users that have high in-degree values have high chance to be seen and to be retweeted by many other users . The in-degree is calculated for each user on the constructed social network graph at the last phase.

3.4. The Frequency Analysis of the Positive Hashtags

The collected positive hashtags appear on table 2 is used at this phase to analyze the tweets of the selected and the ranked top influential users. The latest tweets (about 3200 tweets) of each ranked users are collected to perform a hashtag frequency analysis on these tweets. The positive influential user who tweets or retweets positive information about the prevention, and the protection from COVID-19 pandemic always uses the positive hashtags on his tweets. Based on the frequency of the appearance of the positive hashtags, a new sorted list is created to represent the top positive influential users who are more likely to use positive hashtags about COVID-19 pandemic. The sorted list shows the top positive influential users, who can be used to post and share useful and helpful information about the control of COVID-19 pandemic.

4. The Experiments and the Results

This section shows the experiment results on the collected dataset and shows the discovered insights about the collected tweets and the detected top positive influential users. Also, it shows useful information about the most popular positive hashtags that appear on the tweets of the top positive influential users. All experiments are performed on a machine with Intel core i7 with 8 Giga of Ram, and all experiments are implemented with Python 3.7.

Table 3 An overall view of the created Twitter social network graph

Metric	Value
Number of nodes	4646319
Number of edges	7241884
Average degree	1.5586

The users of the collected tweets and their followers are used to construct the social network graph. As the following relationship is used as the edges between users as mentioned before. An overall view of the created social network graph appears on table 3. As it shows the total number of nodes of the constructed graph and the number of the edges between the users. Also, it shows the average degree of the users or nodes appear on the social network graph. The size of the required seed set of the top influential users depends on the main purpose of the experiment for example Table 4 shows the top detected 40 influential users. The top influential users appear on descending order. For each top user there are two values: the user_id and the username, that appear on the user’s Twitter account. The accounts of poplar news agencies like @TheSun , @Daily_Express appear at the top of the list of the top influential users. The hashtags frequency analysis is applied on the most recent tweets of the detected top 40 influential users to determine polarity of their tweets and to rank the influence effect as positive or not. The collected positive hashtags appear on table 2 are used for the frequency analysis process. Table 5 shows the ranking of the top 10 positive influential users of the created Twitter social network based on the results of the frequency analysis process. The ranking has been created using the frequency analysis results of the lasted tweets (up to 3200 tweet) of each detected top influential users. The ranking of the top positive users can change over the time, as it depends on the frequency of appearing of the positive hashtags on their tweets. Figure 2 shows the frequency of appearing of the top positive 5 hashtags on the latest tweets of the detected top 40 influential users. The #lockdown hashtag is the most common hashtag appears on the most recent tweets. Also, the hashtag #staysafe appears frequently on the latest tweets.

Table 4 The top 40 influential users of the social network

User_Id	User_Name	User_Id	User_Name
34655603	@TheSun	135857034	@D_Raval
17895820	@Daily_Express	31129844	@NHSEnglandLDN
16596200	@natalieben	15994601	@demagazine
1964862775	@Underground_RT	16615594	@grattongirl
15484198	@georgegalloway	313890182	@caoilfhionnanna
12874852	@wellbelove	2645483767	@AFNCCF
31252613	@davemacladd	915895342532583424	@BenDoBrown
108286674	@BernardMarr	365941621	@ImperialMed
31095945	@shaancheema	515932927	@LoveUrdoorstep
81136269	@MiddleEastMnt	331672974	@theJeremyVine
330509397	@pdiscoveryuk	289980669	@ppvernon
399307197	@Catapult_UK	92986215	@RESCUE_UK
1242631568	@Angie_RejoinEU	19915362	@DFID_UK
35538459	@KajEmbren	21004673	@iancowie
2354368831	@LondonNetworker	108995096	@RnfrstAll_UK
806127351922888704	@ThriveLDN	36912323	@grattonboy
20329672	@friends_earth	746684881623724032	@DrATesta
2320715580	@AntiRacismDay	440982753	@ashnagesh
162071541	@ShaunLintern	390628590	@andy_woodfield
619917425	@zsahLTD	310189843	@BIHRhumanrights

Table 5 The detected top 10 positive influential users of the social network

User_ Id	User_name	Positive hashtags frequency
36912323	@grattonboy	48
16615594	@grattongirl	25
31129844	@NHSEnglandLDN	25
19915362	@DFID_UK	22
2645483767	@AFNCCF	21
365941621	@ImperialMed	17
108286674	@BernardMarr	12
399307197	@Catapult_UK	12
1242631568	@Angie_RejoinEU	10
515932927	@LoveUrdoorstep	10

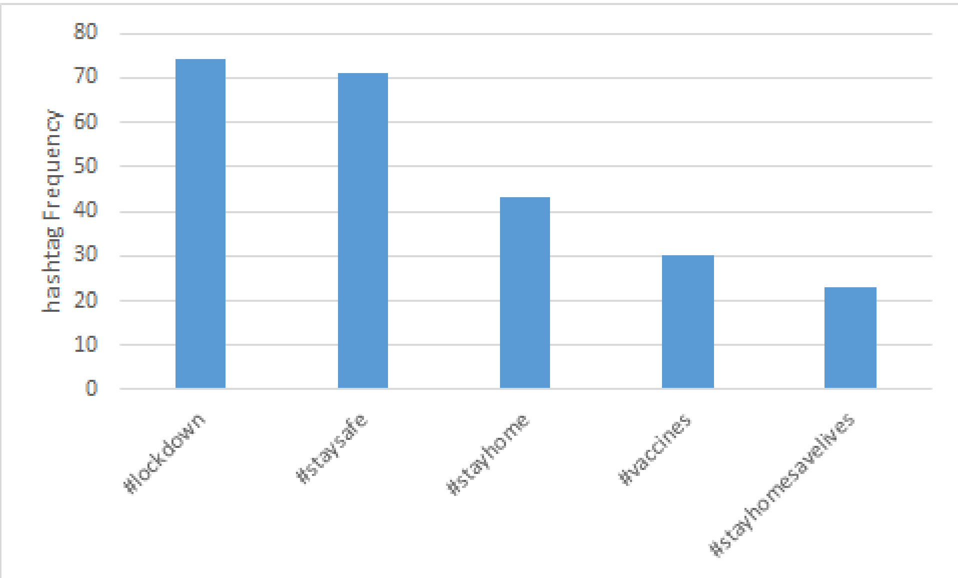

Figure. 6: The frequency of the appearance of the top 5 positive hashtags.

5. Conclusion

The prevention and control of the spread of Covid-19 pandemic is one of the critical directions that can help the world to overcome health care crises that caused by the spread of Covid-19 pandemic. Social networks like Twitter can play a vital and critical role in supporting the efforts toward reducing the number of new infections and the number of new deaths. The detection of the top positive and negative social network influencers can help health care organization to share and publish useful and helpful information about the protection rules and the correct and bad habits that can help in controlling the spread of Covid-19 pandemic. The proposed approach uses LKG influence maximization approach to detect the top positive influencers. The proposed approach has the following phases: first collecting related tweeted about Covid-19 using related hashtags. Also, collecting the most positive hashtags about Covid-19. The Twitter API is used to get related Covid-19 pandemic tweets. Also, it is used to extract the related users and their followers. The second phase creates the social network graph of the users and their followers of the collected tweets. The third phase is based on apply LKG influence maximization approach to detect the top influencers of the social network. The last phase is based on using the collected positive hashtags to analyze the lasted tweets of the detected top influencers to rank them based on the frequency of the appearance of the positive hashtags on their tweets. The future work will focus on applying the proposed approach on more Twitter datasets with different sizes and using datasets for other social networks like Facebook and Instagram.

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