Evaluating Roles of Central Users in Online Communication Network: A Case Study of #PanamaLeaks

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Abstract

Social media has changed the ways of communication, where everyone is equipped with the power to express their opinions to others in online discussion platforms. Previously, a number of studies have been presented to identify opinion leaders in online discussion networks. Feng (“Are you connected? Evaluating information cascade in online discussion about the #RaceTogether campaign”, Computers in Human Behavior, 2016) identified five types of central users and their communication patterns in an online communication network of a limited time span. However, to trace the change in communication pattern, a long-term analysis is required. In this study, we critically analyzed framework presented by Feng based on five types of central users in online communication network and their communication pattern in a long-term manner. We take another case study presented by Udnor et al. (“Determining social media impact on the politics of developing countries using social network analytics”, Program, 2016) to further understand the dynamics as well as to perform validation. Results indicate that there may not exist all of these central users in an online communication network in a long-term manner. Furthermore, we discuss the changing positions of opinion leaders and their power to keep isolates interested in an online discussion network.

Keywords: Complex network, Social network analysis, opinion formation

1. Introduction

To exchange opinions and information, internet is being used all-around the world. With increased use of internet, social media also became popular and a central medium for communication. In recent times, social networking has become de facto medium for communication among the same social group or network [1]. People participate in online discussion by using different platforms like Facebook, Twitter, YouTube and other social networking tools [2]. Twitter is one of the popular social networking tool (micro blogs) among others, where people broadcast brief update messages [3].

In scientific literature, a number of studies have been carried out using Twitter data. For example, Ch’ng in [4] used Twitter data to find generation of online communities and Baek in [5] argued roles and positions of participants in an online community. Geo located tweets are used
by Blanford in [6] to capture regional connections and cross border movement. Twitter data is even used for evaluation of inter organizational disaster coordination networks, created in result of disaster [7]. Lee et al. in [8] demonstrated how scholars are using Twitter communication network for informal scholarly communication. Authors used social network analysis methods in all of the above-mentioned studies. Social network analysis is a strategy for analyzing social structures [9]. Aim of all the above studies in different fields is to find the influential nodes in network. In online communication network, these nodes are called opinion leaders.

Rogers defined opinion leadership as “the degree to which an individual is able to influence other individuals’ attitudes or overt behavior informally in desired way with relative frequency” [10]. The concept of opinion leadership originates from two step flow theory, the theory posits that information first comes from mass media to opinion leaders and then this information is transmitted to society via opinion leaders [11]. Opinion leaders are opinion broker in two sense, first opinion leaders influence is between two social groups rather than in-between social group and second they are transition between two network mechanism responsible for spreading the idea [12].

For identification of opinion leaders in Twitter network, Borge in [13] used social network analysis techniques on following-follower and mention network. Some researchers proposed different algorithms to find opinion leaders in social networks. For example, Aleahmad et al. proposed OLFinder in [14] and Huang proposed a Dynamic Opinion Rank algorithm in [15]. Li et al. in [16] proposed framework for opinion leader identification, which consist of five stages. First is keyword blog search; second is ontology extraction; ontology-assisted extraction and hot blog identification is third and fourth respectively; fifth and last stage of framework is opinion leader identification. The method of identifying opinion leaders in virtual communities proposed by Zhang in [17] consist of five stages: first, find twenty participators who are active with large followers; second, to investigate details of these active users, construct a relational matrix; third, centrality analysis; fourth, identify opinion leaders by comparing standardized degree of network users; last, if centrality and map analysis fails then correlation analysis is used. Researchers also applied two step flow theory [11] for identifying opinion leaders in online social network.

By adopting two step flow theory, Feng in [18] proposed another approach to identify central users in the online communication network. In this work, the author identified five types of central users in Twitter network: conversation starter, influencer, active engager, network builder, and information bridge. However, Feng study analyzed tweets in only four-days time span to trace communication patterns that is not appropriate because opinion in a society may vary with time. The proposed approach needs to be applied for trend analysis on longitudinal network.

In this context, this study explores communication patterns among participants of online discussion network in longitudinal manner by adopting previous approach proposed by Feng in [18]. In this study, we use “PanamaLeaks” as case study. International Consortium of Investigative Journalists’ raised issue of Panama Leaks by leaking 11.1 million records from Panama-based law firm, Mossack Fonseca [19]. We retrieve Twitter data using #PanamaLeaks keyword from April 2017 to August 2017. The research questions we address are: Weather central users identified by Feng study exist in online communication network in longitudinal manner?. If yes, then what are the changes in communication pattern of central users?. For validation, we apply the same approach on another case study of #NeigieraDecides presented in [20].
Our main contributions can be listed as follows:

- To identify most central users in longitudinal network of #PanamaLeaks.
- To analyze the flow of information among the participants of online longitudinal discussion network in #PanamaLeaks.

The reminder of the paper is structured as follows: Section 2 presents background, Section 3 presents our proposed method and dataset followed by results presented in section 4, Discussion is formulated in section 5.

2. Background

In this section, we present characteristics and communication patterns of the most central users identified by Feng in [18].

2.1. Conversation starter

A conversation starter is a user in network with numerus “in-degree” links and a few or none “out-degree” links. Conversation starter is the one, who is responsible for starting the original topic and flow of information in the network. However, the control on flow of information in network is not under control of the conversation starter. Figure 1 shows connection pattern for conversation starter in the network.

![Figure 1: Connection Pattern for “Conversation Starter” in online discussion network. Circles are presenting users in the network. Circle filled with black color is “Conversation Starter”. Many arrows pointing towards “Conversation Starter” presents many users in the network mentioning/retweeting “Conversation Starter” tweet.](image)

2.2. Influencer

An influencer is opinion leader in the network. Influencer in a network has plentiful “in-degree” links and few “out-degree” links. Influencer does not initiate the topic of conversation in the network, however influencer do influence opinion of other users in the network by creating frequent tweets that are retweeted by other users. Figure 2 shows connection pattern for influencer in the network.

![Figure 2: Connection Pattern for “Influencer” in online discussion network. Circles are presenting users in the network. Circle filled with black color is “Influencer”. Many arrows pointing towards “Influencer” presents many users in the network mentioning/retweeting “Influencer” tweet.](image)
2.3. Active engager

An active engager in a user in online discussion network with many “out-degree” and a few or none “in-degree” links. Active engager is eager to distribute information and make connections in online discussion network. Active engager is also opinion expresser in network. Figure 3 shows connection pattern for active engager in the network.

2.4. Network builder

Despite having a few “out-degree” and a few or none “in-degree” links in online discussion network, network builder plays an important role in the network. Main role of network builder is connecting two or more influencers in the network. Figure 4 shows connection pattern for network builder in the network.
2.5. Information bridge

An information bridge is a user in online discussion network with a few “in-degree” and “out-degree” links. Information bridge role is to assist influencer and active engager in the network to connect with other users (Feng 2016). Note that in both case studies, #Panamaleaks and #NigeriaDecies which we took for validation. We are unable to find such user in the online discussion network (see section 5). Figure 5 shows connection pattern for information bridge in the network.

3. Proposed Methodology

3.1. Tool

We choose NodeXL and Gephi as tools to analyze #PanamaLeaks network. NodeXL is an extensible toolkit to download and analyze network data [21]. NodeXL is capable of calculating network
matrices like “in-degree”, “out-degree”, “betweenness”, “density”, “modularity” etc. NodeXL generates excel-based reports and it is capable of downloading and analyzing data of several social network platforms like Twitter, Flickr and Facebook. In Twitter user network, a Twitter user is vertex in NodeXL and edge represents the relationship between users. Relationship between two vertices can be direct or un-directed. In Twitter user network, “in-degree” of each vertex is how many users in network have mentioned or retweeted his/her tweet. Retweets by a user in the network and other users mentioned by that specific user is out-degree of that vertex.

Along with finding the most central users of #PanamaLeaks network, we aim to visualize #PanamaLeaks network dynamically to find structural changes in the network. We choose Gephi social network analysis tool [22] for network visualization due to its capability for visualizing large, complex and dynamic networks. Gephi is capable of visualizing network with many different algorithm like Force-Atlas, Fruchterman-Reingold, Yifan Hu etc [23].

3.2. Data Source

We used NodeXL Twitter Search Network data collector to get tweets having #PanamaLeaks. It took us six months to collect these tweets because twitter streaming API only allows downloading previous seven days of tweets. We choose #PanamaLeaks as keyword to download tweets. Our dataset contains 10612 nodes and 24623 edges exist in the #PanamaLeaks network during March 2017 to August 2017.

For validation purpose, we took #NigeriaDecides case study data set is used in [20]. The author used #NigeriaDecides as a query to download tweets and generated network of tweets, mentions and replies, which is same as #PanamaLeaks case study. #NigeriaDecides case study data set consist of 1752 nodes and 6343 edges from 15 April 2015 to 20 April 2015.

In both case studies networks, nodes are the twitter users and edges are the relation between two twitter users. NodeXL add an edge, when one user tweets, retweets or mention other user/users in his/her tweet. Edges coming towards one users is “in-degree” of that specific user and edges going from that user to others in network are “out-degree” of that specific user. If a user creates new tweet/tweets without mentioning, replying or retweeting another users tweet, NodeXL adds self-loop around that user in the network.

3.3. Methods

We combine all the data (Tweets downloaded using NodeXL during six months) and then divide it into six months of different networks according to the dates of tweets from March 2017 to August 2017. We requested NodeXL to generate following matrices “in-degree”, “out-degree”, “betweenness centrality”, “density”, “clustering coefficient”, and “modularity” for each month independently. “In-degree” is simple count of unique incoming connections/links towards a user/entity in a directed graph. Whereas “out-degree” is simple count of unique links/connections from a user. “Betweenness centrality” of the node (A unique user in a network) is how many times a node appears in the shortest path between other nodes (other users in the same network) [24].

“In-degree”, “out-degree” and “betweenness centrality” are the three measures used by Feng in [18] for identifying most central users in online discussion network. That is the reason we also used these three measures on #PanamaLeaks case study. We identified top ten central users based on “betweenness centrality” for each months in the #PanamaLeaks network. We also identified
top ten central users in the #NigeriaDecides case study used in [20] for validation purpose. For visualization of connection patterns for most central users in #PanamaLeaks network, we use Yifan Hu algorithm for both case studies. Figure 7 shows connection pattern for conversation starter for #PanamaLeaks and #NigeriaDecies. Figure 8, 10 and 12 shows connection patterns for influencer, active engager and network builder in the #PanamaLeaks network for each month from April 2017 to August 2017. Figure 9, 11 and 13 shows the connection patterns for #NigeriaDecides network.

We used social network analysis measures like “density”, “clustering coefficient”, and “modularity” to analyze overall communication pattern among the participants of the #PanamaLeaks network. To check the impact of conversation starter and influencer on the online discussion network, we use number of unique users coming into #PanamaLeaks network every month.

For visualization of overall communication pattern among #PanamaLeaks network participant. We created dynamic network of #PanamaLeaks using Gephi. We implemented month wise time stamp on the network based on tweet date. We used Yifan Hu algorithm, one of the many available algorithm for network visualization in Gephi. Figure 15a, 15b, 15c, 15d, 15e and 15f are showing communication patterns between all users of #PanamaLeaks network for March, April, May, June, July and August respectively. Figure 16 shows overall visualization of the complete six months network from March 2017 to August 2017 using Yifan Hu algorithm. Our overall research methodology has been shown in figure 6.

4. Results

In this section, we present series of experiments carried out in our study.
4.1. Conversation starter

According to the two-step flow theory, information flows from mass media to opinion leaders and then transmitted to the population via opinion leaders [11]. In light of the above, we took “siasatpk” as our conversation starter as it is a mass media platform. As per the result of NodeXL, conversation starter topped the list as expected. According to results of March, April, May, June, and July “in-degree” of “siasatpk” is 211, 137, 203, 446 and 1463 respectively. Whereas, “Out-degree” of “siasatpk” for March, April, May, June, and July is 1, 3, 2, 7 and 22 respectively. “siasatpk” who is playing the role as conversation starters in #PanamaLeaks network remains the first or second most influential participant of the network from March to July. “In-degree” of “siasatpk” is zero in the month of August because “siasatpk” stop taking participation in discussion from August (See Table 1).

Table 1: Presenting “in-degree”, “out-degree”, “betweenness centrality” and “rank” of “siasatpk” playing role as “Conversation Starter” in the #PanamaLeaks network. The number “1” in rank column presents that “conversation starter” is the most central user in #PanamaLeaks network.

| Month | In-degree | Out-degree | Betweenness   | Rank |
|-------|-----------|------------|---------------|------|
| March | 211       | 1          | 492974.973    | 1    |
| April | 137       | 3          | 461067.857    | 2    |
| May   | 203       | 2          | 975715.667    | 2    |
| June  | 446       | 7          | 1219538.696   | 1    |
| July  | 1463      | 22         | 7539507.557   | 1    |
| August| 0         | 0          | -             | -    |

“saharareporters” with (in – degree = 345, out – degree = 13 and betweenness – centrality = 616332.423) is playing the role of conversation starter in the #NigeriaDecides case study, which we used for validation. As far as the connection pattern for conversation starter of #PanamaLeaks network, Figures [7a][7b][7c][7d] and [7e] are showing the five months connection pattern of conversation starter. Mostly isolates are pointing towards the conversation starter (mentioning or retweeting tweets of conversation starter). Conversation starter is acting as a hub in the #PanamaLeaks network. Results of the #NigeriaDecides case study used for validation revels the same pattern of communication between conversation starter and other participants of the network. (See Figure [7f]).
Figure 7: Connection Pattern for “Conversation Starter” of every month. Middle node of every figure is “Conversation Starter”. Size and color of nodes is according to their degree. Thus, the nodes bigger in size are high degree nodes and smaller nodes are nodes having low degree. Whereas, green nodes are nodes having lowest degree and color tends to change towards white with increase in degree.
4.2. Influencer

There can be more than one influencer in the online discussion network as result shows. Here we present top three influencer in #PanamaLeaks network of each month based on “betweenness centrality”. In March, “qaiserthethia” with ($in – degree = 139, out – degree = 12$) is the third most central user of the network. Fourth most central user of the March network is “alirazatweets” with ($in – degree = 150, out – degree = 1$). “xaifoo_official” is the fifth most central user in March network with ($in – degree = 90, out – degree = 1$).

In April, “ptiofficial” is the most central user of the network acting as an influencer in the network with ($in – degree = 266, out – degree = 1$) which means 266 other users have mentioned or retweeted “ptiofficial” tweets. Third most central user is “qaiserthethia” with ($in – degree = 107, out – degree = 12$) and “amranafahad” with ($in – degree = 116, out – degree = 2$) is fourth most central user of April network.

In May, the most central user is “khaleejmag” with ($in – degree = 347, out – degree = 1$). “diyarahman99” is the third most central user of May network with ($in – degree = 176, out – degree = 1$) and “maryammsharif” with ($in – degree = 59, out – degree = 0$) is the fourth most central user of May network.

In June, second, fourth and sixth most central users are “dunyanews”, “imrankhanpti” and “ptiofficial” with ($in – degree = 290, out – degree = 17$), ($in – degree = 105, out – degree = 0$) and ($in – degree = 80, out – degree = 1$) respectively playing role as influencers in the network.

In July, “imrankhanpti” with ($in – degree = 181, out – degree = 0$), “dunyanews” with ($in – degree = 122, out – degree = 15$) and “defencepk” with ($in – degree = 111, out – degree = 1$) are the second, fourth and fifth most central user in the network.

In August, “Shahzad_ind” with ($in – degree = 721, out – degree = 2$) and “yadavtejaswi” with ($in – degree = 622, out – degree = 0$) are the top two most central users in network.

The overall results of the top three influencers of each month is shown in table 2.
Table 2: Top Three “Influencers” of #PanamaLeaks network for every month based on “Betweenness Centrality”

| Month | Name of User         | In-Degree | Out-Degree | Betweenness  | Rank |
|-------|----------------------|-----------|------------|--------------|------|
| March | qaiserthethia        | 139       | 12         | 315421.518   | 3    |
|       | alirazatweets        | 150       | 1          | 251914.020   | 4    |
|       | xaifoo_official      | 90        | 1          | 200590.403   | 5    |
| April | ptiofficial          | 266       | 1          | 596473.970   | 1    |
|       | qaiserthethia        | 107       | 12         | 329445.157   | 3    |
|       | amranafahad          | 116       | 2          | 288166.206   | 4    |
| May   | khaleejmag            | 347       | 1          | 1313558.254  | 1    |
|       | diyarahman99         | 176       | 1          | 608312.772   | 3    |
|       | maryamnsharif        | 59        | 0          | 551766.163   | 4    |
| June  | dunyanews             | 290       | 17         | 836335.327   | 2    |
|       | imrankhanpti         | 105       | 0          | 288851.658   | 4    |
|       | ptiofficial          | 80        | 1          | 213124.288   | 6    |
| July  | imrankhanpti         | 181       | 0          | 800178.225   | 2    |
|       | dunyanews             | 122       | 15         | 705731.185   | 4    |
|       | defencepk             | 111       | 1          | 601869.039   | 5    |
| August| shehzad_ind          | 721       | 2          | 328635.667   | 1    |
|       | yadavtejashwi        | 622       | 0          | 194985.667   | 2    |

Figure 8a shows the connection pattern of “qaiserthethia, who is playing role as influencer” in the month of March. Figure 8b shows connection pattern “ptiofficial”, acting as top influencer in the month of March. Many arrows are pointing towards this node can be seen in figure 8b and most of these nodes are small. Which means mostly isolates like to mention or retweet influencer in the network. “khaleejmag” is the top influencer of May network. Connection pattern of “khaleejmag” is shown in 8c. June result shows, that conversation starter and active engager of June both mentioned top influencer of that month. However, most nodes connecting with the “imrankhanpti” are small, which means they are also isolates having low connectivity in the network. Figure 8d, 8e, 8f are showing the connection patterns of top influencer of June, July and August respectively. All of the above figures are showing same pattern, which shows connection pattern of influencer in the network remain similar.
Figure 8: Connection Pattern for “Influencer” of every month. Middle node of every figure is “Influencer”. Size and color of nodes is according to their degree. Thus, the nodes bigger in size are high degree nodes and smaller nodes are nodes having low degree. Whereas, green nodes are nodes having lowest degree and color tends to change towards white with increase in degree.
In #NigeriaDecides network, “thisisbuhari”, “mbuhari”, “inecnigeria” are the top three influencers ranked by “betweenness centrality” playing the role of influencer with \((in – degree = 262, out – degree = 0, betweenness – centrality = 215550.136)\), \((in – degree = 169, out – degree = 0, betweenness – centrality = 199496.055)\), \((in – degree = 67, out – degree = 0, betweenness – centrality = 142580.817)\). Figure 9 shows the top influencer “thisisbuhari” of #NigeriaDecides. Results are consistent with #PanamaLeaks case study as well as Feng study [18].

![Figure 9: Top “Influencer” of #NigeriaDecides case study. Node in the center named as “thisisbuhari” is the top “Influencer” of #NigeriaDecides network. Size and color of nodes is according to their degree. Thus, the nodes bigger in size are high degree nodes and smaller nodes are nodes having low degree. Whereas, blue nodes are nodes having lowest degree and color tends to change towards white with increase in degree.

4.3. Active engager

Result shows that in the network of March second most central user with \((in – degree = 0, out – degree = 65)\) is “sugar9940” an active engager. In network of April “sugar9940” again act as an active engager with \((in – degree = 0, out – degree = 41)\) and became fifth most central user in the network. Seventh most central user “umj3rry” is active engager in network of May with \((in – degree = 0, out – degree = 56)\) and in June it’s once again “sugar9940” with \((in – degree = 0, out – degree = 96)\). In network of July and August “lavajatonews” with \((in – degree = 0, out – degree = 65)\), \((in – degree = 0, out – degree = 14)\) respectively is active engager. “lavajatonews” is third most central user of July network and seventh most central user of August network playing role as active engager (See table 3).
Table 3: Presenting “in-degree”, “out-degree”, “betweenness centrality” and “Betweeness wise rank” of the top “Active Engager” of each month in the #PanamaLeaks network.

| Month  | User name  | In-degree | Out-degree | Betweenness    | Rank |
|--------|------------|-----------|------------|----------------|------|
| March  | sugar9940  | 0         | 65         | 356338.123     | 2    |
| April  | sugar9940  | 0         | 41         | 216878.111     | 5    |
| May    | umj3rry    | 0         | 56         | 357661.301     | 7    |
| June   | sugar9940  | 0         | 96         | 530891.138     | 3    |
| July   | lavajatonews | 0      | 65         | 798249.408     | 3    |
| August | lavajatonews | 0      | 14         | 1360.000       | 7    |

Figures [10] is showing connection pattern for active engagers from March to August. In March, “sugar9940” is playing the role of active engager by retweeting/mentioning other participants of the network. “sugar9940” mentiond participant having high degree like “qaiserthethia”, “alirazatweets” and “siasatpk”, connection pattern of March active engager can be seen in [10a] “sugar9940” is again playing the role of active engager in April, Figure [10b] shows the connection pattern of “sugar9940”. Mentioning “qaiserthethia”, “maryamnsharif” and “imrankhanpti” three influencers in April network is the reason of his central position in the network. “umj3rry” takes the role of active enager in May network. Figure [10c] shows the connection pattern of “umj3rry”. By mentioning conversation starter, two influencers and other participants in June “sugar9940” again is the active engager as shown in figure [10d]. Figure [10e] shows the connection pattern for active engager of July and August month respectively. Interesting thing to note is that, in-degree for active engagers of all the months is zero. Which means either no participant has mentioned or retweeted active engager’s tweet.
Figure 10: Connection Pattern for “Active engager” of every month. Middle node of every figure is “Active engager”. Size and color of nodes is according to their degree. Thus, the nodes bigger in size are high degree nodes and smaller nodes are nodes having low degree. Whereas, green nodes are nodes having lowest degree and color tends to change towards white with increase in degree.
“wakiligentleman” is playing role as *active engager* in the network of #NigeriaDecides with $\text{in-degree} = 1$ and $\text{out-degree} = 26$. He is the seventh most central user of the network. “Betweenness centrality” of “wakiligentleman” is 112865.285. By mentioning/retweeting *influencers* as well as *conversation starter* in his tweets, he got high betweenness centrality. Figure 11 shows the connection pattern of “wakiligentleman”, results are consistent with #PanamaLeaks case study with many out-going connections.

![Figure 11: Connection Pattern for “Active Engager” of #NigeriaDecides network.](image)

Figure 11: Connection Pattern for “Active Engager” of #NigeriaDecides network. Node in the middle of figure is “Active Engager”. Size and color of nodes is according to their degree. Thus, the nodes bigger in size are high degree nodes and smaller nodes are nodes having low degree. Whereas, blue nodes are nodes having lowest degree and color tends to change towards white with increase in degree.

### 4.4. Network builder

“shahwar125” with only $(\text{in-degree} = 0, \text{out-degree} = 2)$ is interestingly sixth most central user of the March network playing role as *network builder*. With only $(\text{in-degree} = 0, \text{out-degree} = 7)$ “ambitiousfree” is again the sixth most central user of April network because he mentioned two influencers “maryamnsharif” and “amranafahad” in his tweets and build a strategic location in the network like “shahwar125” in the network of March month. “ali_axhar” with $(\text{in-degree} = 20, \text{out-degree} = 8)$, “deziggnerumer” with $(\text{in-degree} = 0, \text{out-degree} = 18)$ are the network builders for month of May and June respectively. In July we could find “.waqas788” as *network builder* on thirteenth position with $(\text{in-degree} = 5, \text{out-degree} = 21)$. In August with $(\text{in-degree} = 0, \text{out-degree} = 3)$ “foroneindia” is the network builder. He is the fourth most central user in the network. No *influencer* in the network of all months has mentioned *network builders* in his/her tweet but still by connecting two or more Influential, *network builders* got central positions in the network. The overall results of top *network builder* in the network is shown in table 4.
Table 4: Presenting “in-degree”, “out-degree”, “betweenness centrality” and “rank” of top “Network Builder” of each month in the #Panamaleaks network based on “Betweenness Centrality”.

| Month | User name       | In-degree | Out-degree | Betweenness     | Rank |
|-------|-----------------|-----------|------------|-----------------|------|
| March | shahwar125      | 0         | 2          | 186462.694      | 6    |
| April | ambitiousfree   | 0         | 7          | 162629.964      | 6    |
| May   | ali_axhar       | 20        | 8          | 295700.335      | 10   |
| June  | deziggnerumer   | 0         | 18         | 267362.714      | 5    |
| July  | _waqas788       | 5         | 21         | 276354.023      | 13   |
| August| foroneindia     | 0         | 3          | 2880.000        | 4    |

Node in the middle of Figure 12a “shahwar125” is network builder of March. With only two out-degree links, he is the sixth most central user in network. “shahwar125” built a strategic location in network by mentioning/retweeting only two participants having high degree. Figures 12b 12c 12d 12e 12f shows the connection pattern for network builder of April, May, June, July and August respectively. All the above figures show similar pattern of communication. All network builders have few “in-degree” and “out-degree” links; however, they build strategic location in the #PanamaLeaks network by mentioning influencers or conversation starter.
Figure 12: Connection Pattern for “Network Builder” of every month. Middle node of every figure is “Network builder”. Size and color of nodes is according to their degree. Thus, the nodes bigger in size are high degree nodes and smaller nodes are nodes having low degree. Whereas, green nodes are nodes having lowest degree and color tends to change towards white with increase in degree.
“teamagbaje2015” is playing the role as network builder in #NigeriaDecides network with in−degree = 13 and out−degree = 3. He is the fifth most central user of #NigeriaDecides network by only mentioning two influencer “thisisbuhari”, “demolarewaju” and conversation starter “saharareporters” of the network. This result is also consistent with #PanamaLeaks network. Figure 13 is showing the links of network builder of #NigeriaDecides network.

Figure 13: Connection Pattern for “Network Builder” of #NigeriaDecides network. Node in the middle of figure is “Active Engager”. Size and color of nodes is according to their degree. Thus, the nodes bigger in size are high degree nodes and smaller nodes are nodes having low degree. Whereas, blue nodes are nodes having lowest degree and color tends to change towards white with increase in degree.

4.5. Information bridge

Results reveal that there is no information bridge in #PanamaLeaks six months network. Information bridge is the user, who mention/retweets influencer tweet and that same tweet is again retweeted by active engager [18]. We could not find any user with few “in-degree” and “out-degree” links, who has retweeted influencer tweet and then that same tweet is retweeted by active engager. We applied this aproach to #NigeriaDecides case study [20] for validation purpose and according to the results; there exist no user like information bridge. Although, we were able to find conversation starter, influencer, active engager and network builder in #NigeriaDecides case study also.

4.6. Structural analysis

Figure 14a shows the number of unique users participating in #PanamaLeaks online discussion every month. Number of unique users coming into #PanamaLeaks discussion network was 1277 in March. In April and May 1412 and 1750 unique users came into the network respectively. 1487 unique users joined discussion in June and 3626 joined discussion in July. However, there is a sudden decrease in number of unique users participating in #PanamaLeaks discussion in August with 880 new unique users coming into the network. In September, there are negligible number of users discussing the issue of Panama Leaks anymore. That is the reason we only analyzed this network until August. Figure 14b shows the density of #PanamaLeaks network. Gradual decrees in the density of the network can be seen. However, there is a sudden increase
in density after July. Average clustering coefficient of #PanamaLeaks from March to August is shown in Figure 14c. Average clustering coefficient of the network starts from 0.049 on March and with gradual increase ends at 0.312 on August. Modularity of the #PanamaLeaks network is 0.773821, 0.656387, 0.696806, 0.579446, 0.49243 and 0.381433 for March, April, May, June, July and August respectively (See Figure 14d).

Figure 14: Number of Unique users are shown in 14a. Overall Density of #PanamaLeaks network is shown in 14b. 14c is showing Average Clustering Coefficient of the network. Figure 14d is showing Modularity of the network.

Figure 15 shows interaction patterns of users, there exist many isolates pointing towards the influencers and conversation starter in the network. Figure 15a shows the network of March and communities forming around conversation starter and influencers can be seen. These communities keep on growing until July, which can be seen in figure 15b, 15c, 15d, 15e and 15f. However, in August when major influencers and conversation starter left the discussion, communities started to dissolve which can be seen in figure 15f. A combine visualization of #PanamaLeaks network
from March to August is shown in figure 16. A circle of participants around the graph can be seen. These participants are not connected to any influencer or conversation starter in the #PanamaLeaks network.
Figure 15: Dynamic Graph Visualization of #PanamaLeaks network for each by Gephi using Yifan Hu algorithm. Communities forming around “Conversation Starter” and “Influencers” are presented in different colors.
5. Discussion

5.1. Conversation starter

A conversation starter is one, who is center of the network and connects many “isolates” who otherwise have few or no links in the network [18]. These are the participants with high betweenness [25]. Our results revealed the same as many “isolates” retweeted or mentioned “siasakpk” in their tweets. There were some influential mentioning conversation starter in their tweets but they are very few, mostly “isolates” tends to connect with conversation starter to gain information. Twitter users with high connectivity are better at influencing information flow in Twitter network [26]. This makes the conversation starter center of the network by various incoming connections. However, when conversation starter stops taking participation in the network (Stop Tweeting about the Topic) “isolates” also lose interest in the online conversation. As results revealed that in August when conversation starter is no more in the network, there is sudden decrease in the people discussing about the topic online. However, until the conversation starter keeps on participating in the discussion. Conversation starter remains on the top central positions in the network. (See Figure[17].)
5.2. Influencer

There exist influencers in the online discussion network [18] with plentiful “in-degree” and few “out-degree” links. They are called opinion leaders in the network and isolates like to mention them in their tweets. Isolates also like to retweet opinion leader’s tweet and these opinion leaders are usually mass media organizations or celebrities in different fields of life [18]. Opinion leaders create many tweets to influence other users in online discussion. In this way, they act to influence opinion in an online discussion network. Information is going from opinion leaders to users with less connectivity and this supports the argument by [27, 28] that opinion leaders by using their network connectivity replicate asymmetric offline power in online discussion. The participant like influencer who has high degree in network act as hub in the network [29]. However, Opinion leader’s influence is not consistent as the results show in #PanamaLeaks study their influence can increase/decrease with the passage of time. There can be changes in the “betweenness centrality” of network influencers as well. Figure [18] shows the changing in betweenness centrality of five selected influencers in the #PanamaLeaks network.
Figure 18: Changes in “Betweenness Centrality” of selected “Influencers” in #PanamaLeaks network.

5.3. Active engager

A user with many “out-degree” and none or few “in-degree” links is active engager in the network [18]. Results also reveal that there always exist an active engager in the network from start of conversation until end. However, position of active engager is not consistent and other active engager can take his/her place with the passage of time. Active engager is also among the top ten most central users of the network. Results show that active engager is one who is active and with intention to get information. However, there are usually few or no user in the network to follow or mention him in their tweets. From the centrality point of view, active engager is an important user. However, Active engager in a society is a person with special knowledge, who has potential to become influencer [30].

5.4. Network builder

Network builder in a network has few or none “in-degree” and few “out-degree” links [18]. His basic role in the network is to associate two or more influential nodes in network. By this, network builder builds a strategic location in network due to which it gets high centrality. However, in [18] “wnkr” is a network builder and its in-degree is “0”. Which means no one either has mentioned or retweet “wnkr” in their tweets. In #PanamaLeaks network, network builders follow the same tendency. In this context, we can conclude that network builder do help in creating connection between two or more influencers in the online discussion network. However, influencers usually do not mention or reply on their tweets. Therefore, their impact on the opinion in a network is petite.

5.5. Information bridge

Information bridge is a user with few ”in-degree” and “out-degree” links, who connects an influencer and active engager as noted in [18]. However, results of six months of network shows that there is no user such as information bridge exist in the network. We implemented this concept on the dataset #NigeriaDecides used in [20] for validation purpose. Result shows that in the #NigeriaDecides, there does not exist any user who has retweeted influencer tweet and that tweet
is retweeted by active engager. Active engager’s basic role in network is to get engage with other users [18], and for this purpose; active engager likes to retweet mostly influencer/conversation starter tweets. Active engagers do not mostly retweet/mention “isolates” in their tweets. In this context, we can conclude that there is very less chance that an active engager retweets same tweet in which a person with few “in-degree” and “out-degree” has mentioned influencer.

5.6. Network structure

Unique users have increased until June and then there is a sudden decrease in the number of unique users as shown in figure [14a]. When conversation starter stop taking participation in the online discussion there is a sudden decrease in number of unique users participation. Users with high connectivity like conversation starter can influence the participation of users [31]. In this context, opinion leaders have the power to keep isolates interested in the online discussion. Network density can decrease with the number of increase users in the network and increase when number of participants decrease [8], density of the network is showing same tendency. Participant of the online discussion tends to cluster around the influential participants and with the passage of time in presence of conversation starter and influencers, participant became less independent as modularity decreased [25]. However, with many participants having low degree pointing towards the conversation starter and influencer. We can conclude that they play role as hub in the online discussion network.
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