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Araştırma Makalesi ● Research Article

A Social Network Analysis Overview of Turkish Political Communication Competition on Twitter

Türkiye'de Twitter Üzerinden Siyasal İletişim Rekabetine Sosyal Ağ Analizi Üzerinden Bir Bakış

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Abstract: One of the primary purposes of political communication research is to determine the position of the public on any political issue. It is now possible to gather and evaluate information about people's political lives from a sizable data pool around the globe. In the newly emerging field known as Computational Social Sciences, computer science is employed to acquire and analyze these data. Through the emergence of a trend on social media, Turkey has recently witnessed a race between supporters of the ruling party and opposition groupings. In this study, two pro-government and pro-opposition trends (On Twitter) were taken into account when conducting social network analyses. Data were obtained from Twitter. According to the research, the pro-government trend spread at a rate of 155 tweets per hour, while the opposition-supported trend expanded at a rate of 127 tweets per hour. The graphs' observations show that spreading the opposition trend involves the usage of fake accounts more frequently than spreading the government-supporting trend. However, it has been observed that fake accounts are effective in the opening and course of both trends. Accordingly, it is thought that fake accounts seriously contribute to trend formation on Twitter.

Keywords: Political Communication, Computational Social Sciences, Twitter, Trend, Social Network Analysis

Öz: Siyasal iletişim araştırmalarının temel amaçlarından birisi kamuoyunun siyasete ilişkin herhangi bir konuda pozisyonunu tespit edebilmektir. Tüm Dünya'da büyük bir veri yığını üzerinden insanların siyasal hayatına ilişkin veri elde etmek ve analiz etmek imkânı doğmuştur. Hesaplamalı Sosyal Bilimler olarak ifade edilen yeni gelişmekte olan disiplinde bu verilerin elde edilmesi ve analiz edilmesi için bilgisayar bilimlerinden istifade edilmektedir. Son dönemde Türkiye'de sosyal medya üzerinden trend oluşturmak suretiyle iktidar ve muhalefet ittifaklarının taraftarlarının yarışına şahit olunmaktadır. Bu çalışmada iktidar ve muhalefet yanlısı iki trend ele alınarak sosyal ağ analizleri gerçekleştirilmiştir. Veriler Twitter dan elde edilmiştir. Araştırmada muhalefet destekli trendin saatlik yayılım hızı 125 tweet/saat, iktidar yanlısı trendin saatlik yayılım hızı 165 tweet/saat olarak bulunmuştur. Grafiklerden gözlemlere göre muhalefet trendinin yayılımında iktidarı destekleyen trendin yayılımından daha fazla sahte hesap kullanılmaktadır. Ancak her iki trendin de açılış ve seyrinde sahte hesapların etkili olduğu gözlemlenmiştir. Buna göre Twitter'da trend oluşturmada sahte hesapların ciddi katkısı olduğu düşünülmektedir.

Anahtar Kelimeler: Siyasal İletişim, Hesaplamalı Sosyal Bilimler, Twitter, Trend, Sosyal Ağ Analizi

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Introduction

Twitter is one of the platforms where the struggle for social media dominance and the creation of political agendas is most intense in Turkey. It is now simpler to understand which trend in social media supports or disparages which alliance since the day when the political structure based on alliances became prevalent in the nation's politics. How a political hashtag gains traction in such a short period is curious, though. This study aims to learn more about the network structures that supporters of the ruling and opposition alliances use to create trends by starting hashtags. By using visualization, it has been attempted to show how political messages have been distributed to communicate with social media users.

Everything has a pattern. Understanding the problem is made much easier by the pattern's detection. Social media is currently the most accessible medium for the image and pattern of political life, which is a reality that is widely acknowledged. Social media are internet-based platforms that enable users to instantly post their own material (Kaplan and Haenlein 2010). People have the chance to build a new network structure by opening up these shares to the general public (Fuchs 2011). It makes sense that political broadcasts on these networks spread more quickly than through more conventional communication channels. On the other hand, a "trend" is a mass broadcast that has developed with a different distribution and speed from individual broadcasts.

There have been attempts to rename this field as digital approaches have become more prevalent. "Political Communication 2.0" is the first of these ideas (Bostancı 2014). Some studies use e-Politics to describe it (Wattal et al. 2010). Due to its practicality, Twitter can be said to be unique among social media platforms regarding the specificity of information distribution or, more specifically, the pace of political communication. For this reason, the study was built on Twitter.

The main reason for choosing social network analysis in the research is to look at the structure of a trend before users, not the trend itself. The question "What is the relationship between these articles becoming a trend?" can be answered when phrased as a relational look (Gençer 2017). In summary, an effort to understand and compare the characteristics of social network clusters (communities) subject to political competition with the network analysis approach is mentioned.

Literature Review

Finding out how the public feels about a particular political topic is one of the critical goals of political communication research. Political communication scholars are now focusing on social media because of how efficiently it is used in today's politics. Social media may be used as a tool and database to gauge public sentiment toward political issues and policy proposals and to build support among the general public for candidates running for office (Zeng et al. 2010). It should be stressed that the world is in a time in political history where whoever uses this database the best will always be one step ahead.

Information about the pertinent literature is provided in this section of the study to express the social media data in political communication and the place of these data in political communication.

A brief overview of political communication

To clarify the conceptual underpinnings of the study, it is crucial first to examine the development of the idea of political communication and its relationship to social media. Political communication is one of the ideas for which no single definition represents a notion.

The concept of communication as a discipline was influenced by historical events like Nazi propaganda during World War II (Schramm 1983). Fear and worry have grown worldwide due to the political propaganda that has been spread during the conflict using media technologies. Instead of focusing on the actual operations of the soldiers in the field during this time, academics took action after approaching government authorities for advice on how to counter the effects of enemy propaganda at the time (Paul F. Lazarsfeld, Berelson, and Gaudet 1960). Due to the circumstances at the time, the topic of these early studies differed significantly from the breadth of modern political communication (Rogers and Chaffee 1983). The field, afterward known as "Political Psychology," was related to what was being attempted at the time (Monroe et al. 2009).

The study of political and communication scientist Harold Lasswell, which uses the phrases "To whom, gets what, how," and "Who says what, through what channels, and what is the effect," can be regarded to be the one in which the first examples of political communication in its modern sense are found (Jamieson and Kenski 2017; Lasswell 1948). Studies incorporating political processes into all communication-related fields have emerged over time. It shouldn't be restricted to just elections, or electoral processes have become apparent over time (Erdoğan 1999).

One of the widest descriptions from this perspective can be demonstrated as the relationship between political players and ideologies (Aziz 2021). This term makes it evident that political communication should consider all facets of politics. Because ideologies are one of the variables that influence how voters behave politically, and because voters determine the subject matter and mode of communication with other political participants, mainly within the framework of these ideologies.

If the goal is communication, human beings want the strongest. Within the context of communication and ties indicated above, everyone in political life wishes to employ efficient communication channels. If there is a political institution, it is only logical that it will try to influence the political agenda, or more specifically, the topics on which the political dialogue is most vigorous (Bachrach and Baratz 1962). With the advancement of internet technology, this condition changes the landscape of political communication. Since they first confronted the reality of the internet and social media, communication scientists have been obliged to look beyond conventional approaches.

It has become vital for a social scientist to collaborate with computer science, or in other words, with mathematics, to collect and analyze data using social media. The growth of the "Computational Social Sciences" field, which incorporates big data and coding, as well as the demand for political communication, indicates that social scientists will also need to use artificial intelligence in the future.

Political research's new frontier is social media – Computational Social Science era

Political debate is more vigorous in social media, as was said in the preceding section. Undoubtedly, Turkey is experiencing the same problem as the rest of the world. Institutions of politics and politicians frequently behave following this fact. Studies demonstrate that all parties seeking to engage with voters and communities analyze social media data scientifically (Kavanaugh et al. 2012; Paris and Wan 2011).

The first documented use of social media in the context of political persuasion occurred during the US elections of 2008 (Wattal et al. 2010). The Pew Institute reported that 57% of voters obtain political material online, which was the primary information that informed the deployment of this strategy by US Presidential candidates in 2008. According to this study, most internet users vote in online forums (Smith 2009). On microblogging sites, American voters have provided practical examples of political communication (especially on Twitter) (Golbeck, Grimes, and Rogers 2010).

Later, political campaigning activities manifested in more extreme locations, giving rise to the term "Twitter Revolution" (Stieglitz and Dang-Xuan 2013). For instance, during Iran's 2009 elections and ensuing protests, voters and protesters communicated with one another on Twitter (Gaffney 2010). The Arab Spring, which everyone is familiar with and lasted for years, was characterized by the same circumstance. At the same time, it started to show itself in European countries such as Germany (Tumasjan et al. 2011) and Sweden (Conover et al., 2011: p.89).

While these changes are occurring around the globe, it is apparent that scientific inquiry on the topic has also begun in Turkey. The use of social media platforms for political communication by political parties, their leaders, and executive managers of political parties as well as voter interactions in the 2011 elections were studied in a project funded by TUBITAK SOBAG (Bayraktutan et al. 2014). After the 2011 elections, social media data has become helpful in political research for several publications in Turkey (Atabek 2020; Bal and Delal 2019; Ceng 2018).

Obtaining and analyzing data about people's political lives from a sizable data pool all across the world is now both possible and required for scientists. Since 2008, numerous approaches have been explored for using social media data to examine all political events worldwide, including those in Turkey. Data mining, or the methods of gathering and analyzing data using computers and the internet, has become essential for social scientists, which caused the creation of a new field known as computational social sciences (CSS). Social scientists can collect data using a set of codes, but they also need assistance from computer science or should pick up coding skills. The article "Computational Social Science and Sociology" can be used for more details (Edelmann et al. 2020).

Even though CSS is a relatively new field, it has a history and will continue to develop as long as the internet and big data do. In social sciences, analyzing social networks and group formations is a crucial problem. One of the effective methods in this regard is social network analysis. This study also examines social networks.

Engagement Theory

Why political institutions make communication studies through social media? This can be explained by "Engagement Theory" (Solis, 2010). This idea was put forth by Brian Solis and is based on the idea that organizations should use social media to engage with their target consumers in order to build strong brands in terms of public relations. It is important to remember that the idea of "PR 2.0," which Solis first proposed years ago, serves as the foundation for engagement theory in terms of social media.

"PR 2.0" is about relationships, evolving "from pitching to participating, from selling a story to telling a story" (Solis & Breakenridge, 2009)

As a continuation of PR 2.0 theory, engagement theory has carried this concept of storytelling to the dimension of direct contact with the target group. In terms of political communication, establishing direct communication with the target group and ensuring the rapid dissemination of the desired propaganda through the target audience in the context of political propaganda can also be evaluated within the framework of this theory.

Social network analysis and social media networks

John Barnes first used the term "social networks" in 1954 (Serrat 2017). Barnes was an anthropologist and drew attention to the social network structures of primitive tribes. He used the term to map the relationships that bind social units together (Wasserman and Faust 1994). The topic of social network analysis is currently being discussed much outside the realms of anthropology and social psychology. In addition to human society or communities, it is an essential topic of examination in the operations of many institutions, including banks, non-governmental organizations, governments, and businesses (Durland and Fredericks 2005). On the other hand, the paper "The Development of Social Network Analysis" gives thorough material to explore the concept's history (Freeman, 2004.

The ability to map complicated systems based on relationships and condense them into a straightforward narrative makes social network analysis valuable. It is pretty convenient for a business or bank to be able to classify its clients based on their relationships and look at the electoral network structures of a political party.

The idea of system dynamics states that each component has a system within itself since the real world is made up of many intricately intertwined pieces. The relationship between the separate systems created by these little elements makes up the entire system (Bala, Arshad, and Noh 2017). In this complicated structure, social networks represent social ties as a system. These social networks in social media can be thought of as networks that share information. It is a truth that people use these information networks to accomplish their knowledge sharing, dissemination, or other social goals.

A finite number of participants and links can represent social networks in social media (Wasserman and Faust 1994). There are two methods for analysis. Graphic representation is the first of these. And statistical modeling is the second (van Duijn and Vermunt 2006). The topic of graphical representation is covered in this study.

In SNA, graphs are constructed using two essential elements – vertices (nodes) and edges (Oliveira and Gama 2012). Groups and social network infrastructures can be identified using this type of graph in terms of the social sciences. In this study, analysis was carried out over groups (clusters - communities). Although there are numerous small and large communities in the content of a trend, the graphics are only available for the five most interacting communities, as stated in the findings section. The reason for this is the determination of the following features:

"How separate are the subplots (do they overlap and share members, or do they split the network or group them)? How significant are the connected subgraphs? Are there a few large groups or more

small groups? Are there certain actors who appear to be playing network roles? For example, act like nodes connecting the graph, or who is isolated from the groups?"

(Jamali and Abolhassani 2006).

The researcher is given the following details about the social media network structure she/he is working on by the three features described above from the map produced by social network analysis. The size of highly interactive network graphs within a network is the first factor. This size provides the researcher with a view from the point of view of the second question. Is there a particular actor or actors who seem to be playing network roles? In other words, does the graphic reflect a real or fictional system?

Bots (fake robotic accounts) are one of the most common applications in social media networks. Researchers utilize a variety of mathematical models and artificial intelligence techniques to address this issue in social network analysis. With the model they developed, Kaur, Uslu, and Durresi enabled the determination of the density and truth coefficients in the SNA graphs(Kaur, Uslu, and Durresi 2019). This means that the density and truth coefficients of the graphs displaying a dense and uniform heap are low or fake networks, and the opposite is found in irregular geometries and scattered graphs.

In this study, analyzes were also carried out by examining the features mentioned above and graphic structures.

Methodology

This section contains a description of the research's data and the tools and procedures utilized to analyze it.

Data

The 24-hour data of the hashtags "#BıktıkYavBıktık" (Of Opposition Supporters) and "#20YıldaDevrimYaptık" (Of Ruling Party Supporters) trending on Twitter on 10-11 June 2022 were downloaded from the Twitter platform to give a random sample. In order to create these records in the R language, Twitter API[1] membership was provided and the package named "rtweet"[2] was used. In this process with R, the Twitter API randomly gives the user the data according to the time interval.

Twitter social network analysis with R

Project applications can be constructed by creating an account on the pertinent website created for developers, known as the Twitter API for data mining with R on Twitter. Researchers get four keys (passwords) to use with the R programming language as a result of Twitter approving this application.

There are two known R packages that have Twitter API support for entering relevant keys. These are the "twitteR" and "rtweet" packages, respectively. In this study, the "rtweet" package was used. The intended use of the "rtweet" package is the collection and organization of Twitter data (Kearney 2020).

It is the "search_tweets" function used to obtain data with "rtweet". The keyword to search for, the amount of samples to obtain, and the data language are all entered in this function. The upper limit of the search was defined as 4000 tweets and around 8000 tweets were collected because a sample of nearly 4,000 was observed across 24-hour intervals. Data sets were created with 90 variables belonging to these tweets. The data of the obtained trends were assigned to two separate variables and recorded.

For the social network analysis of the tweets obtained, the tweets were divided into hourly segments. These intervals are cumulatively superimposed, and each new image depicts the entire network structure from the first hour. The steps in the social network analysis of tweets obtained with R are as follows (Algoritma, 2020):

Loading Related Libraries:

First, the relevant libraries are loaded. From these libraries, data editing is provided with the "tidyverse". It is possible to obtain social network graphics with "tidygraph", "gggraph" and "igraph" libraries. Finally, the "rtweet" packages explained above have been installed. Codes for this operation:

- library(tidyverse)
- library(tidygraph)
- library(gggraph)

[1] https://developer.twitter.com/en

[2] https://cran.r-project.org/web/packages/rtweet/rtweet.pdf

➢ library(igraph)
➢ library(rtweet)

Obtaining Data from Twitter:

In this step, the word searched, and the number of searches are expressed to a variable.

```
Variable_name <- search_tweets( "Keyword", n = 4000, include_rts = TRUE)
```

The keyword expressed in parentheses is queried as stated above, with "n" numbers and including retweets. The frequencies are obtained to see how many of the obtained data are Retweets and how many are original tweets.

```
Table(variable_name$is_retweet)
```

When this function is run, FALSE (original tweet) and TRUE (retweet) frequencies are obtained. Because the question asked with R is “is this tweet a retweet?” .

Preparing Data for Social Network Analysis:

Here, the first step is to obtain the dissemination clusters. With the code below, users who have retweeted from the most to the least are clustered.

```
variable_name %>%
group_by(screen_name) %>%
summarise(total_retweet = sum(retweet_count)) %>%
arrange(desc(total_retweet)
```

When the function is run in this way, it offers retweet rankings in descending order (desc = descending). Afterward, the data was tried to be cleaned with the following steps:

- The character values (string) from the screen_name and mentions_screen_name columns are cleared.
- Separate names in the mention_screen_name column have been moved to separate lines.
- The missing or empty data in the mention_screen_name column has been deleted.
- The data in the screen_name and mentions_screen_name columns are arranged as “from” and “to” network connections, respectively.
- Finally, these are assigned to the edge_df variable

```
edge_df <- tweets %>%
select(screen_name, mentions_screen_name) %>% #1st
separate_rows(mentions_screen_name, sep = " ") %>% #2nd
filter(mentions_screen_name != "") %>% #3rd
rename(from = screen_name, to = mentions_screen_name) # 4th
```

The “edge” data was thus obtained. Afterwards, the second data needed for network analysis, “Node” data, came to be obtained. To obtain this data, mappings from “from” and “to” data were used.

```
nodes_df <- data.frame(name = unique(c(edge_df$from,edge_df$to)),
stringsAsFactors = F)
```

Graphics infrastructure:

The design of the tbl graph() non-directional (assumes that the links are bidirectional) graph was constructed after acquiring the edge and node data.

```
graph_tweets <- tbl_graph(nodes = nodes_df, edges = edge_df, directed = F)
```

Centrality Measurement:

The following are the goals of the measurements that were made as part of the crucial network analysis stage of determining the centrality of connections.

1. Degree: To find highly connected, famous individuals, likely to hold most information, or individuals who can quickly connect to the broader network.
2. Betweenness: To find individuals influencing the flow around a system.
3. Closeness: To find individuals in the best position to influence the entire network in the fastest way possible.

4. Eigen: It measures the impact of a node based on the number of connections to other nodes in the network, then goes a step further by taking into account how well connected a node is, and then detects the characteristics of its connections over the network, such as how many connections it has.

```
➢ graph_tweets <- graph_tweets %>%    activate(nodes) %>%
mutate(degree = centrality_degree(), # Degree
between = centrality_betweenness(normalized = T), #Betweenness
closeness = centrality_closeness(), # Closeness
eigen = centrality_eigen() #Eigen
)
```

This graph data is then converted into a data frame.

```
➢ network_act_df <- graph_tweets %>%
activate(nodes) %>%
as.data.frame()
```

The purpose of transforming this data into a data frame is to determine which username is the most popular user in terms of centrality. For this;

```
➢ pop_username <- data.frame(
  network_act_df %>% arrange(-degree) %>% select(name) %>% head(),
  network_act_df %>% arrange(-between) %>% select(name) %>% head(),
  network_act_df %>% arrange(-closeness) %>% select(name) %>% head(),
  network_act_df %>% arrange(-eigen) %>% select(name) %>% head()
) %>% setNames(c("Degree","Betweenness","Closeness","Eigen"))
```

When this process is completed, the most popular users are listed on the R screen from top to bottom.

Data Visualization:

The purpose of visualization is to detect network clusters (communities). For this reason, one of the most frequently used methods in visualizing community structures is the "Louvain"[3] method.

```
➢ set.seed(123)
➢ graph_tweets <- graph_tweets %>%
activate(nodes) %>%
mutate(community = group_louvain()) %>%
activate(edges) %>%
filter(!edge_is_loop())
```

Then, the process of determining the number of communities and the number of users in the community is carried out.

```
➢ graph_tweets %>%
activate(nodes) %>%
as.data.frame() %>%
 count(community)
```

In this way, all clusters obtained can be viewed on the screen. Naturally, many large and small clusters (communities) may emerge. It is possible to identify an important person from each cluster, the

[3] https://neo4j.com/docs/graph-data-science/current/algorithms/louvain/

user at the center of the community. In this way, it can be determined who is the central (important) person in disseminating tweets by the communities.

```
➢ important_user <- function(data) {
name_person <- data %>%
as.data.frame() %>%
filter(community %in% 1:5) %>%
select(-community) %>%
pivot_longer(-name, names_to = "measures", values_to = "values") %>%
group_by(measures) %>%
arrange(desc(values)) %>%
slice(1:6) %>%
ungroup() %>%
distinct(name) %>%
pull(name)
  return(name_person)
}
```

Creating an object belonging to this central user facilitates the drawing of the graphic.

```
➢ important_person <-
graph_tweets %>%
  activate(nodes) %>%
  important_user()
```

In the last step, visuals can be obtained with graphic functions.

```
➢ set.seed(123)
➢ graph_tweets %>%
  activate(nodes) %>%
  mutate(ids = row_number(),
       community = as.character(community)) %>%
  filter(community %in% 1:5) %>%
  arrange(community,ids) %>%
  mutate(node_label = ifelse(name %in% important_person, name,NA)) %>%
  ggraph(layout = "fr") +
  geom_edge_link(alpha = 0.3 ) +
  geom_node_point(aes(size = degree, fill = community), shape = 21, alpha = 0.7, color
= "grey30") +
  geom_node_label(aes(label = node_label), repel = T, alpha = 0.8 ) +
  guides(size = "none") +
  theme_void() +
  theme(legend.position = "top")
```

These codes enable the creation of the network structures that are illustrated in the findings section. Communities are established in this manner as well.

Findings

This section presents the findings obtained with the applications of the data expressed in the method section and the network analysis methods.

Trend 1:

Between 10 - 11 June 2022, the spread of the opposition-featured "#BiktikYavBiktik" trend on social media, depending on time intervals, was determined as follows.

According to the data obtained from the sample, the first broadcast time of the statement of the said trend is 10 June 2022 at 21:57:29. It has been observed that 553 tweets containing the trend expression were sent in approximately two hours and four minutes from this time to 23:59:59. Four hundred eighteen of these are Retweeted tweets. The image of the spread of the trend in the first two hours is as follows.

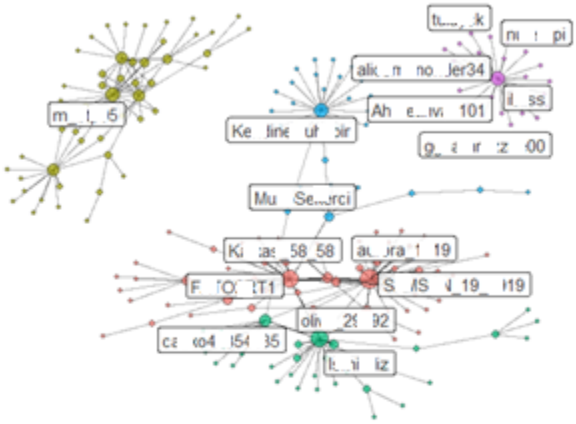

Figure 1. Spread of #BiktikYavBiktik Trend in the First Two Hours

The five most engaged clusters for the first two hours are illustrated. When attention is paid, the two clusters appear to be independent, while the other three appear to be interconnected. The next two hours of the trend are after midnight. During this time, 151 tweets added to the previous 553 tweets were observed. In the content of the trend, which reached a total of 704 tweets, 531 Retweets were detected. Accordingly, the spread of the trend four hours after the first hour appears as follows.

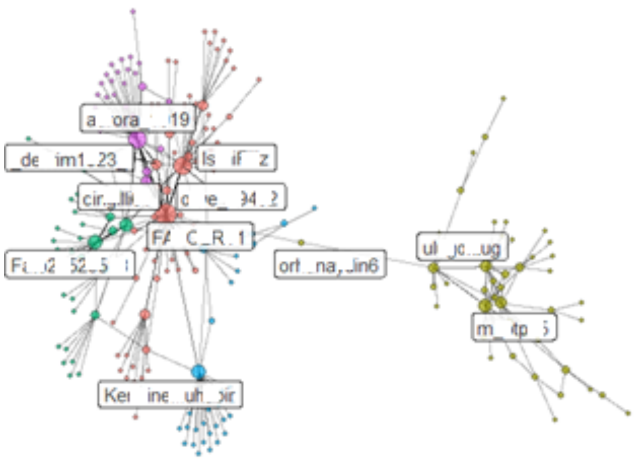

Figure 2. Image of the Spread of the Trend in the First Four Hours

In the first four hours and the first two hours, it is observed that a user from the user network with green dots connects to other clusters.

In the second four-hour segment of the trend, the number of Retweets increased to 613. However, since it was after midnight, it was observed that a total of 96 tweets were sent and the total number of tweets was 800. The visual obtained in the first 8 hours in total is as follows.

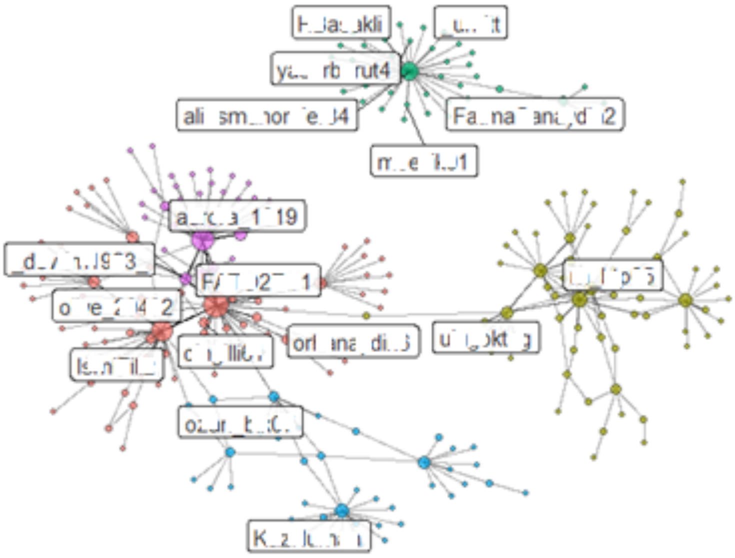

Figure 3. Map of the Spread Over the First Eight Hours

It is observed that a new independent cluster appears at the top in the second four hours compared to the first four hours and exhibits a different spread from previous broadcasts.

When evaluated for the first twelve hours, it was observed that the total number of tweets increased by 516 and reached 1316, and 1077 of these tweets were Retweets. The spread of the trend in the first twelve hours is illustrated as follows.

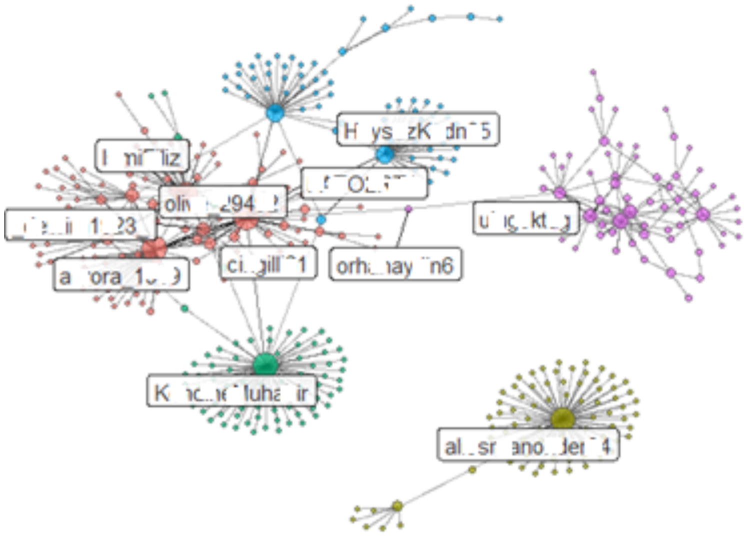

Figure 4. Network View in the First Twelve Hours

The independent spreads of two of the five clusters above are noteworthy. On the other hand, the network with green dots centered cluster also continues to be partially independent.

In the next twelve hours, 1742 more tweets were added to the current tweet count, and the total number of tweets was found to be 3058. It is seen that the number of Retweets among the total tweets is 2617 and 85.87%. The appearance of the spread obtained in the first twenty-four hours is;

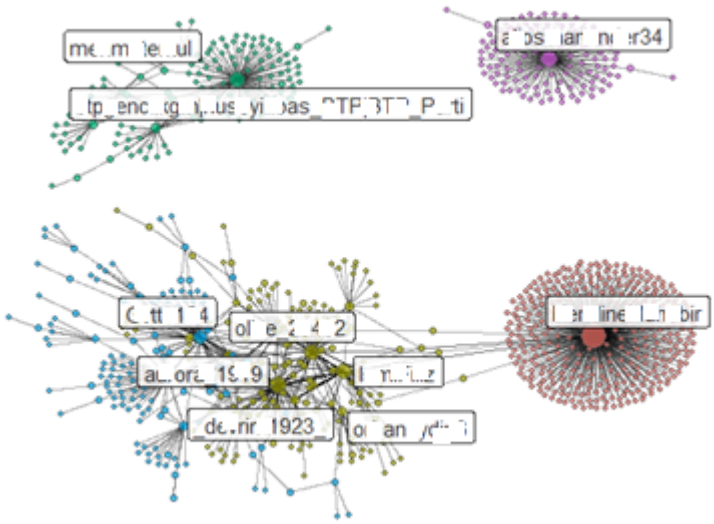

Figure 5. Image of the Spread of the Trend in the First Twenty-Four Hours

The twenty-four-hour view gives a more precise image than the previous images. Four communities have been identified that are effective in spreading the trend in twenty-four hours. It has been observed that the top right and bottom communities of these communities are more homogeneous (it is likely to be a bot network), while the top left and bottom communities have a more real network structure.

All of the trends in the research were examined on a twenty-four-hour basis. However, since the samples may contain intervals of more than twenty-four hours, tweets outside the working hours were not reflected in the findings. Accordingly, the increases in the number of tweets in the first twenty-four hours according to time intervals are as follows.

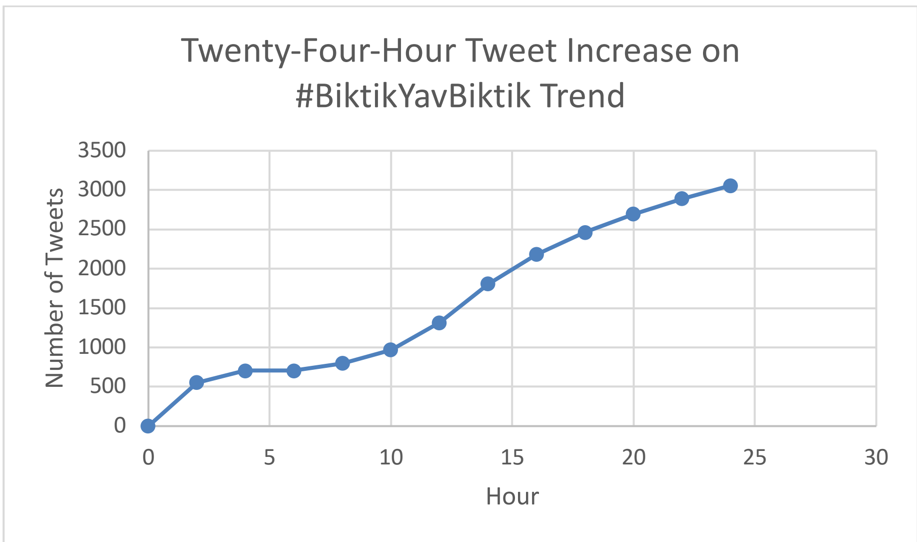

Figure 6. Increases of Hourly Tweets

Considering that there are not many tweets between two and eight at night, it has been determined that the hourly spread between eight in the morning and two at night is 165 tweets on average. However, if nighttime hours are taken into account, this averages 127 tweets per hour.

Trend 2:

#20YıldaDevrimYaptık trend was spread by the supporters of the ruling alliances, and its spread on social media between 10 - 11 June 2022 was determined as follows. The content of the said trend supports the government.

The number of tweets reached by the trend in the first two hours is 985. 907 of them were identified as Retweets. As in the previous trend application, two, four, eight, twelve, and twenty-four-hour spreads are visualized.

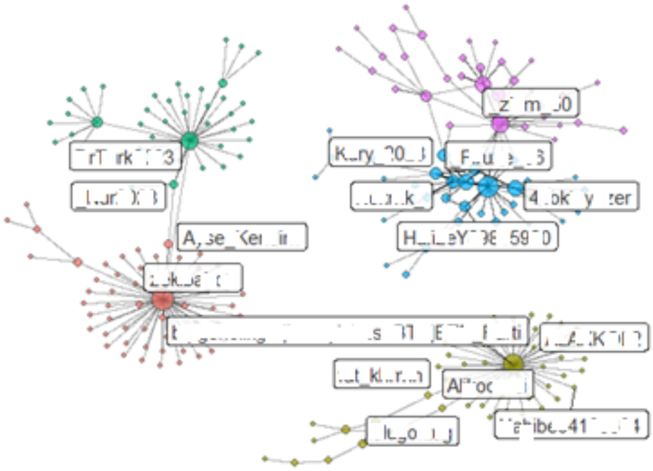

Figure 7. The Spread of the #20YıldaDevrimYaptık Trend in the First Two Hours

The first two-hour view for the five most engaged clusters has four separate cluster views that act alone. Only the two left clusters have network interaction at two points. In the second two hours (four hours in total), the total number of tweets reached 1370, and the number of Retweets reached 1281. The five clusters with the highest spread are visualized in each analysis.

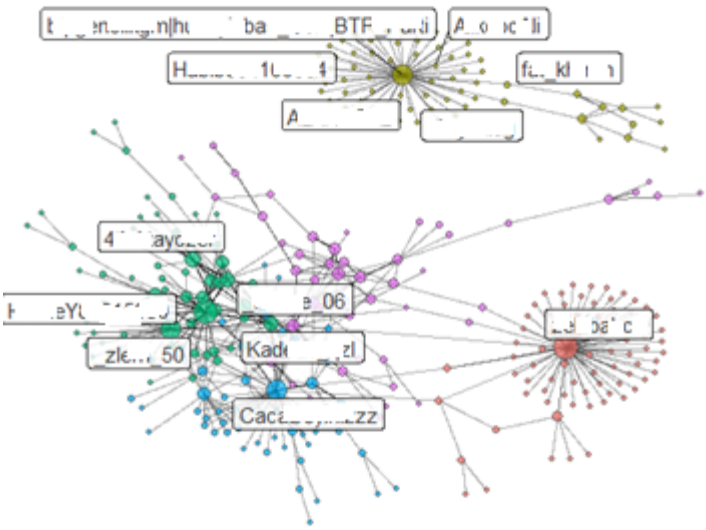

Figure 8. The Spread of the #20YıldaDevrimYaptık Trend in the First Four Hours

When the picture in the first four hours is examined, two separate independent groups draw attention. In the second four hours (eight hours in total), the total number of tweets was 1624. Exactly 1500 of these are Retweets.

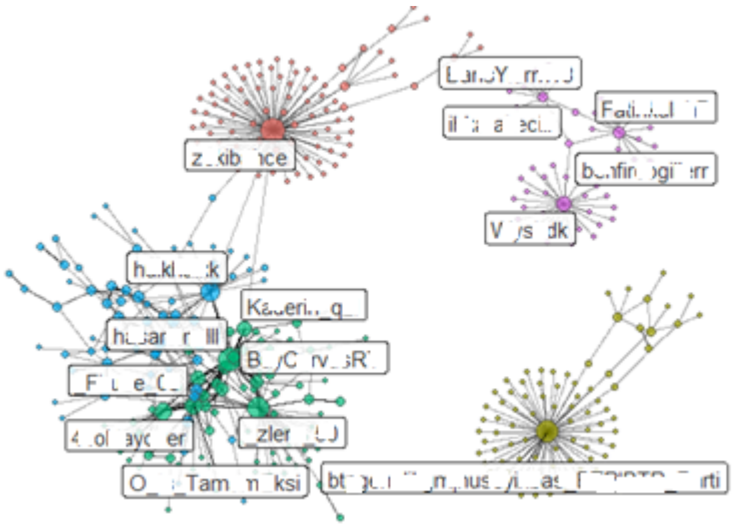

Figure 9. The Spread of the #20YıldaDevrimYaptık Trend in the First Eight Hours

Although the number of clusters moving together in eight hours (according to colors) seems to be three clusters, the bond between the upper left and lower groups is weak. On the other hand, the right-side clusters act entirely independently. The number of tweets reached by the trend in the first twelve hours is 2075 according to the sample. 1937 of them have Retweet feature.

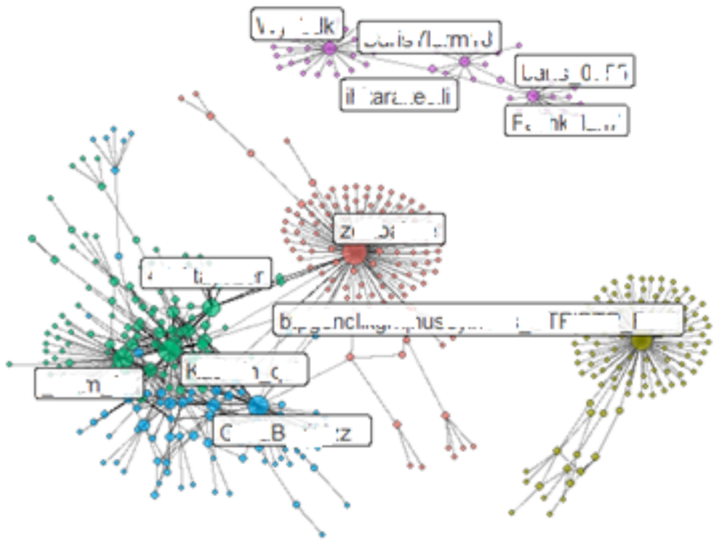

Figure 10. The Spread of the #20YıldaDevrimYaptık Trend in the First Twelve Hours

Although no change in the network structure moves together due to the first twelve hours, there is expansion. Finally, the number of tweets reached by the trend in the first twenty-four hours is 3715. 3127 of them are Retweets.

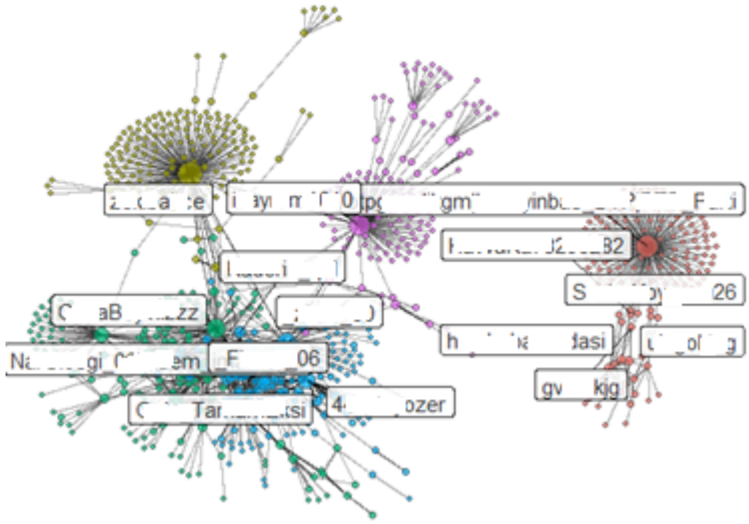

Figure 11. The Spread of the #20YıldaDevrimYaptık Trend in the First Twenty-Four Hours

Four communities have been identified that are effective in spreading the trend in twenty-four hours. It has been observed that among these communities, the communities on the right and the top left are more homogeneous (likely to be a bot network), and the communities at the bottom have a more real network structure.

All of the trends in the research were examined on a twenty-four-hour basis. However, since the samples may contain intervals of more than twenty-four hours, tweets outside the working hours were not reflected in the findings. Accordingly, the increases in the number of tweets in the first twenty-four hours according to time intervals are as follows:

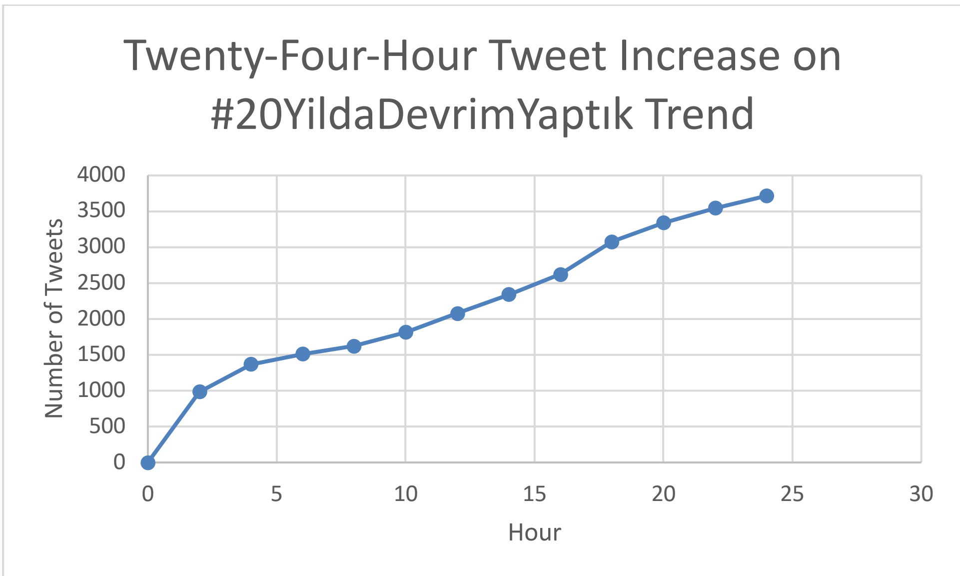

Figure 12. Increases in Twenty-Four Hour Tweets

According to the data obtained in the first twenty hours of the #20YıldaDevrimYaptık trend, the hourly tweet average was 155.

Conclusions

The primary purpose of this study is to investigate the political trend formation efforts of the supporter groups, called the government and the opposition, using the social network analysis method. For this purpose, the social network structure of two trends, one supporting the government and the other supporting the opposition, were examined. In the network analysis, the visualizations were made with the five most interacting clusters. Accordingly, the five clusters with the highest interaction of both trends were taken as a basis.

The motor power of both trends forms three large clusters distributed from a single center and connected to the same user. The difference between the trend number two (supporting the power) and the first trend (supporting the opposition) was determined as the central cluster, in which two separate clusters act independently, and the cluster in which individual users interact, albeit with a little connection, and are not fed by the same user at the center.

Accordingly, the trend supporting the government has more random user interaction than the trend supporting the opposition. In other words, the actual spread rate of trend number two is higher than trend number one. Clusters that move independently and have regular geometry are considered to be clusters that provide automatic distribution.

It is evaluated that both trends have reached the number of tweets close to each other in twenty-four hours. On the other hand, the hourly rate of spread of the first trend (127 tweets per hour) was less than the second (165 tweets per hour). As stated above, although automation-related dispersions (clusters with smooth geometry) were higher in the first trend, the higher rate of spread in the second trend is thought to mean that trend number two interacts more with real users.

Finally, when analyzed according to the model developed by Kaur, Uslu, and Durresi (2019), it was observed that the graph of the trend number 1 was between 65-70%, and the trend number two, which was created by fake accounts, was spread by fake accounts by around 40%.

As a result, differences in the progress and spread of opposition and pro-government trends draw attention. It is seen that the pro-government trend has a more robust structure than the pro-opposition trend, due to the high rate of spread and the relatively small network of fake accounts it contains. It is impossible to measure the government's political communication power or opposition on social media through only two trends. On the other hand, it is possible to evaluate certain time intervals through these measurements in future studies.

When examined theoretically, as it can be understood from the above-mentioned findings, it does not seem possible to fully explain the fact that bot accounts are used as much as real users in political propaganda with the theory of "Engagement". However, Solis's attempt to display the illusion that the "Engagement" theory, which was brought to the literature, by using bot accounts as well as real accounts by political institutions, seems to have increased the support of the public relatively is also a subject of research.

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