UNDERSTANDING MANIPULATIVE ACTIONS AND POLITICAL LANGUAGE ON TWITTER: EXPLORING TRENDING TOPICS AND THE 2023 TURKISH PRESIDENTIAL ELECTION

by
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ABSTRACT

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Keywords: 2023 Turkish presidential election, manipulation, political language, sentiment analysis, social media, trending topics

This thesis examines coordinated activities and reflections of public events via sentiment scores on Twitter, in the context of trending topics in Turkey and tweets sent related to Turkey's presidential election in 2023. There are two objectives of this study. The first one is to understand how manipulative actions take place on Twitter, especially in trending topics, and to check whether similar actions occur in election-related discussions. The second one is to examine how public events and the political language used by presidential candidates are reflected in Twitter data, especially during the election period. Our analysis encompassed two datasets, consisting of tweets related to trending topics and tweets specifically mentioning the presidential candidates. To identify manipulative actions, we leveraged the suspension status of each tweet. Additionally, in the sentiment analysis part, we examined the sentiment scores of tweets based on various factors, including their types, suspension status, mentioned candidates, and the followers' status of the respective candidates. Through our comprehensive analysis, we offer profound insights into the impact of political events and electoral outcomes on the aforementioned dimensions, thereby enhancing our understanding and providing valuable insights into the utilization of political language.

ÖZET

TWITTER'DA MANİPÜLATİF EYLEMLERİN VE SİYASİ DİLİN ARAŞTIRILMASI: TRENDING TOPICS VE 2023 TÜRKİYE CUMHURBAŞKANLIĞI SEÇİMİ

FURKAN OKUYUCU

Veri Bilimi YÜKSEK LİSANS TEZİ, TEMMUZ 2023

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Anahtar Kelimeler: 2023 Türkiye cumhurbaşkanlığı seçimi, sosyal medyada manipülasyon, siyasi dil, duygu analizi, sosyal medya, trending topics

Bu tez, Türkiye'deki trending topics ve 2023 Türkiye Cumhurbaşkanlığı seçimi ile ilgili gönderilen tweet'ler bağlamında, Twitter üzerindeki koordine edilmiş manipülatif aksiyonları ve seçim süresince gerçekleşen olayların duygu durumu skorları üzerindeki etkisini incelemektedir. Bu çalışmanın iki ana amacı bulunmaktadır. İlk amacı manipülatif eylemlerin trending topics'e girmiş hashtaglerde nasıl gerçekleştiğini anlamak ve benzer eylemlerin seçimle ilgili tartışmalarda da olup olmadığını kontrol etmektir. İkinci amacı ise toplumsal olayların ve cumhurbaşkanı adayları tarafından kullanılan siyasi dilin Twitter'daki duygu durumu üzerine nasıl yansıdığını incelemektir. Analizimiz trending topics'lere atılan tweet'ler ile içerisinde cumhurbaşkanı adaylarınının geçtiği tweet'leri içeren iki veri kümesini kapsamaktadır. Methodoloji olarak manipülatif eylemlerin belirlenmesi için her tweet'in Twitter tarafından sağlanan askıya alınma durumu kullanılmıştır. Duygu analizi bölümünde de tweet'ler, türleri, askıya alınma durumları, içerdiği adaylar ve kullanıcıların ilgili adayları takip etme durumu gibi çeşitli faktörler özelinde incelenmiştir. Analizimiz sayesinde siyasi olayların ve seçim sonuçlarının yukarıda bahsedilen faktörler üzerindeki etkisine kampsa bir bakış sağlıyor ve seçim süresindeki olayların duygu durumu üzerindeki yansımaları hakkında bilgiler sunuyoruz.

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To my family...

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1. INTRODUCTION

In the era of high technological developments, the importance of communication tools especially the importance of social media has increased dramatically. Social media has become a powerful medium for expressing ideas and participating in public debates with an enormous number of users all around the world. With this number of users, it plays a vital role in shaping public opinion.

This great power can be used both for good and bad agendas. Like in the case of the earthquake that happened in Turkey, lots of people are organized throughout this medium(Elci, 2023). But it can also be used to manipulate public opinion via disinformation campaigns like in the case of US elections (Bovet & Makse, 2019). Twitter itself as a platform detects such manipulative detection and as a result suspends accounts and tweets to prohibit their disinformation campaigns. Furthermore, different studies highlight the importance of the detection of manipulative actions and suggest techniques to detect them(Davis, Varol, Ferrara, Flammini & Menczer, 2016; Elmas, Overdorf, Ozkalay & Aberer, 2021; Pacheco, Hui, Torres-Lugo, Truong, Flammini & Menczer, 2020; Sharma, Qian, Jiang, Ruchansky, Zhang & Liu, 2019; Varol, Ferrara, Davis, Menczer & Flammini, 2017).

Studies demonstrate that social media, with its vast user base, plays a pivotal role in reflecting public opinion (Bollen, Mao & Zeng, 2011; Chaudhry, Javed, Kulsoom, Mehmood, Khan, Shoaib & Janjua, 2021). Especially representing the public attitude towards a topic. One feature of Twitter that represents publicly-spoken hot topics is trending topics. It consists of a list of 50 words that are popular at a time. Utilizing a real-time algorithm, it identifies the latest and emergent subjects of interest, granting users the opportunity to engage with these dynamic discussions [1]. In this study, we conducted an analysis of manipulative actions on trending topics in Turkey to gain a deeper understanding, particularly focusing on coordinated attacks.

One use case of social media for expressing public opinion is elections(Chaudhry

[1]Twitter Trends FAQ, https://help.twitter.com/en/using-twitter/twitter-trending-faqs

et al., 2021). It gives voters a chance to interact with candidates through their campaign and express their feelings and needs to them(Vaccari, Valeriani, Barberá, Bonneau, Jost, Nagler & Tucker, 2015). The presidential election in Turkey in 2023 was not an exception but a significant example to see the reflections of public opinion on social media. There were 4 candidates in the election and each one of them used Twitter in the election period along with their followers to shape public opinion and express their political agenda.

Twitter has another feature named mention which enables users to mention a specific user while writing tweets, fostering interaction and communication among users [2]. For example, in a political context, individuals may mention a political figure in a tweet discussing public issues to draw their attention, or users can use mentions to express their opinions directly to the mentioned user regarding their actions. In this thesis, we conducted a sentiment analysis and analyzed the tweets mentioning the candidates throughout the 2023 Turkish Presidential election period, aiming to provide a comprehensive understanding of the public opinion towards the candidates and to examine the sentiments expressed during certain crucial political events.

1.1 Motivation and Research Questions

Detecting and understanding manipulative behaviors are important to increase public awareness and decrease the effects of disinformation campaigns. In this study, we aim to analyze the manipulations that took place on the trending topics. Following that we want to observe the same manipulative actions on election-related tweets, to see whether similar disinformation campaigns are held during the election campaign period. In our analysis, we utilized the suspension status of a tweet and user provided by Twitter[3].

Tweets play a significant role in understanding the reflections of events both politically and generally on public opinion (Bollen et al., 2011; O'Connor, Balasubramanyan, Routledge & Smith, 2010; Pagolu, Challa, Panda & Majhi, 2016; Sharma & Ghose, 2020). Elections times are important periods to analyze the reflections of political campaigns and political events on the public, to better understand the

[2]Twitter Mention and Replies, https://help.twitter.com/en/using-twitter/mentions-and-replies

[3]Twitter Suspension Policies, https://help.twitter.com/en/rules-and-policies/notices-on-twitter

political language used and its effect. One way of interpreting the tweets sent by users is using their sentiment scores. Sentiment scores represent people's emotions, opinions, and attitudes towards some topic. In this research, we aim to examine how events shape the overall sentiment scores of the users by examining tweets sent to trending topics and election-related discussions. We have limited our election-related discussions only to tweets mentioning candidates over the election campaign, to better examine the effects of events on each candidate separately.

Therefore we can summarize our research questions as follows;

- How do coordinated activities and manipulative behaviors manifest in Twitter data related to both general trending topics and election discussions?
- How does sentiment analysis of Twitter data reflect the impact of external events on trending topics and election-related discussions?

By addressing these questions, this thesis contributes to a deeper understanding of Twitter's role in shaping public opinion and its implications for politics and elections.

1.2 General Flow of the Thesis

The general flow of the thesis can be outlined as follows:

Chapter 2 delves into the literature review, exploring various topics such as trend manipulation on social media, sentiment analysis on social media, election-related discussions on social media and studies related to trending topics.

Chapter 3 focuses on the dataset used for the research, covering data collection methods, including trending topics and the election dataset.

The methodology used in the thesis is explained in Chapter 4. It includes details on sentiment analysis techniques, such as the Bidirectional Encoder Representations from Transformers (BERT) and the methods used to detect coordinated activities.

Chapter 5 presents the results of the study, analyzing manipulations, sentiment analysis on various aspects

Finally, Chapter 6 provides a conclusion, highlighting the summary of the findings.

2. LITERATURE REVIEW

2.1 Trending Topics

Twitter has a valuable feature that shows trending keywords as a list which is called trending topics. The trending topics differ based on region, giving users to chance to engage in conversations that are relevant to their location. This functionality facilitates real-time participation, ensuring that users are connected to the latest events and can actively contribute to the ongoing discussions (Annamoradnejad & Habibi, 2019). There is one study that tries to classify trends into three categories which are positive, neutral, and negative according to the topic of the discussion to better assess the characteristics of this feature. They have found that the distribution of the trending topics varies with respect to their category (Saquib & Ali, 2017).

Trending topics play a crucial role in shaping the conversations in the application. In a study conducted by Carrascosa, González, Cuevas & Azcorra, it has been found that Trending Topics, similar to mainstream advertising channels like TV and ads, are extensively utilized for marketing purposes. The study highlights that reaching users is crucial in advertising, and Trending Topics are viewed by a large number of Twitter users when they access the application thus enabling people to reach millions of users. This underscores the significant role of Twitter in the realm of advertising and marketing.

Users normally expect to see original content on the application thus having trust in the content they see. There are manipulative actions to benefit from this trust which we later examine in detail in section 2.2. Twitter itself tries to eliminate such behaviors but it is not enough at detecting all manipulated actions. In a study there is one new attack named ephemeral astroturfing affecting trending topics is discovered. This attack is defined by the action of sending and deleting tweets related to a certain topic and manipulatively increasing the total number of tweets sent to a topic and creating a fake trending topic (Elmas et al., 2021). In this study, researchers found that half of the trends in Turkey are fake.

This significant role and the attacks that we mentioned make it important to analyze the manipulative actions on trending topics to inform the public and increase awareness to limit the effect of bad agendas. In contrast to prior studies that utilized a 1% sample of Twitter's archive data to analyze trending topics, our approach involved the development of a comprehensive data collection pipeline(Elmas, 2023; Elmas et al., 2021). This pipeline enabled the collection of all tweets associated with trending topics, specifically focusing on hashtags. By adopting this method, we aimed to provide additional insights and potential characteristics of manipulative behaviors.

2.2 Manipulation On Social Media

One of most the crucial capabilities of human beings is decision-making. This process involves the use of various information coming from different sources. To complete the decision-making process we classify these pieces of information as true, false or doubtful and move on to a decision with that state of mind. This process highlights the importance of our perception of true or false in the mediums that we use to access new information. With lots of information coming from different users, social media is one of the main sources of information in the digital era. This highlights the critical importance of defining the information we expose on social media as true or false. On digital sources, information is spreading at a much faster rate compared to traditional information sources like newspapers. It has been observed that the speed of spread is even significantly faster for false information than the spread of true information. Research indicates that this false information can cause problems in different areas varying from economics to well being of people (Vicario, Bessi, Zollo, Petroni, Scala, Caldarelli, Stanley & Quattrociocchi, 2016; Vosoughi, Roy & Aral, 2018).

The high rate of spread and the significant effect on different areas makes it important to increase people's awareness of manipulative actions on information-sharing mediums such as social media. The use of social media as a tool to get information has increased dramatically over several years. The wide use enables people to both get information from different resources and to be the source of the information as well. The number of abused uses of this power to manipulate public opinion in different areas such as elections, public health, and finances has increased. Along with that, the number of studies analyzing the effects of such actions on public opinion gained importance in recent times (Sharma et al., 2019).

Manipulation on social media can be defined as the use of misleading exploitative actions to influence and control the perceptions and actions of people using such platforms. This manipulation can be done by individuals and also by entities like the Internet Research Agency (IRA). The manipulative actions of the IRA were then requested to be examined by the US Senate and it has been found that different strategies are employed to manipulate social media like using bot accounts, amplifying manipulative content, and creating strategic hashtags (DiResta, Shaffer, Ruppel, Sullivan, Matney, Fox, Albright & Johnson, 2018).

These manipulative actions also have reflections on democratic processes. This specific area is defined as the foreign information manipulation and interference (FIMI) by European External Action Service (EEAS) Strategic Communications, Task Force and Information Analysis Data Team (2023) .The manipulative actions are also taken by Eurepean Union(EU) seriously. There are works defining the stance of EU on the disinformation campaigns and defining frameworks to be used for further analysis(Pamment, 2020). These efforts highlights the EU's proactive actions in protecting the integrity of democratic procedures within the digital sphere.

Twitter is also one of the social media platforms which has been affected by this manipulation. There are different types of manipulation techniques on Twitter used for spreading misleading information and some of them can be listed as astroturfing, usage of bot accounts and coordinated attacks (Davis et al., 2016; Elmas et al., 2021; Pacheco et al., 2020; Sharma et al., 2019; Varol et al., 2017).

Bot accounts can be defined as accounts controlled by programs that automatically perform certain actions on social media while interacting with people. While they can be utilized for positive purposes, like a bot tweeting weather conditions, they can also be used for manipulative agendas, like a bot amplifying misleading information about a company and affecting its stock prices. Since most of these accounts lack labels to differentiate them from real human users and given that the information they disseminate plays a significant role in our perception of truth or falsehood, detecting and identifying these accounts becomes crucial (Ferrara, Varol, Davis, Menczer & Flammini, 2016).

Various features are employed to distinguish these accounts from regular ones. Some notable ones include account-specific information such as username, handle, tenure and account activities like involvement in the spread of fake news. Additionally, context-related factors like the usage of words, URLs, mentions, and hashtags in tweets, as well as the creation of social networks through following and followed relations, are taken into consideration in the studies (Chu, Gianvecchio, Wang & Jajodia, 2010; Davis et al., 2016; Ruchansky, Seo & Liu, 2017).

These bot accounts can also act in a more coordinated manner to amplify their messages while showing a more organic behavior compared to single bot accounts. The main dimensions of these coordinations can be listed as time, topic, content and action. An action can be taken by multiple malicious accounts within a predefined time window to increase the effect of the message on users, it is an example of coordination done at time dimension. In the medium of Twitter, any tweet, reply, or quote action that is done by multiple accounts within a specific time interval can be given as an example of this (Ng & Carley, 2022; Pacheco et al., 2020).

There are models developed to predict such manipulative actions at the account and tweet level but they face limitations when the activity is a coordinated one (Grimme, Assenmacher & Adam, 2018). Consequently, there are studies targeting specifically detecting coordinated attacks. They target different dimensions of coordination like examining tweets sent at similar times to see if they act in a coordinated manner to manipulate and amplify misleading information (Chavoshi, Hamooni & Mueen, 2016). One another dimension of coordination is context. Researchers investigate tweets that share similar content and use similar hashtag sequences, share similar images and co-retweet the same context to detect such coordinated attacks (Chen & Subramanian, 2018; Pacheco et al., 2020).

Coordinated manipulative actions on Twitter also exploit one of its crucial features: Trending Topics. Specifically, an attack known as ephemeral astroturfing is employed to generate manipulated trends for disinformation campaigns. In this context, a group of bot accounts strategically post tweets including targeted keywords and they delete these tweets after some time. This coordinated manipulation results in the targeted keyword becoming a trending topic, effectively reaching a large number of users. To study and analyze such attacks, the researchers took advantage of Twitter archive data, which included a sample of 1% of tweets. They manually labeled trends as fake or not and checked the deletion status of these tweets (Elmas, 2023; Elmas et al., 2021). In this study, we aimed to gain deeper insights and understand the coordinated behavior of such attacks by using our data collection pipeline which collects all the tweets sent to a hashtag. To label the data we took advantage of Twitter's suspension status of the tweets.

2.3 Sentiment Analysis and Political Discussions on Social Media

With the increasing number of users, social media platforms have become a place to share ideas and elections are not an exception to this use. Politicians are taking help from professional social media administrators to adjust their profiles and posts to amplify the voice of their political campaigns. Social media gives politicians who are not given much chance to speak on main media to reach out to the voters. It can sometimes be in the favor of the politicians like reaching out to lots of people, but it can also be extremely harmful since there is no boundary between the people and politicians, and any message can be interpreted in the wrong way and would be hard to return from (Hong, Choi & Kim, 2019). There are also other studies analyzing different aspects of the elections on Twitter like political polarization and the impact of Twitter on votes (Conover, Ratkiewicz, Francisco, Goncalves, Menczer & Flammini, 2021; Kruikemeier, 2014).

In recent years social media has become a key reflector of public opinion on different events. Particularly Twitter has gained lots of attention from researchers in different domains to analyze and understand the response of the public to events (Pagolu et al., 2016). Sentiment analysis is one natural language processing technique to analyze the response of the users. It extracts the sentiments from the texts sent by users to social media platforms (Yue, Chen, Li & et al., 2019). Yue et al. divides the usage areas of sentiment scores on social media into three parts which are commercial, public security, and political. For commercial purposes, it can be used in different areas from advertising and recommendation to stock market prediction. Another use of the method can be public security, since manipulators can use such platforms to amplify their messages, regulatory authorities can take action before things get spread. The last usage is political cases. Social media has become a key factor in the elections in many different countries by giving chance for people to interact and involve in political debates. There are studies analyzing the reflections of such political events on the Twitter sentiment like in the study conducted by Ali, Pinto, Lawrie & et al. about the US Presidential Elections in 2020.

The studies indicate that there is a high correlation between sentiment scores and polls, indicating that sentiment analysis can be used to analyze past events but also can be used as a predictive mechanism to tailor the political campaigns (Ansari, Aziz, Siddiqui, Mehra & Singh, 2020; O'Connor et al., 2010). For instance, in the 2012 US Presidential elections, the political campaign of Obama take advantage of the sentiments of voters and took precautionary actions to target specific audiences

(Joel Schectman Reporter, 2012). Another example is Brexit in 2016. The sentiment scores of tweets are used to analyze public opinion about Brexit. The results of this analysis indicate that there is significant divergence between the young and elder users in the platform regarding the topic of interest while the younger are sending tweets that support the decision of staying, the elders represented the opposite (Hürlimann, Davis, Cortis, Freitas, Handschuh & Fernández, 2016). There are other studies conducted in different countries like Spain and Nigeria during election periods to better understand public opinion (Oyewola & others, 2023; Rodríguez-Ibáñez, Gimeno-Blanes, Cuenca-Jiménez, Soguero-Ruiz & Rojo-Álvarez, 2021). In the 2019 Spanish elections, researchers analyzed the tweets mentioning political parties and candidates. Furthermore, sentiment scores are also used to analyze the public opinion on the elections in India and the researcher's findings were in parallel with the actual results of the elections (Sharma & Ghose, 2020). In our study we also analyze the tweets mentioning candidates but in a different context which is the 2023 Turkish presidential elections to understand how public opinion is reflected in Twitter.

The behaviors of users on political discussions on Social media are also analyzed. In one study the attitude of polarization was examined on different events both political and nonpolitical to answer the question of whether social media is used to just amplify the ideas similar to the supported and thus leading to more polarization of groups or used as a chance to interact with people from opposite views and to reach to a common understanding. For the political events, they found that users tend to create polarized networks by absorbing and amplifying ideas similar to their own, but this differs on non-political debates (Barberá, Jost, Nagler, Tucker & Bonneau, 2015). In their study on political polarization in Twitter, Conover et al. analyzed user networks on tweets during the 2010 US congressional election period. Their findings revealed a polarized structure in retweet networks, showing distinct clusters among individuals with varying political opinions. In this thesis, we checked whether similar attitudes occur in the 2023 Turkish presidential elections and tried to answer whether certain tweet types like retweets, tweets, replies and mentions differentiate with respect to their sentiment scores among political groups and indicate polarization.

In the context of sentiment analysis on political discussions, we aimed to contribute to the literature by conducting a comprehensive analysis of sentiment scores within the context of the 2023 Turkish Presidential election. With a specific focus on the sentiment scores of tweets mentioning the candidates, our objective was to gain valuable insights into the public's opinions and reactions towards each candidate, while also examining the presence of similar polarized user behavior within Turkish political discussions. Furthermore, we analyzed the sentiment scores of tweets, categorizing them based on their types and users' following status of candidates, with the aim of identifying potential patterns or similarities like the ones found in previous studies conducted during elections in different countries. By examining these aspects, we aimed to shed light on the dynamics of sentiment expression in the context of political discussions on Twitter during the 2023 Turkish presidential election period.

2.4 2023 Turkish Presidential Elections

Studying Turkish elections is important because of many reasons. The first one is that Turkey serves as a vital bridge connecting Western and Eastern societies due to its strategic geopolitical position. Within this context, it still holds critical responsibilities in securing regional security and stability, evident in its effective refugee management strategies and active military engagements within the broader region. The second one is that Turkey encounters a shift in its foreign policies in recent years. Turkey still takes NATO membership as important but at the same time builds closer relationships with Russia and China. (Oğuzlu, 2020) Since the winner of the elections will shape the country's foreign policies on the topics mentioned, it makes Turkey important to examine. Thirdly, competitive multiparty elections have been a longstanding characteristic of Turkey's history and the 2023 Presidential Election was not an exception.(Esen & Gumuscu, 2023) This competitive field enables researchers to better understand the dynamics of elections, political language and applications of democracy. Lastly, there are also studies indicating the uneven playing field in the previous Turkish Elections in favor of the ruling party.(Esen & Gumuscu, 2016) This is believed to be caused by deteriorations in the democratic processes.(Klimek, Jiménez, Hidalgo, Hinteregger & Thurner, 2018; McCoy, Rahman & Somer, 2018; Somer, 2016) The 2023 presidential election is a significant case study to check whether this notion holds true, and if so, to what extent it impacts the democratic process. Lessons learned from the Turkish context can enrich our understanding of the complexities and challenges in democratic processes, thereby enhancing the ability to develop strategies to create better political systems worldwide.

The 2023 Turkish presidential elections consisted of two rounds: the first on the 14th of May and the second on the 28th of May. Initially, four candidates were in the race: Kemal Kılıçdaroğlu, Muharrem İnce, Recep Tayyip Erdoğan, and Sinan Oğan. After the results of the first round, Erdoğan and Kılıçdaroğlu advanced to the second round and Erdoğan emerged victorious in the elections, securing the highest number of votes in both rounds and ultimately winning the presidential race (Supreme Election Council of Turkey (YSK), 2023).

2.4.1 Candidates

In the 2023 presidential elections, Erdoğan, the leader of the governing party, ran as the candidate of the People's Alliance (Cumhur İttifakı). He secured the highest number of votes in both rounds of the election. Kılıçdaroğlu, the leader of the main opposition party, was announced as the candidate of the Nation Alliance (Millet İttifakı), which includes 6 opposition parties, on the 6th of March (Uras, 2023). Although he garnered the second-highest number of votes in the first round, earning him a spot in the second round of the election, he lost in the second round. Oğan was declared as the candidate of the Ancestor Alliance (ATA İttifakı), comprising two opposition parties, on the 11th of March (Alan, 2023). He did not have enough votes in the first round to go into the second round. Just 7 days after the first election, on the 21st of May, the Ancestor Alliance (ATA İttifakı) dissolved. While both parties in the alliance expressed their support for Kılıçdaroğlu in the second round, Ogan took a different stance, publicly declaring his support for Erdogan in the second round on the 22nd of May (Turak, 2023; Turan, 2023). Ince was declared as the candidate of the Homeland Party(Memleket Partisi) on the 13th of March. Just three days before the second round, Muharrem İnce withdrew his candidacy without endorsing any other candidate. Throughout the election period, İnce had faced criticism for potentially dividing opposition votes (Kirby, 2023). In our study, we analyze tweets mentioning each of the four candidates during the election campaign period to compare and evaluate the reflections of events on the political campaigns of each candidate individually.

2.4.2 Final Results

The first round of voting took place on May 14th and none of the candidates secured a majority at this round. The voter turnout for this round was approximately 87.04%. Recep Tayyip Erdoğan obtained the highest vote share of 49.52%, followed by Kemal Kılıçdaroğlu with 44.88%, Sinan Oğan with 5.17%, and Muharrem İnce with a mere 0.43%. As no candidate surpassed the required 50% threshold, the top two contenders advanced to a second round of elections on May 28th. Following the first round, Sinan Oğan publicly declared his support for Recep Tayyip Erdoğan, a move that had a significant impact on the evolving dynamics. Eventually, on May 28th, Erdoğan emerged as the victor with 52.18% of the votes, securing his position as the elected leader (Supreme Election Council of Turkey (YSK), 2023; Turak, 2023).

During the 2023 Turkish presidential elections, there was a significant disparity in media access. For instance, the state broadcaster, TRT, which is expected to maintain impartiality, allocated 32 hours of airtime to Erdoğan while only granting Kılıçdaroğlu 32 minutes (Esen & Gumuscu, 2023). It is important to highlight that as opposed to traditional broadcasting sources, on Twitter all candidates had an equal ability to share their opinions with voters. During the election period, all candidates actively used Twitter to share their opinions and reach out to the public. Kılıçdaroğlu utilized Twitter with sharing videos he prepared. With these videos, he reached generally his own young supporters (Esen & Gumuscu, 2023). In our research, we analyze the dynamic relationship between events and public opinion on Twitter, with the help of sentiment scores of tweets as valuable indicators during the election period. Our findings offer profound insights into how events are perceived and reflected in the digital sphere of public discourse during the 2023 Turkish presidential elections.

3. DATASET

In the dataset section, we begin by detailing the data collection process for both trending topics and election-related discussions. Subsequently, we provide descriptive information about the trending topics and election data, analyzing various dimensions such as time, tweet type, mentioned candidates, and followers of candidates.

3.1 Data Collection

This section explains how we gathered the data used in our analysis for both trending topics and election-related discussions.

3.1.1 Trending Topics

To conduct a study on coordinated activities on hashtags that become trend topics, we needed to collect the tweets sent with that particular hashtag. To do so we created a data collection pipeline. This section explains the pipeline created to collect the trending topics dataset.

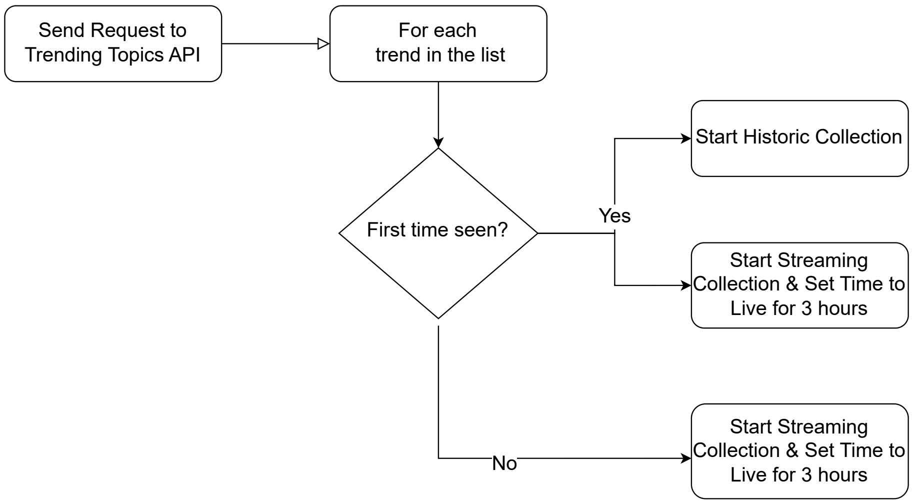


Figure 3.1 Data collection pipeline

Our pipeline consists of two crucial components: first, the collection of trending topics, and second, the acquisition of tweets sent to hashtags that are present in the trending topics list, as illustrated in Figure 3.1.

First, we collect trending topics via Twitter's trend API endpoint[1] with the help of the Tweepy package[2]. Trending topics are collected every 15 minutes which is also the main period of our data collection pipeline. At each request, we collect 50 trending topics for Turkey.

Secondly, we collect tweets that are sent under trending topics via Twitter's streaming API v1.1 again with the help of the Tweepy package. We give a list of keywords to the API and it returns all the tweets that match at least one of the keywords in our list. The list is updated every 15 minutes so in total every day we update this list 96 times. If a new hashtag comes up we add it to the list and if a hashtag is not seen on the trending topics list anymore we start a time to live for it. If we do not see the hashtag in the trending topics list for 3 more hours then we remove it from the stream collection list. We do this to not lose any data for the cases in which a hashtag gets out and gets into the trending topics list frequently. We observed from the analysis of the lifetime of trending topics that if a hashtag is not seen for 3 hours it is likely that it will not be a trending topic soon. Additionally, we observed that there were tweets posted prior to the inclusion of the hashtag in the trending topics list. Upon further investigation, we discovered that by exclusively collecting tweets that were sent subsequent to their appearance on the trending topics list,

[1] Trend API, https://developer.twitter.com/en/docs/twitter-api/v1/trends/trends-for-location/api-reference/get-trends-place

[2] Tweepy, https://www.tweepy.org/

we were able to capture approximately 80% of the tweets associated with trending topics. Using this pipeline, we collected tweets sent to trending topics in Turkey from December 20, 2022, to March 15, 2023.

Table 3.1 showcases a collection of example tweets extracted from the Trending Topics dataset. In the first row, the hashtag “#yeniyıldaneisterdim” is accompanied by a tweet expressing a desire for the future of education and specifically requesting the appointment of 20,000 preschool teachers. Moving on to the second row, the hashtag “#EYTdePazarlıkYok” represents a sentiment that there should be no bargaining when it comes to the rights earned, suggesting that the issue should be resolved without negotiation. The third row features the hashtag “#YaliCapkini”, with a tweet expressing a playful remark about Ferit who is a character in a Turkish series. Lastly, the hashtag “#ReisBedelliyeRevize” is presented in the fourth row. The accompanying tweet highlights a series of demands, including the erasure of penalties, revision of the fee for the military conscription exemption and the removal of certain conditions related to military service.

Table 3.1 Example Tweets from Trending Topics Dataset

Hashtag	**Tweet**
#yeniyıldaneisterdim	Gelecek için eğitimi 20 BİN OKUL ÖNCESİ öğretmeni ataması ile süslenmesini isterim 82 #yeniyıldaneisterdim
#EYTdePazarlıkYok	Kazanılmış hakkın pazarlığı olmaz #EYTdePazarlıkYok
#YaliCapkini	Ferit gel git kafasi iyice gitti hayirli olsun #YaliCapkini
#ReisBedelliyeRevize	Cezalar silinsin. Bedelli ücreti revize edilsin. Kışla şartı kaldırılsın. Sayın devlet büyüklerimiz çözüm bekliyoruz. #ReisBedelliyeRevize

3.1.2 Election Dataset

The dataset that we used to analyze the election-related discussions in this study is “Secim2023: First Public Dataset for Studying Turkish General Election”. The dataset includes tweets sent by different political users which are mainly party leaders, major city mayors, members of the Grand National Assembly and the candidates for the presidential election. The retweets are collected at a ratio of 10% and replies are at a rate of 20% due to the rate limits of Twitter’s API.(Najafi, Mugurtay, Demirci, Demirkiran, Karadeniz & Varol, 2022) In our research, we focused mainly on the tweets mentioning the candidates for the 2023 Turkish presidential elections to better observe the political language used by the candidates and their followers. To do so we extracted the mentioned tweets of candidates and their followers from the Secim2023 dataset. Our analysis focused on the tweets sent from April 1st to June 23rd. including both the first election (14 May 2023) and the second one (28 May 2023). In our analysis, we classified a user as a follower of a candidate if they were identified as a follower at least once in the bi-weekly updated dataset of candidate followers spanning the months of April to May. Follower information is also extracted from the Secim2023 dataset. In addition to tweets mentioning the candidates over the election period, we have also performed a special analysis on election days, by analyzing all the tweets sent during the day of the elections.

Table 3.2 Example Tweets from Secim2023

Mentioned Username	**Tweet**
vekilince	Her zaman arkandayız @vekilince
vekilince	Senin hançerini de unutmayacağız @vekilince
DrSinanOğan	Sen gerçek bir milliyetçisin Sinan bey.
DrSinanOğan	@DrSinanOğan Sana hakkımı helal etmiyorum
DrSinanOğan	@DrSinanOğan Seni seviyorum helal olsun sana başkanım
kilicdarogluk	RT İstifa et @kilicdarogluk

Table 3.2 gives insights about the Secim2023 dataset by presenting example tweets, along with the mentioned usernames in the tweets. In the first example, the username “vekilince” is mentioned in a tweet expressing continuous support, stating “Her zaman arkandayız” (We are always behind you). This tweet highlights a sense of solidarity and allegiance towards the mentioned user. In the second example, the same username “vekilince” is mentioned again in a tweet emphasizing that they will not forget any harm caused, stating “Senin hançerini de unutmayacağız” (We will not forget your dagger as well). The tweet suggests a sense of vigilance and remembrance of any negative actions associated with the mentioned user. The third shows an example tweet mentioning “DrSinanOğan” and the tweet complements the person, stating “Sen gerçek bir milliyetçisin Sinan bey” (You are a true nationalist, Sinan bey). This tweet expresses admiration and recognition for the mentioned individual’s nationalist beliefs. Moving on to the fourth example, the same username “DrSinanOğan” is mentioned in a tweet where the author expresses the sentiment of not forgiving, stating “Sana hakkımı helal etmiyorum” (I do not forgive you for what you’ve done). This tweet suggests a grievance or disagreement with the mentioned

individual. In the fifth row, another tweet is directed at “DrSinanOğan” expressing affection and extending well wishes, stating “Seni seviyorum helal olsun sana başkanım” (I love you, may you be blessed, my president). This tweet conveys a positive sentiment and a supportive tone toward the mentioned user. Lastly, the table includes a retweet (RT) mentioning the username “kilicdarogluk” along with the comment “İstifa et” (Resign). This retweet reflects a demand or expectation for the mentioned user to resign. Overall, the table presents a snapshot of the Secim2023 dataset by showcasing various mentioned usernames and the corresponding tweets.

3.2 Dataset Analysis

In this section, we share descriptive analysis of both datasets on different dimensions including tweet counts, user counts, candidates, user’s following status of candidates, type of the tweets and suspension status of the tweets.

3.2.1 Tweets and Users

In the subsections below we share the total number of tweets and users in two datasets.

3.2.1.1 Trending Topics

In total, there are 117.955.613 unique tweets and 3.733.796 unique users and 4241 unique hashtags in our trending topics dataset. Figure 3.2 shows the number of tweets and users on a daily basis. The spike on the 6th of February corresponds to the earthquake that happened in Turkey in which social media played a role in the organization of people to help.

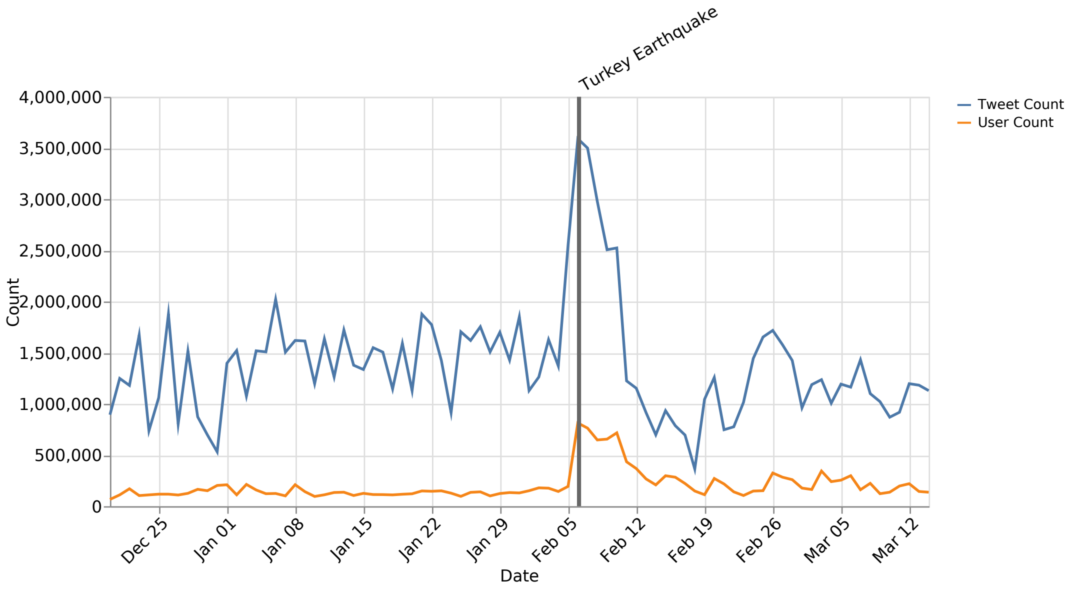


Figure 3.2 Daily Count of Unique Users and Tweets Sent to Trending Topics from 20.12.2022 to 15.03.2023

3.2.1.2 Election Dataset

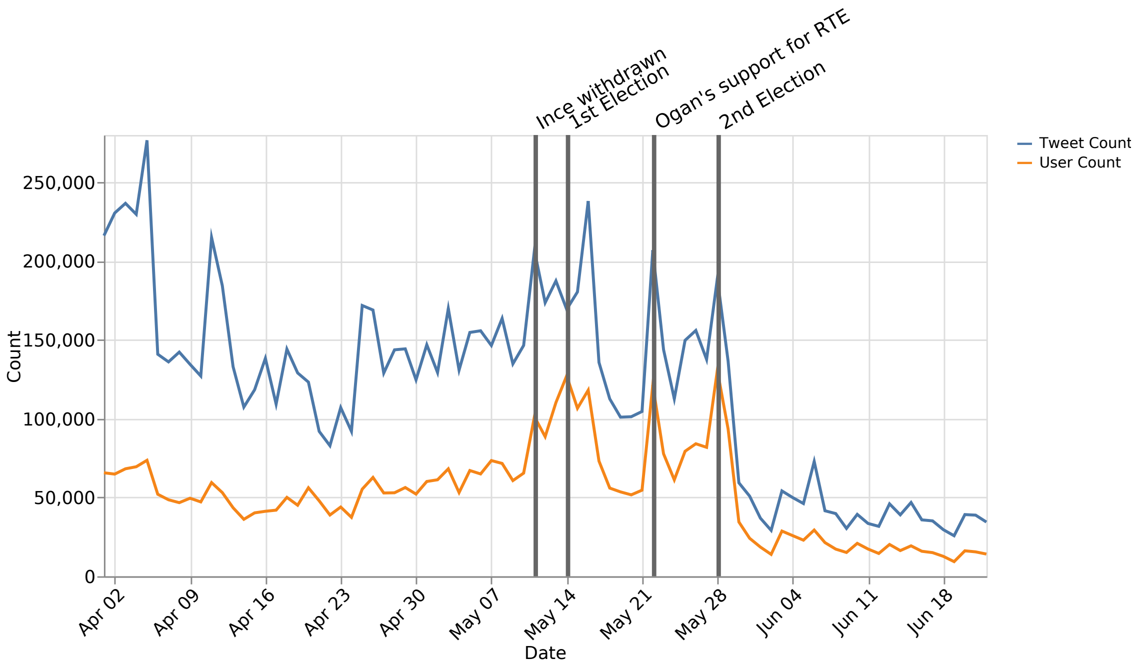


Figure 3.3 Daily Count of Unique Tweets and Users Mentioning Candidates from 1st of April till 23th of June

In total, there are 9.060.197 unique tweets and 1.077.926 unique users in our dataset, mentioning the candidates throughout the election period. Figure 3.3 shows the number of tweets and users on a daily basis. The spikes corresponding to the political events can be seen in the figure as well. Both the number of tweets and users have a trend of increase towards the election dates. After the elections, they decrease. The withdrawal of İnce from the candidacy on the 11th of May, and Oğan's announcement of his support for Erdoğan are also days where we can see the increase in the number of tweets and users.

3.2.2 Candidates

There were 4 different candidates for the presidential election in Turkey in 2023; Kemal Kılıçdaroğlu, Muharrem İnce, Recep Tayyip Erdoğan and Sinan Oğan. Figure 3.4 shows the change in the number of tweets mentioning the users over time. The number of tweets mentioning İnce decreases after his announcement of withdrawal from the elections. At the beginning of April the number of tweets mentioning İnce was higher than the ones mentioning Oğan. This difference changes in the opposite direction as we move towards to 1st election and increases in favor of Oğan after İnce's withdrawal. The number of tweets mentioning Oğan reaches its peak when he announces his support for Erdoğan on the 22nd of May. We can also see that the number of tweets mentioning Kılıçdaroğlu reaches its peak after the first election and in the second election the numbers stay lower than in the first election, while the number of tweets mentioning his opponent Erdoğan stays similar.

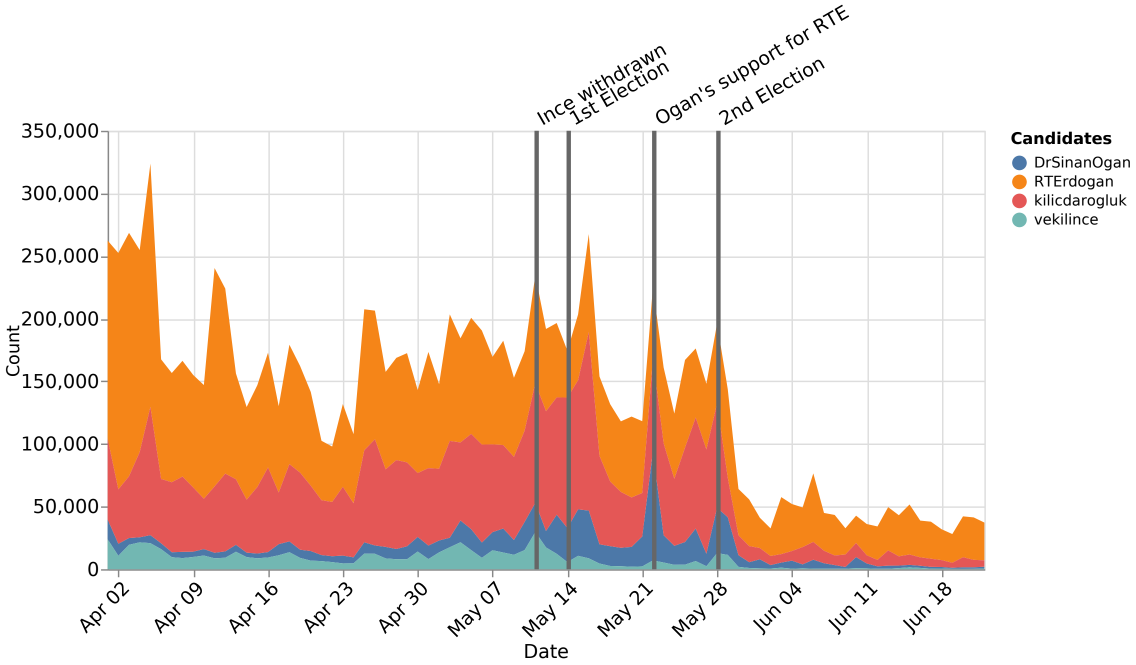


Figure 3.4 Daily Count of Unique Tweets and Users Mentioning Candidates in April and May 2023, Segmented by Candidate

Figure 3.5 illustrates the overlap of candidates in tweets, revealing interesting insights into user behavior. Notably, approximately 90% of the tweets mention only one candidate, indicating a focused approach in political discussions where users tend to express their opinions by mentioning a single candidate. The smallest proportion (0.13%) came from tweets mentioning three candidates, namely Kılıçdaroğlu, İnce, and Oğan, together. On the other hand, the most significant intersection occurs in tweets mentioning both Kılıçdaroğlu and Erdoğan, accounting for 8.9% of the total. According to the election results, they were the ones with the highest voter support and from this graph, we can say they also tend to be mentioned together more frequently than other candidates.

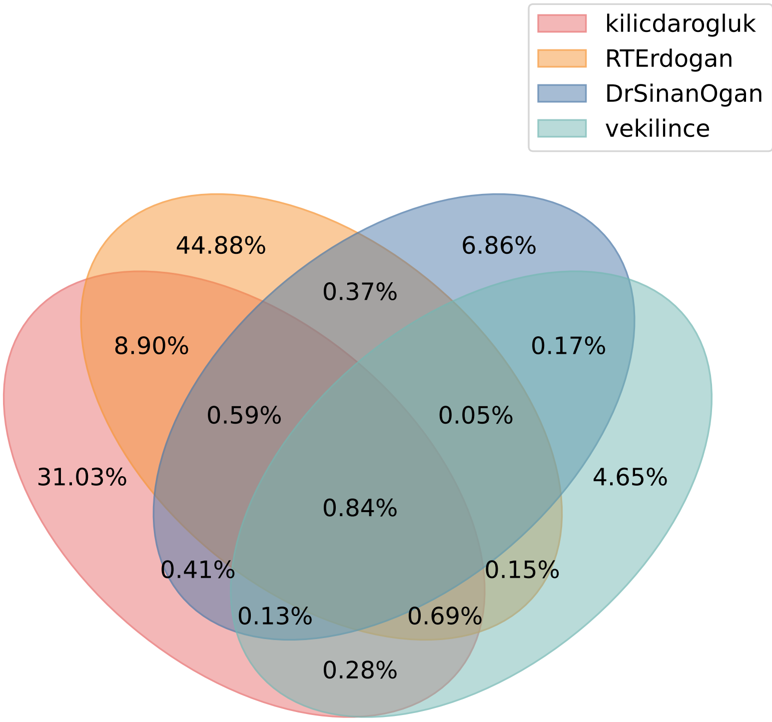
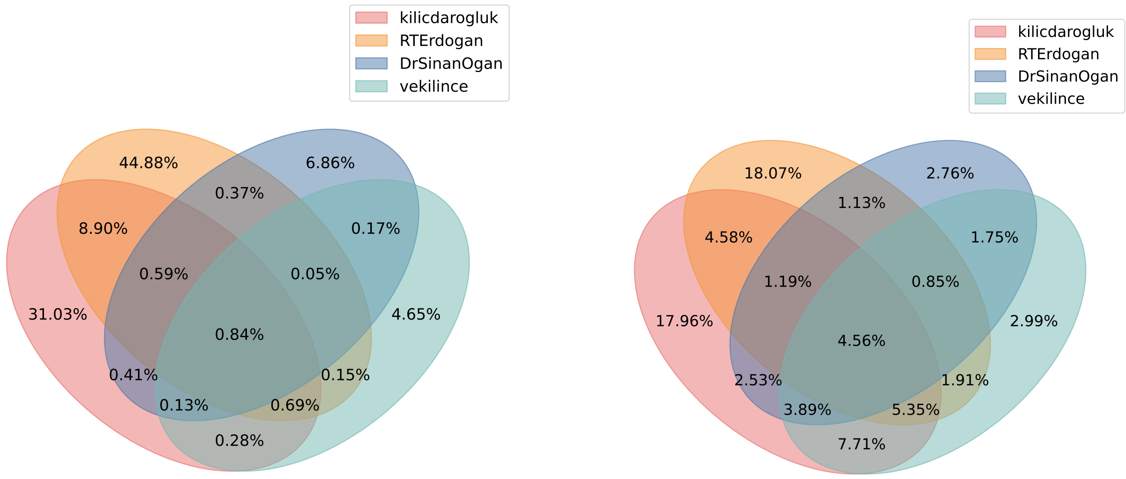


Figure 3.5 The overlap of mentioned usernames in tweets

3.2.3 Candidate Followers

Different user patterns are observed based on the user's following status of the candidates between two datasets. In Figure 3.6a, we observe that 48% of the users in the trending topics dataset do not follow any of the candidates, whereas this ratio is relatively lower (indicating higher political involvement) in the election dataset. This indicates that the election dataset is more focused on political discussions, while the trending topics dataset covers a wide range of topics, including sports, economics, religion, and entertainment.

In Figure 3.6b, it can be seen that approximately 77% of the users in the election dataset follow at least one of the candidates, while the remaining 23% do not follow any candidate. Additionally, 43% of the users only follow only one of the candidates, suggesting a preference for specific political affiliations.



(a) Trending Topics (b) Election Dataset

Figure 3.6 User Following Statuses of Candidates

Figure 3.7 and 3.8 illustrate the total number of followers each candidate has on Twitter and the ratio of users who sent tweets mentioning any of the candidates on both datasets. In the election dataset, Recep Tayyip Erdoğan has the highest number of followers, approximately 20 million, while Sinan Oğan has the lowest with 2 million followers.

Interestingly, the engagement of Sinan Oğan's followers is the highest, with a ratio of nearly 10%, while Recep Tayyip Erdoğan's followers exhibit the least involvement, at approximately 2%. This distinctive level of engagement for Sinan Oğan is also evident in the trending topics dataset, where he maintains a high ratio of 18%. This difference in engagement may be influenced by various factors, including the demographic characteristics of the followers in terms of age and gender. Furthermore, the number of inactive or idle followers for other candidates might be higher, whereas Sinan Oğan, being a relatively new figure compared to other candidates in the elections, might have a smaller number of such idle followers.

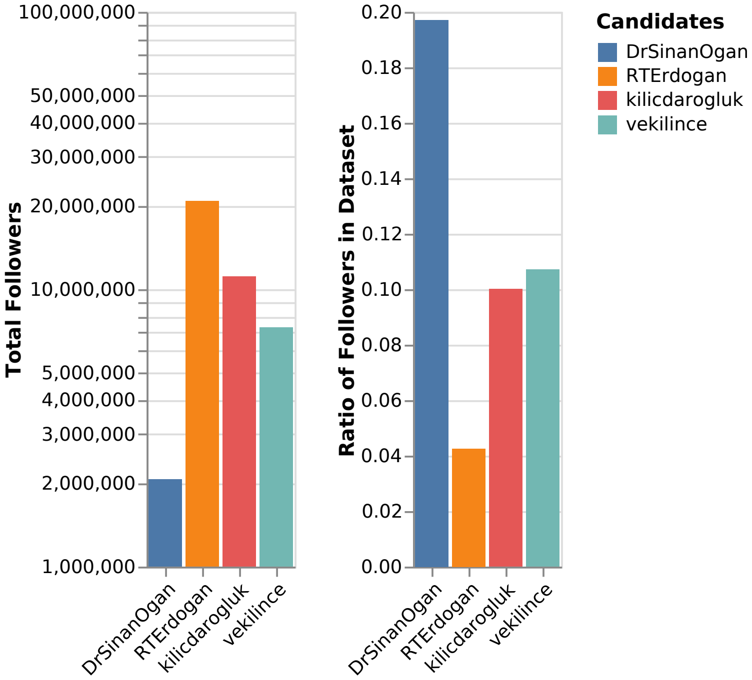


Figure 3.7 Follower counts of the candidates and their involvement in Trending Topics Dataset

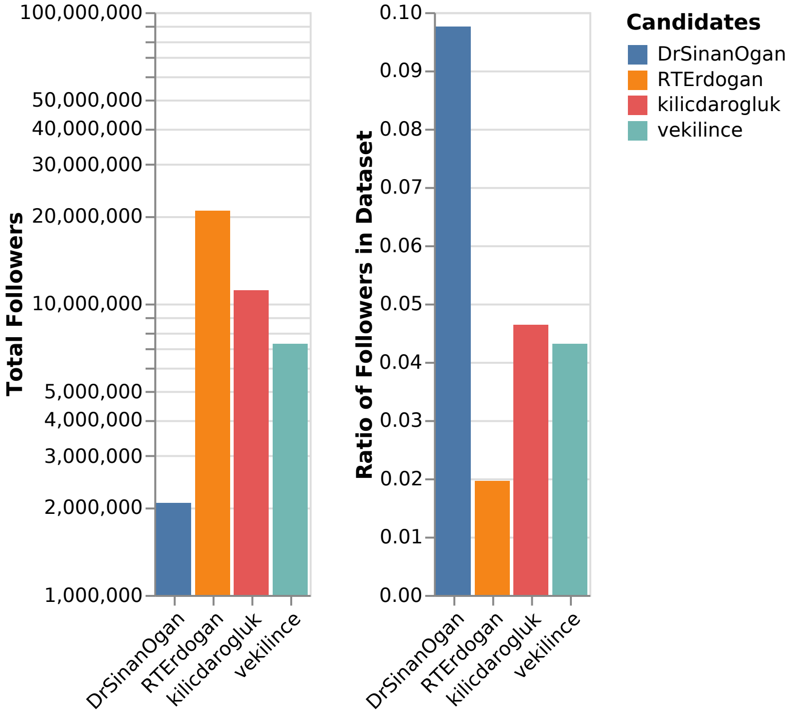
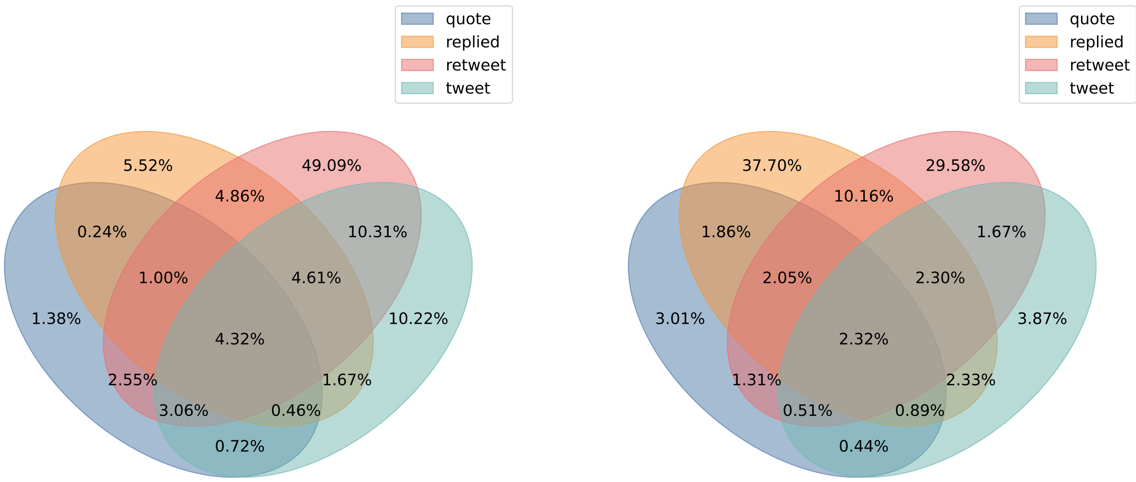


Figure 3.8 Follower counts of the candidates and their involvement in Election Dataset

3.2.4 Type of Tweets

There are 4 different types of tweets in our dataset. A user can tweet something she wrote herself, can retweet, reply or quote tweets of other users. Figure 3.9 shows the distribution of these types in our dataset. The most widely used types are replies and retweets which account for the 83% of the tweets in our dataset. Around 38% of the users in our dataset just replied and 30% of them just retweeted. Only 7% of the user in the dataset did not reply to or retweet any tweet that contains one of the candidates. In the trending topics dataset, the user behaviors differentiate.



(a) Trending Topics

(b) Election Dataset

Figure 3.9 The overlap of users with respect to their usage of different types of tweets

In Figure 3.10, it can be seen that the behaviors of users are different among the two datasets. In the Trending topics ratio of users who are at least once retweeted is 80% while in the election dataset, it is 50%. On the other hand, the ratio of the user who replied at least once is 60% in the election dataset which is 37% more than the users in the trending topics dataset. From this, we can say that people tend to get in the debates more in the election-related tweets with respect to the tweets in trending topics. Moreover, it is essential to note that in the election dataset, only 20% of replies and 10% of retweets are collected. Even with these sampling ratios, replies are significantly prevalent, indicating a high level of engagement in debates with replies in election-related discussions compared to trending topics.

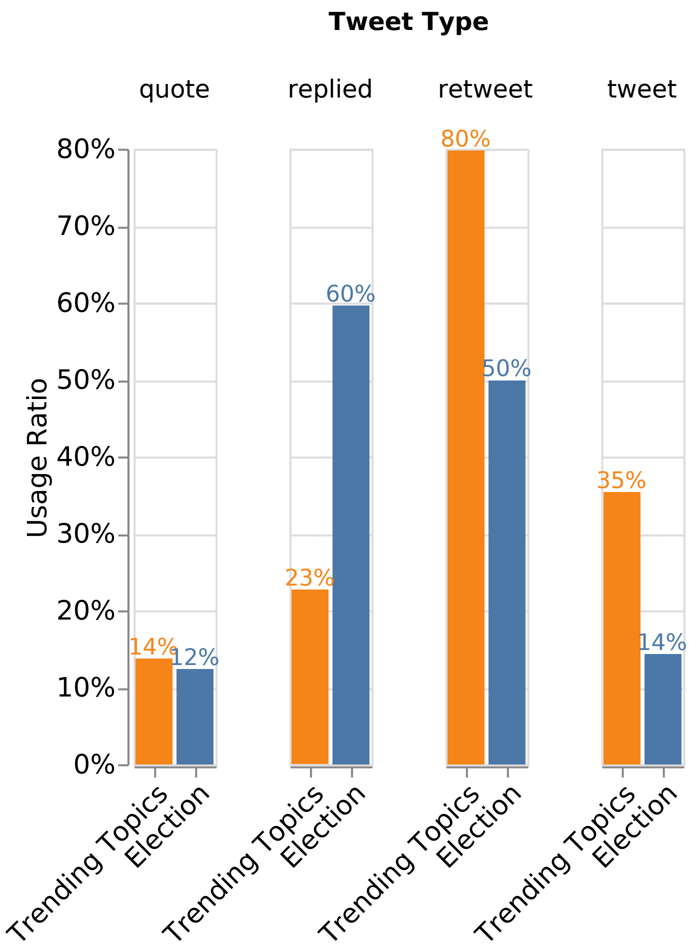


Figure 3.10 Comparison of User Ratios with respect to their Usage of Different Tweet Types

4. METHODOLOGY

In this section, the methods used to extract the sentiment scores of tweets and their manipulative information are explained.

4.1 Sentiment Analysis and Modelling

4.1.1 Sentiment Analysis

Sentiment analysis is an NLP(Natural Language Processing) technique used to determine the expressed emotions in a text in a more quantitative way. It helps researchers to identify people's opinions towards a topic. If it is applied on a broader scale like the tweets sent by a vast majority of people, it plays a role in representing public opinion. There are different language models trained on specific texts, in this study, we preferred to use the BERT model trained on Turkish text which is BERTurk. Using this model, we calculated sentiment scores in our two datasets, which are the trending topics dataset and the election dataset. Then we used sentiment scores along with different dimensions like mentioned users, follower groups, and tweet types to analyze how events especially during the election campaign reflected on public opinion.

4.1.2 Bidirectional Encoder Representations from Transformers (BERT)

In recent years transformer-based NLP models specifically BERT have changed the NLP applications dramatically, like sentiment analysis, question answering, and text classifications (Devlin, Chang, Lee & Toutanova, 2019). There are different versions of BERT trained on domain-specific data to perform better, but the underlying architecture is similar. There is one BERT model trained on Turkish text whose name is BERTurk (Schweter, 2020). In this study, we used the fine-tuned version of BERTurk for sentiment analysis (Savas, 2023).

4.2 Coordinated Activity Detection

Coordinated activities are one of the manipulative actions on social media to shape public opinion according to one's personal agenda. Manipulative activities take place at both individual and group accounts level. Twitter itself also detects and suspends such actions. We used Twitter's API to check whether a tweet is suspended, protected, deactivated, or still reachable by users. We also found an indicator of coordinated activities.

4.2.1 Suspended Tweets

Twitter provides researchers with an API endpoint name Compliance API[1], which returns the compliance status of the tweets and users at the time of the request. The status can be protected, deactivated, or suspended. The explanation of the statuses is as follows;

- Suspended: If a tweet or user violates the Twitter Rules, it is suspended by Twitter. The reasons can be from the following; spam, account security at risk, and tweets behaving in an abusive way.
- Protected: If users have protected his/her accounts or tweets they became invisible to everyone except their followers.

[1] API Documentation, https://developer.twitter.com/en/docs/twitter-api/compliance/batch-compliance

- Deactivated: If users deactivate their accounts or tweets the API returns their status as deactivated.

If the tweet is accessible and there is no restriction on it, the API does not return anything for it. We utilized the API to gather the compliance status of tweets within our trending topics dataset on June 3, 2023, while for the election-related tweets, we obtained this information on June 21, 2023. We then used this information to analyze the suspended tweets and users to get better insights into manipulative actions in both trending topics and election-related tweets.

4.2.2 Concurrent Actions

In our research, we have identified an important feature that serves as an indicator for a particular type of attack employed by a group of users to manipulate trending topics. This feature is calculated by counting the number of tweets directed towards a specific hashtag that is currently trending, all within the same second. For instance, if a tweet mentions hashtag "x" at a time "t" and no other tweets including hashtag "x" are sent at the same time "t," it is counted as 1 concurrent action. However, if the tweet is sent to hashtag "x" at time "t" along with 99 other tweets directed towards "x" within the same second, then the concurrent actions for this tweet would be 100. With this feature, we aimed to capture coordinated bot accounts used to manipulate a trending topic acting together at the same second.

By utilizing this feature, we were able to distinguish instances of coordinated attacks on trending topics. Coordinated groups in this attack create an artificial appearance of organic support for certain topics. This feature shows how the frequency of tweets directed towards a specific hashtag within the same second can be a valuable metric in identifying coordinated manipulation efforts.

To gain deeper insights, we cross-referenced this feature with Twitter's suspension data and analyzed the suspension status of tweets with high concurrent actions. We further extended this methodology to investigate if similar attacks were occurring on election-related tweets that mentioned the candidates.

Table 4.1 Example Tweets for Coordinated Actions

Hashtag	**Text**	**Tweeted At**	**Concurrent Actions**
#yolsuzekrem	Aziz İstanbullular, sizi sürekli bozulan, kaza yapan, yanan otobüslere, çalışmayan metrolara, yürüyen merdivenlere mahkum eden Ekrem, 2019 yerel seçimlerinden sonra kurulan reklam şirketlerine oluk oluk para aktarıyor.#YolsuzEkrem	2023-01-09 20:00:19	1
#yolsuzekrem	sinek mantarı kaypakça begonya Mesudiye akliyeci bombalatabilmek #YolsuzEkrem klorürlendirmek selülozlu bisküvi	2023-01-09 20:06:51	100
#yolsuzekrem	çeşnisiz plazma çıtlama treyler ilke çıplaklaştırmak sürükletmek üsküf yordam sevindirebilme #YolsuzEkrem kuşhane	2023-01-09 20:06:51	100
#yolsuzekrem	#YolsuzEkrem yüklüce tanrısız yüceltilmek çıkmalı öküzburnu boşlama cisimleşebilme araklayabilmek Danimarka kırmızı...	2023-01-09 20:06:51	100
#yolsuzekrem	reel kesim ağlatabilmek denetletme #YolsuzEkrem samaryum tofu	2023-01-09 20:06:51	100
#yolsuzekrem	pare pastırmalı #YolsuzEkrem oturak kündesi caydırış ofsayt dayamak destekleşmek ikram anahtar bitkiler mumhane hafif sanayi	2023-01-09 20:06:51	100

The table 4.1 shows preliminary results to better understand the feature we mentioned. In the first tweet, the user mentions the hashtag "#yolsuzekrem" which indicates that the tweet is related to discussions about corruption allegations against Ekrem İmamoğlu who is the mayor of İstanbul. The content of the tweet contains a negative portrayal of İmamoğlu, stating that he is responsible for various issues in İstanbul, such as malfunctioning buses, accidents, and burning buses, as well as non-functional subways and escalators. The tweet further suggests that İmamoğlu is funneling large amounts of money into advertising companies after the 2019 local elections. The concurrent action for the first tweet is 1. This means that at the time of its posting, no other tweets mentioning the same hashtag were sent within the same second.

However, after 6 minutes, a total of 100 tweets were sent in the exact same second, all containing the hashtag "#yolsuzekrem". The concurrent action count for these 100 tweets is recorded as 100. Some of these tweets can be observed in Table 4.1 as well.

These tweets share a common characteristic of containing random lexicon words. This behavior is analyzed in another study (Elmas, 2023). The presence of these lexicon words in the tweets may suggest a potential pattern or similarity in the language used for manipulation or influencing public opinion. But in the scope of this study, we focused on the time dimension of this coordinated attack by taking advantage of our feature. To sum up, this set of tweets appears to be attempting to create a manipulation by negatively framing İmamoğlu and portraying him as corrupt and responsible for various problems in Istanbul by creating a fake trend and the number of concurrent actions indicates coordination.

5. RESULTS

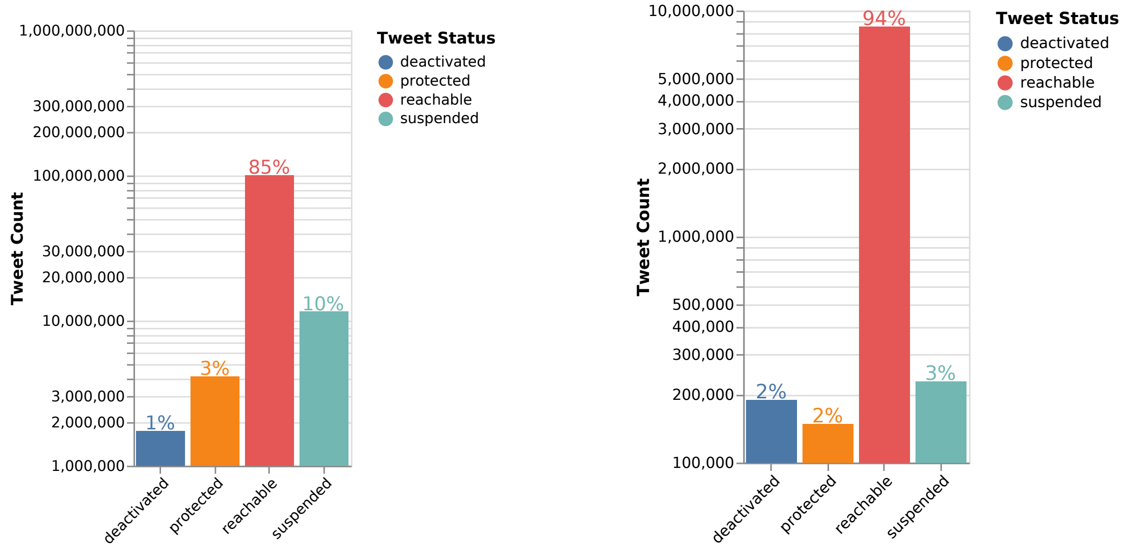
In this chapter, we share our results based on two main branches which are manipulations and sentiment analysis.

5.1 Manipulations

We have used two different methods to analyze the manipulation on our datasets. In this section, we share the results of analysis on two datasets segmented by the method used.

5.1.1 Compliance Status

Figure 5.1 shows the status of the tweets at the time we sent the request to compliance API. In the election dataset, 94% of the tweets are reachable and only 3% are suspended, while in the trending topic dataset, the suspension rate is at 10%. The reason behind it can be the time passed after the tweet was sent since we checked the status of tweets around similar times. This increases the number of suspended tweets. Another reason behind this can be the high manipulative activities on trending topics like astroturfing attacks.



(a) Trending Topics Dataset (b) Election Dataset

Figure 5.1 Statuses of Tweets and Users Retrieved from the Compliance API

Figure 5.2 shows the ratios of tweets mentioning candidates with respect to their status on 21.06.2023 which is the date we collected this information via Compliance API. Most of the tweets are still reachable for all candidates with ratios higher than 90%. Deactivation ratios are higher for İnce and Oğan, standing at 3%. In comparison, Erdoğan's deactivation ratio is 1.5%, accompanied by a corresponding number of tweets totaling 30k, 20k, and 80k, respectively.

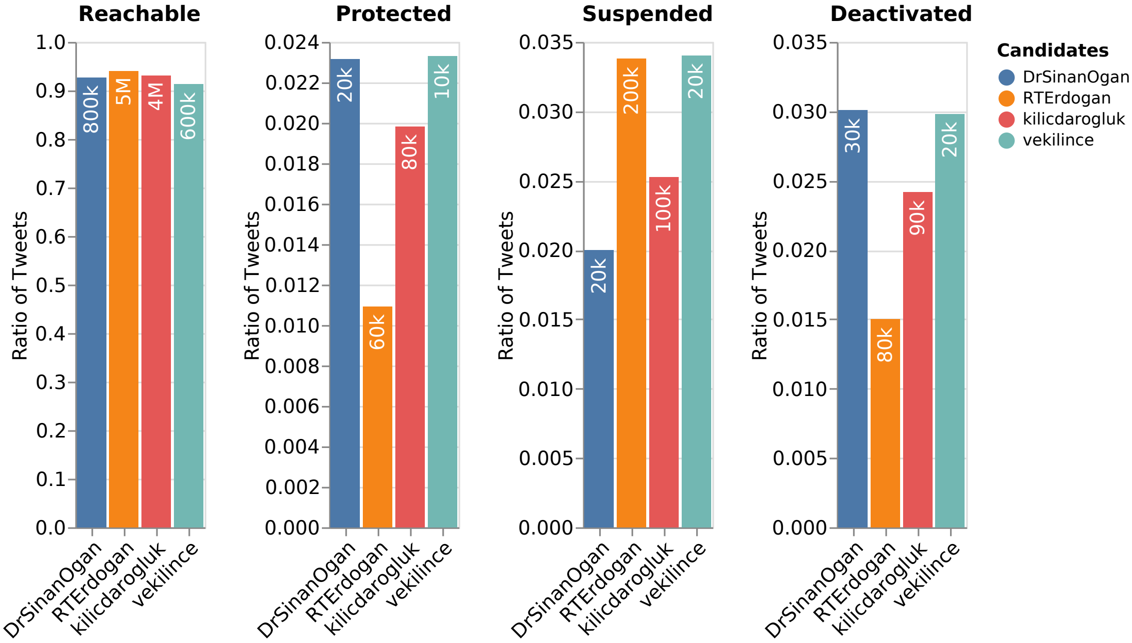


Figure 5.2 Distribution of Tweet Statuses Segmented by Mentioned Candidate

5.1.2 Concurrent Actions

Figure 5.3 shows the concurrent actions with respect to the statuses of the tweets in two datasets. The bar charts display the mean values for each tweet status along with the 95% confidence intervals. It can be seen that the in Trending Topics dataset, the suspended tweets have 15 as the concurrent action average which is approximately 50% higher than the other tweet statuses which are deactivated, protected or reachable. This observation suggests that coordinated efforts among accounts may be taking place to manipulate trending topics, and Twitter's detection and suspension mechanisms are effectively targeting such coordinated activities. Furthermore, this finding underscores the significance of our feature, concurrent actions, in detecting potential manipulative behavior.

However, we cannot see such a difference in the election dataset, also the number of tweets that are sent at the same second mentioning a candidate is dramatically smaller with respect to trending topics. It shows that the coordinated attack that we observed in the trending topics dataset does not occur for the tweets mentioning candidates. This further may be studied by examining the tweets sent to the hashtags related to elections.

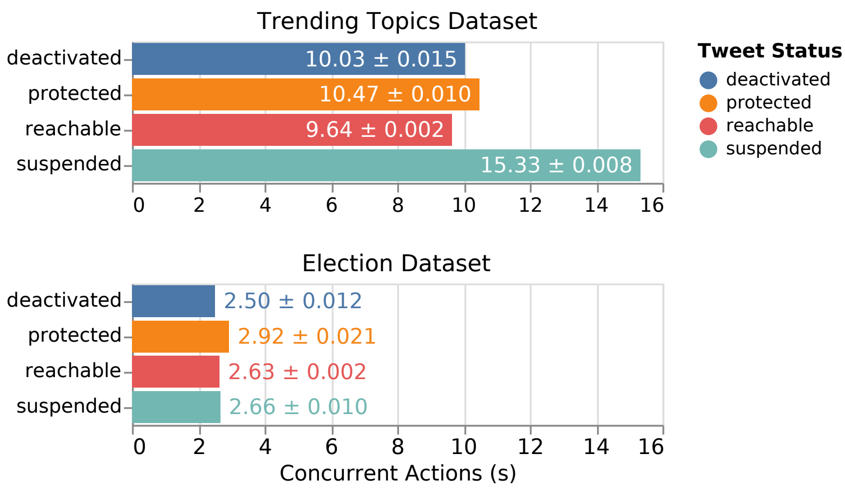


Figure 5.3 Comparison of Concurrent Actions in Trending Topics and Election Datasets across Different Tweet Statuses

5.2.1 Trending Topics

Figure 5.4 shows the average sentiment scores of the tweets sent to trending topics on a daily basis. On the 6th of February, there was an earthquake in Turkey, affecting millions of people. The effect of this earthquake can be seen in the graph. The sentiment scores of the tweets on trending topics drop dramatically, and it does not reach the same level of sentiment score till the 19th of February. this shows us the sentiment score's power at reflecting public opinion via tweets.

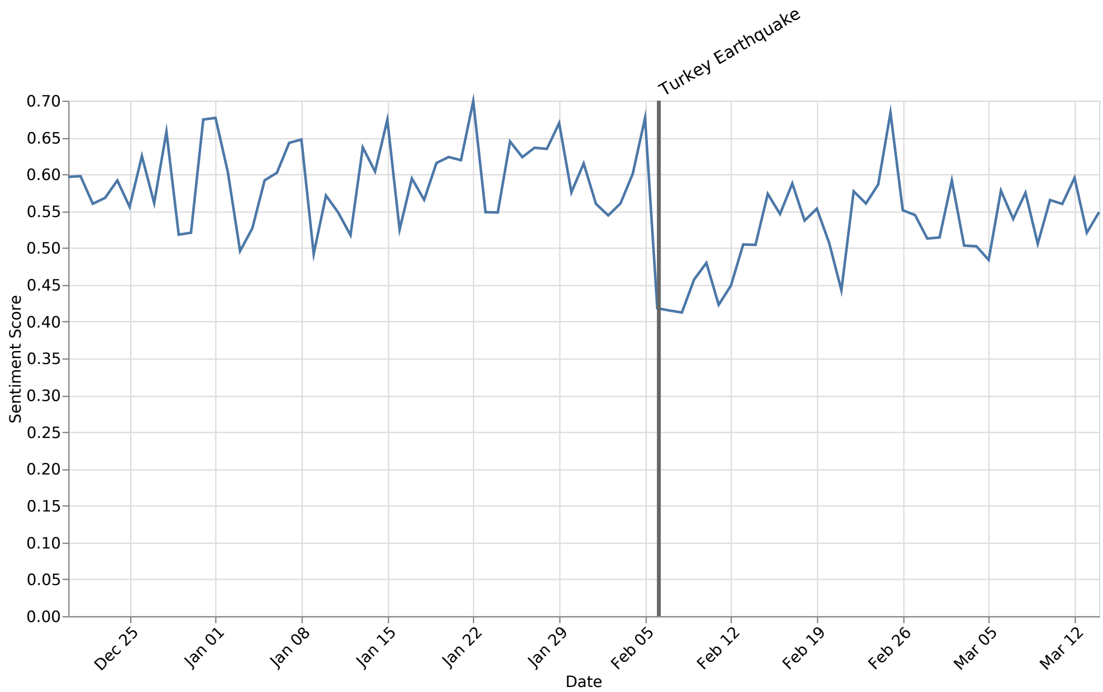


Figure 5.4 Daily average sentiment scores of the tweets in trending topics between 20.12.2022 and 15.03.2023

5.2.2 Candidates

Figure 5.5 shows the average sentiment score of the tweets mentioning the candidates. Erdoğan has the most positive score with 0.51 while İnce has the lowest with 0.3.

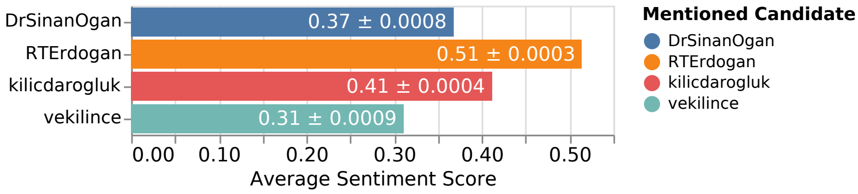


Figure 5.5 Average sentiment scores of the tweets in April and May 2023, segmented by mentioned candidate

Figure 5.6 shows us the sentiment scores of the tweets mentioning the candidates on a daily basis. We observe an increase in the sentiment score towards the elections in general. It can be observed that Erdoğan has the most positively scored sentiments on each day throughout the election on a daily basis. İnce has the lowest scores on the daily average in general but this changed after the second election with tweets mentioning Kılıçdaroğlu becoming the least score, after the defeat to Erdoğan. We have analyzed the post-election periods in more detail in the section on Election Days.

The given percentages, with İnce at 66%, Oğan at 71%, Kılıçdaroğlu at 72%, and Erdoğan at 80%, represent the share of tweets exclusively mentioning each candidate. Around 30-20% of tweets mentioning a candidate also mentions another candidate. This dynamic creates a connection in the average daily sentiment scores of tweets mentioning the candidates.

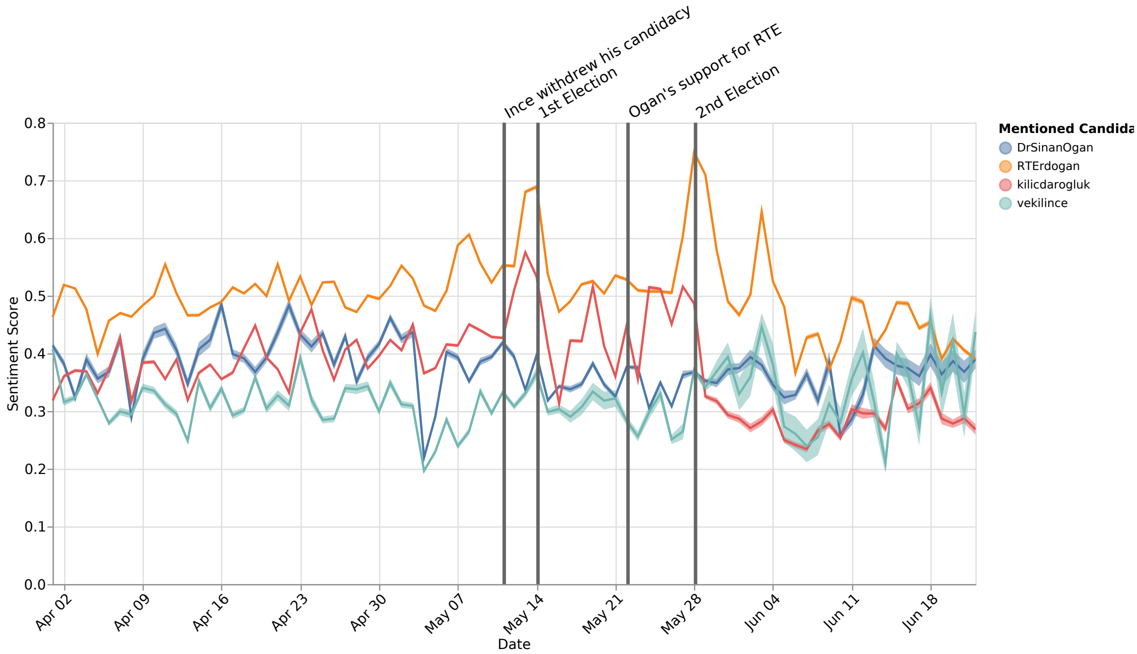


Figure 5.6 Daily Average sentiment scores of the tweets in April and May 2023 with their confidence bands, segmented by mentioned candidate

5.2.3 Reflection of Events

Throughout the election period, there were lots of major political events that shaped the election campaigns. In the following figures, we analyzed the reflections of 4 different events on the candidates with respect to different groups of followers. The events can be seen in Table 5.1.

Table 5.1 Timeline of Events during Election Period

Date	Event
2023-05-11	İnce withdrawn
2023-05-14	1st Election
2023-05-22	Oğan's support for Erdoğan
2023-05-28	2nd Election

On the 11th of May, 3 days before the elections one notable event took place which was the withdrawal of İnce from the race. During his announcement, he did not indicate any support for any of the other candidates. Before his announcement, he was claimed for dividing the votes by the opposition. He was the candidate of the opposition party in the previous election. When compared with the previous day in

Figure 5.7, it can be seen that the sentiment scores of people following Kılıçdaroğlu and Oğan have increased more compared to followers of Erdoğan while the followers of İnce stayed neutral.

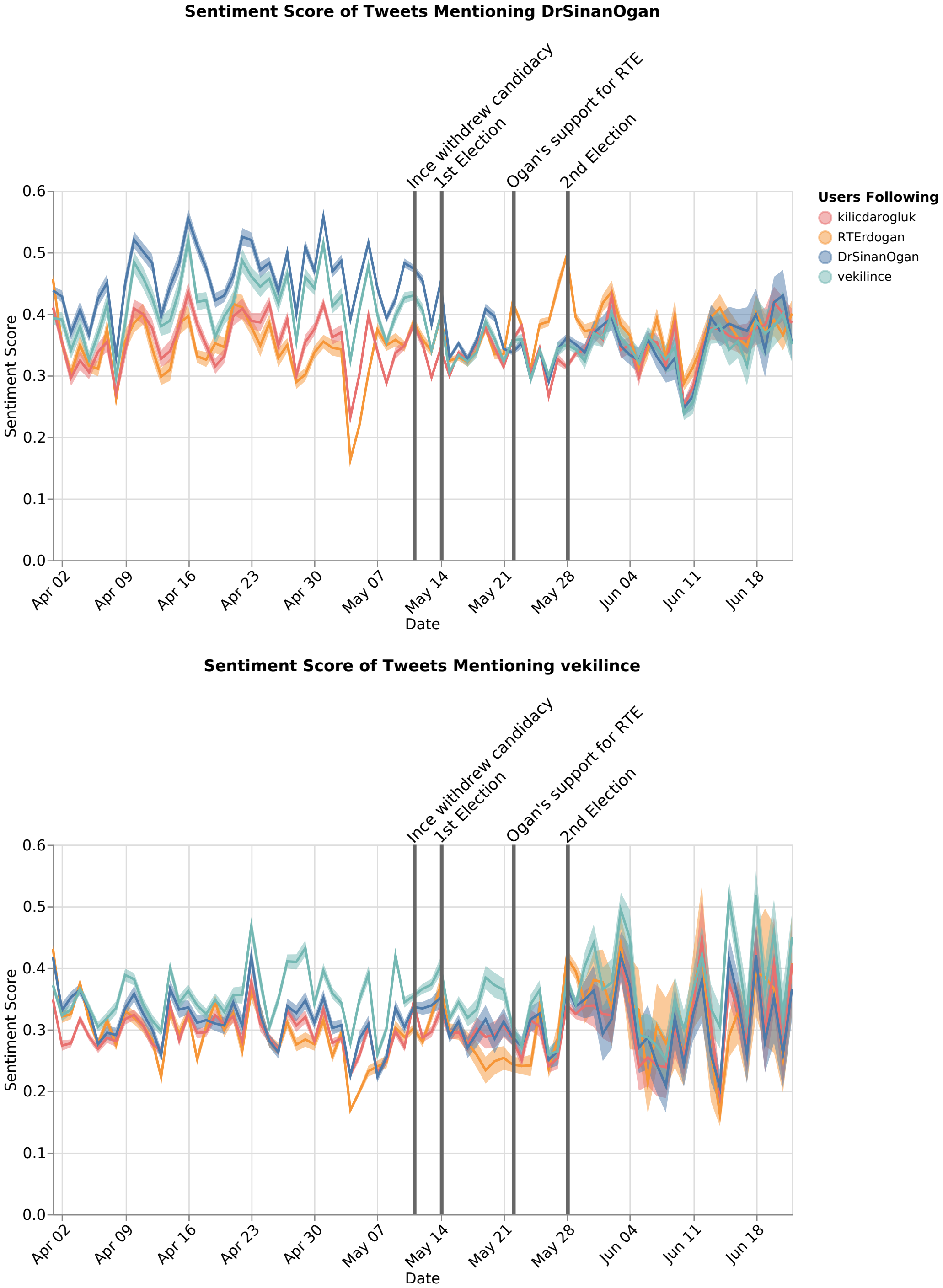


Figure 5.7 Daily average sentiment scores of tweets mentioning İnce and Oğan segmented by followers candidates

Elections took place on the 14th of May, we see a drop for all candidates on the day following the elections. At midnight, it was clear that the elections will be finalized in the second round which was held on the 28th of May. When compared with other candidates Kılıçdaroğlu has the greatest drop after the first elections which can be seen from Figure 5.7 and Figure 5.8.

After the first elections, Oğan has become a person of interest since Kılıçdaroğlu and Erdoğan were the two candidates that will run for the presidency on the second run, and Oğan's support for either of the candidates was expected by the public. On the 22nd of May, he announced his support for Erdoğan. In Figure 5.7, we can see the effect of this event on tweets mentioning Oğan by the followers of each candidate. It can be observed that starting from the day of his announcement people following Erdoğan have started to send more positive tweets than his own followers. With this positive attitude, the sentiment score difference between tweets sent by Erdoğan and his followers has increased in a way that followers of Erdoğan tweeted even more positive tweets each day. Before his announcements, there were even days when followers of Erdoğan sent the least positive tweets for Oğan. When compared with the pre-election period we can see that the sentiment scores of the tweets sent by his own followers steadily decreases.

The last major event in the election period is the second election which is held on the 28th of May. As we mentioned earlier there were 2 candidates which are Erdoğan and Kılıçdaroğlu. In the second round, Erdoğan won and his opponent Kılıçdaroğlu lost. We can see from the figures that the defeat of Kılıçdaroğlu has been reflected by a significant decrease in the sentiment scores of the tweets mentioning him. The effect of election days is analyzed separately in the following sections.

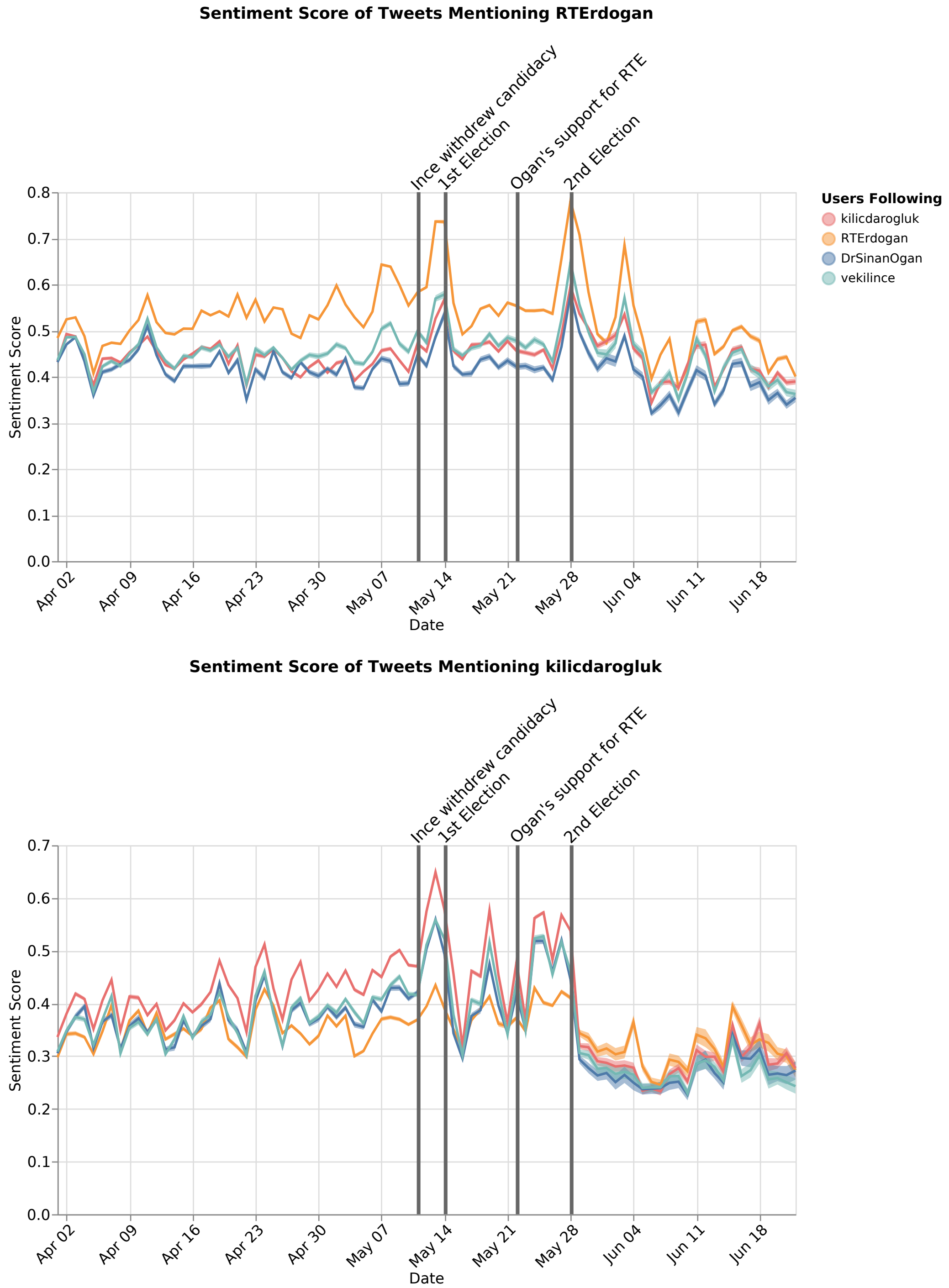


Figure 5.8 Daily average sentiment scores of tweets mentioning Erdoğan and Kılıçdaroğlu segmented by candidate followers

5.2.4 Candidate Followers

The followers of the candidates also play a role in reflecting the public opinion of supporters of these candidates. In the following figure, we see the average sentiment scores of the followers of the candidates. If a person follows more than one candidate, his/her sentiment score is counted on all of the candidates he/she follows. It can be observed that the gap between the candidates is higher in the Election dataset. Tweets mentioning the candidates have a lower score in general compared to trending topics. Erdoğan's followers sent the highest-scored tweets which is a finding in parallel with the one we observed in the sentiment score of the mentions. Oğan's followers have the lowest. Here İnce is not the lowest like in the case of mentioned tweets. Erdoğan's high score can be caused by its followers, but İnce's lowest score on the mentions can be caused by the attitude of other candidates' followers towards İnce.

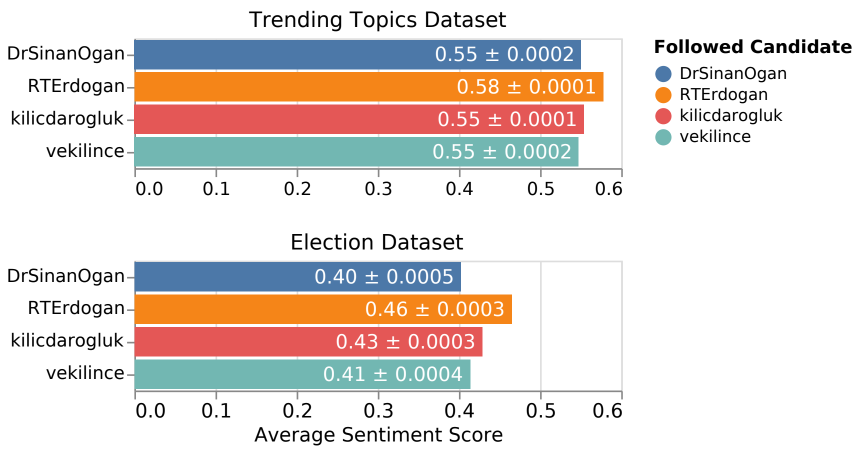


Figure 5.9 Comparison of Average Sentiment Score in Trending Topics and Election Datasets across Different Tweet Statuses

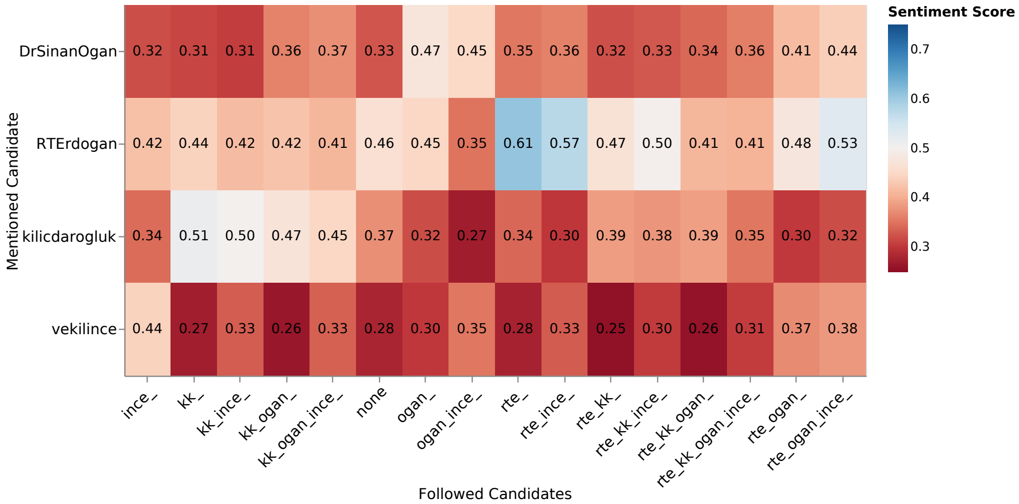


Figure 5.10 Sentiment Score Heatmap of Mentioned Tweets based on User's Following Status of Candidates

Figure 5.10 shows the sentiment score of the mentioned tweets with respect to the user's following status of candidates. Here we divided the follower groups into 16 to compare each group separately. On the y-axis, we have the name of the candidates that the user is following, on the y-axis we have the mentioned candidates. From this figure, we can see that the most positively mentioned are sent by people who are only following Erdoğan mentioning Erdoğan. The ones that have the lowest score belong to İnce, with user groups following Erdoğan, Kılıçdaroğlu, and Oğan. We found that the tweets with the highest scores for the candidates are sent by people who are only following that candidate.

When users exclusively follow a particular candidate and do not follow any other candidate, this following status may indicate a higher level of commitment and loyalty toward that candidate. These dedicated followers may send tweets which are supporting their engaged attitude in the candidate's political campaign. As a result, their tweets may have a higher chance of consisting of strong positive sentiments, supporting their followed candidate and amplifying their messages more than other user groups.

On the other hand, users who follow multiple candidates may have diverse political preferences or are undecided about whom to support fully. As a consequence, their tweets may contain a broader range of sentiments, both positive and negative.

This finding can also be attributed to different psychological phenomena. It can be caused by their emotional attachment to the candidate their following which may increase the need to send more passionate tweets regarding the candidate they follow. It can be caused by their confirmation bias which leads people to share information that supports their beliefs in a way tweets with positive sentiments. These results give us insights into the commitment and enthusiasm among a candidate's followers and assess the overall sentiment landscape of election-related tweets.

5.2.5 Sentiment Divergence

In Figure 5.10, we have seen the sentiment score of tweets mentioning the candidates across various user groups. In Figure 5.11, we are examining the user sentiment divergence, which represents the disparity between the sentiment scores of the most positively mentioned candidates and the most negatively mentioned candidate within each user group. Notably, individuals who solely follow Erdoğan exhibit the highest user sentiment divergence of 0.34. On average, the tweets they sent mentioning Erdoğan get the highest sentiment score with 0.61, while the tweets they mentioned İnce get a score of 0.28. Similar to our findings in Figure 5.10 we observed that as the number of candidates followed by the user increases, the user sentiment divergence gradually diminishes, reaching its lowest point among the user group following all of the candidates.

This implies that individuals who follow multiple candidates tend to express more balanced sentiments in their tweets, distributing their positive and negative sentiments across various candidates.

The higher divergence among exclusive followers suggests a more polarized and emotionally charged response. They sent tweets with stronger support for their preferred candidate and more negative sentiments towards other candidates than people who follow multiple candidates. As opposed to that, lower divergence among users following multiple candidates indicates a more balanced sentiment landscape, reflecting a broader range of opinions and preferences.

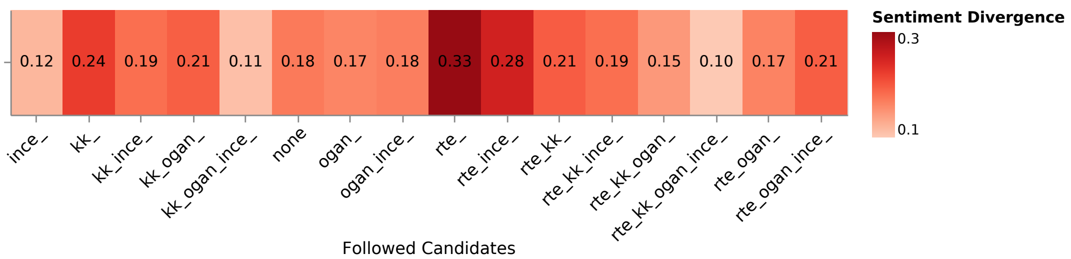


Figure 5.11 Difference in Sentiment Scores between Most Positively Mentioned Candidates and Most Negatively Mentioned Candidate across User Groups

5.2.6 Tweet Status

Figure 5.12 shows the sentiment score of the tweets with respect to their statuses in two different datasets. We see that the sentiment scores of tweets from different statuses are similar for both datasets. When we compare the two datasets we see that sentiment scores are smaller in the election dataset in general. It can be observed that in the Election dataset, suspended tweets have the lowest score with 0.36.

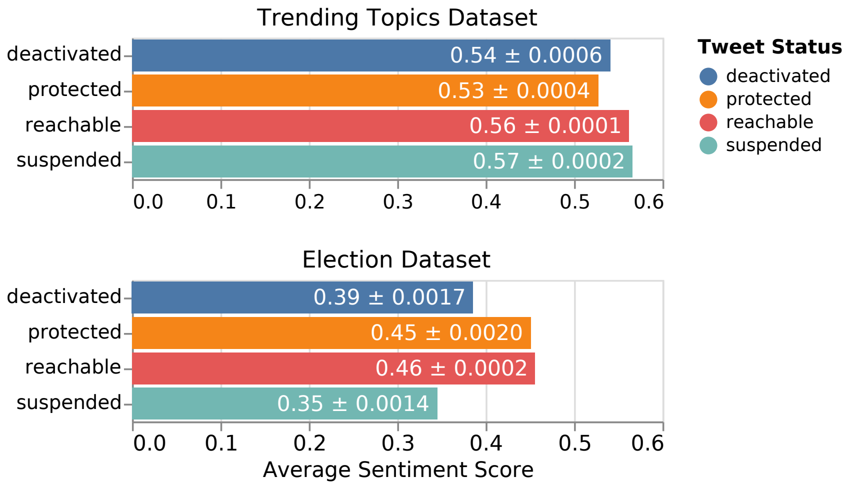


Figure 5.12 Comparison of Average Sentiment Score in Trending Topics and Election Datasets across Different Tweet Statuses

5.2.7 Tweet Types

In the previous sections, we observed that the sentiment score of the tweets in the Election dataset is lower in general. In Figure 5.13, we see the comparison in terms of tweet types. The trend applies for the quote, reply and tweet with smaller sentiment scores in the Election dataset but retweets behave differently. Retweets in the Election dataset have higher sentiment scores than retweets in Trending topics.

Retweets in both datasets, tend to carry more positive sentiment than other types this may be caused by the fact that this feature is generally used to amplify a message users support. People also may have a tendency to amplify positive messages like the ones sent by their supported candidates instead of tweets with low sentiments. On the other hand, replies consistently exhibit the lowest sentiment scores among the tweet types. This can be explained by the fact that replies are commonly employed for engaging in debates and discussions with individuals who hold opposing viewpoints. This may cause a higher likelihood of encountering negative sentiments in replies.

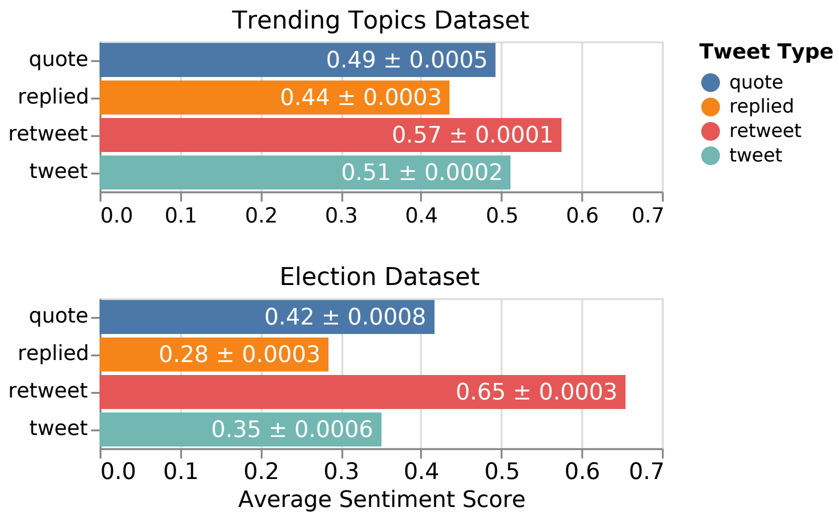


Figure 5.13 Comparison of Average Sentiment Score in Trending Topics and Election Datasets across Different Tweet Types

Figure 5.14 shows the sentiment scores of mentioned candidates with different types of tweets. As we have seen in Figure 5.13 retweets have the most positive sentiment scores while replies have the lowest. The highest score belongs to retweets mentioning Erdoğan while the lowers belongs to replies mentioning İnce. İnce has the lowest scores for quotes and tweets as well.

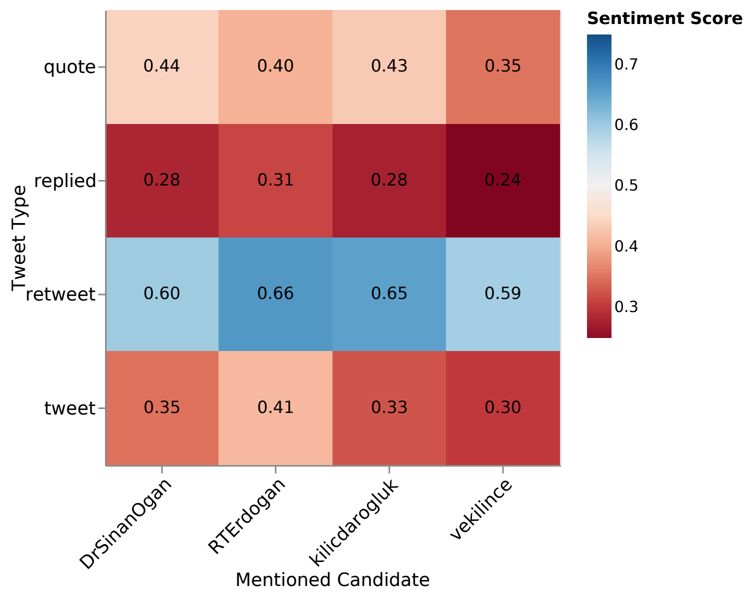


Figure 5.14 Sentiment Scores of Mentioned Candidates Across Different Types of Tweets

Figure 5.15 shows the sentiment score of the tweets with respect to different user groups which are formed based on the following statuses of the candidates. Once again, we see that retweets achieve the most positive sentiment scores for all user groups. The people following Oğan and İnce together have the lowest score for tweets. The most positive sentiments belong to people following only Erdoğan or Erdoğan together with İnce for retweets.

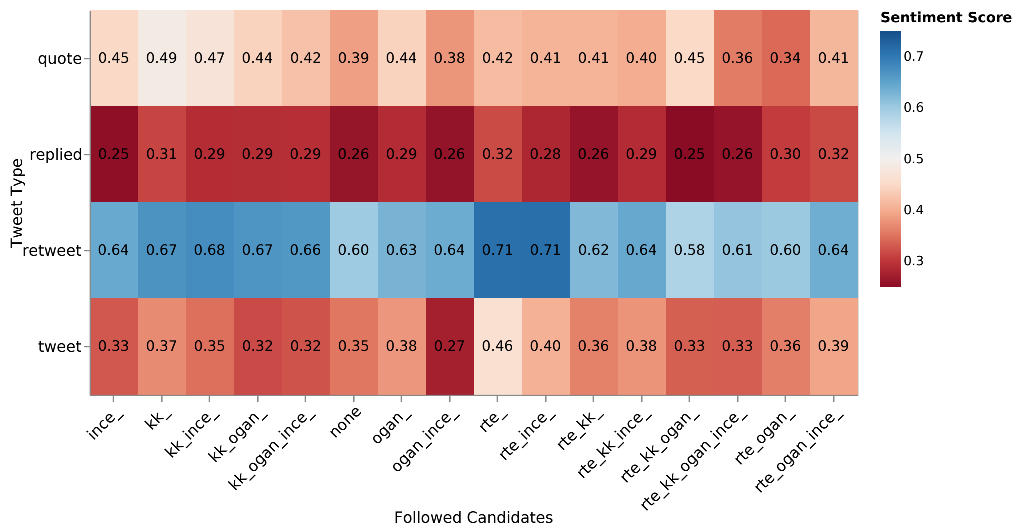


Figure 5.15 Sentiment Score Heatmap of Tweets Across User Groups Based on Candidates' Following Statuses

5.2.8 Election Days

Table 5.2 shows some of the key events and announcements made by the candidates during the election days.

Table 5.2 Timeline of Events on 1st Election Day

Date	Event
2023-05-14 08:00:00	Start of voting
2023-05-14 17:00:00	End of voting
2023-05-14 19:55:00	Kılıçdaroğlu: "Öndeyiz"(We are ahead)
2023-05-15 00:35:00	Kılıçdaroğlu: 1st Press Conference
2023-05-15 02:00:00	Erdoğan: "Balkondayız"(We are at balcony)
2023-05-15 03:00:00	Kılıçdaroğlu: We will in the second round

Figure 5.16 shows the sentiment scores of tweets sent at 1st election day with respect to followers of the candidates. The tweets include not only the mentions but all of

the tweets sent during the day. At 19:55 Kılıçdaroğlu sent a tweet indicating that he is the one that is ahead on the preliminary election results. The followers of Kılıçdaroğlu responded to that tweet in a very positive way which can be seen from the increase in the sentiment score. The sentiment score of the tweets sent by Kılıçdaroplu followers has become the most positive. As time passed the results has become in favor of Erdoğan, and at 2:00 AM he tweeted “We are the balcony” (Balkondayız). By using the balcony term he refers to his previous victories in which he made speeches after the results from the balcony. This tweet, in a way, implied that Kılıçdaroğlu did not win the first election. Despite not securing a victory himself, Erdoğan skillfully directed the sentiment score of his followers in a positive direction with this announcement.

1 hour after Erdoğan’s announcement, Kılıçdaroğlu made a second announcement saying the elections will be finalized in the second round and they will win the second round. After this announcement, we see a decrease in the sentiment score of the tweets that are sent by Kılıçdaroğlu’s followers. This decrease in the sentiment score may be caused by various factors, one can be the realization that their candidate did not secure an outright victory in the first round or it can be a later response to the optimistic tone set by Erdoğan’s tweet.

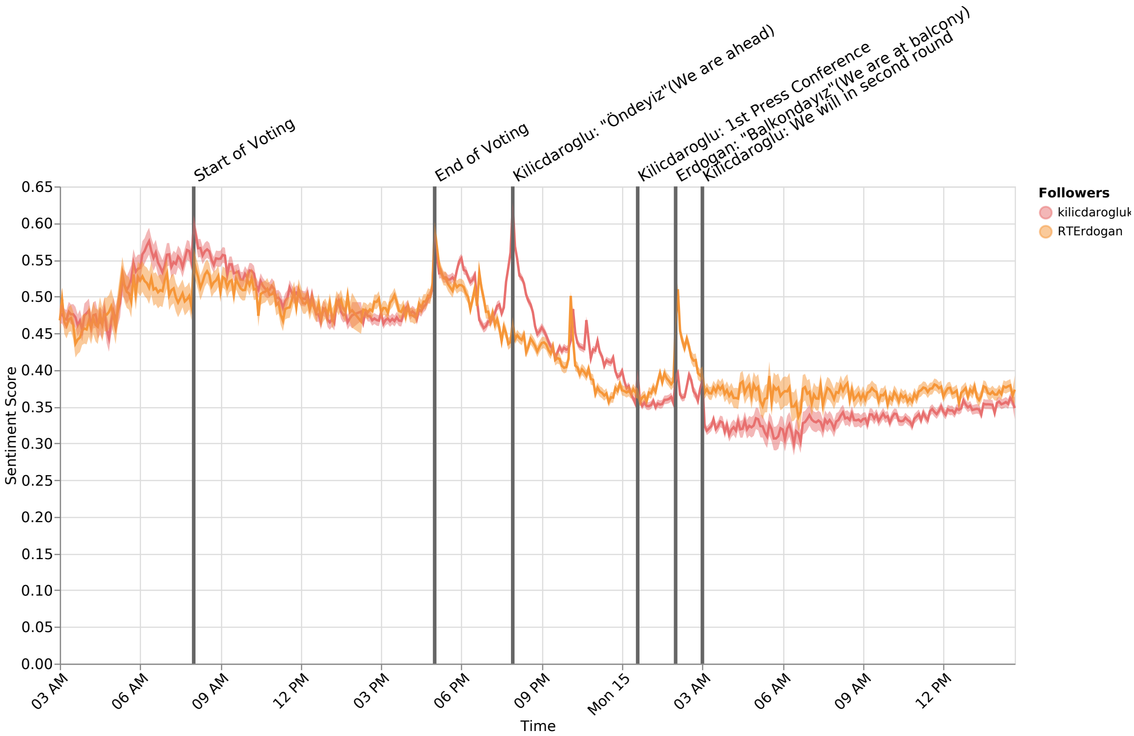


Figure 5.16 Average Sentiment Scores of Tweets Sent by Followers of Candidates during the 1st Election Day, Calculated in 5-Minute Intervals

Table 5.3 Timeline of Events on 2nd Election Day

Date	**Event**
2023-05-28 08:00:00	Start of voting
2023-05-28 17:00:00	End of voting
2023-05-28 19:00:00	Erdoğan is ahead on the results of both agencies

Table 5.3 shows some of the key events and announcements made by the candidates during the second election day and Figure 5.17 shows the sentiment scores of tweets sent on 2nd election day with respect to followers of the candidates. Erdoğan and Kılıçdaroğlu were the only candidates in the second round. Since there were only two candidates and there is no other voting taking place, the results have finalized in a quicker manner than the 1st round. There are two agencies that announce the preliminary election results in Turkey which are Anadolu Agency and Anka Agency.

In the preliminary results, there was some discrepancy among the two agencies. Anadolu Agency declared Erdoğan as the leading candidate, whereas Anka Agency indicated the opposite. However, by 19:00, both agencies reported Erdoğan as the candidate in the lead. After this event, we observe a noticeable and significant decrease in the sentiment score of tweets sent by Kılıçdaroğlu's followers. This decrease in sentiment may have been influenced by a sense of disappointment or concern among his supporters due to the clear lead established by Erdoğan in the election results. The rapid shift in sentiment scores reflects the real-time impact of political events on Twitter discussions and emphasizes the role of social media in shaping public opinion during elections.

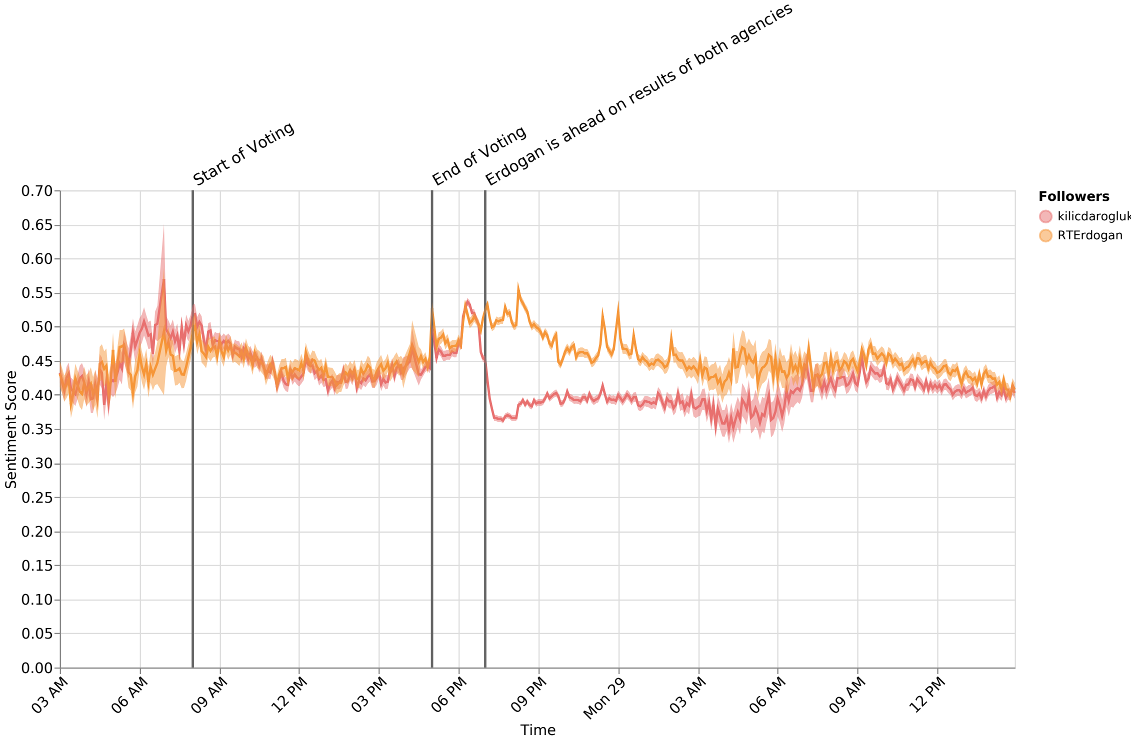


Figure 5.17 Average Sentiment Scores of Tweets Sent by Followers of Candidates during the 2nd Election Day, Calculated in 5-Minute Intervals

6. CONCLUSION

In this study, we wanted to analyze the coordinated manipulative activities and reflections of events on the tweets in the scope of trending topics and Turkey's 2023 presidential election with the help of sentiment scores.

We conducted our analyses on two different datasets, the first one containing the tweets sent to Turkey's trending topics while the second one was the tweets sent mentioning the presidential candidates in the 2023 Turkey election. We have two main branches of analysis, which are coordinated manipulative actions and the sentiments of the tweets. For the first branch of our analyses, we have used the tweet's status returned by Twitter after some period of time which gives information about whether a tweet is suspended by Twitter or not. In addition to Twitter's response, we have also used another metric named concurrent actions count to detect a specific type of attack performed on trending topics. For the sentiment analysis which is the second part of our analysis, we have utilized the BERTurk model which is a language model trained on Turkish texts and gives the sentiment scores of the tweets. Using the tweet's statuses and the concurrent actions count we have found that tweets suspended by Twitter in trending topics have significantly higher concurrent action counts indicating a coordinated activity detected by Twitter. In light of our findings in the trending topics dataset we have analyzed the same activities on the election dataset mentioning the candidates, we have not encountered such manipulation in the latter one. We believe the reason behind it is that the attack uses hashtags instead of mentions.

After the analyses of manipulative actions, to better understand the public's response to events on Twitter we performed sentiment score analysis on both datasets. Overall we have observed that major events like the earthquake that happened on the 6th of February and the elections held on the 14th and 28th of May 2023 have significant reflections on the sentiment scores. We then added different dimensions to our analyses which are, the type of tweet, the suspension status of the tweet, the candidate that the tweet mentions, candidates followed by the user who sent the tweet. Considering the tweet types, we have found that retweets have significantly higher sentiment scores while replies have the lowest sentiment scores in both datasets. Especially in election-related discussions, the gap is even higher between the sentiment scores of replies and retweets. We believe it is caused by the polarized nature of the elections, the ones who support and the ones that do not. Retweet is a feature mainly used to amplify the supported message while replies are generally used to get in a debate with someone.

Another dimension to classify the supporting behavior of users can be done using the set of candidates they follow. Since we have 4 candidates we have 16 different combinations and thus 16 different user groups and one group that does not follow any of the candidates. We have observed that for each candidate the tweets with the highest sentiment scores are sent by the group of people that only follows the mentioned candidate. We have defined a metric of polarization as the difference between the highest and the lowest sentiment score of the tweets mentioning the candidates for each user group. We have observed as the number of followed candidates increases the polarization decreases.

After getting the overall understanding of sentiments, we performed analyses using time as another dimension and expected to see the reflection of events on sentiment score. On the overall election period, we highlighted 4 major events which are the withdrawal of one candidate (İnce), 1st election, the announcement of support of one candidate(Oğan) to another (Erdoğan) after 1st election, and finally the second election. Overall, the supporters of candidates sent the most positive tweets mentioning the candidate. But after the announcement of Oğan's support for Erdoğan, the followers of Erdoğan sent tweets mentioning Oğan which are more positive than his own followers.

The election days and events taking place on these days are also analyzed. In the first election, the sentiment score of candidates do not diverge much since there was no certain winner. In the second round, this behavior dramatically changes, while the sentiment score of tweets mentioning the winning candidate (Erdoğan) increased and other candidates' decreased causing diverged results starting from the moment in which preliminary results showed that the winner is ahead. After the second election, the candidate that lost reached its all-time lowest sentiment score.

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APPENDIX A

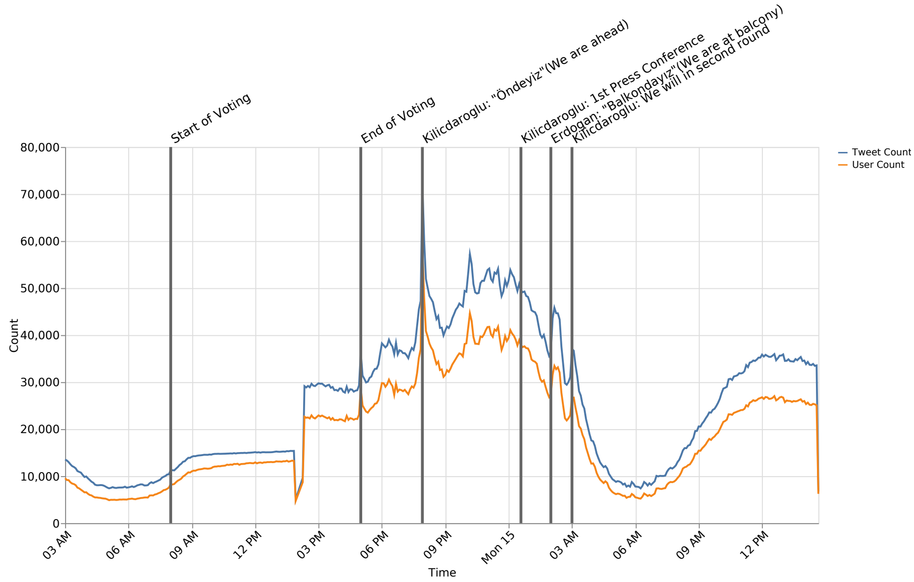

Figure A.1 Tweet and user count on the 1st election day

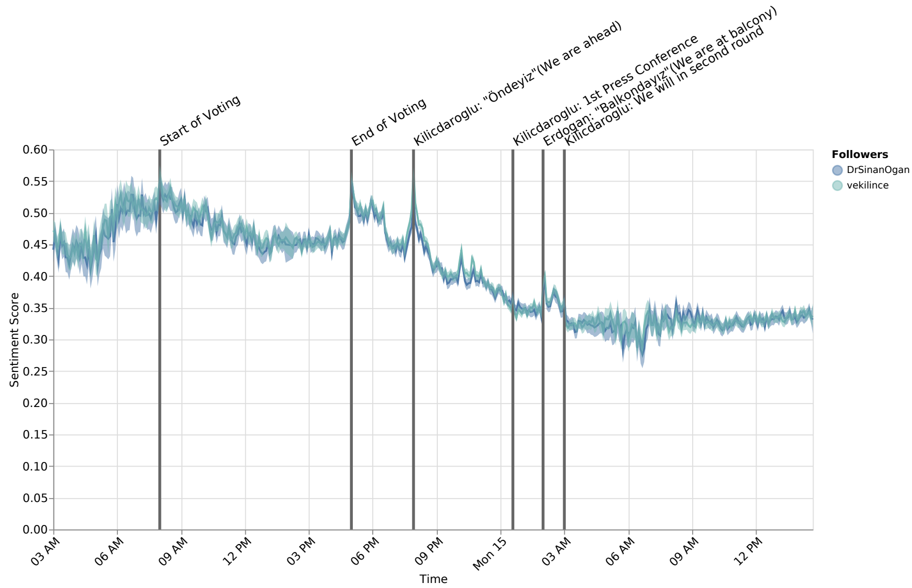

Figure A.2 Sentiment Score of followers of Oğan and İnce on the 1st election day

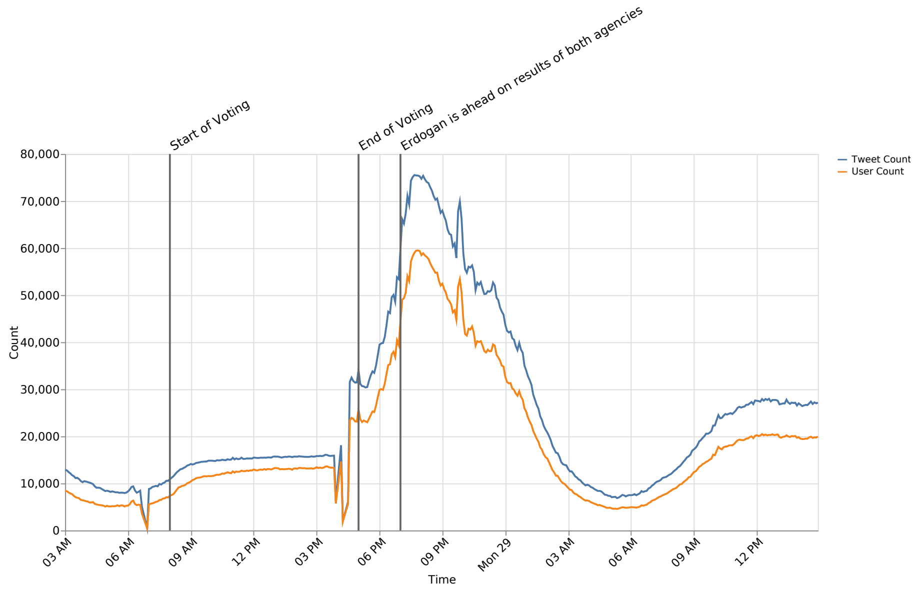

Figure A.3 Tweet and user count on the 2nd election day

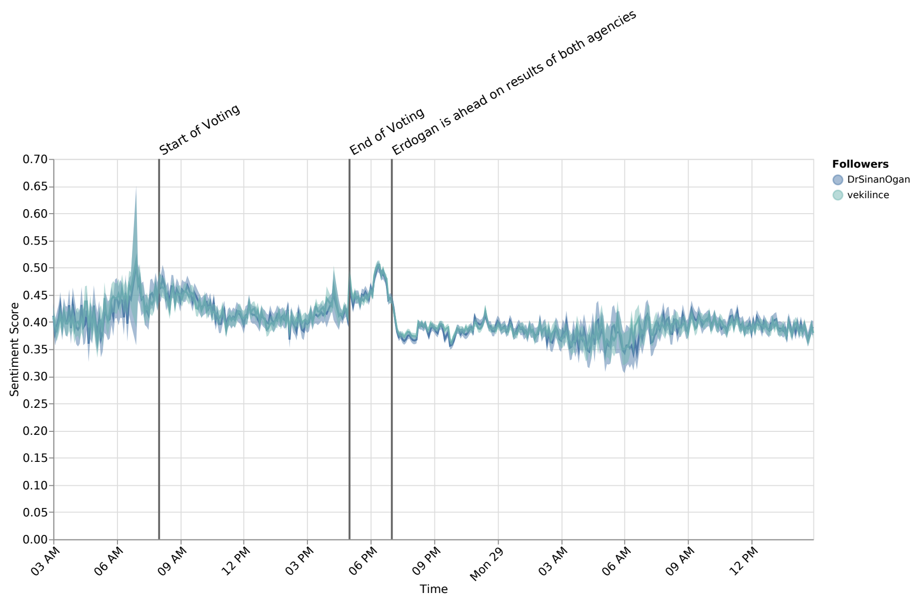

Figure A.4 Sentiment Score of followers of Oğan and İnce on the 2nd election day

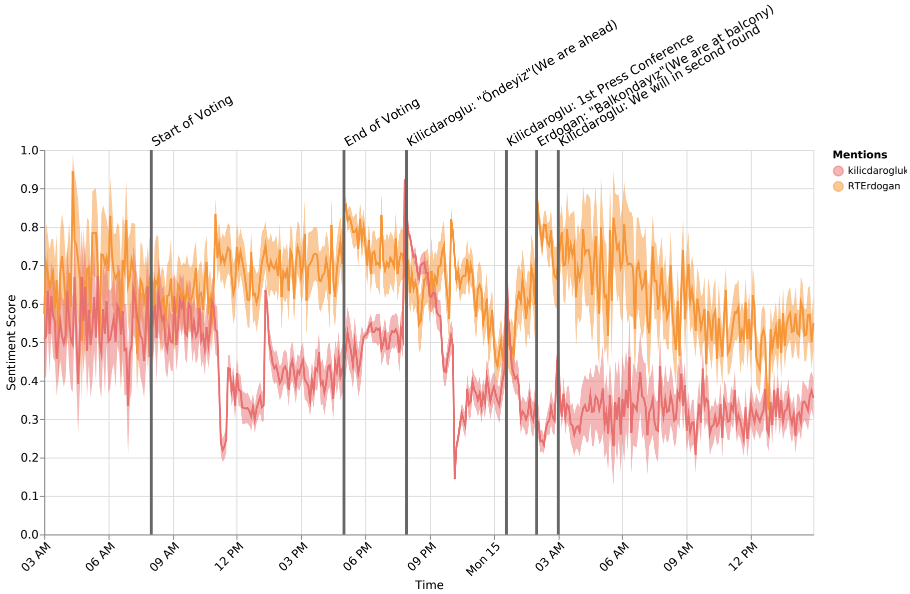

Figure A.5 Sentiment score of tweet mentioning Kılıçdaroğlu and Erdoğan on 1st Election

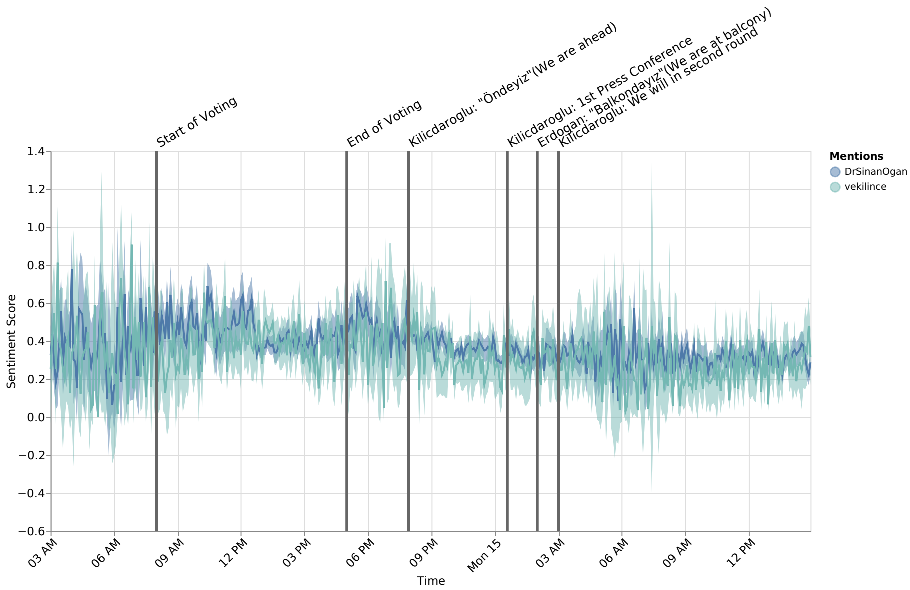

Figure A.6 Sentiment score of tweet mentioning İnce and Oğan on 1st Election

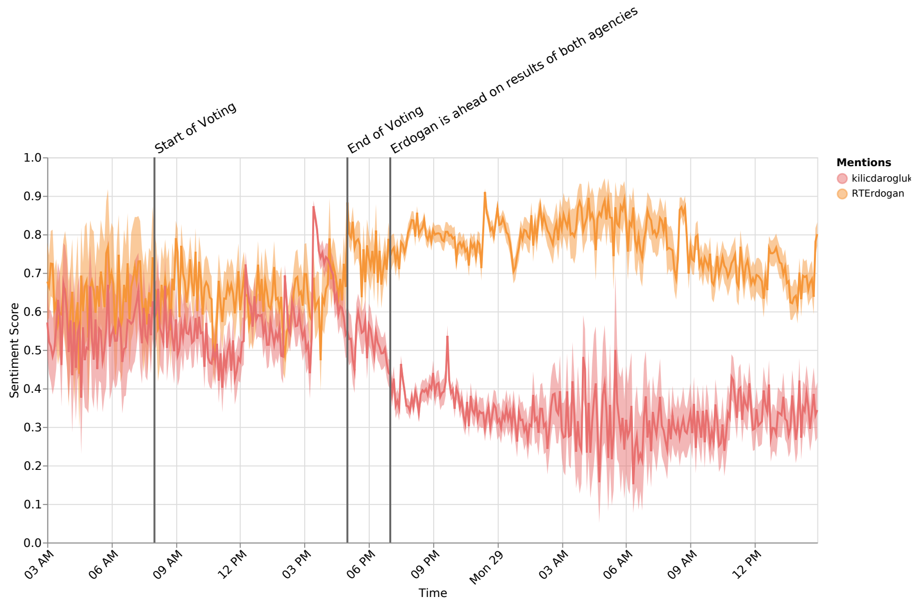

Figure A.7 Sentiment score of tweet mentioning Kılıçdaroğlu and Erdoğan on 2nd Election

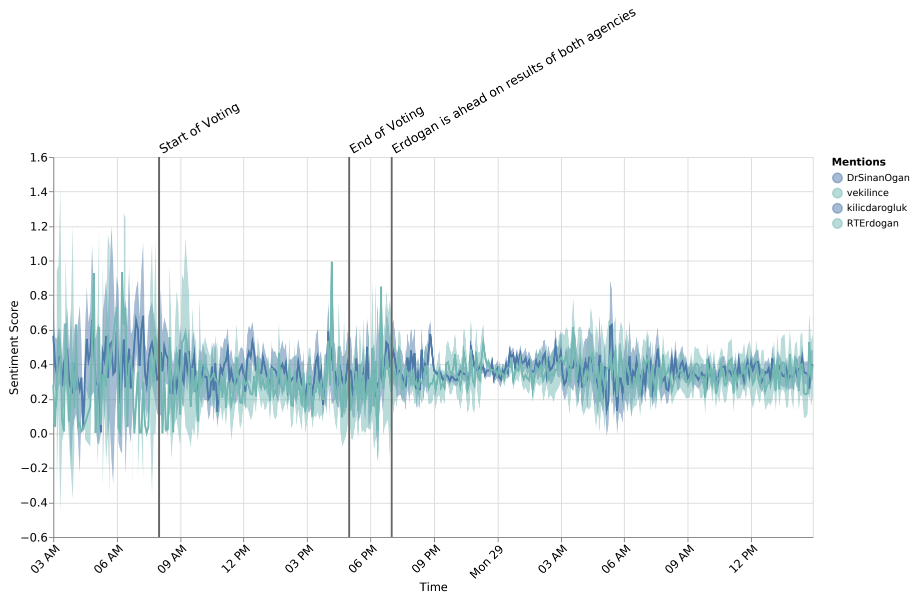

Figure A.8 Sentiment score of tweet mentioning İnce and Oğan on 2nd Election

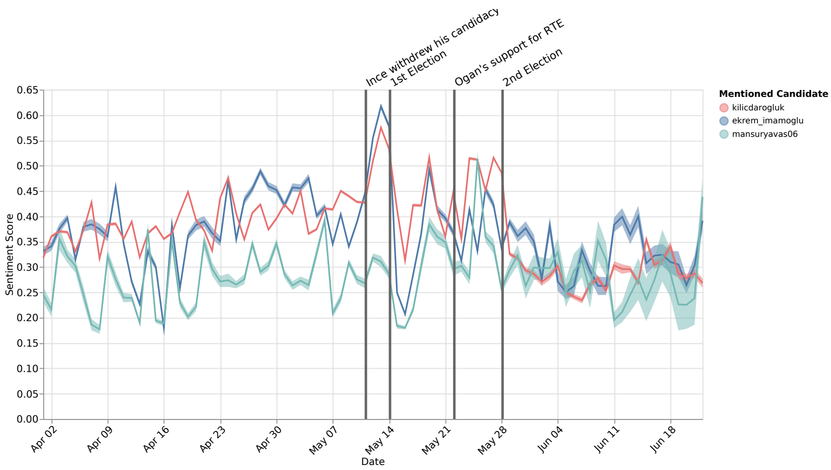

Figure A.9 Sentiment Score of mentioning İmamoğlu and Yavaş

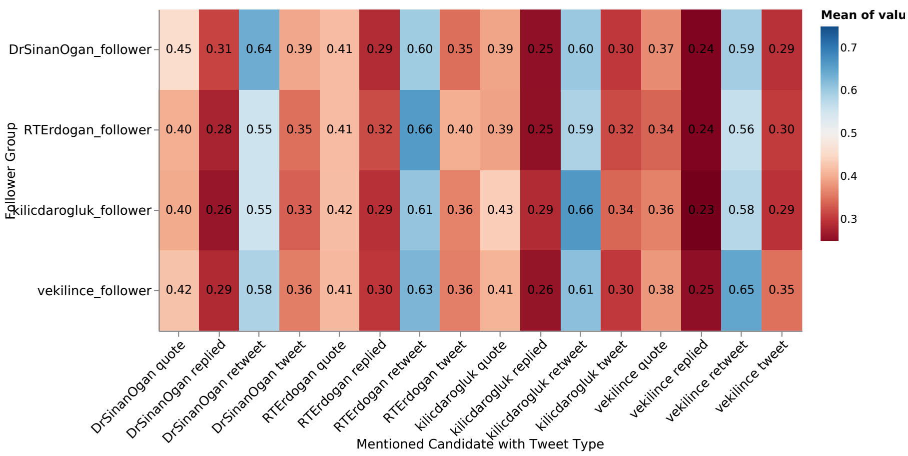

Figure A.10 Sentıment score of follower groups with respect to type of tweets they used for each candidate

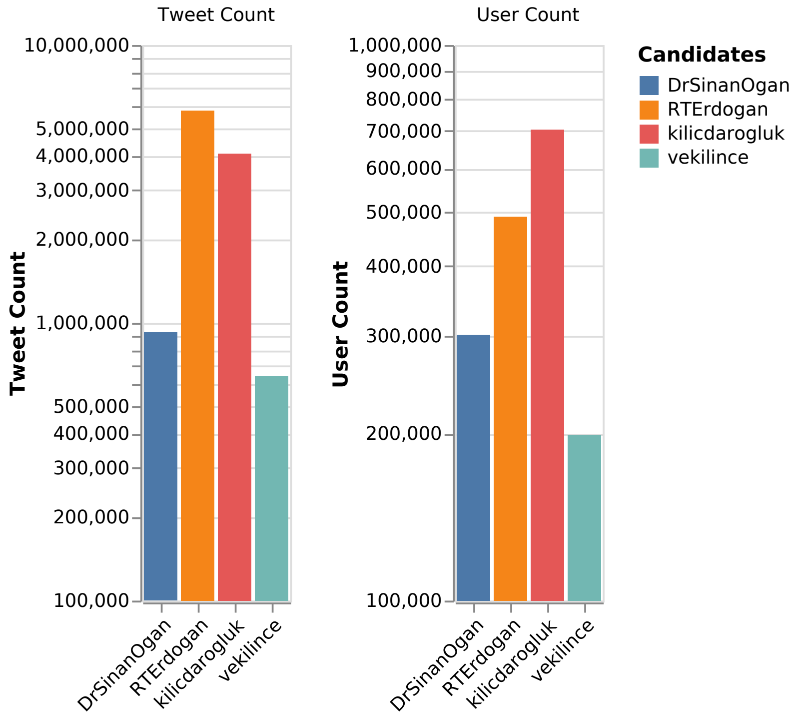

Figure A.11 Total Count of Unique Tweets and Users Mentioning Candidates in April and May 2023

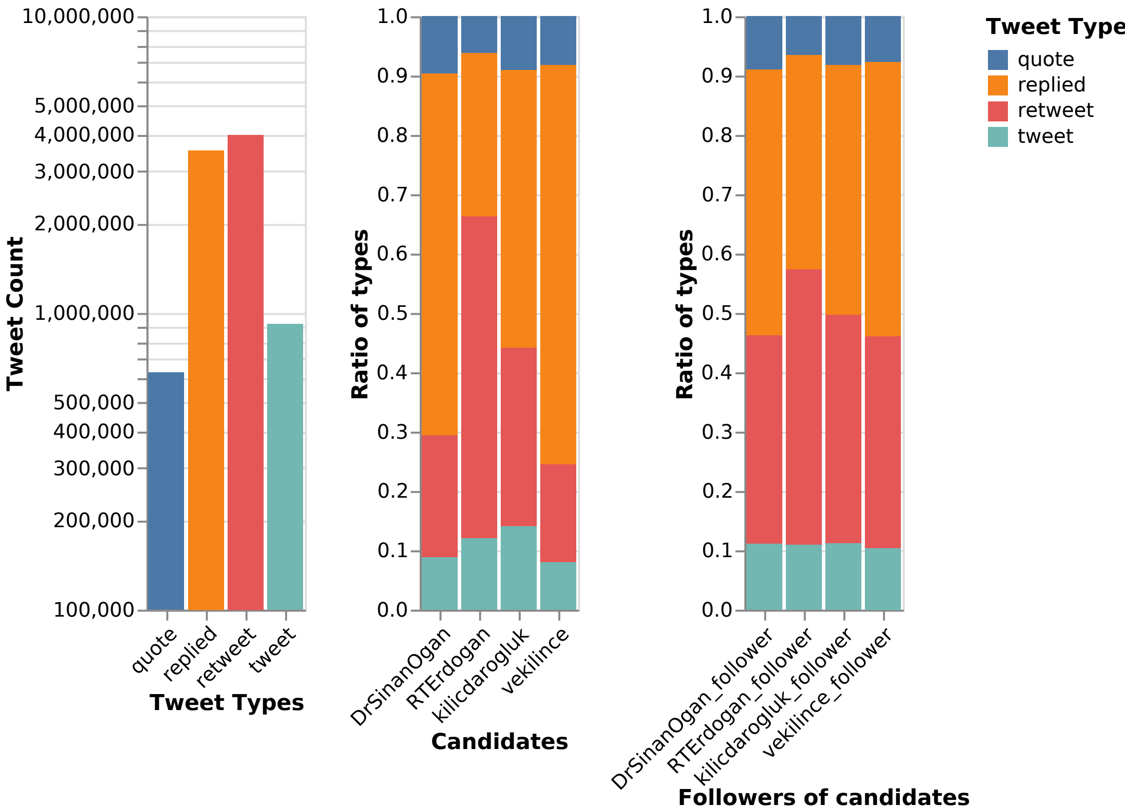

Figure A.12 Distribution of Tweets by Type, Segmented by Mentioned Candidates and Followers of Candidates

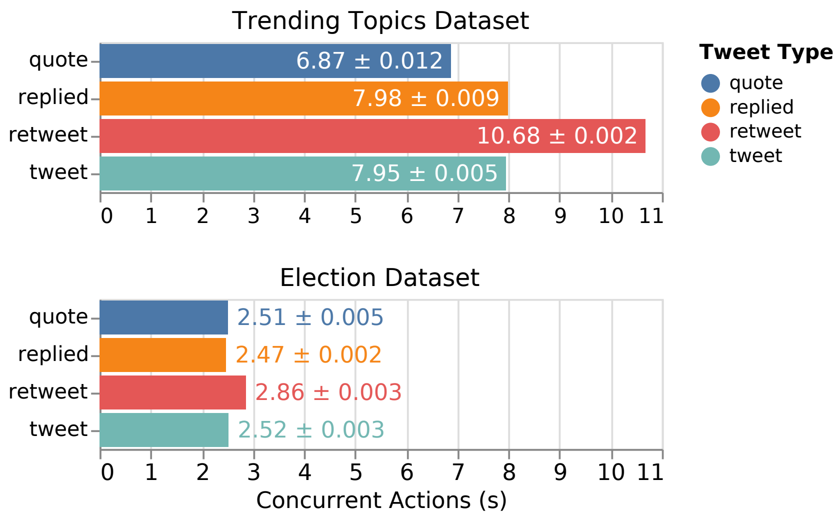

Figure A.13 Comparison of Concurrent Actions in Trending Topics and Election Datasets across Different Tweet Types

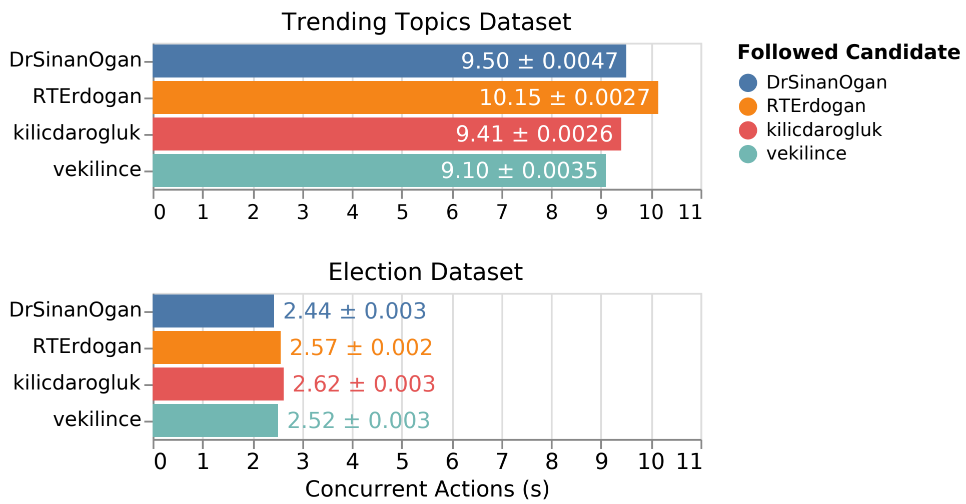

Figure A.14 Comparison of Concurrent Actions in Trending Topics and Election Datasets across Different Follower Groups

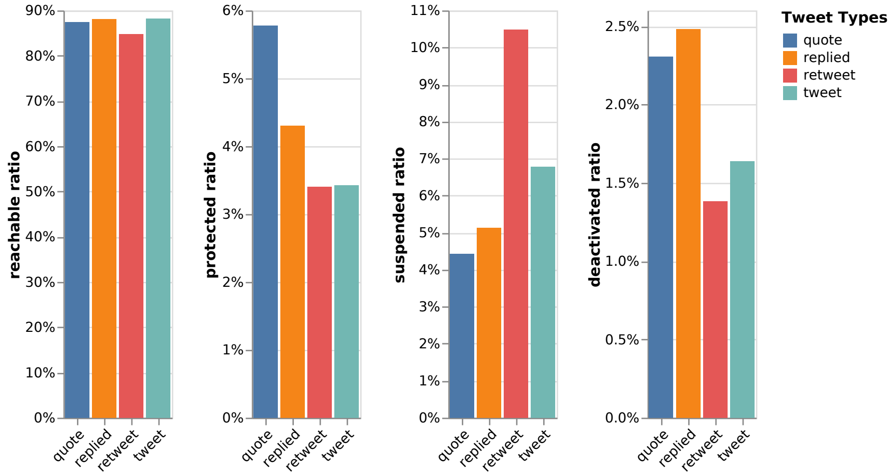

Figure A.15 The status of tweets in Trending Topics with respect to their types

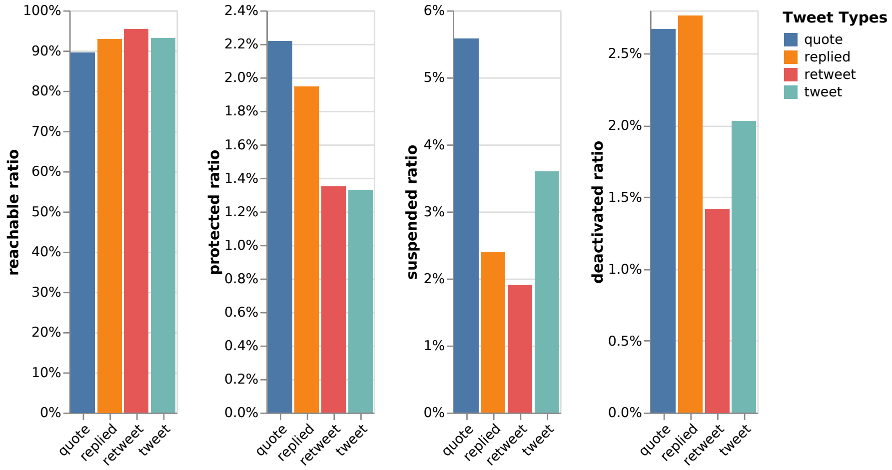

Figure A.16 The status of tweets in Election Dateset with respect to their types

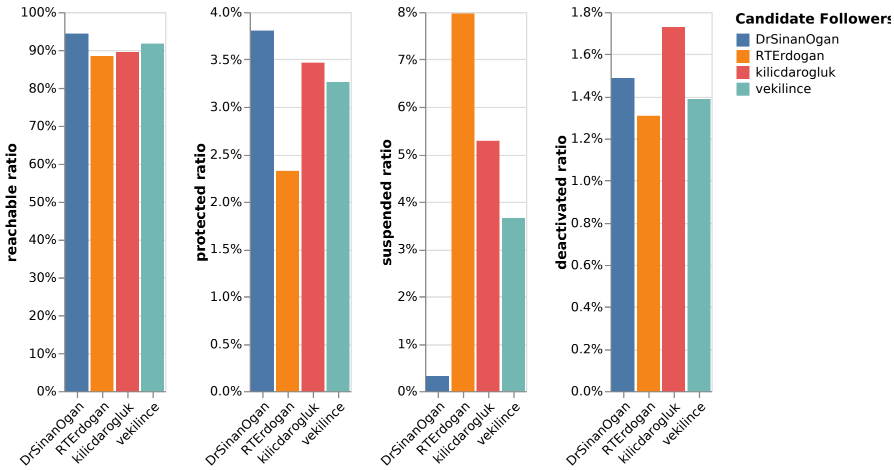

Figure A.17 The status of tweets in Trending Topics with respect to candidate followers

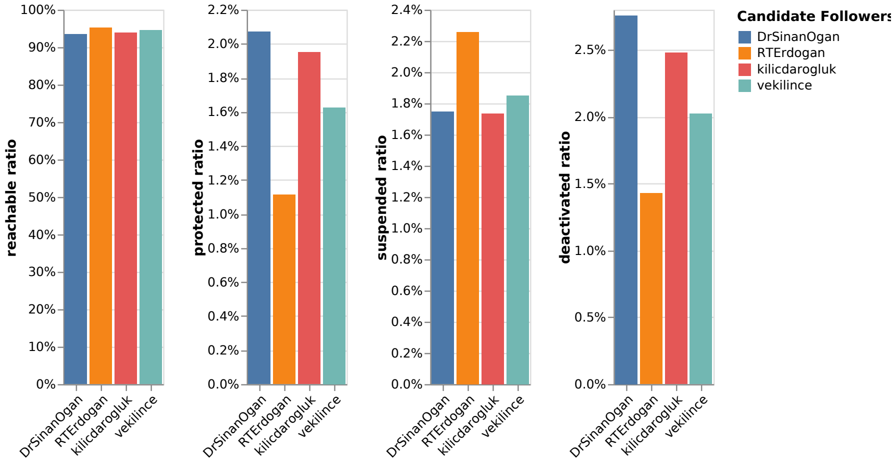

Figure A.18 The status of tweets in Election Dataset with respect to candidate followers

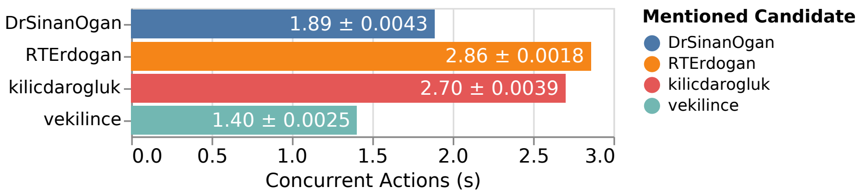

Figure A.19 Concurrent actions with respect to mentioned candidate