Anti-American Stance in Turkey: A Twitter Case Study

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Abstract: The availability of social media and biased actors exacerbated Anti-American and Anti-Western views to extremes. In this paper, we report our efforts in analyzing anti-American views on Twitter. We have collected over three years of Turkish tweets related to the US, translated them into English, and analyzed these tweets using various computational social science tools. We found that Turkish tweets related to the US are significantly negative, and emotions reflect disgust and anger. Furthermore, we found that the source of the negative views stems from political actors like Trump or Biden rather than general hatred. Our results shed light on potential policy plans and interventions.

Keywords: Targeted Sentiment Analysis, Emotion Analysis, Disinformation, Anti-Americanism

1. Introduction

As global Internet coverage and social media grow ever more widespread, the strategic potential of this cyberspace as a means of engaging rivals is beginning to be realized, such that cyberspace has been recognized as the fifth domain of force (Welch, 2011). Thus, it provides a platform for disseminating controlled or uncontrolled narratives from various actors. There is a vast amount of work on the information warfare aspect of cybersecurity, specifically on how public opinion is being shaped by external actors (Margolin, Hannak & Weber, 2018). Russia has been a major international actor in taking advantage of free speech and free information access in western countries and conducting cyber campaigns to gain an advantage (Narayanan, Howard, Kollanyi & Elswah, Mona, 2017). One of the well-known cases of involvement is the recent US elections, as confirmed by US intelligence agencies (Mueller III, 2019). Less-known Russian operations include the campaign against the opposition leader Alexei Navalny (Alieva & Carley, 2021), among many others (Beskow & Carley, 2020).

Furthermore, social media can also reflect the views of populations (Momtazi, 2012), people living in certain regions (Ghahramani, Galle, Ratti & Pilla, 2021), and even particular social groups (Schneider & Carpenter, 2019). Thus, we can mine social media data to (1) investigate how actors use it to gain an advantage and (2) understand people's stances against any topic. Computational social science tools help us tackle these tasks.

In this paper, we analyze anti-American views in Turkish Twitter messages published from 2019 to March 2022. We use various natural language processing techniques applied to these tweets to investigate the following questions.

- What are general sentiment and emotion trends in US-related tweets?
- How different are these trends in other Turkish tweets?
- What are the common targets of these trends?

1.1 Social Media and Disinformation in Turkey

Often referred to as "fake news", disinformation, or the production and targeted dissemination of misleading content to "generate profits, pursue political goals, or maliciously deceive", (Humprecht, Esser & Aelst, 2020) is just one of the ways of influencing cyberspace, and one that has come under increasing scrutiny by state and non-state actors. Disinformation is not limited to cyberspace, and it is possible for mass media news networks to produce disinformation on behalf of a foreign or domestic actor (Palmieri et al., 2022). Still, the global reach of social media platforms means that disinformation can be spread transnationally. Disinformation is not the same as misinformation, which is the unintentional spread of incorrect or misleading information, but misinformation can result from disinformation when spread by individuals who are disinformed (Humprecht,

Esser & Aelst, 2020). Disinformation is also not to be confused with influence operations, the leaking or dissemination of actual content to influence the domestic population of a target country, but influence operations are often included under the same umbrella as disinformation, and a prolonged influence campaign can include both. The means by which disinformation campaigns and influence operations are carried out are very similar: social media bots, troll armies, and astroturfing techniques are used on a massive scale (Kirdemir, 2020).

Disinformation campaigns are rampant in the Republic of Turkey, where President Recep Tayyip Erdoğan and the Justice and Development Party (AKP) take a direct hand in attempting to control social media narratives. In the aftermath of the 2013 Gezi Park protests, the AKP began to employ a troll army of roughly 6,000 users, nicknamed "AK Trolls", whose task is to promote pro-Erdoğan tweets, accounts, and narratives and harass opponents on Twitter (Akiş, 2022). Although Twitter suspended many of these accounts in 2020 (Benedictus, 2016), the AK trolls remain at large. In addition, a social media law proposed in August 2021 made spreading "fake news" punishable with up to five years in prison (Wilks, 2021); this, in combination with the social media censorship law of July 2020, demonstrates Erdogan's more formal attempts to control social media.

2. Data Collection

We collected Turkish tweets from Twitter using Twitter's Filtered stream API. We constructed two datasets; the first one is a dataset of USA-related Turkish tweets (collected by sending relevant keywords as inputs to the API). Some of the keywords are "abd", "amerika", "amerikan", "amerikanci", "coni", "biden", "trump", "sanders", "obama", "pentagon"; we also specified Turkish as the language in this filtered stream. The tweets are collected from January 2019 to March 2022. The second dataset consists of a sample of general Turkish tweets from September to December 2021. We collected a sample of general Turkish tweets to understand the general sentiment and emotions as a baseline and compared them with the Turkish tweets related to the USA. We translated these tweets to English using Google Translate's API.

When collecting and analyzing our data, we had to look for various ways to minimize bias. Our study wanted to look at Turkish sentiment towards the USA. However, there are Turkish people living across the world, so to minimize geographical bias, instead of collecting tweets that were tweeted in Turkey, we collected tweets in the Turkish language, to understand the sentiments of Turkish people across the world. Another bias is sentiment bias, which we investigated in greater detail. We collected tweet samples written in Turkish to understand the general sentiment and emotions as a baseline and compared them with the Turkish tweets related to the USA, to eliminate any sentiment bias. We also took all Turkish tweets with relevant keywords and not just a sample. We also avoided retweets

because certain tweets by government officials or politicians would get more traction if we counted retweets.

USA related Turkish tweets (before excluding retweets): From January 2019 to March 2022, there were a total of 47,629,360 tweets related to the USA containing at least one of the keywords. There were 10,347,907 tweets in 2019; 13,767,535 tweets in 2020; 17,380,699 tweets in 2021 and 6,133,219 from January to March 2022. The average number of daily Turkish tweets related to the USA is around 40,160.

USA related Turkish tweets (after excluding retweets): We excluded retweets from our analysis. From January 2019 to March 2022, there were a total of 13,941,788 unique Turkish tweets related to the USA. Of these, there were 2,939,517 tweets in 2019; 4,195,548 tweets in 2020; 4,853,341 tweets in 2021 and 1,953,382 tweets from January to March 2022. The average number of unique daily Turkish tweets related to the USA is around 11,755 tweets.

A sample of general Turkish tweets: The number of general Turkish tweets we collected from September 2021 to December 2021 is 4,226,680. Note that we missed data for a few days due to outages. Figure 1 shows the number of daily general Turkish tweets and Turkish tweets related to the US.

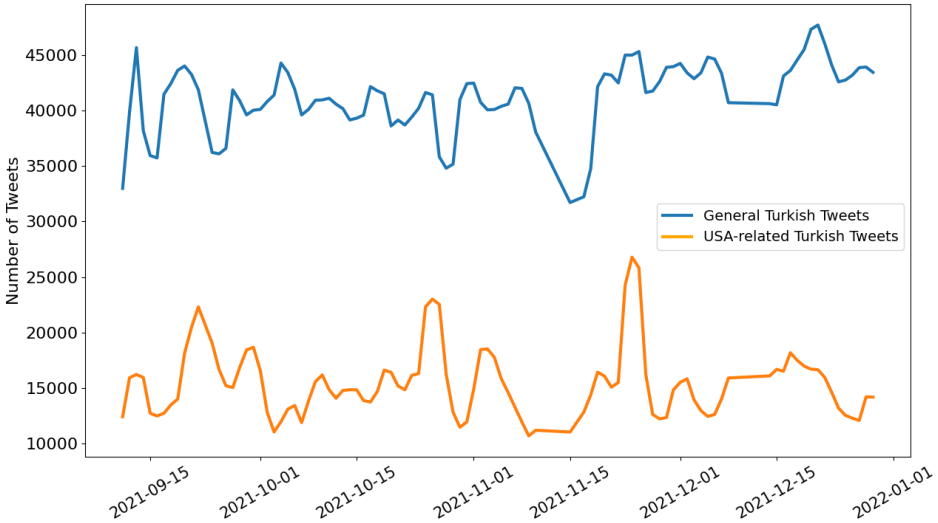

Figure 1. The size of general Turkish tweets vs. Turkish tweets related to USA

3. Methods

3.1 Classical Sentiment Analysis

Sentiment analysis of a text determines if it expresses emotions that are positive, negative, or neutral (Zhang, Wang & Liu, 2018). Each tweet is assigned a score that represents the entire text's sentiment level and polarity. If the sentiment score is less than 0, the text has negative polarity; if the score is equal to 0, the text is neutral; if the score is greater than 0, the text has a positive polarity. For conducting this classical sentiment analysis, we used Afinn (Nielsen, 2016), a Python on the English translations of the tweets. Afinn uses a wordlist-based approach to score sentences.

3.2 Targeted Sentiment Analysis (TSA)

Targeted Sentiment Analysis is more detailed than classical sentiment analysis in the sense that it identifies the sentiment and sentiment polarity of a text towards a particular target, such as a person or country. For example, a sentence like 'I like Mr. X, but I do not like Mr. Y' has two targets: Mr. X and Mr. Y. TSA can identify that the sentiment toward Mr. X is positive, while the sentiment toward Mr. Y is negative. The classical sentiment analysis for this sentence would have been neutral because one positive and one negative score of the same verb (i.e., "like") would cancel each other. TSA uses Named Entity Recognition (NER), which identifies targets such as an object or people in a text (Pei, Sun & Li, 2019). It allows us to identify the sentiments of the text towards different entities. TSA is also called aspect-based sentiment analysis in the literature (Pei, Sun & Li, 2019).

We performed TSA using the NewsSentiment package (Hamborg & Donnay, 2021). This package implements a model that can interact with multiple embeddings from, for instance, a pre-trained language model (e.g., Roberta (Liu et al., 2019) and other knowledge sources. NewsSentiment works on news and social media data and provides the probability that the sentiment is classified as positive, negative, or neutral towards a particular target. Since NewsSentiment requires targets up front, we performed TSA on the keywords 'Biden', 'Trump', 'The US', and 'The USA.'

3.3 Emotion Analysis

Emotion analysis of a text can identify emotions such as joy, anger, fear, and sadness (Zhang, Wang & Liu, 2018). We used Pysentimiento to conduct emotion analysis of the tweets (Pérez, Giudici & Luque, 2021). Pysentimiento is a transformer-based emotion analysis package based on the social language model BERTweet (Nguyen, Vu & Nguyen, 2020). As a result, Pysentimiento returns six particular emotions (joy, sadness, anger, surprise, disgust, and fear) and "other", all can have different scores adding up to 1.0.

3.4 Limitations

Our study has a few limitations. Some limitations were that sentiment and emotion analysis cannot identify sarcasm. In social media, sarcasm is prominent, and the algorithms are usually not able to identify this sentiment. Also, emotion analysis classifies the tweet's emotions into six that are too broad and need to be more specific. Another limitation is that Twitter data has a lot of noise. There is an abundance of trolls, bots, and spam tweets, which can skew our results. We also gave keywords to pull data, but this could have pulled in irrelevant data which happened to have that keyword.

4. Results

4.1 What are general sentiment and emotion trends in US-related Turkish tweets?

Figure 2 shows the daily average Afinn-based sentiment score of US-related translated tweets. There is a clear trend of highly negative average sentiment scores almost for the entire data collection timeframe. We notice a few positive scores here, the highest one recorded close to the 2020 US Presidential Elections.

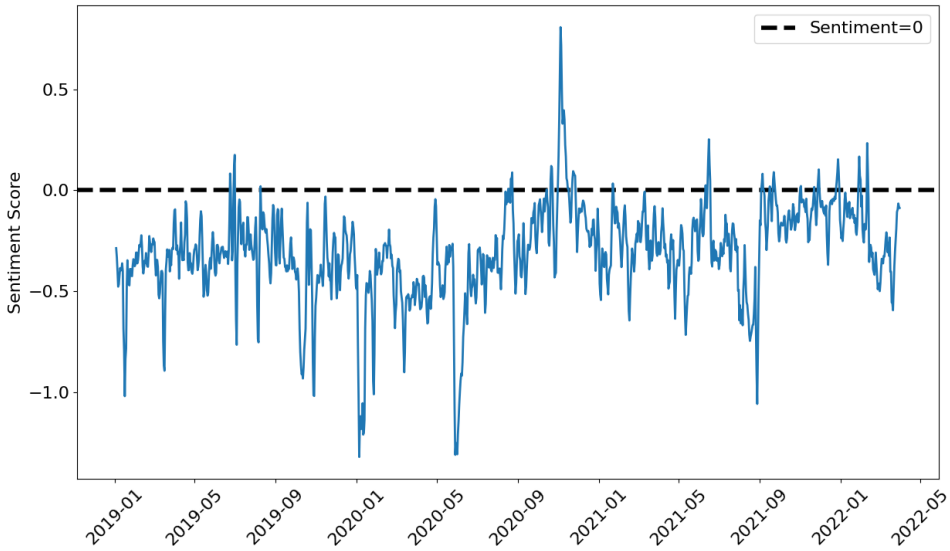

Figure 2: Afinn sentiment score

Figure 3 illustrates the distribution of different emotions over time. We observe the most prevalent emotion is *disgust*, followed by *anger*. We also observe some peaks, namely *anger* on Oct 7, 2019, *fear* from March 10-13 2020; and *disgust* on July 22, 2021 and from August 15-20, 2021. The anger was in response to Trump's threatening to "destroy and obliterate" the Turkish economy (Sonmez 2019) and possibly the Turkish invasion of Syria as well, since there are a lot of references to the US arming "terrorist organizations" (the YPG) (The Guardian, 2019). The fear peak could be in response to the US suspending travel to Europe, but some users were also getting angry over the New York Times and the BBC using pictures of mosques in Turkey to represent Europe (Allyn & Romo, 2020).

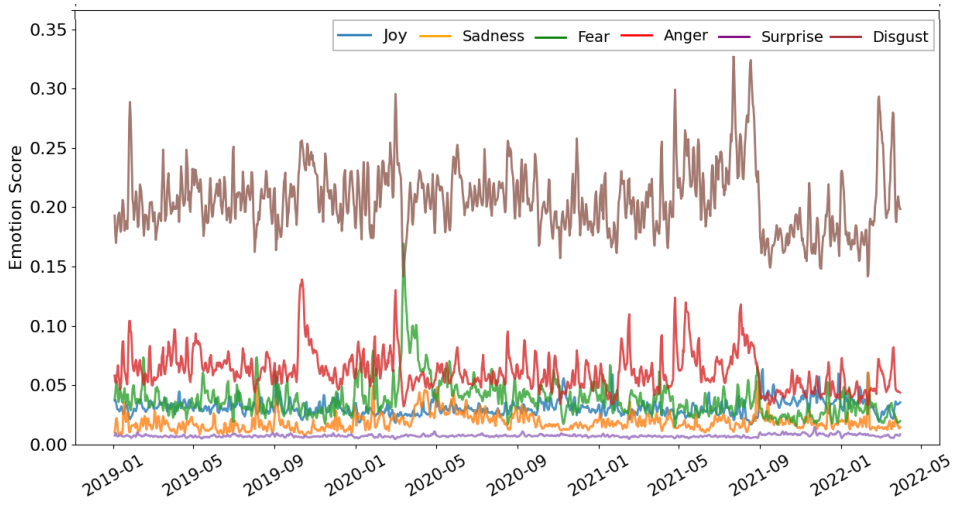

Figure 3: Emotion Analysis of Turkish tweets related to the USA

4.2 How different are these trends in other Turkish tweets?

Figure 4 shows the sentiment score for approximately three months in which we captured both USA-related and general Turkish tweets. We can observe that the general sentiment of Turkish tweets is positive, and the tweets

have a higher sentiment score in comparison to Turkish tweets related to the USA. This result suggests that the baseline sentiment score for USA-related tweets is negative, which reflects negative views against the US in Turkey (Global indicators database, 2021).

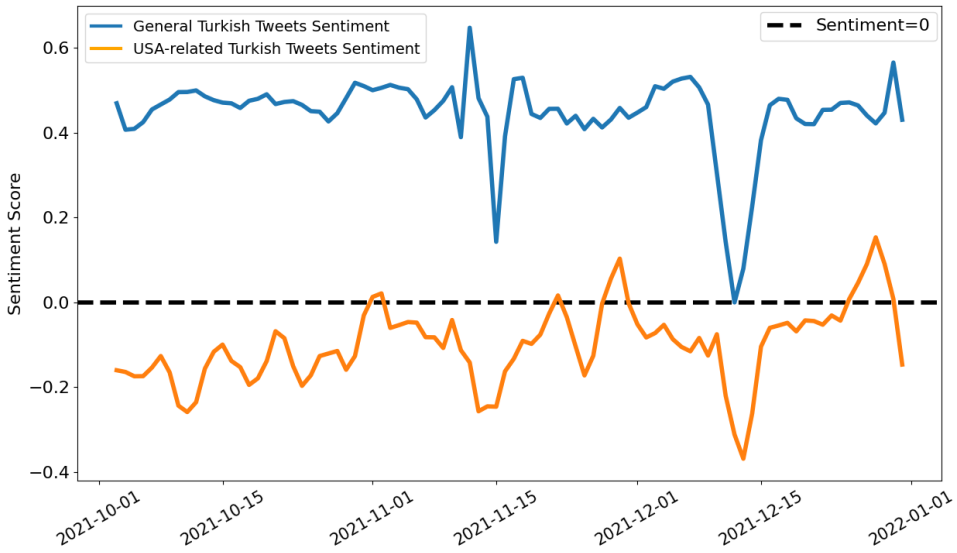

Figure 4. Daily average sentiment score of general Turkish Tweets vs. Turkish tweets related to USA.

From the emotion analysis plots in Figure 3, we can see that Turkish tweets related to the USA tend to be dominated by feelings of *disgust*, followed by *anger* and *fear*. On the other hand, general Turkish tweets are dominated by feelings of *happiness* followed by *disgust* and *sadness*, as seen in Figure 5. We can argue that generally, Turkish tweets have high feelings of happiness but tweets mentioning about the USA tend to have high feelings of disgust, confirming a negative stance against the US.

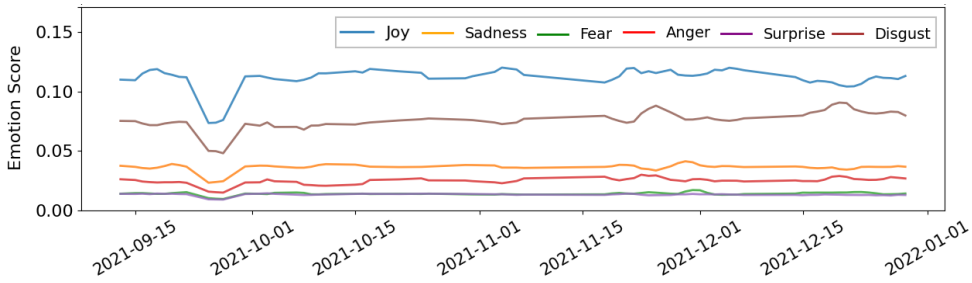

Figure 5: Emotion analysis results of general Turkish tweets

4.3 What are the common targets of these trends?

The final task is to understand why we observed such a negative stance in tweets related to the United States. In this case, we identified three targets: Trump, Biden, and the USA. The idea here is to understand whether the negative stance is against political actors or the US itself as a country. We first filtered from our original tweet dataset tweets containing these keywords. Figure 6 shows the number of tweets mentioning Trump, Biden, or US/USA daily. We then conducted TSA on these separate datasets.

Trump. The target 'Trump' is mentioned in 1,099,307 unique tweets from 2019 to January 7, 2021. Figure 7 shows the daily average probability of a tweet having negative or positive sentiment toward Trump. The bar plots also have error bars which tell us how confident we can be in our results. There are many peaks in the number of tweets about Trump and the significant events. Some of the notable events are as follows.

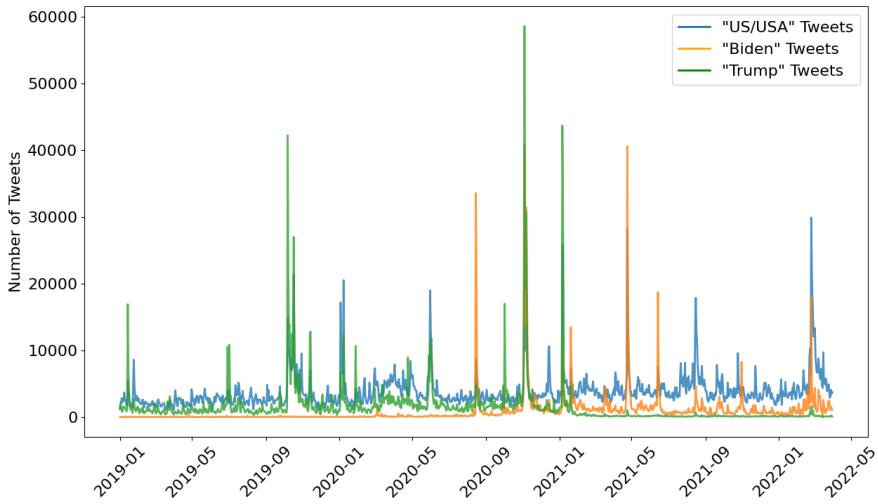

Figure 6: Number of tweets about Trump, Biden and US/USA

- January 2019: Trump vows to "devastate Turkey economically" if the Kurds are attacked (Hudson & Fahim, 2019).
- June 2019: Trump meets with Erdogan, and mentions he was open to withholding sanctions (CNN, 2019).
- October 2019: Trump announces sanctions on Turkey as a result of their invasion of northern Syria (BBC News, 2019};
- November 2019: Trump holds a press conference with Erdogan at the White House (Nakamura, DeYoung & Kim, 2019).
- Late April 2020: Trump holds a telephone conversation with Erdogan, and agrees on close cooperation on coronavirus management (Al-monitor, 2020).
- January 2021: The January 6th insurrection and response to the Capitol riots (Zaman, 2021).

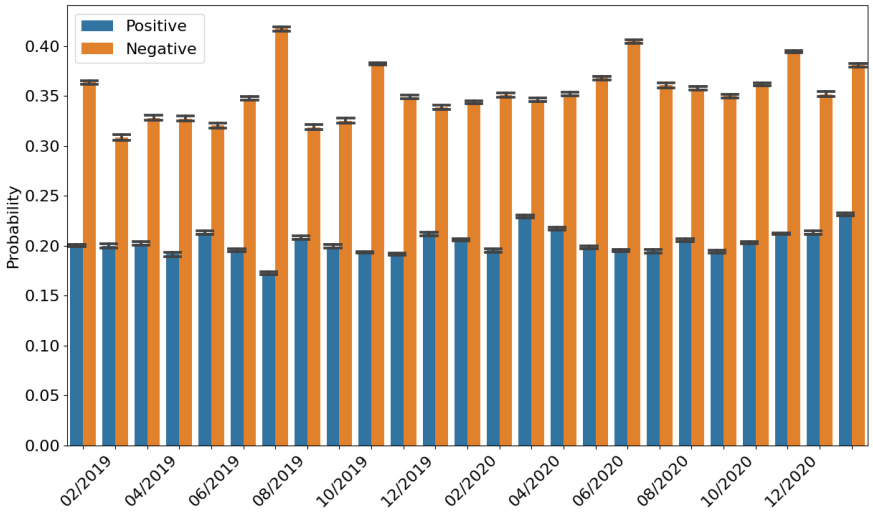

Figure 7: Probability of negative and positive sentiment toward Trump

Biden. The target 'Biden' keyword is mentioned in 1,113,909 unique tweets. Figure 8 shows the daily average probability of a tweet having negative or positive sentiment toward 'Biden'. We can see that not many tweets mention Biden in the earlier part of 2020, even though we collected Turkish tweets with the word 'Biden' in them in 2020 as well. There are many peaks in the number of tweets about Biden, and significant events associated with them are as follows.

- August 2020: Joe Biden's comments against Erdogan and the AKP in December resurface (Spicer, 2020).
- November 2020: The US election (Reuters, 2020).
- April 2021: Biden recognizes the Armenian genocide (Coskun & Evans, 2021) showing the highest negative percentage.

- June 2021: Biden at the NATO summit (Pamuk, Baczynska, Gumrukcu & Toksabay, 2021).
- October 2021: Biden meets Erdogan at G20 summit (Miller, 2021).
- February 2022: Biden came up on the day of the invasion of Ukraine, since he was issuing public statements and implementing sanctions. (Mason, Holland & Bose, 2022).

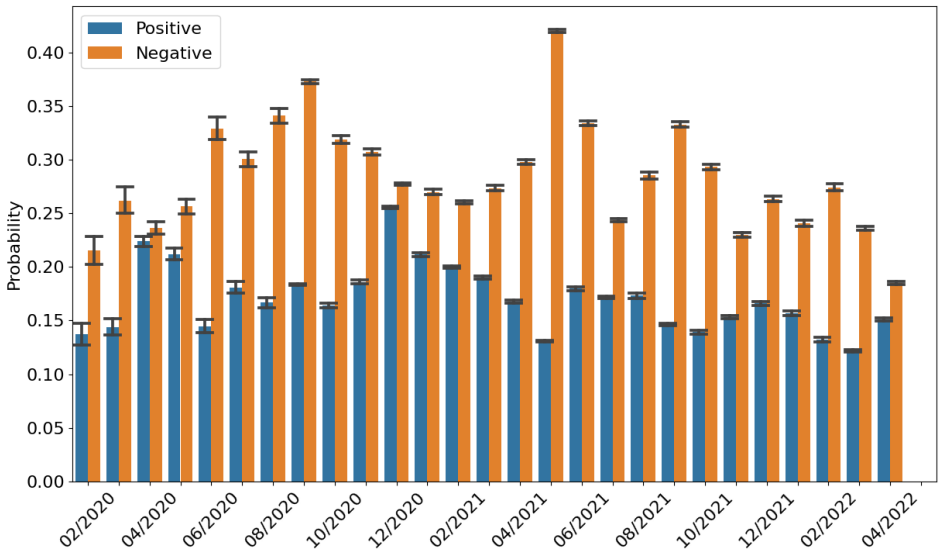

Figure 8: Probability of negative and positive sentiment towards Biden

The US and The USA. The targets 'The US' and 'The USA' are mentioned in 4,559,158 unique tweets. Figure 9 shows the daily average probability of a tweet having negative or positive sentiment toward the US/USA. Unlike the Trump and Biden targets, the US/USA target receives a much more balanced sentiment. For many of the months recorded in this dataset, there is a slightly higher presence of negative sentiment.

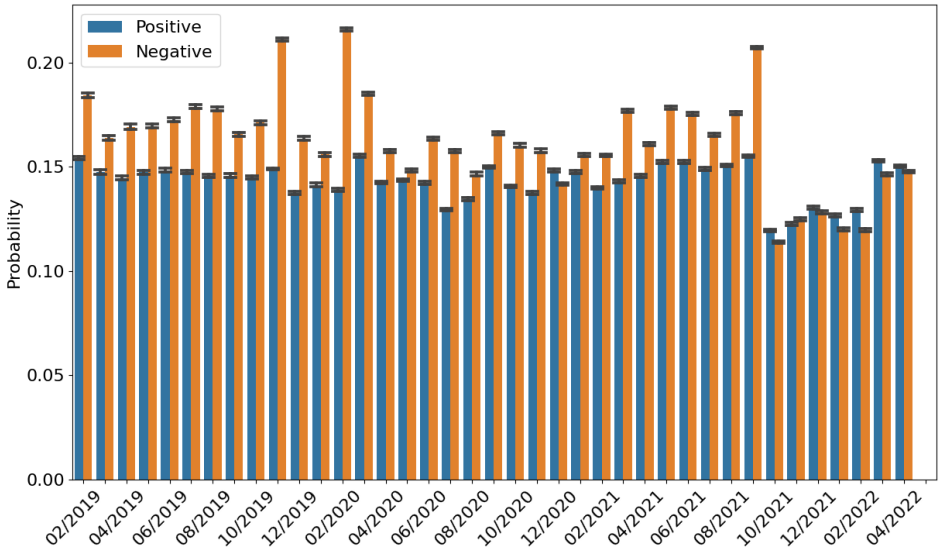

Figure 9: Probability of negative and positive sentiment towards US/USA

5. Conclusion

In this paper, we analyzed anti-American views in Turkish social media from 2019 to March 2022. We chose Twitter as our social media use case and collected data using the Twitter API. We used natural language processing algorithms like sentiment and emotion analysis to identify the general sentiment and emotions towards the USA. After that, we performed targeted sentiment analysis to understand who the common targets of these trends are. By analyzing individual targets of Trump, Biden, and the US/USA, we can conclude that Turkish Twitter users tend to hold more negative views towards political actors like US presidents. Negative sentiment against the country itself is weaker. While more research is needed, we can argue that if the US aims to reduce the Anti-American stance in other countries, a good starting point would be the narratives shared by the President.

Acknowledgements

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