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Bachelor's Thesis in Informatics in Informatics

From Hashtags to Ballot Boxes: A Close Look at the 2023 Turkish Election

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Von Hashtags zu Wahlentscheidungen: Ein umfassender Blick auf die Türkischen Wahlen 2023

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I confirm that this bachelor's thesis in informatics is my own work and I have documented all sources and material used.

Munich, 15.03.2023 Efe Sener

Acknowledgments

Abstract

Contents

1 Introduction

In recent years, governments and the public have realized the importance of social media, especially Twitter/X, which has a decisive role in mobilizing social and political activism (Uysal & Schroeder, 2019). Twitter has been instrumental in studying human behavior with social media data (Pfeffer et al., 2023), described as a digital social telescope by researchers in the social science field (Mejova et al., 2015). It has provided a somewhat free environment and guided social and political debates to gain new dimensions (Yerlikaya & Toker, 2020), where individual users can directly and publicly address comments to their representatives under conditions of anonymity (Theocharis et al., 2020). The robust rise in Twitter's popularity has stemmed from increasing accessibility to technology and affordability. Millions of people consume news from social media sites like Twitter (Anwar et al., 2021). In Turkey's case, Twitter began to be taken seriously after the unrest in the Middle East, especially after the Gezi Park protests in 2013 (Zaharna & Uysal, 2016), where Twitter was one of the most valuable media for protestor communication, given censorship (Ogan & Varol, 2017). In 2020, Turkey was ranked as the 10th most-used language on Twitter, with around 560 thousand tweets posted daily (Alshaabi et al., 2021).

This thesis aims to analyze the Twitter data, provided by Sabanci University (Najafi et al., 2022), to understand the Turkish Twitter discourse surrounding the May 2023 elections. Using innovative topic modeling techniques, this thesis will discover the most prevalent topics in Turkish Twitter between July 2022 and June 2023. It will uncover how these topics correlate with real-life events and how they reflect the election agendas of parties. This thesis will also compare the results with results observed in other countries. In a non-English-speaking country like Turkey, this thesis furthermore seeks to find solutions to the need for a more thorough and data-driven analysis of political discussions on Turkish Twitter.

In this chapter, the thesis starts by explaining the historical context and then continues to present the current political landscape. It demonstrates the importance of the May 2023 elections, emphasizes the significance of Twitter in Turkish politics, and deep dives into research questions. In the next chapter, the thesis examines various related works, asking similar questions and analyzing their results. After that, the thesis explains the Twitter dataset and used methodologies while collecting and analyzing the data. Next, the thesis deep dives into the analysis results, and later discusses the findings by interpreting them, highlighting both the limitations and future work. The final section summarizes the results and its implications.

1.1 Background

It is crucial to examine Turkey's historical political context to understand the current complex political landscape and the May 2023 elections.

After the collapse of the Ottoman Empire, the Turkish Republic was declared in 1923. Some attempts were made, but the first multi-party elections were held in 1946. Until 1945, the Republican People's Party (CHP) was the only party in the parliament, and until 1950 it was the ruling party. The CHP was founded by Mustafa Kemal Atatürk, also the founder of the Turkish Republic.

With a multi-party system in a young republic, political power was now open to various groups. Different and new ideologies arose and started to organize politically (Rabasa & Larrabee, 2008). The military saw their role as the protector of the Republic and Atatürk's ideologies and overthrew the governments in 1960, 1971, and 1980. The 1980 military coup, which introduced a new constitution, was after a period of political fragmentation and civil instability in the 1970s.

During the 1970s, political Islamism started to emerge, which challenged the secularist nationalism and modernization ideologies of the CHP (Yilmaz & Bashirov, 2018). Changes in the political structure, the constitution, and civil liberties, major economic crises in 1994 and 2001 (Ardan, 2023) contributed to Islamic political groups' political influence and strength, to the emergence of new political players and parties like the Justice and Development Party (AKP) (Rabasa & Larrabee, 2008).

Since 2002, AKP has been in power in Turkey. Out of 15 elections, AKP just lost the local elections in 2019, in which the opposition coalition won more than four significant municipalities. Especially in Istanbul, the opposition won twice because the first election was canceled. For the May 2023 elections, the main opposition coalition was established from CHP, Good Party (IyiP), Felicity Party (SAADET), Democrat Party (DP), and two new parties were established out of AKP: Democracy and Progress Party (DEVA) and Future Party (GP) (Atila, 2022). Even though most of the polls favored the opposition in the May 2023 elections (Saç & Çoban, 2023), AKP has won the majority of the parliament and Recep Tayyip Erdogan was elected in the kickoff elections for the third time as president, after serving two terms as president and two terms as prime minister since 2003.

1.2 Research Questions

This section introduces the research questions guiding this thesis, which are based on qualitative methods to analyze the Twitter discourse surrounding the May 2023 elections in Turkey.

The research questions are divided into two parts. The first part will cover the main research objective of this thesis, which is the analysis of the topic modeling results. The first question is as follows: "What were the most prevalent topics in Turkish Twitter discussions during the May 2023 elections?". This question is necessary to understand the main topics of the May 2023 elections discussed in social media.

The next question is "How do real-life events during the election period correlate with shifts in discussion topics on Twitter, and in what ways do these shifts mirror political movements?". This question focuses on the reflection of real-life events and political movements in Twitter discussions.

The third question is about parties and their election agendas: "How do the Twitter discussions about the ruling party and the opposition during the election lead-up reflect and compare to their respective election agendas and public statements?". This question is essential to understand the reflection of the election agendas of the parties and the differences between them on Twitter.

With these questions in mind, the second part of the research questions covers the comparison of the results of the topic modeling with other research, where a similar approach was used for different countries. The main question is as follows: "How do the key themes, content, and engagement levels in the Turkish Twitter discourse surrounding the May 2023 elections compare with those observed in the past elections in other countries?".

2 Related Work

The recent advances in Natural Language Processing (NLP) and easy access to open-source models allow researchers to study text data by performing sentiment and emotional analysis, topic modeling, semantic search, and many more. Large language models by OpenAI considerably explain how fast the NLP field develops.

In this thesis, topic modeling is performed on massive text data. Topic modeling is an unsupervised tool that helps extract the underlying themes from the given text data. There are several topic modeling approaches, and this thesis focuses on neural topic modeling. Unlike conventional models like Latent Dirichlet Allocation (LDA), a generative probabilistic model introduced by Blei et al. (2003), neural topic models have been used in important NLP tasks, including text generation, document summarisation, and translation, fields to which conventional topic models are complex to apply (Zhao et al., 2021). This thesis uses the neural topic model BERTopic, introduced by Grootendorst (2022), which is explained in detail in Chapter 3.

A tremendous number of studies have applied topic modeling in their research. In the political science field, Ilyas et al. (2020) performed topic modeling using LDA to discover daily discussion topics on Twitter about Brexit and to find out whether the topics discussed on Twitter were representative of actual events taking place, aligning with the second research question of this thesis. They found out that their model was representative of the actual events. Kaiser et al. (2020) used a structural topic model (STM), similar to LDA, to analyze the right media coverage during the 2016 US elections. The analysis shows that a media outlet is identified between the extreme far-right and mainstream right by finding out that they cover extreme and conservative topics. For the 2020 US elections, Anwar et al. (2021) applied topic modeling using BERTopic on pro-Trump tweets to analyze the most mentioned words for each topic and how frequent the topics were, aligning with the first research question of this thesis. Gritto (2022) applied BERTopic along with other German BERT models on Twitter data from German politicians and analyzed their results, aligning with the third research question of this thesis. She discovered that using BERTopic with the Sentence-BERT (SBERT) model yielded more valuable and significant topics. On the other hand, Contreras et al. (2022) used both LDA and BERTopic on Spanish Panamanian parliamentary proceedings. The research suggests that both models perform well with long multilingual political texts despite the small dataset.

It is essential to mention that according to the available literature, few studies apply topic modeling to multilingual political data. For the Turkish language, since the introduction of BERTurk by Schweter (2020), which is based on the BERT model by Devlin et al. (2019) trained on Turkish dataset, the Turkish NLP community is getting bigger and bigger day by day. Recently, a new model called TurkishBERTweet trained on the Turkish Twitter dataset was presented by the same team[1] that released the public social media dataset #Secim2023[2] (Najafi & Varol, 2023). The team has used TurkishBERTweet to conduct daily sentiment analysis and various other analyses on the #Secim2023 dataset, which will be discussed later.

This thesis will build upon the mentioned research and conduct one of the first neural topic modeling researches on a massive political Turkish language dataset using BERTopic. As mentioned in previous research, BERTopic yields more valuable and significant topics than other topic models, which is why this thesis will use that model. Since Najafi and Varol (2023) and also Najafi et al. (2022) analyze the same dataset as this thesis, but with different approaches and questions, this thesis will also use their results while answering the research questions.

[1] Center of Excellence in Data Analytics, Sabanci University, Turkey
[2] Najafi et al., 2022.

3 Experiments

This thesis uses the BERTopic model to apply topic modeling on the #Secim2023 dataset. Before diving into the results and discussion, this chapter explains the dataset, how the tweet hydration[1] is performed on the tweets from the dataset, how BERTopic and neural topic modeling works generally.

3.1 The Dataset

The dataset published by Najafi et al. (2022) consists of tweet IDs collected daily between July 2022 and June 2023, a total of around 250 million tweets. The frequency of the collected tweets is shown in Figure 3.1.

Due to Twitter's Developer Agreement and Policy[2], a public dataset can only include (tweet) IDs. In order to access all tweet information, they must be hydrated. Typically, a year before, a research group would have had access to Twitter Academic API[3] and used packages like Hydrator[4] to gather tweet information quickly. Unfortunately, after Elon Musk bought Twitter, Academic API was restricted and then shut down at the end of May 2023 (Calma, 2023), before the start of this thesis. Today, there are only paid options starting from 100$ for 10,000 tweets per month, 0.3% of what was previously available for free access in a single day.

If one has tweet IDs, other methods exist to hydrate the tweets nowadays. All of the following methods use some embedded retrieval mechanism to gather the tweet information. The first method uses Twitter's official page to retrieve embedded posts or videos given the tweet ID: https://publish.twitter.com. The second method, also used in this thesis, is implemented by React engineers in-house: https://github.com/vercel/react-tweet. One can have a JSON output with sufficient information for analysis by sending HTTP requests and tweet ID as a parameter. As seen in Figure 3.1, the collected tweets (blue) are less than the total tweets in the dataset (orange). One of the main reasons for that is the deleted tweets. Since the hydration timeline for this thesis

[1]The process of retrieving a tweet's complete information with only tweet ID.
[2]https://developer.twitter.com/en/developer-terms/agreement-and-policy
[3]https://developer.twitter.com/en/use-cases/do-research/academic-research
[4]https://github.com/DocNow/hydrator

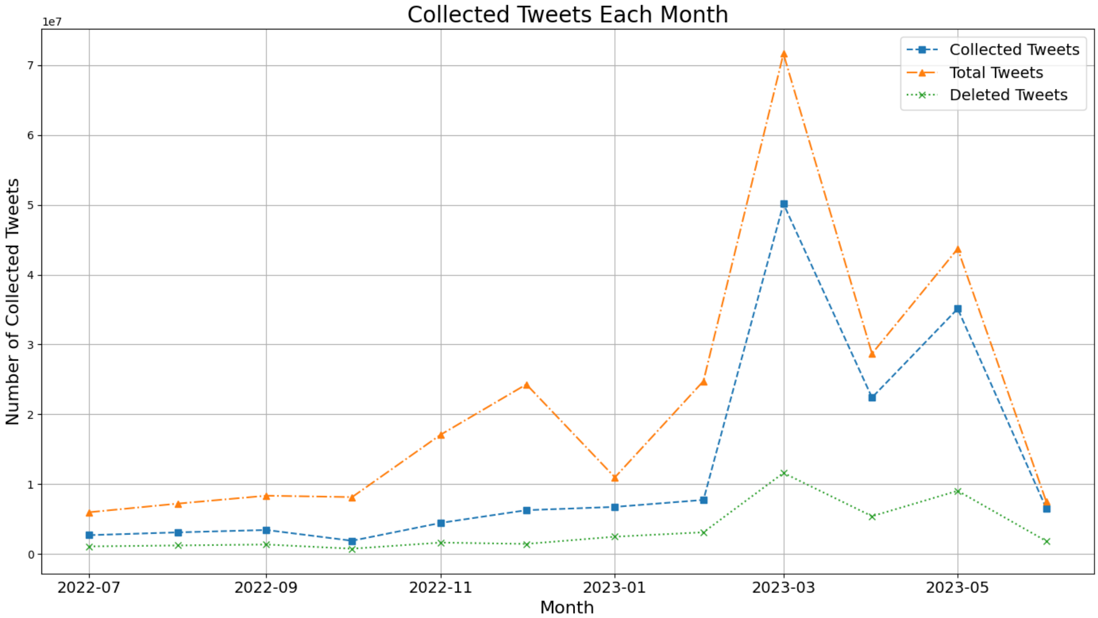

Figure 3.1: Number of collected tweets from #Secim2023 database monthly from July 2022 to June 2023. The orange line displays the total number of tweets in the database, the blue line displays the total number of collected tweets from the database and the green line displays the deleted tweets on the month of hydration, around December 2023.

was between October 2023 and January 2024, and the tweets are between July 2022 and June 2023, there are approximately 50 million deleted tweets in the dataset (green).

There are several reasons why there are lots of deleted tweets. The main reason for the vast number is the deletion of highly interacted original tweet posts. According to Twitter, if the original tweet is deleted, the reposts to that tweet are also not available anymore[5].

Furthermore, the question of why people deleted their posts in the first place can be answered in two aspects. First, as mentioned in this New York Times article by Klosowski (2022), whether the person posting is a public figure or not is not essential: companies in the hiring process could run a social media background check, leading to rejection. Secondly and even worse, the government can pull an old tweet out of context and use it against the person, leading to an arrest. The Turkish government's control over social media is widely recognized. It has instituted nationwide bans before

[5]https://help.twitter.com/en/using-x/repost-faqs

and has arrested people accused of “provocative posts” continuously (Scott, 2023). Freedom House’s 2023 report states that Turkey’s global and internet freedom scores are classified as “not free” (Freedom House, 2023). These reasons could have eventually led to the deletion of many tweets after the election.

The gap between collected plus deleted tweets and total tweets lies under restricted rate limits[6]. During hydration, every second or third response was empty, which led to second and third hydration batches of the missing tweets. Due to time limitations and the lengthy duration of big data analysis, the hydration process resulted in the maximum feasible collection of tweets within the constraints.

3.2 The Methodology

As mentioned in the previous chapter, topic modeling is an unsupervised tool that helps extract the underlying themes from the given text data. BERTopic is a neural topic model, one of many topic modeling approaches. Due to time constraints and the time plan of this thesis, only the BERTopic model is used for topic modeling. Since several methods could be used, it is important to mention why BERTopic is used and why the others are not. Egger and Yu (2022) found out that for short and unstructured texts like Twitter data, BERTopic can extract contextual information, and it offers the most potential compared to different embedding-based topic models like Top2Vec. According to their research, BERTopic has high versatility and stability across domains and supports different topic modeling variations. Like other embedding-based topic models, it allows multilingual analysis, and there is no need for preprocessing of the original data. However, the embedding approach might cause too many topics and outliers in some cases, which makes the results more challenging to interpret and should be examined in detail. Some long documents could occasionally involve multiple topics, but in this approach, every document is assigned to a single topic, which could be a disadvantage.

According to Grootendorst (2022), BERTopic generates topic representations in six steps. First, without preprocessing, each document must be embedded using a pre-trained model. In this thesis, the SBERT model is used, introduced by Reimers and Gurevych (2019). SBERT modifies the BERT model and derives semantically meaningful sentence embeddings, also from multilingual documents, allowing tasks like clustering or information retrieval via semantic search. SBERT also allows the selection of various pre-trained multilingual models supporting more than 50 languages[7]. This thesis uses the *paraphrase-multilingual-MiniLM-L12-v2* model, which supports Turkish and is the

[6]https://business.twitter.com/en/blog/update-on-twitters-limited-usage.html
[7]https://www.sbert.net/docs/pretrained_models.html

fastest and one of the best performers among other multilingual models (Reimers & Gurevych, 2020). This part of the pipeline allows to do chunk embeddings, saving the results and using them later, making the big data analysis easier with restricted hardware availabilities.

Secondly, the dimensionality of these resulting embeddings is reduced to optimize the clustering process by the Uniform Manifold Approximation and Projection (UMAP) algorithm, which plays a massive role in big data analysis (McInnes et al., 2020). Afterward, these low-dimension embeddings are clustered using the Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) technique, and the resulting clusters consist of semantically similar documents. This step allows unrelated documents to be assigned as noise or outliers, which improves the result, and both of these steps can be influenced very much by changing the parameters of the algorithms.

Fourthly, each cluster is tokenized using a Vectorizer like CountVectorizer[8]. Together with the weighting of these tokens, where a custom class-based variation of the Term Frequency – Inverse Document Frequency (c-TF-IDF) algorithm is used, they are responsible for creating the topic representations. Like the previous step, this step also allows room to play with various parameters to tune the model, which affects the results considerably.

At last comes the topic representation, where the topics can be fine-tuned using various methods. This thesis uses KeyBERTInspired and Maximal Marginal Relevance (MMR) models[9], which can be easily imported from the BERTopic library. They leverage the c-TF-IDF algorithm and weights keywords to represent the related topics. This thesis also leverages the power of LLMs by OpenAI, specifically GPT-4 Turbo, to better represent the resulting topics. One can also leverage other open-source LLMs, but most only support English or a few other languages.

[8] https://maartengr.github.io/BERTopic/getting_started/vectorizers/vectorizers.html
[9] https://maartengr.github.io/BERTopic/getting_started/representation/representation.html

4 Results

4.1 Analysis of data findings

Citation test (Lamport, 1994).

5 Discussion

x

5.1 Limitations

Citation test (Lamport, 1994).

5.2 Future Work

Citation test (Lamport, 1994).

6 Conclusion

6.1 Section

Citation test (Lamport, 1994).

Acronyms must be added in `main.tex` and are referenced using macros. The first occurrence is automatically replaced with the long version of the acronym, while all subsequent usages use the abbreviation.

E.g. `\ac{TUM}, \ac{TUM}` ⇒ Technical University of Munich (TUM), TUM

For more details, see the documentation of the `acronym` package[1].

6.1.1 Subsection

See Table 6.1, Figure 6.1, Figure 6.2, Figure 6.3.

Table 6.1: An example for a simple table.

A	B	C	D
1	2	1	2
2	3	2	3

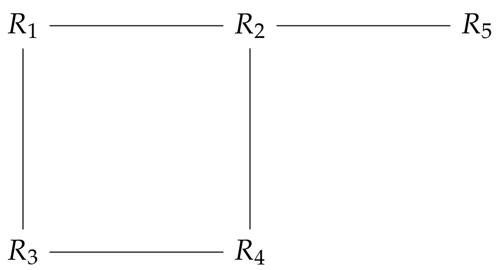

Figure 6.1: An example for a simple drawing.

[1]https://ctan.org/pkg/acronym

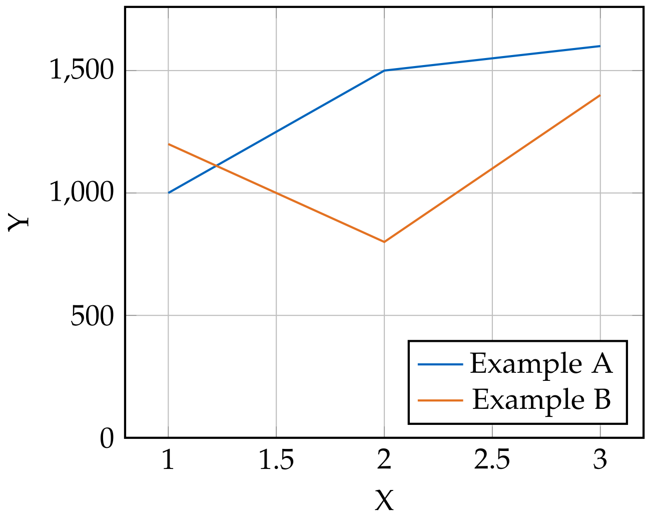

Figure 6.2: An example for a simple plot.

```
SELECT * FROM tbl WHERE tbl.str = "str"
```

Figure 6.3: An example for a source code listing.

Abbreviations

TUM Technical University of Munich

CHP Republican People's Party

AKP Justice and Development Party

DEVA Democracy and Progress Party

IyiP Good Party

SAADET Felicity Party

DP Democrat Party

DEVA Democracy and Progress Party

GP Future Party

NLP Natural Language Processing

List of Figures

List of Tables

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