

A Real-Time Platform to Monitoring Misinformation on Telegram

Ivandro Claudino, Thiago Gadelha, Tiago Vinuto, José Wellington Franco, José Maria Monteiro and Javam Machado

Universidade Federal do Ceará, Brazil

jose.monteiro@lsbd.ufc.br, javam.machado@lsbd.ufc.br

Keywords: Misinformation, Monitoring, Telegram, Social Media.

Abstract: The large-scale dissemination of misinformation through social media has become a critical issue, harming public health, social stability and democracy. In Brazil, 79.9% of the population uses social networks, and the Telegram is present in 65% of the country's smartphones. Due to its popularization, many groups have used this instant messaging application to spread misinformation, especially as part of articulated political or ideological campaigns. Telegram provides two essential features that facilitate the spread of misinformation, public groups and channels. Through these resources, false information can deceive thousands of people in a short time. In this context, we present MST, a Real-Time platform to find, gather, analyze and visualize misinformation on Telegram. To evaluate the proposed platform, we built a dataset from the Brazilian general election campaign in 2022, obtained from Telegram public chat groups and channels.

1 INTRODUCTION

In 2022, the proportion of smartphones with Telegram installed grew in Brazil from 45% to 60%. Currently, Telegram instant messaging application is present in 65% of Brazilian's smartphones¹. If on one hand, this platform offers security and privacy to its users, on other hand it is an environment with weak or no moderation, which has contributed to the spread of misinformation. Through Telegram, misinformation can deceive thousands of people in a very short time and cause significant harm to individuals and society. In this context, misinformation has been used to change political scenarios, contribute to the spread of diseases, and even cause deaths (Martins et al., 2022; Silva and Benevenuto, 2021).

Telegram is a quite popular application due to its versatility and ease of use. It make it possible to instantly share different media types, such as images, audios, and videos. Besides, it provide two significant features: public chat groups and channels. They are accessible through invitation links and, usually, they have specific topics for discussion, such as politics and health. Telegram allows users to join or even share their public groups and channels to simultaneously connect to hundreds of people at once, and quickly receive and share content among themselves.

¹ <https://www.mobilitytime.com.br/dados-de-mercado/>

In this way, public groups and channels are very similar to social networks. They have been used to spread misinformation, especially as part of articulated political or ideological campaigns. Furthermore, misinformation spreads faster, deeper, and expansive than legit information. Further, due to the high volume of information that we are exposed to, we have a limited dexterity to distinguish true information from misinformation (Martins et al., 2022; Martins et al., 2021a; Silva and Benevenuto, 2021).

In this context, monitoring the content that circulates in Telegram public groups and channels is a fundamental task to identify and understand the spread of misinformation and get insights to address this problem. However, collecting a database of messages already in circulation on Telegram is a challenging task. To fill this gap, we built the MST, a real-time platform to monitoring the Misinformation Spreading on Telegram. To evaluate the MST platform, we used it to build a dataset, concerning the Brazilian general elections campaign in 2022, obtained from public chat groups and channels on Telegram.

The remainder of this paper is organized as follows. Section 2 presents the main related work. Section 3 describes the MST platform. Section 4 details a case study performed in order to evaluate the proposed platform. Conclusions and future work are presented in Section 5.

2 RELATED WORK

Recently, some efforts towards research involving Telegram instant messaging application have been developed. A detailed analysis of Iranian users' behavior in Telegram was presented in (Hashemi and Chahooki, 2019). More than 900,000 Persian channels and 300,000 Persian supergroups have been discovered, crawled and inspected in this study. Besides, the authors devised a method to measure group qualities in Telegram. In (Ng and Loke, 2021), the authors analyzed a Singapore-based COVID-19 Telegram group with more than 10,000 participants focusing on five dimensions: participation, sentiment, negative emotions, topics, and message types. In (Baumgartner et al., 2020), the authors collected a large volume of data composed of almost 28,000 channels on Telegram, giving rise to a useful data set that can be used to study politics, protests, online social movements and disinformation in the context of mobile applications. During the process the authors collected data and metadata from public channels and from this they built a list of channels focused on important topics, such as right-wing extremist politics. In the Baumgartner et al.'s work (Baumgartner et al., 2020) both the data and the source code used to collect it, were made available.

Paz et al. (de Paz et al., 2022) performed an analysis about disinformation spreading on Telegram and proposed a way to identify the origin of the published content. The work presented in (Nobari et al., 2021) provided an in-depth look at how messages conveyed from telegram go viral. The authors performed a study based on a real dataset obtained from Telegram. They looked several aspects such as, the information flow and the characteristics of viral messages. In (de Paz et al., 2023), the authors presented an analysis of misinformation cross-platform dynamics by focusing on communications published by COVID19 negationists on Twitter and Telegram. Herasimenka et al. (Herasimenka et al., 2022) analyzed 200,000 Telegram posts and observed that links to known sources of misleading information are shared more often than links to professional news content, but the former stays confined to relatively few channels. They also concluded that, contrary to popular received wisdom, the audience for misinformation is not a general one, but a small and active community of users. Akbari et al. (Akbari and Gabdulhakov, 2019) investigated the Telegram ban in Russia and Iran, when both governments demanded access to the content shared by the users and the platform refused to provide it. Besides, they provided an overview of the actors, methods, and tools that are instrumentalized against Telegram.

In (Júnior et al., 2021) the authors collected 1,405,997 messages from 122 Brazilian political groups and channels on Telegram, covering the period from January 2018 to April 2021. Besides, using this dataset, they performed some data analysis techniques, observing the network created in the platform as well as a closer look in the dynamics of messages and members in this platform. Their findings showed that the political discussion on Telegram took a leap in the beginning of 2021 (up to 3 times compared to the end of 2020 in the number of messages). In addition, the authors observed a significant volume of referrals on Telegram, as well as a significant amount of links to content on other platforms such as YouTube, evidencing the use of Telegram as a vector for content sharing. They concluded that the large groups structure of Telegram are effective in spreading the messages through the network, with the content being viewed by numerous users and forwarded multiple times. Furthermore, they observed a relevant amount of messages attacking political personalities and spreading unchecked content about COVID-19 pandemic.

In (Dargahi Nobari et al., 2017), the authors developed a crawler to collect public data from Telegram, including messages, users, groups, channels and their relationships. In addition, they created a mention graph and applied the page rank algorithm in order to understand the differences concerning link patterns between Telegram and other networks. In (Paschalides et al., 2020), the authors presented MANDOLA, a big-data processing system that monitors, detects, visualizes, and reports the spread and penetration of online hate-related speech using big-data approaches. MANDOLA consists of six components that intercommunicate to consume, process, store, and visualize statistical information regarding hate speech spread online. They also proposed a novel ensemble-based classification algorithm for hate speech detection. Khaund et al. (Khaund et al., 2021) presented a methodology to collect and analyze data from Telegram. They conducted both text and network analysis to gain insights into political discourse and public opinion. Their findings included the use of Telegram by politicians to connect with their voter, promote their work as well as ridicule their peers. Besides, the channels were actively used to disseminate information on political affairs while the chat groups to discuss views about the government. Benevenuto et al. presented in (Júnior et al., 2022a; Júnior et al., 2022b) the "Telegram Monitor", a web-based system that monitors the political debate in this platform and enables the analysis of the most shared content in multiple channels and public groups.

3 THE MST PLATFORM

The MST (Misinformation Spreading on Telegram) platform architecture comprises nine components, as illustrated in Figure 1. Next, we will discuss in detail each one of these components.

3.1 Telegram Connector

The main goal of this component is make possible gathering data from Telegram using a common interface. It converts each captured message to the JSON (JavaScript Object Notation) format and send it to the Message Broker (Redis). We chose JSON because it is a language-independent, standard format for storing and exchanging data. Besides, the Telegram Connector sends each captured media file to the File Server component. In order to avoid storing duplicate media files, we apply the MD5 hash algorithm on the file content and generate a unique identifier, which is used as the name of the media file. Thus, we avoid wasting disk space, as well as making it possible to aggregate similar content and quantify how many times each one was shared by the users, with the purpose of understand the popularity of each content. Listing 1 illustrates an example of JSON “file” caught the Telegram Connector.

3.1.1 Finding Groups and Channels

The first step in collecting data from Telegram is to find groups and channels of interest. We divide this task into seven steps:

- **Step 1:** Initially, a manual search is performed on Telegram grouping links of public channels and chat groups based on a list of keywords (as our case study aims to investigate the Brazilian far-right groups, we used terms such as: bolsonaro, captain, patriots). So, based on how Telegram group invitation links are structured, we searched for URL patterns such as `https://t.me/joinchat/<GroupID>` and `https://telegram.me/<GroupID>` on popular search engines (e.g. Google), besides we also looked for the terms in the keywords list using Telegram’s search feature. Then, we insert the found links in a file called “CandidateGroups”;
- **Step 2:** We performed a search for Telegram invitation links in public datasets of Whatsapp messages like (Martins et al., 2022; Martins et al., 2021a; Martins et al., 2021b; de Sá et al., 2021). Then, we insert the found links in the “CandidateGroups” file;

- **Step 3:** In this step, from the “CandidateGroups” file a manual selection of groups and channels that are inline with the research goals was performed, that is, the selected groups should be focused on the Brazilian far-right themes.
- **Step 4:** We then joined the selected groups with a new Telegram account.
- **Step 5:** We collect the messages that travel in the selected groups through the Telegram API.
- **Step 6:** Weekly, we parse the collected messages searching for new invitation links, that is links that re are not previously collected, and insert the found links in a new version of the “CandidateGroups” file.
- **Step 7:** Finally, we repeat the steps 3 to 6 for the “CandidateGroups” file built at the previous step.

3.1.2 Gathering Data

This subsection briefly describes how the MST platform collects the content that travel in groups and channels using the Telegram official API. So, to collect these contents, we created a Telegram account for this research and developed an application² written in Python using the Telethon library³ (library that aims to facilitate integration with the Telegram API). This Python applications obtains metadata concerning groups and/or channels and users, besides text messages a media files (images, audios and videos).

The Telethon library allows the creation of a client to establish a connection between the MST platform and the Telegram environment. The purpose of this connection is to keep the client running as long as the connection is not interrupted. As we aim to capture text messages and media content in real time, we chose to keep the client running constantly. An event handler in the client is triggered when there is a notification of a new message. Thus, the client receives the identifier and the textual content of this new message. Next, the client uses Telethon library to obtains more detailed information, including text message, date, time, among others. With this information, the client builds a JSON file and send it to the Message Broker, as illustrated in Listing 1. Despite Telethon library abstracts and simplifies interactions with the Telegram API, it uses a specific class for different type of content (images, audio/video, URLs, among others) and for each type of chat. In addition, these different classes have some distinct attributes. This fact was an important challenge for coding the Telegram Connector.

²<https://core.telegram.org/#getting-started>

³<https://github.com/LonamiWebs/Telethon>

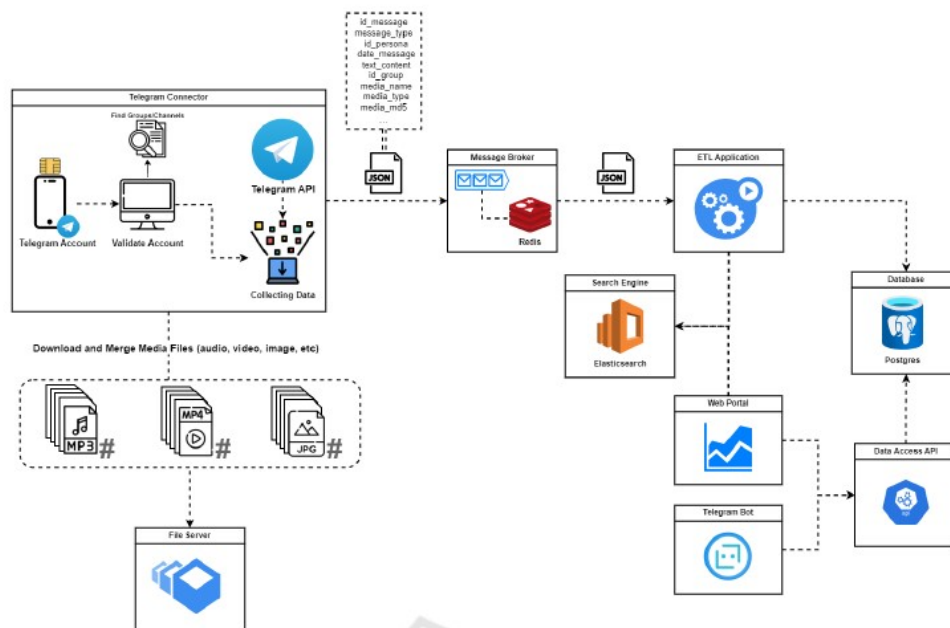


Figure 1: MST Architecture.

3.2 Message Broker

Message Broker is a software that make it possible that applications, systems and services communicate with each other and share information. It is responsible for validating, storing, routing and delivering messages to the appropriate destinations. In the MST platform, the Message Broker acts as an intermediary, allowing the Telegram Connector to send messages to the ETL Application. This facilitates the decoupling of components within the proposed architecture. The Message Broker allows reliable storage and ensures message delivery. It has a set of message queues, which store and sort messages until the ETL Application can process them. Furthermore, it ensures that each queued message is consumed only once. To implement the Message Broker, we use Redis, which is an in-memory, key-value, open source, versatile and easy-to-use storage system. In addition, it provides high performance, persistence and data replication.

3.3 ETL Application

The ETL Application is responsible for text messages processing, which includes different tasks, such as parsing, anonymization, misinformation detection and sentiment analysis. Many of these tasks use the services of the Data Processing API. We took into consideration privacy issues by anonymizing users' names and cell phone numbers. For this, we create an anonymous and unique ID for each user by using an MD5 hash function on their username. Similarly,

we create an anonymous alias for each group. After a text message processing, the ETL Application component sends the resulting data to a Relational Database Server (PostgreSQL) and a Search Engine (Elasticsearch).

3.4 File Server

The File Server component is responsible for store the media files (e.g. audios, images and videos) captured by the Telegram Connector in a persistent and safe manner. In order to avoid to store several copies of the same content, we used the following strategy:

- First, we apply the MD5 algorithm on the bytes of the media content, which are present in the metadata provided by the Telegram API, and generate a hash code (an unique identifier) that is used as the name of the media file on the server;
- Next, we verify if there is a file with the same name of the hash code generate previously. In negative case, we download and store the media file. In affirmative case, we don't download the media file, since it is already stored in our server, avoid processing and storing overhead.

However, this strategy doesn't work for some content types, such as SVG images and MKV videos, since their bytes are not present in the metadata provided by the Telegram API. In this case, we download the media file, generate the hash code, and then we check if this content has been previously downloaded. In affirmative case, we delete this media file.

```

{
  "id_message": "1049819",
  "messenger": "telegram",
  "message_type": "Url",
  "id_persona": #####,
  "date_message": "2022-09-28T16:18:09+00:00",
  "text_content": "Banco Mundial confirma fala de Paulo Guedes: PIB do Brasil tende
    a crescer mais que o da China \u261b https://terrabrasilnoticias.com/2022/09/
    banco-mundial-confirma-falaa-de-paulo-guedes-pib-do-brasil-tende-a-crescer-mais-
    -que-o-da-china/\n\nBom dia \ud83d\udd25\ud83d\udd25\n\n@FYIBRASIL",
  "id_member_telegram": #####,
  "id_group": #####,
  "media": "ca9a6c25f29526930d60852a74ab6940 (1).jpg",
  "media_name": "",
  "media_type": "url",
  "media_url": "https://terrabrasilnoticias.com/2022/09/banco-mundial-confirma-
    falaa-de-paulo-guedes-pib-do-brasil-tende-a-crescer-mais-que-o-da-china/",
  "media_md5": "ca9a6c25f29526930d60852a74ab6940",
  "display_name": "Banco Mundial confirma fala de Paulo Guedes: PIB do Brasil tende
    a crescer mais que o da China - Terra Brasil Not\u00edcias\nCompartilhe: A
    nova previs\u00e3o do Banco Mundial \u00e9 de que o PIB (Produto Interno Bruto)
    ",
  "address_message": "",
  "latitude_message": 0,
  "longitude_message": 0,
  "contacts_message": null
}

```

Listing 1: Example of a JSON Caught from Telegram.

In negative case, we don't need do anything.

3.5 Database

The Relational Database Server supports storing and querying data on the traditional flat model. Thereunto, it uses PostgreSQL⁴, a free and open-source relational database management system (RDBMS) emphasizing extensibility and SQL compliance. It is important to highlight that the audios, images, and videos are stored by the File Server. The PostgreSQL database stores only the path to these files.

3.6 Search Engine

The Search Engine component aims to provide textual queries directly on the captured messages. For this, it uses Elasticsearch⁵, a search engine based on the Lucene library that provides a distributed, multitenant-capable full-text search engine with an HTTP web interface and schema-free JSON documents.

⁴<https://www.postgresql.org/>

⁵<https://www.elastic.co/elasticsearch/>

3.7 Web Portal

Today, there is a great need for displaying massive amounts of data in a way that is easily accessible and understandable. In this context, data visualization is a way to represent information graphically, highlighting patterns and trends in data and helping to achieve news insights. It enables the data exploration via the manipulation of charts and images. More specifically, it enables users to analyze the data by interacting directly with a visual representation of it. In this work, the Web Portal component is a web application developed using Python programming language and Django 3 framework, which explores relational (from PostgreSQL) and textual (from Elasticsearch) data.

3.8 Telegram Bot

Telegram Bot is a proactive chatbot built from Telegram which automatically detects and alerts the presence of misinformation in social chats. Initially, they need to be added to a certain group. Then it will automatically monitor and analyze the content that travels in the group. Finally, if they detect that certain content has a high probability of containing misinformation, an alert message is sent to the group.

4 CASE STUDY

To evaluate the MST platform, we performed an exploratory case study using a dataset covering the Brazilian general elections campaign in 2022 collected by Telegram. We used the MST platform to monitor right-far Telegram groups and channels in the period between September 27, 2022, and November 15, 2022, which comprises part of the electoral period of the 1st round and all of the 2nd round of 2022 general Brazilian elections. This case study was influenced by (de Sá et al., 2021; Júnior et al., 2022a). So, many data analysis techniques were applied to this dataset to get insights about misinformation spreading. The dataset built contains 513,961 messages obtained from 14,085 users from 180 Groups/Channels.

4.1 Messages Characterization

Initially, we will present some visualizations to characterize the built dataset. Figure 2 shows the distribution of messages sending time by the day hours on Telegram. As we can imagine, the peak of sending messages occurs at the time reserved for lunch (between 12 and 15 hours) and in the early evening, just after work hours. Figure 3 shows the distribution messages sent time by day on Telegram. As we can imagine, the peak of sending messages occurs on October 2nd (the date of the first round of elections) and October 30th (the date of the second round of elections).

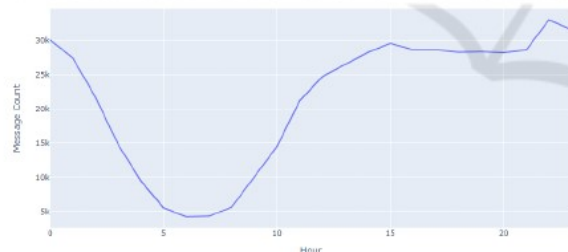


Figure 2: Number of Messages by Hour.

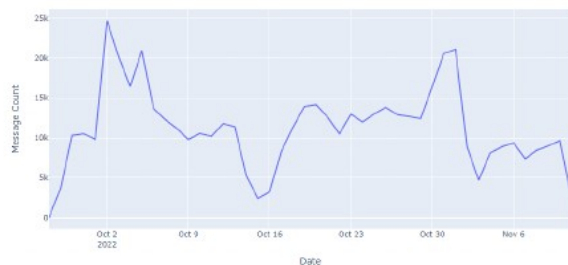


Figure 3: Number of Messages by day.

4.2 Vocabulary Characterization

Another aspect that needs to be analyzed is the characteristics of the vocabulary used in the text messages since there is a strong relationship between the used vocabulary and the social network, in this case, Telegram. Figure 4 shows the word cloud highlighting the most popular words on monitored Telegram public chat groups and channels. Deserve mention the terms related with the Brazilian far-right, such as: Bolsonaro, presidente, Brasil, forças armadas, exército, direita, verdade, Deus and família. Furthermore, we can highlight terms related with the far-right opponents, such as: Lula, esquerda, petista, comunista, bandido and ladrão. Finally, we can observe terms related to conspiracy theories, such as: TSE, fraude, urna, voto and Alexandre de Moraes.



Figure 4: Word Cloud on Telegram.

4.3 Misinformation Analysis

In order to evaluate the misinformation potential in the used dataset, we applied the misinformation classifier proposed in (Cabral et al., 2021) on the text messages caught by MST. It is important to highlight that this classifier was trained with a dataset collected and labelled during the 2018 Brazilian General Elections. This misinformation classifier receives a text message as input and generates as output a value between 0 and 1, indicating the probability that the text contains misinformation. Texts with values greater than 0.5 were considered misinformation, messages with values between 0.3 and 0.5 were designated inconclusive (neutral), while texts with values less than 0.3 were treated as non-misinformation. Figure 5 shows that the used classifier considered that 25.31% of the caught text messages contained misinformation. Figure 5 shows the distribution of the misinformation probability.

The creators of misinformation use various stylistic tricks to promote the success of their contents,

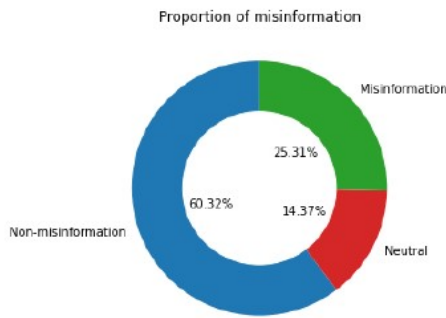


Figure 5: Proportion of Misinformation.

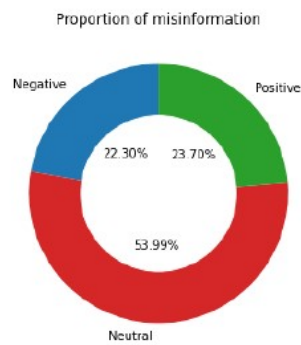


Figure 7: Proportion of Sentiment Analysis.

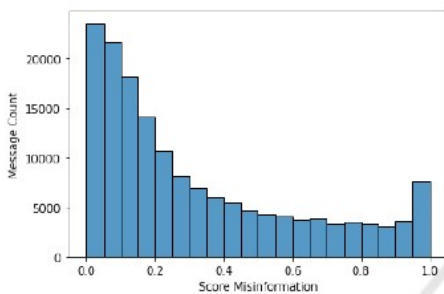


Figure 6: Distribution of the Misinformation Probability.

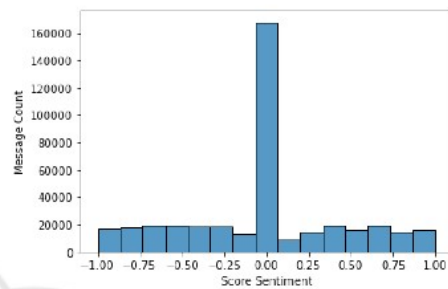


Figure 8: Distribution of the Sentiment Analysis.

with one of them being to excite the sentiments of the recipients. Often, misinformation is associated with the presence polarity (positive and negative), which is used by content producers to misdirect readers. Consequently, Sentiment Analysis (SA) provides crucial information on the content of a Telegram message to determine whether it is trustworthy or should be considered as misinformation.

In this context, we applied the LeIA tool on the text messages caught by MST platform. LeIA receives a text message as input and generate as output a value between -1 and 1, called sentiment score. Values close to 1 indicate high positivity, values close to -1 denote high negativity, and values close to 0 imply neutrality. Figure 7 shows the proportion between positive, negative and neutral messages. Texts with sentiment score greater than 0.3 were considered “Positive”. Messages with sentiment score less than -0.3 where designated “Negative”. Texts with sentiment score between -0.3 and 0.3 were treated as “neutral”. Analyzing Figure 7, we can note that almost half of the messages have high polarity (“Positive” or “Negative”). Messages with high polarity could be used to generate alerts or should be given priority when going through veracity verification processes. Figure 8 illustrates the sentiment score distribution.

5 CONCLUSIONS

Due to its popularization, many groups have used Telegram to spread false information, especially as part of articulated political or ideological campaigns. The large-scale and fast spread of misinformation through Telegram messages poses a significant social problem, harming public health, social stability and democracy. Telegram provides two essential features that facilitate the spread of misinformation: public groups and channels. Through these resources, misinformation can deceive thousands of people in a short time. In this context, we presented MST (Misinformation Spreading on Telegram), a Real-Time platform to find, gather, analyze and visualize misinformation on Telegram. To evaluate the proposed platform, we built a dataset from the Brazilian general election campaign in 2022, obtained from Telegram public chat groups and channels. The MST platform and the built dataset are available at our public repository⁶. We hope that MST platform can help journalists and researchers to understand the misinformation propagation in Telegram. As future works, we want to analyze how misinformation spread among the chat groups using complex networks.

⁶<https://gitlab.com/jmmonteiro>

REFERENCES

- Akbari, A. and Gabdulhakov, R. (2019). Platform surveillance and resistance in iran and russia: The case of telegram. *Surveillance & Society*, 17:223–231.
- Baumgartner, J., Zannettou, S., Squire, M., and Blackburn, J. (2020). The pushshift telegram dataset. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 14, pages 840–847.
- Cabral, L., Monteiro, J. M., da Silva, J. W. F., Mattos, C. L. C., and Mourão, P. J. C. (2021). Fakewhatsapp.br: NLP and machine learning techniques for misinformation detection in brazilian portuguese whatsapp messages. In Filipe, J., Smialek, M., Brodsky, A., and Hammoudi, S., editors, *Proceedings of the 23rd International Conference on Enterprise Information Systems, ICEIS 2021, Online Streaming, April 26-28, 2021, Volume 1*, pages 63–74. SCITEPRESS.
- Dargahi Nobari, A., Reshadatmand, N., and Neshati, M. (2017). Analysis of telegram, an instant messaging service. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, pages 2035–2038.
- de Paz, A., Suárez, M., Palmero, S., Degli-Esposti, S., and Arroyo, D. (2022). Following negationists on twitter and telegram: Application of ncd to the analysis of multiplatform misinformation dynamics. In *Proceedings of the International Conference on Ubiquitous Computing & Ambient Intelligence (UCAI 2022)*, pages 1110–1116. Springer.
- de Paz, A., Suárez, M., Palmero, S., Degli-Esposti, S., and Arroyo, D. (2023). Following negationists on twitter and telegram: Application of ncd to the analysis of multiplatform misinformation dynamics. In Bravo, J., Ochoa, S., and Favela, J., editors, *Proceedings of the International Conference on Ubiquitous Computing & Ambient Intelligence (UCAI 2022)*, pages 1110–1116, Cham. Springer International Publishing.
- de Sá, I. C., Monteiro, J. M., da Silva, J. W. F., Medeiros, L. M., Mourão, P. J. C., and da Cunha, L. C. C. (2021). Digital lighthouse: A platform for monitoring public groups in whatsapp. In Filipe, J., Smialek, M., Brodsky, A., and Hammoudi, S., editors, *Proceedings of the 23rd International Conference on Enterprise Information Systems, ICEIS 2021, Online Streaming, April 26-28, 2021, Volume 1*, pages 297–304. SCITEPRESS.
- Hashemi, A. and Chahooki, M. A. Z. (2019). Telegram group quality measurement by user behavior analysis. *Social Network Analysis and Mining*, 9:1–12.
- Herasimenka, A., Bright, J., Knuutila, A., and Howard, P. N. (2022). Misinformation and professional news on largely unmoderated platforms: the case of telegram. *Journal of Information Technology & Politics*, 0(0):1–15.
- Júnior, M., Melo, P., da Silva, A. P. C., Benevenuto, F., and Almeida, J. (2021). Towards understanding the use of telegram by political groups in brazil. In *Proceedings of the Brazilian Symposium on Multimedia and the Web*, pages 237–244.
- Júnior, M., Melo, P. F., Kansaon, D., Mafra, V., Sá, K., and Benevenuto, F. (2022a). Telegram monitor: Monitoring brazilian political groups and channels on telegram. *CoRR*, abs/2202.04737.
- Júnior, M., Melo, P. F., Kansaon, D., Mafra, V., Sá, K., and Benevenuto, F. (2022b). Telegram monitor: Monitoring brazilian political groups and channels on telegram. In Bellogín, A., Boratto, L., and Cena, F., editors, *HT '22: 33rd ACM Conference on Hypertext and Social Media, Barcelona, Spain, 28 June 2022- 1 July 2022*, pages 228–231. ACM.
- Khaund, T., Hussain, M. N., Shaik, M., and Agarwal, N. (2021). Telegram: Data collection, opportunities and challenges. In Lossio-Ventura, J. A., Valverde-Rebaza, J. C., Díaz, E., and Alatrística-Salas, H., editors, *Information Management and Big Data*, pages 513–526, Cham. Springer International Publishing.
- Martins, A. D. F., Cabral, L., Mourão, P. J. C., Monteiro, J. M., and Machado, J. (2021a). Detection of misinformation about covid-19 in brazilian portuguese whatsapp messages. In *International Conference on Applications of Natural Language to Information Systems*, pages 199–206. Springer.
- Martins, A. D. F., da Cunha, L. C. C., Mourão, P. J. C., de Sá, I. C., Monteiro, J. M., and de Castro Machado, J. (2021b). Covid19.br: A dataset of misinformation about covid-19 in brazilian portuguese whatsapp messages. In *III Dataset Showcase Workshop, DSW 2021, Rio de Janeiro, RJ, Brazil, October 4-8, 2021 (To appear)*. SBC.
- Martins, A. D. F., Monteiro, J. M., and Machado, J. C. (2022). Understanding misinformation about COVID-19 in whatsapp messages. In Chiusano, S., Cerquitelli, T., Wrembel, R., Nørnvåg, K., Catania, B., Vargas-Solar, G., and Zumpano, E., editors, *New Trends in Database and Information Systems - ADBIS 2022 Short Papers, Doctoral Consortium and Workshops: DOING, K-GALS, MADEISD, MegaData, SWODCH, Turin, Italy, September 5-8, 2022, Proceedings*, volume 1652 of *Communications in Computer and Information Science*, pages 14–23. Springer.
- Ng, L. H. X. and Loke, J. Y. (2021). Analyzing public opinion and misinformation in a covid-19 telegram group chat. *IEEE Internet Computing*, 25(2):84–91.
- Nobari, A. D., Sarraf, M. H. K. M., Neshati, M., and Daneshvar, F. E. (2021). Characteristics of viral messages on telegram; the world's largest hybrid public and private messenger. *Expert systems with applications*, 168:114303.
- Paschalides, D., Stephanidis, D., Andreou, A., Orphanou, K., Pallis, G., Dikaiakos, M. D., and Markatos, E. (2020). Mandola: A big-data processing and visualization platform for monitoring and detecting online hate speech. *ACM Trans. Internet Technol.*, 20(2).
- Silva, M. and Benevenuto, F. (2021). COVID-19 ads as political weapon. In Hung, C., Hong, J., Bechini, A., and Song, E., editors, *SAC '21: The 36th ACM/SIGAPP Symposium on Applied Computing, Virtual Event, Republic of Korea, March 22-26, 2021*, pages 1705–1710. ACM.

Dados Internacionais de Catalogação na Publicação
Universidade Federal do Ceará
Sistema de Bibliotecas

Gerada automaticamente pelo módulo Catalog, mediante os dados fornecidos pelo(a) autor(a)

G12r Gadelha, Thiago da Costa.

A Real-Time Platform to Monitoring Misinformation on Telegram / Thiago da Costa
Gadelha. – 2023.
8 f. : il. color.

Trabalho de Conclusão de Curso (graduação) – Universidade Federal do Ceará, Centro
de Ciências, Curso de Computação, Fortaleza, 2023.

Orientação: Prof. Dr. José Maria da Silva Monteiro.

1. Misinformation. 2. Monitoring. 3. Telegram. 4. Social Media. I. Título.

CDD 005
