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IVAN SLOBOZHAN

Studying Online Social Media Engagement in CIS Countries during Protests, Mass Demonstrations and War

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To my grandparents

ABSTRACT

Protests and conflicts have become influential forces for bringing about change and shaping the political and social landscapes not only on a local demographic level but also on a global scale. In the modern era of the Internet and online social media, protests have increasingly utilized digital platforms to facilitate discussions, coordinate actions, and spread respective agendas. Despite this, there is still a lack of understanding regarding the interconnections between such political and socioeconomic events and the actions of individuals and organizations, particularly in Commonwealth of Independent States (CIS) countries.

To address this gap, this PhD thesis aims to undertake a comprehensive analysis of social media and the behaviour of active participants during significant political and socioeconomic events in CIS countries. We study at the following three levels of analysis:

1. **One-side, individual level**. In this aspect of our research, we focused on analyzing how individuals' behaviour on a specific Facebook group, representing one side of the conflict, was influenced by external events. Specifically, we looked at the changes in behaviour among active participants on the group's page before and after the Euromaidan revolution in Ukraine. Our investigation revealed that users altered their language patterns, which we attribute to political and historical factors.
2. **One-side, collective level**. In the next study, we examine the behaviour of numerous groups aligned with one side of the conflict. Specifically, we focused on observing the dynamics of multiple groups in Telegram that are likely to facilitate protests in Belarus during the 2020 protests. Our analysis entailed studying the activity of people on Telegram and tracking the evolution of their interests using more than four years of data spanning before, during, and after the protests.
3. **Two-sides, collective level**. In the last dimension of our analysis, we undertook a comparative study of the behaviour of organizations aligned with the two conflicting sides. Our specific focus was on examining the actions and strategies employed by the most prominent and influential mass media outlets in Ukraine and Russia during the Russian invasion of Ukraine in 2022. In particular, interest was how these outlets shaped their propaganda efforts in response to the conflict that influenced the behaviour of individuals.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ORIGINAL PUBLICATIONS

Publications included in the thesis

I **Ivan Slobozhan**, Tymofii Brik, and Rajesh Sharma. " Differentiable characteristics of Telegram mediums during protests in Belarus 2020." In **Social Network Analysis and Mining** 13, no. 1 (2023): 1-19.

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II **Ivan Slobozhan**, Tymofii Brik, and Rajesh Sharma. "Longitudinal change in language behaviour during protests: A case study of Euromaidan in Ukraine." In **Social Network Analysis and Mining** 12, no. 1 (2022): 1-12.

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I **Ivan Slobozhan**, Peter Ormosi, and Rajesh Sharma. "Detecting shadow lobbying." In **Social network analysis and mining** 12, no. 1 (2022): 1-11.

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II Pavlo Tertychnyi, **Ivan Slobozhan**, Madis Ollikainen, Marlon Dumas. "Scalable and Imbalance-Resistant Machine Learning Models for Anti-money Laundering: A Two-Layered Approach." In **International Workshop on Enterprise Applications, Markets and Services in the Finance Industry**, pp. 43-58. Springer, Cham, 2020.

Lead author. The author performed the implementation and the analysis of the experiments and contributed substantially to the ideas.

III **Ivan Slobozhan**, Peter Ormosi, and Rajesh Sharma. "Which bills are lobbied? Predicting and interpreting lobbying activity in the US." In **International Conference on Big Data Analytics and Knowledge Discovery** (2020), Springer, Cham, 285-300.

Lead author. The author performed the implementation and the analysis of the experiments and contributed substantially to the ideas and the writing.

1. INTRODUCTION

In recent years, there has been a noticeable wave of protests, mass demonstrations, and even armed conflicts, capturing the global community's attention. These events span a wide range of geographic locations and encompass different agenda, such as the Arab Spring [WSS13] in the Middle East, the Black Lives Matter movement in the United States [MRB18], the Umbrella Movement in Hong Kong [Ort15], and even a full-scale Russian invasion of Ukraine in 2022. These examples represent just a fraction of the more than two hundred significant protests, mass demonstrations and wards demonstrations that have unfolded in over one hundred countries[1]. A striking commonality among these events is their reliance on social media platforms.

Protests, demonstrations and wars worldwide have increasingly leveraged major social media platforms such as Twitter, Facebook, and Reddit. The research community has extensively studied the usage and impact of these platforms in the context of protests, especially in English-speaking countries, where the majority of the population uses these platforms. Surprisingly, there is a noticeable lack of attention given to the study of protests in countries where English is not commonly used, such as Commonwealth of Independent States (CIS) countries which comprise of Post-Soviet countries. This is particularly unexpected considering that such countries often experience various forms of protests, including large-scale demonstrations and even armed conflicts, as seen in the CIS region in the past decade [SP16; BK21; SU15].

Furthermore, protests on social media exhibit diverse layers of involvement. Discussions may be centred around a particular viewpoint within a specific social group on platforms like Facebook. Additionally, at a higher level, people may communicate with different groups for notification and coordination. Finally, on the broader level, individuals and organizations from various countries, holding different opinions, may share different agendas and even influence the behaviour of individuals using propaganda and misinformation.

In the subsequent sections, we will discuss our primary contribution, which focuses on analyzing the behaviour of individuals and organizations on social media within the countries of the Commonwealth of Independent States (CIS) at three different organizational levels: i) one-side of the conflict on individual level (Section 1.1), ii) one-side on collective level (Section 1.2), iii) two-sides, collective level (Section 1.3).

- *One side Vs. Two sides:* In the context of protests, "one side" refers to a situation where the analysis or focus is primarily on a specific group or viewpoint, disregarding the opposing side. For instance, in a protest scenario, if we solely concentrate on the protesters and overlook the perspective of the government or ruling authorities, it can be considered a one-sided approach.

[1] `https://carnegieendowment.org/publications/interactive/protest-tracker`

On the other hand, when both opposing parties or viewpoints, such as the protesters and the government, are considered and analyzed, it is referred to as a two-sided approach.

- *Individual Vs. Collective:* This refers to the differentiation between the behaviour or actions of individual participants and the collective behaviour exhibited by a group on social media platforms. More precisely, "individual" refers to individual users' actions, opinions, or engagement, considering their perspectives and behaviours. In contrast, "collective" refers to the joint behaviour, actions, or interactions of a group of individuals who come together on social media platforms to express shared viewpoints, engage in discussions, or participate collectively in certain activities.

1.1. One-Side, Individual Level Behaviour Analysis

Our first work focuses on understanding the behaviour of individual protesters within a Facebook group during the Euromaidan revolution in Ukraine, which happened in 2014. We specifically explore how the language preferences of Facebook users changed after the protests. We aim to determine whether people choose their language strategically based on the situation rather than following ethnic or national influences.

Our analysis reveals an interesting shift in language usage among active Ukrainian users following the end of the protests. We found that these users started using the Russian language more frequently. This suggests that protesters adapt their language choices strategically, depending on the circumstances, rather than being driven solely by ethnic or national sentiments.

Although the proportion of posts in Russian significantly increased, active users did not respond by switching to the same language in their comments. This suggests that the administrators of the Facebook group were not able to influence the language behaviour of active users. However, we noticed the arrival of many new users who spoke Russian. Active users seemed to engage with them in Russian. We also found that Ukrainian users who usually commented in Ukrainian were more likely to switch to Russian than users who primarily commented in Russian and switched to Ukrainian. This supports the idea that Ukrainian activists strategically use language, adapting to the situation for better communication.

Contribution: Our study confirms the hypothesis that Ukrainian activists strategically choose their language during protests. These findings align with surveys indicating that Ukrainians tend to adjust their behaviours and identities based on the situation rather than changing their core identities. From a policy perspective, our research helps explain why the Russian language continues to be widely used by Ukrainians despite the ongoing conflict with Russia. Online exposure to Russian-language content leads Ukrainian speakers to follow the trend. Therefore, policies mandating Ukrainian language use on media websites may have a long-lasting impact on increasing its usage. Such measures can be more influential in shaping language usage than ethnic mobilization during political protests or wars.

1.2. One-Side, Collective Level Behaviour Analysis

A lot of existing research studies how people use social media to mobilize and coordinate protests. However, some platforms offer more than one kind of medium for communication, in particular, Telegram. We found that a lot of research literature focuses on a single social media platform or sometimes does a comparison of multiple platforms. In our next work, we performed a comparative analysis of three communication mediums in a single platform, that is Telegram. In particular, we performed a comparison analysis of channels, groups, and local chats in Telegram, during protests in Belarus in 2020.

Contribution: Our findings highlight the varying degrees of importance and distinct purposes served by these communication mediums within Telegram. For instance, groups facilitated discussions on nationwide protests, while chats were primarily utilized for local and small-scale demonstrations. On the other hand, Telegram channels stood out due to their unique content. These results underscore the importance of considering these communication mediums independently in future research rather than merging them together.

1.3. Two-Sides, Collective Level Behaviour Analysis

Our final work aims to analyze the patterns of influential politicians' channels in Ukraine and Russia, as well as their propaganda efforts during the Russian invasion of Ukraine in 2022. This research is particularly important because disseminating disinformation and propaganda through social media platforms can have significant consequences for both individuals and society, especially during conflict and war. It is crucial to detect and identify events targeted by propaganda to combat the spread of false information and biased opinions.

Our study proposes an automated approach for identifying real-world events, specifically international conflicts, that are likely to be targeted by propaganda on social media. We specifically concentrate on evaluating data from Ukrainian and Russian news sources available on the Telegram messaging platform during the Russian aggression against Ukraine in 2022.

Contribution: Our primary contribution is the development of a pipeline that analyzes behavioural patterns in mass media, enabling the detection of propaganda and misinformation efforts. By evaluating the dataset's coverage of real-world events, we establish a foundation for identifying events targeted by propaganda. Additionally, our technique matches Telegram posts to external events, revealing inconsistencies between Ukraine and Russia and shedding light on conflicting narratives. The involvement of annotators from different countries ensures a comprehensive and unbiased evaluation.

2. ONE-SIDE, INDIVIDUAL LEVEL BEHAVIOUR ANALYSIS

In the past decade, online social media platforms have become the primary place for protesters worldwide to organize and voice their agenda [AHT18; Dic14; EMP20; Onu15; Met+16; WSS13]. Language preferences as a medium of protest have been extensively studied in protest settings. However, analyzing individual dynamics within multilingual countries during protests remains limited. Most of the research regarding language behaviour report simple aggregated statistics such as the number of messages in the particular language before and after some events [EMP20; Bra19; Etl14]. At the same time, less attention is given to users' analysis and how they changed behaviour throughout the revolution, especially when the language can be viewed as a part of self-identification.

Research Question: In the first work, we aimed to address the following research question: How do individuals on one side of the protests in a single CIS country exhibit language preference behaviour on online social media platforms? Specifically, we analysed the choice between Ukrainian and Russian in Ukraine. Additionally, we aimed to investigate the triggers and motivations behind language shifts among participants. We aimed to understand why some individuals switch their language usage from Ukrainian to Russian and vice versa during protests.

To fill this gap, we study the online behaviour on Facebook during the Euromaidan revolution in Ukraine. Researchers have shown that the Euromaidan revolution was affected by national sentiments and national narratives, which themselves are deeply connected with the national identities of Ukrainians, their language preferences, and support of language policies [Are18; Kul11; Kul19; Met+16; OHS18; ZI20].

The rest of the chapter is organized as follows. Next, we discuss the background (Section 2.1). We then describe the dataset in Section 2.2. Next, we investigate two research questions. In Section 2.3, about *did online activists change users' language usage*? Finally, in Section 2.4 we investigated language behaviour change triggers.

2.1. Background

This paper investigates the online behaviour during the Euromaidan revolution in Ukraine, including several months after the end of the protest. The Euromaidan is well described in the literature [Bra19; OHS18; Zel17; PRR21; Met+16]. Sufficient to say, it was a large grassroots political movement with hundreds of thousands of Ukrainians protesting in Kyiv and other cities across the country. The protest was caused by the President of Ukraine, Viktor Yanukovych, who did not sign an association agreement with the European Union. Instead, he announced that economic ties between Ukraine and Russia would be a priority. A small group of students and young people organized a protest in the center of Kyiv. The police brutally attacked this protest, which mobilized a wide range of social groups to join the protest. New protesters criticized police brutality, the legitimacy of the regime, and the pro-Russian agenda of Viktor Yanukovych. From the very beginning, this protest was significantly affected by social media. With time, in a series of dramatic events, the protest escalated to violent clashes. Hundreds of protesters died. Viktor Yanukovich fled the country to Russia. These events escalated relations between Ukraine and Russia, resulting in the annexation of Crimea and the beginning of war in Donbas.

Researches have shown that Euromaidan led to the decline in support for a close relationship with Russia. In addition, it led to an increase in the proportion of people thinking of Ukraine as their homeland [PR18b]. Other researchers also show that the number of Ukrainians who became proud of their citizenship increased after Euromaidan [Gol+20], and that there was a shift towards national identity consolidation across different social groups and regions [Kul19]. At the same time, the same research has shown that Ukrainians are more likely to shift attitudes to reflect their identities rather than modify their identities [PR18b; PR18a]. This observation is complemented by the fact that average ethnic identities and language practices of Ukrainians changed little after the Euromaidan [PR18b]. This set of findings is essential for our study for two reasons. First, Euromaidan was fundamentally tied with national identities and attitudes. At the same time, these studies show that the identities of Ukrainians were not likely to be induced by online mobilization. In contrast, it was more likely that Ukrainians were using online platforms to express their prior political beliefs.

Although some scholars expected to find an increased "ethnic mobilization" and increased shares of the Ukrainian language on Twitter, they discovered the opposite [Met+16]. They saw an increase in the proportion of the Russian language after the end of the Euromaidan. Similar findings were suggested by Etling, who showed more support for the Euromaidan protests in Russian-language sources than he initially expected [Etl14]. A possible explanation was suggested that Ukrainians used the Russian language strategically (perhaps to target relevant audiences)[Met+16]. Other researchers suggested that the narrative of Twitter posts changed with time. It changed from describing the Euromaidan as a peaceful movement to existential danger to the Russophone population [LM18]. This change of the narrative was likely to be one of the driving forces of the growing proportions of the Russian language. Studies of other platforms beyond Twitter were scarce. A study by Surzhko-Harned and Zahuranec utilized only 1107 posts on Facebook and showed that the protest conceptualized their movement in terms of domestic issues and an anti-regime revolution rather than a geopolitical crossroad between the EU and Russia [SZ17]. Dickinson theorized that Facebook was used for logistics of the protests [Dic14], and Onuch used surveys to confirm that online social media, including Facebook, were used to recruit participants

[Onu15].

Overall, computational studies indicate a general surprise among the international researchers that the proportion of the Russian language online did not diminish with time. In fact, the opposite was observed. At the same time, scholars of the history and politics of Ukraine were not so surprised because they knew for a long time that Ukrainians from different regions use both languages circumstantially (at work or at home) [Are18]. This scholarship indicates that Ukrainian identities do not necessarily correlate with language behaviour, meaning that Ukrainian patriots can express their ideas in both Russian and Ukrainian.

The debate about how Ukrainian users used language during the protest online is still inconclusive. For example, Metzger et al. [Met+16] state explicitly in their paper that: *"... it is also important to move beyond the aggregate level data to consider within-subject variation. This will allow us to look at how specific users change their behaviour over time and to consider alternative explanations for aggregate trend... "* (p. 51). To this date, all empirical knowledge about Euromaidan and online language behaviour is based on aggregated data. Therefore, we still do not know the extent to which users modified their preferences and changed language behaviour with time.

In general, studies of online communications suggest that online platforms can influence changes in individual identities [PYC09; Kla14], cultural taste [Lew+08], and voting attendance [Bak+12; Bon+12]. Moreover, political science theory suggests that online platforms provide unique (and otherwise absent) information about the quality of governments to people, thus increasing the likelihood chances of a person to change their behaviour and join the protest with time [Edm13; Lit16]. In addition to this, online platforms are effective to coordinate people logistically [EMP20; BS12] and engage them emotionally [Jos+18]. Drawing from this scholarship, one can assume that social media should have affected individual behaviour during the Euromaidan. However, the exact influence is yet to be tested. Some scholars would suggest that online users should have increased their personal usage of Ukrainian because the Ukrainian language significantly correlated with a positive evaluation of Euromaidan [Bra19]. Other scholars would suggest that individual language preferences should be volatile because they are affected by circumstances and strategic situations [Met+16]. In what follows, we will test these competing ideas using the longitudinal data of Facebook activists.

2.2. Dataset Description

We collected a dataset from the Facebook group called *EuroMaydan* using the Netvizz application [Rie13] in June 2014.

We select the Facebook platform because it is one of the most popular social networking sites in Ukraine with over 3 million active users by 13 October 2013

[1]. Facebook groups provide a place to connect people with common interests. In groups, the users can share their thoughts and discuss the posts of other participants. The groups are managed by admins or moderators that have superior rights compared to a general group member. For example, admins can restrict the users' rights to make posts in the groups, so the members can only make comments to the posts. This is also the case of *EuroMaydan* group, where the users have such restrictions, while only the admins or group moderators are allowed to make the posts and, as a result, shape the group agenda. There is also a difference in the set of rights between the admin and the moderator however, this is not important for our analysis.

Next, we briefly discuss the difference between two main communication entities in Facebook groups: posts and comments. The main difference between posts and comments is that a post is a message to the group that starts a new thread (or discussion) in a group timeline, while a comment is a response to the post. In what follows, we switch to a more detailed analysis of our dataset.

EuroMaydan group was created on 21 November 2013 and was the largest group dedicated to the protest. The dataset we scraped included 26,631 posts and 1,470,593 comments left by 124,790 users from 22 November 2013 until 31 May 2014. Table 1 shows a more detailed metadata for it. The dataset is fully anonymised and does not contain any information about a users' age, gender, place of living, list of friends, etc. However, the metadata contains users' unique (anonymised) identifiers, which helped differentiate the users, but not the users' real identities. Thus, our analysis and the findings being reported do not violate the privacy of the users.

Column	**Description**
post_id	unique identifier of the post
post_by	unique identifier of the user who published the post
post_text	text of the post
post_published	date when the post was published
comment_id	unique identifier of the comment
comment_by	unique identifier of the user who published the comment
comment_text	text of the comment
comment_published	date & time when the comment was published

Table 1: Metadata

2.3. Did online activists change users' language usage?

In Ukraine, most of the population can speak two languages: Russian and Ukrainian. Ukrainian language [2] is the official language in Ukraine and the predominant one

[1] https://en.wikipedia.org/wiki/Internet_in_Ukraine
[2] https://en.wikipedia.org/wiki/Ukrainian_language

(67.53% of population consider it as a native) [3]. Russian is second most spoken language and is the dominant language in large cities in the eastern and southern parts of the country [BM08]. Sometimes, people switch their preferred languages to match another person's language. For example, students in the university can speak with professors in Ukrainian (the official language) but with their friends in Russian. Another example could be that an individual use the Ukrainian language with friends but Russian at home with family. As we discussed in the previous sections, some researchers suggested that online users were likely to change their language patterns because they were mobilized by crucial political events. Others suggested that users were more likely to change because after the end of the revolution they were exposed to various strategic situations (e.g., they had to argue with Russian speakers in the Russian language or to target international audiences). In this section, we analyze the usage of the the Ukrainian and Russian languages in comments by the users. Following previous scholarship, we analyze trends before and after the end of the Euromaidan and the annexation of Crimea by the Russian Federation [Met+16][4]

2.3.1. Language classification

Our analysis starts with an explanation of how we classify the language of comments because it is one of the pillars of our research question. We first preprocess raw texts of comments using a standard text preprocessing pipeline: lowercase the text, remove punctuation, URLs, and numbers. Then to identify the language of the comment, we use a text language classification model from FastText[5]. To verify the language prediction performance of the FastText model, we calculate the model's accuracy on a sample of 2000 random comments from our dataset. We manually label each of the comments from the sample and then compare the label with the models' prediction. It turns out that the accuracy is 96% for the language classification task, which we consider to be a good indicator of reliable results, and thus we continue our analysis.

We then predict the language of the comment for the rest of the sample. Based on the language prediction, out of all the comments, 59% of them are in Russian, 31% in Ukrainian, and 10% are comments in other languages. We then exclude comments in languages other than Russian and Ukrainian due to their marginal presences, besides they are beyond the scope of our research question.

Then, we sort comments by the *comment_published*. We then aggregate the language of the comment on the level of user. In such a way, we receive a list of values for each user: 'Russian' or 'Ukrainian' (for example, ['Russian', 'Ukrainian', 'Russian', 'Russian', ..., , 'Ukrainian'] for a user with id '1'). Finally, we map these values to binary: 'Russian' to 0 and 'Ukrainian' to 1, assum-

[3] https://en.wikipedia.org/wiki/Languages_of_Ukraine
[4] https://en.wikipedia.org/wiki/2014_Ukrainian_revolution
[5] https://fasttext.cc/

ing that the comment in the Ukrainian language was a success (positive outcome) and comment in the Russian was a failure (negative outcome) in our sample. In addition, we used alternative mapping depending on our research question, where the Ukrainian was a failure (negative outcome) and the Russian was a success (positive outcome). A more detailed explanation is in the following section.

2.3.2. Identifying language change behaviour

To evaluate how many online activists change their language patterns, we count how often they posted in the Russian and the Ukrainian languages. Then, for each user, we performed statistical test for proportions based on normal *T-test* to compare individual proportions of each of the languages before and after the end of the Euromaidan. The T-test is suitable for comparing proportions when dealing with two groups due to its effectiveness with small to moderate sample sizes and its ability to approximate normality even with non-normally distributed data. This makes it a useful choice for hypothesis testing involving proportions. Unlike other approaches, such as chi-squared tests, which are better suited for categorical data with multiple groups, the t-test is specifically tailored for comparing proportions between two groups. This makes it a focused and appropriate tool for analyzing inequalities of proportions in a simplified manner. More, precisely the null hypothesis is $P1$ - $P2 \geq 0$, and the alternative hypothesis is $P1$ - $P2 < 0$, where $P1$ is the proportion of the comments in the Ukrainian language before the end of the revolution and $P2$ is also a proportion of comments in Ukrainian language but after the revolution. In the same manner, we also compare the proportions of Russian comments before and after the end of Euromaidan. We select one-sided hypotheses over two-sided because we are precisely interested in whether the users started to use a particular language more frequently, rather than checking whether there has been any change or not. This statistical approach requires a sufficient number of comments per user. Otherwise, the analysis can be harmed by spurious effects due to a lack of data. As Figure 1 shows that most of the users in our dataset are not active and commented only a few times. More precisely, the mean number of comments per user is 12, while the second (median) and third quartile are 2 and 7, respectively. Therefore, to select only relevant users that can provide us reliable results, we apply a *threshold* by the number of their comments. We define the users who have commented for at least *threshold* number of times as *active users*. To find this *threshold* by the number of comments, we follow the suggestion from Agresti and Franklin [AF07]. The authors propose a rule of thumb for its minimum sample size: at least ten successes and ten failures in each sample. In our case, it means that the user should have at least ten comments in the Russian language and ten comments in the Ukrainian language in one sample (before the split date) and another (after the split date).

Robustness check: . We run robustness checks to make sure that our findings are stable across different thresholds. To this end, we marginally increase our

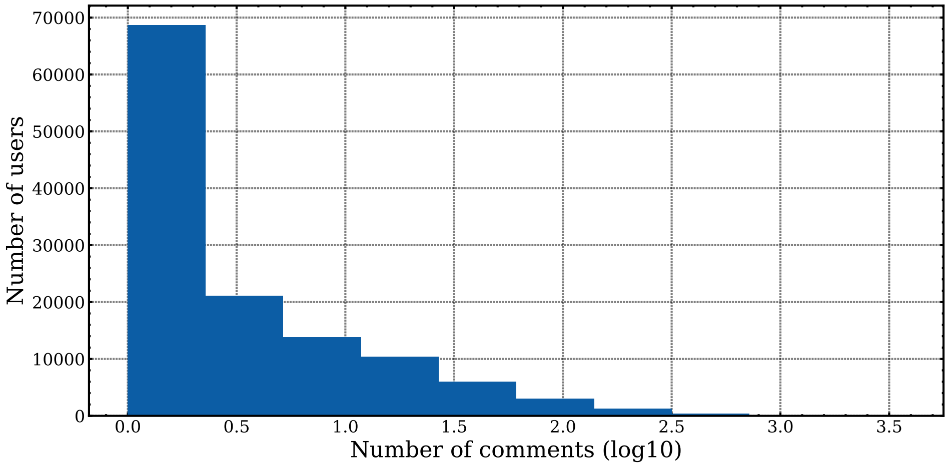


Figure 1: Histogram of the number of comments per user

requirement to the minimal sample size in several steps. Firstly, we select those users with ten comments in the Russian and ten comments in the Ukrainian language (as suggested above) before and after the split date (22 February 2014, the end of Euromaidan). This resulted in 557 users. In addition, we also try a higher threshold: 15 comments in the Russian and 15 comments in the Ukrainian, which resulted in 337 users. Furthermore, we vary our split date, which initially indicates the end of the protest. We repeat our analysis with the split date of one month after (marked as + 1 month) and two months after (marked as + 2 months) the Euromaidan. We do not select the earlier date because we don't have a lot of data one month before the Euromaidan, as our dataset includes comments from roughly the end of November 2013. As a part of the sanity check that our approach is correct, we expect to observe:

1. The higher *threshold* should not significantly alter the proportion of rejections of the null hypothesis.
2. The number of rejections of the null hypotheses should be lower if we choose either one month or two months after the date of the Euromaidan revolution as a split date. This is because the end of Euromaidan, as we assumed, should be one of the most influential events toward Ukrainian self-identification during the period we analyzed. Thus, this should be the date when most people start to change their behaviour in one way or another. Otherwise, we can expect no significant difference between the split dates if the Euromaidan hasn't altered the users' language preferences.

Findings: . We calculate the number of rejections of the null hypothesis for each of the active user, depending on the threshold and the split date. In all the cases, we use a significance level of 0.05. The results for the Russian and the Ukrainian languages can be found in Table 2 and 3, respectively.

We can observe that there is statistical evidence in the change of the language

	Date split		
Threshold	**End of Euromaidan**	**+ 1 month**	**+ 2 months**
10 comments	46%	27%	26%
15 comments	52%	33%	28%

Table 2: Percentage of the active users who started using the **Russian** language more often after the split date

	Date split		
Threshold	**End of Euromaidan**	**+ 1 month**	**+ 2 months**
10 comments	4%	6%	7%
15 comments	2%	6%	4%

Table 3: Percentage of the active users who started using the **Ukrainian** language more often after the split date

behaviour for the *active users* and it passed our robustness check as expected. In addition, it differs for each language. Approximately half of the active users started to use the Russian language more after the end of Euromaidan, while only 4% of active users started to prefer the Ukrainian language more.

In this section, we propose some possible explanations to what we have observed in Section 2.3. We cannot test these hypotheses directly due to the limitations of our data, and we cannot analyze the social and psychological traits of the users since we do not have access to this information (see Section 2.4.4). Nevertheless, we propose several explanations for this behaviour based on the available data of posts and comments in the dataset.

2.4. Language behaviour change triggers

In this section, we propose some possible explanations to what we have observed in Section 2.3. We cannot test these hypotheses directly due to the limitations of our data, and we cannot analyze the social and psychological traits of the users since we do not have access to this information. Nevertheless, we propose several explanations for this behaviour based on the available data of posts and comments in the dataset.

2.4.1. Global influence: link between language preferences in group and language behaviour of active users

First of all, we analyze whether the composition of the group has any effect on language preference. We focus on the Russian language in this part of the analysis because, for this language, we have found strong evidence that there was a change, as approximately half of the *active users* started to use the Russian language more often.

One can think of two alternative scenarios. First, the Facebook group is stable. There are no new users. Therefore, any prevalence of the Russian language can be explained by the behaviour of "veteran users" who prefer to stick to this language. Second, alternatively, it could be the case that the Facebook group is dynamic, and many new users join with time. If these new users prefer to speak Russian, it is likely that they will drive the overall language behaviour. In what follows, we try to analyze this composition effect of old and new users, which we refer as **Global influence**. This mechanism works in a twofold manner. First, when the Russian language dominates, than users receive a clue that there is a respective social norm, and they follow this norm [Kul19]. Second, some users might use the Russian language strategically in order to engage with meaningful conversations and spread their ideas [Met+16]. We cannot disentangle these mechanisms due to the limitation of our data, but at least we can observe the influence of the overall composition effect.

Figure 2 shows the patterns of using the Russian and the Ukrainian languages went hand in hand before February 2014 (the month in which Euromaidan ended). Then, the number of Russian comments increased, especially after March 2014. Figure 3 shows the influx of new users (we define new users as users who made their first comment on a given date) as one possible explanation of this behaviour. The influx of new users clearly coincided with the end of the Euromaidan. Therefore, we can assume that the growing personal preference to use Russian language coincided with the increase of new users.

Some of these new users were likely to be people who joined the Facebook group after the end of the protest to follow the political news. Previous studies showed that most Ukrainian activists were invited to join the protest by their friends and social ties instead of political parties or some other formal organizations [Onu15a; Onu15b]. At the same time it also could be that some of the users which we call "new" were present on the page silently (reading but not commenting). Research on political activism shows that people use social media for logistics of the protest [EMP20]. Therefore, one could reasonably assume that some Ukrainian activists were engaged in reading and passing information during the protest without talking in the comment section. This kind of behavior was observed during Euromaidan [Dic14]. Although we cannot quantify all these groups, it is still evident that the very composition of the group correlated with the personal usage of the Russian language. More than a half of *active users* decided to use the Russian language more often after the end of the Euromaidan, precisely when the influx of new users happened. This finding indicates that online language behaviour is likely to be affected by the very structure of online communication (and not only personal preferences or national sentiments).

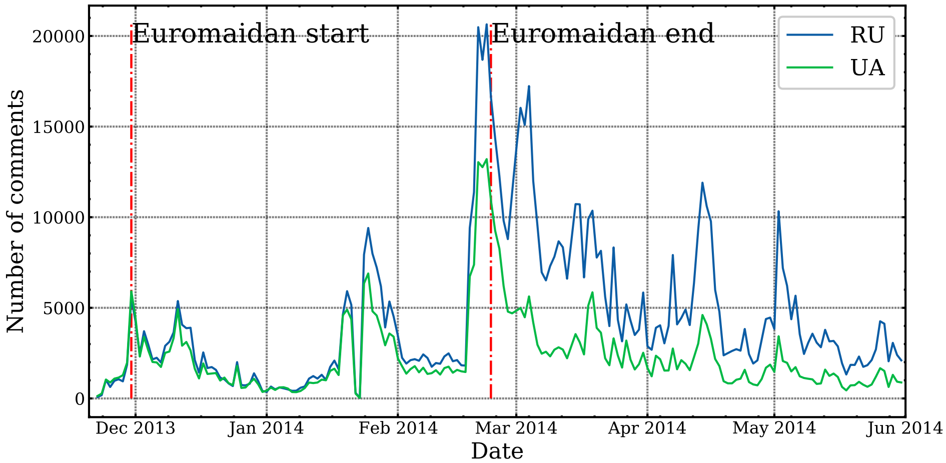


Figure 2: Comments in the Russian (RU) and the Ukrainian (UA) languages

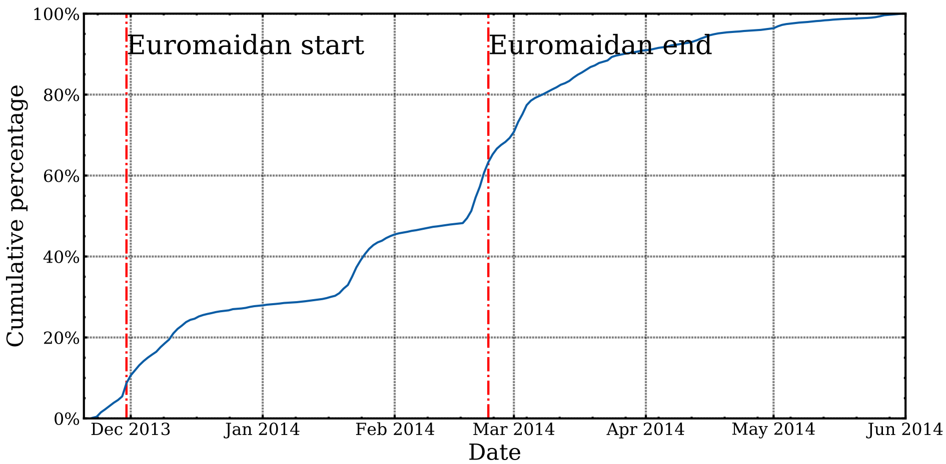


Figure 3: The influx of new users

2.4.2. Local influence: link between post language and comment language

Another reason for the more frequent usage of the Russian language could be that the administrators of the page increased the number of posts in Russian, thus provoking conversations in Russian. Our previous analysis was concerned with comments, while for this analysis we replicate the same data preprocessing and model evaluation for posts as in Section 2.3. Our data shows similar performance results.

Figure 5 shows that, indeed, the percentage of Ukrainian posts dropped down after the end of the Euromaidan from almost 100% to roughly 60 - 70%, meaning that for some reason, administrators or moderators decided to post in the Russian language much more frequently. Another support of this hypothesis is in Figure 4

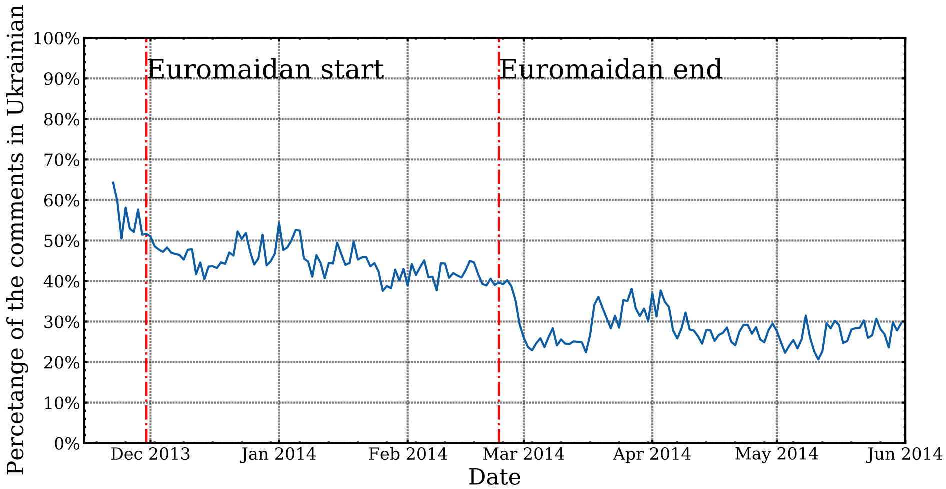


Figure 4: Average of the fractions of the comments in the Ukrainian language per post

that shows a declining trend of the fraction of comments in the Ukrainian language per post from roughly 50% to 30%. In other words, it shows the prevalence of the Russian language not only on a global level as was noticed before, but also all the posts were affected by that, so it had an effect on the local level.

At the same time, we do not find evidence that the post language correlates with the language of the comment. Firstly, we check the Pearson's correlation coefficient for the general population of users between the post language and the comment language. The correlation coefficient is 0.15, which does not indicate a strong relationship, showing that users who leave comments do not mind the language of the post. Then we check the same value but for the two separate samples: comments and posts before the end of Euromaidan and after. The coefficients are 0.05 and 0.12, respectively, which again do not show any strong evidence of the possible correlation. Finally, we test the same hypotheses on the sample of the *active users* (with a threshold of 10 for both Russian and Ukrainian comments). It turns out that in this case, the Pearson correlation coefficient is 0.16 for the whole period. Before and after the split date, the coefficients are 0.06 and 0.15 respectively.

Therefore, we conclude that the language preferences of the *active users* and the general population of users in our dataset cannot be easily nudged or affected by the language of posts. This finding is in line with surveys that showed that Ukrainians were not likely to modify their prior preferences [PR18].

2.4.3. Language 'loyalty'

Finally, in the last part of our analysis, we concentrate on the following question: why do we observe the significant increase of the usage of the Russian language but not for the Ukrainian language? To investigate this question and provide a

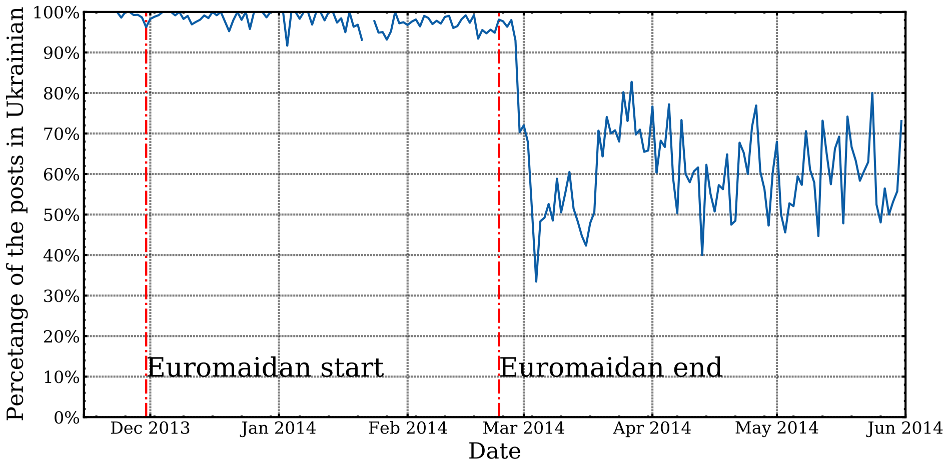


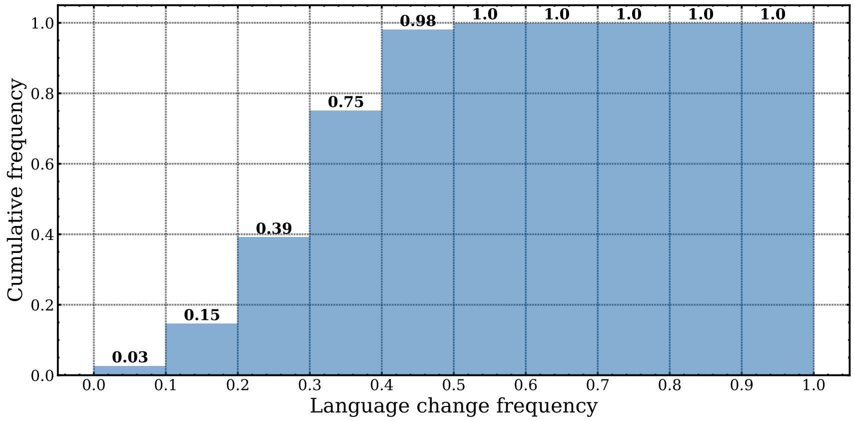
Figure 5: Percentage of the posts in the Ukrainian language

possible explanation, we look closer at the patterns of the language switches and compare how often the *active users* (with threshold 10) switch from the Russian to the Ukrainian language and vice versa. At the same time, we analyze users that use one language much more frequently than another, and we call them as *loyal users* to their preferred language. Here, we define *loyal users* as users who used a particular language in at least 80% of all their comments. We also tried different thresholds (from 60% to 90% and received similar results, so we just report results only for the threshold equal to 80%). This results in approximately 16% the Ukrainian *loyal users* and 10% the Russian *loyal users*, out of the total users, selected as *active users*.

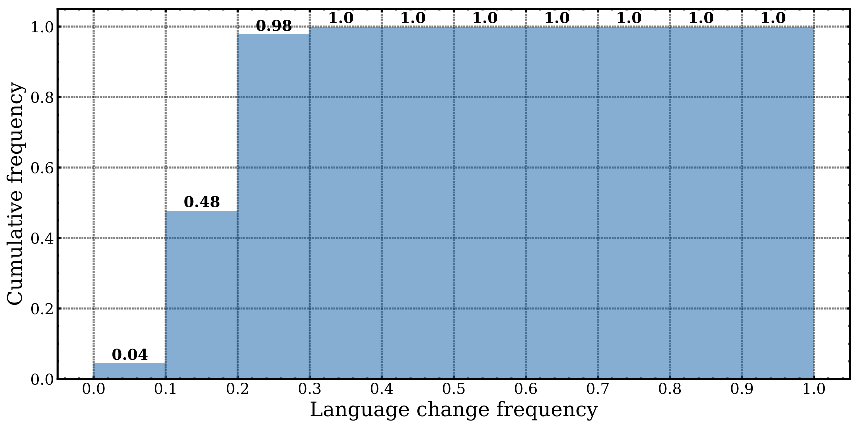
Our first step is to reorganize the language vectors for each user in the following way. If the next language of the comment (ordered by time) is the same as the language of the current one, we put 0 (failure), otherwise 1 (success). After that, we analyze the normalized frequencies of such changes and the lengths of the longest sequences without switches.

Then we analyze how frequently the users switch from one language into another. The comparison between the Russian and the Ukrainian *loyal users* is presented in Figure 6 (a) and (b). These figures show a remarkable difference between the Russian *loyal users* and Ukrainian *loyal users*. Russian *loyal users* almost do not change their language behaviour in 72% of comments, whereas Ukrainian *loyal users* almost do not change their behaviour in only 18% comments. To put it simply, the Ukrainian *loyal users* are more flexible. They use the Ukrainian language once, and then they change it to Russian, and then they go back to Ukrainian, and so on.

These findings again well matched with what we have observed in Sections 4.2 and 5.1. It seems that the influx of new users who commented in the Russian language incentivized those users who initially preferred the Ukrainian to start using the Russian on many occasions. Thus, the Ukrainian *loyal users* had to use



(a)



(b)

Figure 6: Cumulative language change frequency for the Russian (a) and the Ukrainian (b) loyal users

the Russian more often after the end of the Euromaidan.

Summary: . In this section we investigate the possible explanations of why:

1. Users' language behaviour changed (as they started to use the Russian language more than they used before)
2. Why is the proportion of people who started to use the Russian language significantly different from those who started to use the Ukrainian language?

We showed that the general population of users started to use the Russian language more frequently. In addition, right after the Euromaidan revolution, there was an influx of new users who brought the Russian language with them. Additionally, the moderators started to use the Russian language more often in their posts.

However, we didn't find a strong relationship between the language of the post and the comment for the users we analyzed. We found that users who mostly prefer the Ukrainian language switch between the Russian and Ukrainian languages more often. In contrast, users who prefer Russian switch to Ukrainian more rarely. Therefore, we conclude that most of the language change can be attributed to "undecided" flexible Ukrainian speakers who switch from one language to another occasionally depending on the context. These findings are in line with the hypothesis from the literature that Ukrainian activists use language strategically (i.e., to respond to Russian comments) instead of being mobilized ethnically or nationally [Met+16].

2.4.4. Limitations

Although our research is the first to present individual changes in language behaviour during the Euromaidan protest, it still has some limitations. First, we acknowledge that our data are from a single Facebook page. Other researchers investigated many Twitter users or regional platforms [Met+16; Bon+12]. Nevertheless, we chose this group because it was the largest Facebook page which was the most popular among political activists. Therefore, all trends are salient and pronounced there. Not to mention that it provides a significant number of observations. Second, our dataset does not allow us to disentangle all nuanced social and psychological mechanisms that drive human behaviour. Nevertheless, our data analysis sheds new light on individual-level trajectories of online users.

3. ONE-SIDE, COLLECTIVE LEVEL BEHAVIOUR ANALYSIS

In the previous chapter, we analyzed shifts in language preferences for active users as a result of protests. In this chapter, we performed a collective-level behaviour analysis exhibited by one side of the conflict using data collected during the anti-government protests in Belarus. These protests, occurring in 2020, marked a crucial period where online activism played a central role in mobilizing and coordinating the actions of protesters worldwide. Amidst the various social media platforms, Telegram emerged as a prominent communication platform, offering distinct mediums of interaction such as channels, groups, and local chats. Despite the extensive research focused on employing social media for activist purposes, the specific role and impact of Telegram and, in particular, the contribution of each Telegram communication medium, such as channels, groups and local chats throughout these protests, have remained relatively unexplored. This study focuses on the analysis of those communication mediums to determine what role each of these mediums played during the protest events and how mediums they responded to them.

Research Question: Taking this gap into account, in this chapter we investigated *Does user activity differ across Telegram's diverse communication mediums—namely channels, groups, and local chats—during the anti-government protests in Belarus in 2020, and if so, how?*

To understand the differences among the three mediums, we analyzed the number of daily messages posted in each medium (see Section 3.3). We identified the top five spikes in each medium and correlated them with external offline events using information from Wikipedia and news sources like BBC, DW, and others. To explore the topics users discussed in each medium, we conducted a three-stage analysis (see Section 3.4). Firstly, we analyzed the most frequent words in each medium using WordClouds. Secondly, we employed Latent Dirichlet Allocation (LDA) to extract and compare topics among the mediums. We examined topics extracted for the entire data period and also identified significant topics overlapping during the spikes of activity. Next, we investigated whether users' communication varied in different mediums (see Section 3.5). We trained a classifier using TF-IDF and n-grams to predict the medium based on a given text input to achieve this. We utilized logistic regression for classification and performed an error analysis and feature importance assessment.

3.1. Background

Online activism or cyber activism has been widely studied in the scholarship, especially with regards to Twitter and Facebook [SG14]. This activism extends across various topics including but not limited to *#metoo* movement [GS20], education movements, [SAV15], environmental movements [BMC15], and global policy-based activism [Poe14]. A lot of anti-government protests worldwide used online platforms as well [Jos+18; The+15]. The most telling examples are Arab Spring in the Middle East and North Africa in 2010s [AHT18; Ste+15], Russian protests against electoral frauds in 2011 [EMP20], the Euromaidan Revolution in Ukraine [Met+16; Onu15a]. Some researchers used surveys to analyze how protesters used social media. For example, in Ukraine, a survey of students in Kyiv and Lviv showed that YouTube, VKontakte, Twitter, and Facebook assisted the students with the protests [PR15]. Other surveys conducted in Ukraine showed that protesters were invited by their friends and social ties (including online) rather than by parties, NGOs, or other formal organizations [Onu15a; Onu15b]. Similarly, a survey of participants in Egypt's Tahrir Square showed that social media played an impactful role in the protests by engaging users in information diffusion [TW12]. Other researchers analyzed the content of hashtags or posts and also pointed out that online social media were crucial during the protests [Jos+18]. For example, in [Sin21], researchers have analyzed the Twitter users network in Thailand. They observed an increase in the ties between them associated with the goal of taking the protests forward. Similar findings were observed in Turkey during the Taksim square protests[SMA15]. Researchers in [EMP20] used instrumental variables techniques to show a causal link between penetration of Vkontakte, online coordination, and the likelihood of protests in Russia.

3.1.1. The role of Telegram in protests

The platform Telegram recently gained attention in the research community. Researchers [UHK20] analyzed the role of Telegram during protests in Hong Kong in 2019. They found that Telegram became popular among social activists and that it was mostly used by protesters to distribute information. At the same time, it was used to discuss future actions and coordination. However, they blend both channels and group messages in their analysis. In [SCP22], the authors also examined protests in Hong Kong by analyzing the messages from a public channel through different forms of participatory activity. [AG19] analyzed the role of the platform during the protests in Iran and how the government demanded information and private messages from Pavel Durov. Last but not least, [Sch+22] performed a quantitative study about radicalization dynamics in Telegram during COVID-19 protests in Germany, where authors analyzed the contest of nine Telegram channels.

3.1.2. Protests in Belarus

There have been several works covering protests in Belarus, which happened in 2011 [Kar13], 2017 [Han17], 2020 [BK20], [MN21]. Most of these works have not included social media analysis. For example, researchers in [Kar13] performed a comparative analysis of the protests covered by pro and anti-governmental news articles. In [Han17], using the interviews with protesters, observers and opposition leaders, the author proposes that the very nature of how the city area is organized has an influence on the protest. He argues that the city centre does not have a preferable symbolic value to the opposition while also being avoided by the public. Recently, a study of protests in Belarus showed that pre-existing social networks significantly increased the likelihood of protests during the elections on August 9 to 15 [Mat22]. The recent protests, which began in August 2020, have also attracted various studies. However, most of them have a rather sociological and historical vision of the protest. For example, in [BK20], authors discussed historical reasons and social aspects of the protests. Similarly, authors in [MN21] discussed reasons for the protests and possible outcomes. More recent studies analyzed the reasons for the actual outcome of the protests in Belarus 2022 [Mud21], [Rob22]. Several research articles provided quantitative analysis, such as [Nik22], where the author studied the role of emotions in shaping mass mobilization. The closest research to our paper [Her+20] analyzed the protests in Telegram during the Belarus protests in 2020, but they investigated only the role of local chats and did not differentiate the role of different mediums on the protests in Belarus. Moreover, we found only one policy paper that addressed online activism during the protests in Minsk [She20]. In contrast to the previous studies, which investigated one specific medium, our paper is aimed to understand the different characteristics of channels, groups and local chats during the protests in Belarus and compare them.

3.2. Dataset Description

For our analysis we collect a set of messages from Telegram messenger[1] using official Telegram API [2] with a help of Python package Telethon[3]. Telegram has different message communication tools between users, namely *channels*, *groups* and *location based chats* (*local chats)*. Channels and groups share many features, but the main difference is that in channels, there is one to many broadcasting (for example, from a channel creator or admins and moderators to the subscribers, but not vice versa). In groups, the subscribers are allowed to post messages in the news feed. Finally, local chats are designed for small-sized communities that share a specific location. Anyone close to the chat location can find these local chats using a nearby search, without knowing the exact group name or group id to search for it.

Our analysis is based on the data from a set of local chats located all across Belarus, large Belarusian groups without a specific location and active Belarusian news channels. We use a partial set of local chats listed here[4], which was created

[1] `https://telegram.org`
[2] `https://core.telegram.org/`
[3] `https://docs.telethon.dev/en/latest/`
[4] `https://dze.chat`

by activists. We use the word partial because some of the chats are private, so we could not scrape the information from them. Other chats changed their identifiers, so we would not find them using a direct search by chat id. The primal motivation of this map is to share the information about the local chats and encourage people to join them, discuss and share different information between each other.

All the data we collect for this work is from public mediums, which means it is either channel, group or local chat. If the medium is public, it means that anyone can join and read the content of that medium. We didn't scrape any messages or other information if the medium was private. Before analyzing the data, we anonymized all users IDs by assigning random but unique IDs instead of the original one. We also assigned random but unique IDs to each medium. Thus, our analysis and the results we report, do not harm the privacy of the users.

In total, we collect 4,482,070 messages from 654 local chats, 36,206 posts from five large channels and 6,061,56 messages from two big groups from the period of 1^{st} May 2020 to the 29^{th} of November 2020. We show channels', groups' and local chats' basic descriptive statistics in Table 4. We define users as the users with at least one comment during the period we analyze. As channels are one-sided medium (only admins or moderators of the channels can post) we don't have users' information for the channels. We observe that the number of posts is larger for the groups than for other mediums because the number of users is much larger. For the same reasons, the average delay per post (the difference in minutes between consecutive messages) is also the smallest for the groups. The average post length (number of characters), is the highest for the channels.

3.3. Users activity in three mediums

This section investigates **RQ 1** (Does the activity of users differ in mediums?) by analyzing user activity in all three mediums. Specifically, we measure user activity in terms of messages appearing in each of the mediums daily. Figure 7 shows the number of messages daily in each of the mediums. There are multiple spikes in each plot, however, we discuss only the five most significant ones. To select top spikes, we first sort the dates by the number of messages. Then we select the top five dates, but with a constraint that the time window between the two highest days should be not less than ten days. We use this constraint because the most active days cluster together and usually correspond to the same or similar events. After that, we match the spikes' dates with the real events using open source information from Wikipedia and online news sources such as BBC [5], DW [6] and other. More precisely, after selecting a date on which we consider spike appearance, we look at the Belarusian news media as a reference to find the event highlighted on the same date. After that, we report this event as the event corresponding to the spike on a given date of the spike.

[5] `https://www.bbc.com/`
[6] `https://www.dw.com/`

	Mean	Std	Min	Median	Max
Channels					
Posts	7,241	2,227	5,687	6,304	11,118
Post length	233	361	1	119	5,709
Delay	43	10	26	47	52
Groups					
Posts	303,078	271,438	111,142	303,078	495,014
Users	17,695	13,073	8,451	17,695	26,939
Post length	102	201	1	52	6,171
Delay	1	1	0	1	2
Local chats					
Posts	6,853	15,665	1	1,062	113,273
Users	431	1,112	1	105	10,847
Post length	105	248	1	46	8,273
Delay	71	51	0	55	212

Table 4: Mediums basic descriptive statistics

3.3.1. Activity patterns in Channels

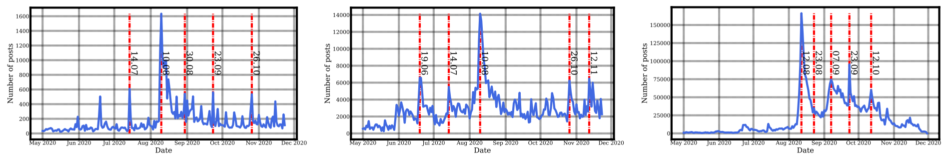
Channels represent top-down communication from an author (admin or moderator) to the audience. Thus, channels are often used as online news feeds. Figure 7 (a) shows the number of messages daily in channels and Table 5 matches the dates of the top five spikes with important events that happened in Belarus on the same date. One can observe that the admins/moderators made a significant number of posts on the dates of some important announcements (1, 2, 4, 5), and some of these announcements were followed by marches or protests (3, 4, 5)

3.3.2. Activity patterns in Groups

Similarly to the channels, Figure 7 (b) shows the number of messages per day in groups and Table 6 highlights the top five spikes in the user activity. Out of five spikes in groups, three of them match with the spikes in channels. We observe two significant pieces of news about severe human rights violations (1, 5) almost ignored by channels and picked up by groups. We can assume that Minsk activists were triggered and invested in human rights issues. They were able to raise this issue in the comments (in groups). However, such discussions were probably missing in channels or less highlighted.

3.3.3. Activity patterns in Local chats

Local chats are designed for individuals connected by some geographical location to exchange messages with each other. Figure 7 (c) shows the number of messages per day in local chats and Table 7 maps the peaks with real events. Interestingly, the activity in local chats is very different from the activity in channels or groups. First of all, compared to other mediums, the top five spikes in local chats might have been triggered by protests or marches (1, 2, 3, 4, 5). In addition, the spike dates do not match the spike dates of other communication tools in almost all cases, except (4), which appears only in channels.



(a) Channels (b) Groups (c) Local chats

Figure 7: Number of posts per day in each medium

Number	Date	Event
1	14^{th} July 2020	Removal of two opposition candidates from the elections.
2	10^{th} August 2020	Lukashenko was announced winner of presidential elections.
3	30^{th} August 2020	Rally against Lukashenko.
4	23^{th} September 2020	State media announced that Lukashenko had been inaugurated. Series of protests.
5	26^{th} October 2020	Lukashenko refused step down from the presidency. Series of protests.

Table 5: Channels' significant events

Number	Date	Event
1	19^{th} June 2020	Lukashenko's announced he had "foiled a coup attempt". Arrest of main opposition rival.
2	14^{th} July 2020	Removal of two opposition candidates from the elections.
3	10^{th} August 2020	Lukashenko was announced winner of presidential elections.
4	26^{th} October 2020	Lukashenko refused step down from the presidency. Series of protests.
5	12^{th} November 2020	Gather to mourn death of protester Raman Bandarenka.

Table 6: Groups' significant events

Number	Date	Event
1	12^{th} August 2020	Protests against government and policy brutality.
2	23^{th} August 2020	Rally against Lukashenko.
3	7^{th} September 2020	Protest against Lukashenko.
4	23^{th} September 2020	State media announced that Lukashenko had been inaugurated. Series of protests.
5	12^{th} October 2020	March of the Seniors.

Table 7: Local chat' significant events

3.3.4. Discussion

As we observe from the analysis of top spikes, the users' activity in each medium is different. On the one hand, the quantity of messages is different. On the other hand, the spikes appear on different days across different mediums. More precisely, we find out that most of the top spikes in channels and groups can be matched with important political announcements. On the contrary, the top spikes in local chats can be matched with major protests or marches. In other words, the issue of protests and human activism could be considered central only for local chats from the very beginning of the political crisis. While previous studies showed that pre-existing social networks are important for future protest activities [Mat22], we also find that active online communication keeps going after protests in August 2020.

To confirm our observations, we extend our analysis to the whole period of data instead of focusing on five data points (with the highest activity). We use a dynamic time wrapping algorithm to find the order of similarity between each pair of communication mediums represented as a time series of the number of comments per day. We use the following steps to calculate similarity between time series. Firstly, to calculate a measure of similarity between each pair of mediums, we align them by the dates on which we have a reported activity for each of the mediums. Next, the dynamic time wrapping algorithm was applied using Manhattan's distance. The results are the following: 1) distance between channels and groups is 5267, 2) distance between groups and local chats is 9304, 3) distance channels and local chats is 20967. This could signify that channels and groups are more aligned in terms of the events that trigger activity, followed by channels and local chats and groups and local chats.

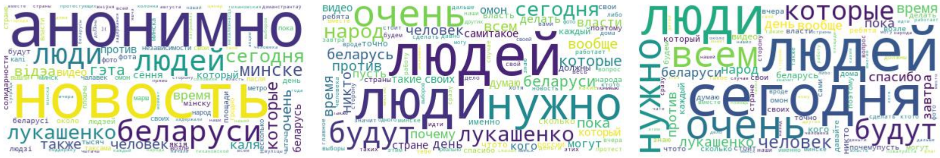
3.4. Topics discussed in three mediums

This section explores **RQ 2:** (What topics do users discuss in each medium?) by analyzing the most frequent words, topics and context of the specific words in each communication tool.

Before diving into each part of the analysis, we describe the preprocessing pipeline we used to clean raw text messages. The pipeline consists of lowercasing the text and removing punctuation and stopwords (English, Russian and Belarusian). After this part, we filter out messages with less than eight words (the median) to leave more meaningful messages. The reason is that most of the messages with less than this threshold, we find as simple and quick replies, for example, "so that am I talking about" or "yes, I agree with you", which can bring more noise than a useful signal to our analysis.

3.4.1. Word clouds

Our analysis starts with comparing the most frequent words in channels, groups and local chats. We plot 100 most frequent words for each medium using WordCloud (see Figure 8 and its translated version in Figure 9). We observe that the most frequent words have lots of overlaps. For example, in all mediums, words such as *Lukashenko*, *Belarus*, *people* are the top ones. A more careful investigation also shows that in channels words such as *news* have similar frequency as *people* and *anonymity*. However, in the local chats other most frequent words are *need*, *today*, *urgent*. This gives us additional evidence that channels were used to inform people of some nationwide events. However, groups and local chats in terms of most frequent words are more similar and both relate to coordination and protest discussion.



(a) Channels (b) Groups (c) Local chats

Figure 8: Word Clouds for each medium

(a) Channels (b) Groups (c) Local chats

Figure 9: Word Clouds for each medium (English translation)

3.4.2. Topic modelling

This part analyzes the topics the users discussed in each communication tool using the topic modelling approach. We use the Latent Dirichlet Allocation (LDA) to find the topics. To select the number of topics, we use the grid search approach by the number of topics (from 1 to 20, with step 2) while finding the number that maximized the Coherence score. We analyze the topics for each medium separately for the whole period of data we collect and call this part of analysis *topic modelling in a global context*. We also analyze topics for each of the top five significant events we find in the previous section, focusing only on the spikes that overlap between any two mediums and call this part of analysis *topic modelling in a local context*.

Topic modelling in a global context. Topic modelling of the whole period of the data period is presented in Table 8 for channels. We present only channels because we do not observe too much variation for the other mediums. Most of the topics we observe can be related to protests, and one can be related to the covid restrictions. We hypothesise that before the active protests, the central topics in Belarus was Covid and Covid restrictions. Afterwards, after the clashes began, the protest activity became dominant and displaced Covid.

Topic modelling in a local context. To perform topic modelling for the specific spike in a given communication tool, we select a day in which a particular spike has occurred and then take all the messages three days before this day and three days after the spike. Table 9 shows the topic modelling per spike for the most active events in channels. Later, Tables 10 and 11 shows the topics and the tokens for the local events in groups and in local chats. We can observe that despite some similarities in the topic, we can clearly observe significant differences that align with our initial hypothesis about the role of different mediums during protests in

Number	Topic	Tokens
1	protests	man, security officer, protest, today, belarusian, get out, time, detain, people, belarus
2	clashes and losses	march, factory, new, grenade, disability, freeze, bot, bntu (university), timelapse, cascade
3	information	bchb (flag), package, special forces, viasna[7], video, win, march, what, on, memes
4	covid restictuions	fashion, fashionable, forever, to be, gas, gomel (city), lockdown, today's march, belaes[8], mask mode (covid restrictions)

Table 8: Global topics (translated from the Russian and Belarusian languages to the English language)

Belarus 2020.

Spike	Number	Topic	Tokens
3*1	1	protest information	person, news, anonymous, offer, people, detain, detention, queue, protest, riot police
	2	protest location	subway, station, coupling, internal, bandit, number, year, beat, hand, close
	3	call for a political choice	choice, necessary, registration, today, headquarters, right, street, want, car, refuse
3*2	1	protest location	uruchye (neighbourhood), house, stone hill, meadow, open, entrance, hospital, room, shooting
	2	arrests	people, this, hand, bahdanovich, from, our cornfields, cornfields, people detained
	3	protest activity	man, people, riot, protest, security officer, report, car, detain, protest, stand
3*4	1	restrictions	girl, media, status, portal, detain, car, person, internet, police, sit
	2	escape	move, urgently, gray, instagram, attack, jay, potato, cruel, run, it
	3	political announcements	inauguration, president, country, student, news, people, news, power, choice
3*5	1	student activism	student, dispersal, bguir, video, photo, bgu, theater, close, grenade, walk
	2	marches	student, strike, man, today, solidarity, march, video, square, protest, column
	3	casual	about, pvt, application, become, this, year, on, tie, time, shrink

Table 9: Channels' events topics (translated from the Russian and Belarusian languages to the English language)

Spike	Number	Topic	Tokens
3*2	1	work	live, plan, power, bot, business, work, very, have, politics, city
	2	protest	know, people, go, protest, think, until, point, become, belarusian, what
	3	political choice	person, choice, necessary, people, say, year, country, can, speak, want
3*3	1	protests	man, people, need, day, very, know, go, protest, now, power
	2	riots	riot, people, country, street, guys, belarus, year, beat, party, truth
	3	revolution attitude	president, military, therefore, violence, channel, thank you, peace, belarusians, everyone, long live belarus
3*4	1	student protests	man, country, know, student, say, speak, power, do, child, due
	2	support	people, want, now, well done, think, can, thank you, live, children, question
	3	protest acitivity	need, people, strike, year, work, go, time, work, factory, watch

Table 10: Groups' events topics (translated from the Russian and Belarusian languages to the English language)

Spike	Number	Topic	Tokens
3*4	1	coordination	now, chat, need, be able, know, work, do, news, year, write
	2	neighbourhood	want, think, photo, city, flag, entrance, group, word, good, neighbor
	3	coordination	man, today, people, very, see, video, go, go out, time, do

Table 11: Local chats' events topics (translated from the Russian and Belarusian languages to the English language)

3.4.3. Contextual difference

Finally, we analyze the context of specific proper nouns such as the names of politicians, famous protesters and particular places, for example, where the significant protests took place. To understand the context of the nouns, we train Word2Vec with a skip-gram model for each medium. The words' embeddings (words' dense representations) generated by Word2Vec with similar contexts tend to lie closer in the embedding space. The cosine distance is frequently used to calculate the distance between the vectors. We use this observation to understand the context of the proper nouns of interest by finding the closest top ten words to

Words	Channels	Groups	Local chats
Lukashenka	quarantine, first, hardly, which, treat, human, full, summer, less, return	win, coming, lose, get out, present, join, shift, shift, weakening, facto	approach, strong, parents, criminal, China, silly, truth, mop, Hitler, wealth
Tikhanovskaya	recognize, result, count, recalculation, deputy, calculation, resignation, early, legitimacy, resolution	Tikhonovsky, Babariko, Tsepkalo, Tikhanovskaya, Kanopatskaya, Tikhanovsky, re-elections, Tikhonovsky, challenger, remaining	Svetlana, Babariko, European Parliament, elected, candidate, Tsepkalo, re-elections, CS, re-election, decisive
covid	tradition, village, spokoino, maximum, tyrant, neighbor, gift, honor, Volodarka, dawn	covid, postpone, fixed, contributor, vaccination, covid, coronavirus, corona, get sick, pcr	psychologist, doctor, university, surprised, in the end, paper, plumber, think, twice, more accurately
Minsk	bring, tikharei, air, uniforms, policemen, paddy wagons, rear, guys, aggressively, drivers	baranovich, column, gallery, Oryol, bangalore, miller, gomel, Kamenka, Rusets, Sukharevo	districts, philharmonic, capital , Oshmyany, columns, Vitebsk , Brest, bus station, sleeping, stele
Tikhonovskiy	mass, European, use, social, general, origin, used, organized, transport, issue	Tikhanovskaya, Tikhanovskaya, Babariko, Tikhanovskaya, withdraw, tenacious, Tikhanovsky, Ermoshin, register, Tikhanovsky	coronation, count, Belarusians, winner, banker, prematurely, nationwide, secret, congratulate, re-elections
constitution	crisis, change, non-recognition, value, strengthen, term, fair, hockey, introduce, violate	constitution, amendment, referendum, constitutional, change, legal, parliament, reform, impeachment, empowerment	reform, amendment, constitutional, change, referendum, constitutional, reform, hasty, substitute, amendments
protest	mobs, payments, peaceful, participant, elemental, protest, flash mobs, join, support, manage	protest, demonstration, marches, resistance, festivities, procession, confrontation, obedient, meeting, actions	failed, demonstration, actions, intimidate, weakening, resistance, Max, peaceful, protest, action
march	grand, thousands, commemorate, Sunday, procession, women's, line up, districts, christ, memory	procession, marches, picket, rally, walk, action, resurrection, demonstration, gathering, Saturday	procession, marches, Sunday, photo report, Saturday, on Sunday, picket, concert, women's, lunch
babariko	race, check, drawing up, ground, judge, conclusion, pre-election, chancellor, cease, investigation	tenacious, tikhanovskaya, tikhonovsky, tikhanovskaya, tikhanovskaya, tikhonovsky, candidate	Tikhanovskaya, Tsepkalo, voice, candidate, Svetlana, CS, fair, recognize, for Tikhanovskaya, amendment

Table 12: Context of specific words

a given proper noun. Then we train the Word2Vec model using gensim[9] package and specify the embedding size equals 100 and a window size equals to five. After the model is trained, we feed specific words (see Table 12, column *Words*). These words we translate to Russian, find top ten words in Russian, and then translate closest ten words back into English for the sake of non-Russian readers. The context of the words is presented in Table 12.

3.4.4. Discussion

We observe that the overlaps in the spikes dates become distinguishable using the topic modelling approach. At the same time, topic modelling confirms our initial hypothesis that separates each of the mediums into announcement related (channels), global coordination (groups) and local coordination (local chats). At the same time, the results obtained after analyzing the global context cannot differentiate these communication tools into specific categories, as most of them intersect in terms of the tokens related to some protest activity and Covid restrictions.

3.5. Predicting mediums

Finally, in **RQ 3** we examine whether it is possible to differentiate a message among different communication mediums. For this, we build a classifier that predicts the type of the medium (channel, group or local chat) from a textual message. Firstly, we filter out the dataset to the messages with at least eight words (median) after the preprocessing (including stopwords removal) to remove noisy signals from the users. That results in 1,588,963 messages in total, with 1,192,794 messages belonging to local chats, 374,344 messages belonging to groups and 21,825

[9] `https://radimrehurek.com/gensim/models/word2vec.html`

to channels. Then, we split randomly our dataset into train and test subsets with a ratio of 80% and 20%, respectively. Because of the significant data imbalance, a stratified split was used to preserve the same ratio of different classes in train and test. For the classification model, we choose logistic regression trained on unigrams and bigrams of TF-IDF features obtained from the preprocessed messages. While building TF-IDF features, we consider only those n-grams that have at least five occurrences in each medium. Given data imbalance problem in our data, we re-weight the same based on the ratio of positives and negatives. We use the "one vs all" approach, where we iteratively train three models for each medium and consider messages from the other two mediums as negative examples.

To understand the models' performance, we use the ROC AUC score and report the metrics in Figure 10. We observe that the highest metrics (ROC AUC = 0.92) we obtain for the channels. At the same time, the ROC AUCs for local chats and groups is somewhat similar, approximately 0.69.

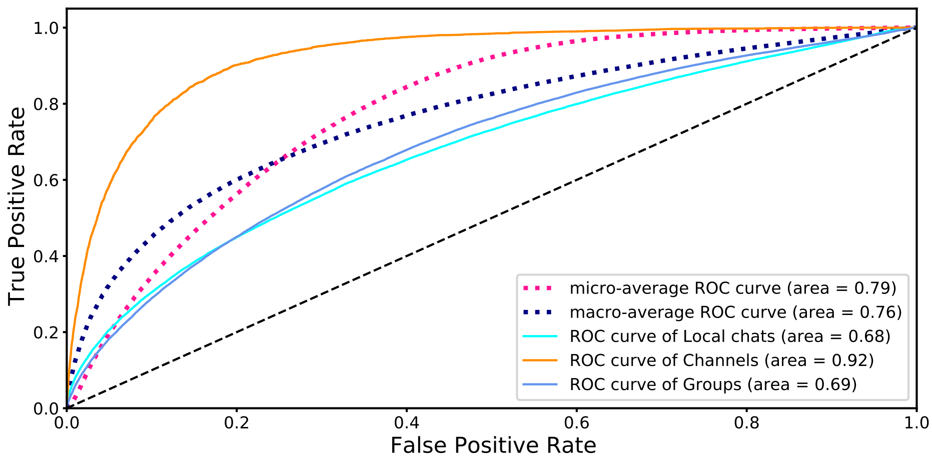


Figure 10: Metrics

As metrics show, the messages from channels are very easily differentiable. This could be because admins in channels use different wording compared to a general Telegram user. At the same time, using simple wording features is not enough to differentiate local chats and groups. However, it again shows a similarity between these two mediums.

3.5.1. Error analysis

We conduct error analysis to understand better which words in a message lead to a better medium type differentiation. We find that distinguishing between local chats and groups is not effectively achieved through TF-IDF, mainly due to the casual language used by users, as indicated in Figure 11. Additionally, the top features for groups and local chats substantially overlap. Furthermore, specific location names rarely appear in the top words, likely because of their infrequent use in everyday conversations, which could otherwise aid in differentiation. In contrast, differentiating channel messages remains relatively straightforward. These messages primarily aim to disseminate information, which can be seen from the dissimilarity in top words compared to other mediums. Consequently, it's evident that relying solely on words isn't sufficient for medium differentiation, especially for groups and local chats.

y=0 top features		**y=1** top features		**y=2** top features	
Weight?	**Feature**	**Weight?**	**Feature**	**Weight?**	**Feature**
+6.460	горячие	+13.564	мкб	+5.508	мкб
+6.387	прислать	+10.458	котаны	+5.118	пп
+5.568	тнб	+8.345	бабарыкі	+5.001	думаю
+5.413	думаю	+7.923	кесулькендня	+4.571	що
+5.130	крыніца	+7.605	лукашэнка	+4.284	понимаю
+4.849	online	+7.342	фоты	+4.064	луки
+4.817	последствие	+7.097	ціханоўскай	+3.992	типа
+4.340	понимаю	+7.089	ціханоўская	+3.941	наогул
+4.310	чате	+6.901	каранавіруса	+3.905	инфа
+4.281	инфа	+6.578	upd	+3.827	лука
+4.067	новость	+6.486	каранавірус	+3.622	смотрю
+3.892	предложить	+6.469	піша	+3.448	ня
+3.866	доброе	+6.464	чытач	+3.443	dissidentby
+3.863	зь	+6.395	цвк	+3.435	подскажите
+3.833	live	+6.380	белта	+3.427	майдана
+3.829	news	+6.300	мінску	+3.383	белоруссии
+3.742	flagshtok	+6.283	ціханоўскую	+3.376	крыніца
+3.608	предлагаю	+6.282	бабарыку	+3.333	elena
+3.533	чаты	+6.256	трёхпроцентного	+3.244	новость
+3.453	чата	+6.214	белаэс	+3.174	ды
+3.350	зубре	+6.000	мзс	+3.135	лулу
+3.273	этаже	+5.960	дэманстранты	+3.123	тады
+3.273	смотрю	+5.934	березино	+3.087	согласен
+3.237	типичная	+5.921	мінска	+3.083	дык
+3.237	согласна	+5.901	лукашэнкі	+3.066	бойкот
+3.174	блин	+5.882	ант	+2.990	тыс
+3.162	ня	+5.875	акрэсціна	+2.967	це
+3.153	походу	+5.854	накопившиеся	+2.967	ви
+3.153	могу	+5.850	лігі	+2.963	блин
+3.135	сельмаш	+5.815	бабарыка	+2.929	жаль
+3.131	админ	+5.808	чытача	+2.924	луку
+3.127	инсайдер	+5.802	сказатб	+2.920	жабка
+3.122	id	+5.800	парада	+2.915	верно
+3.119	личку	+5.739	обнаружен	+2.899	лу
+3.114	подойду	+5.683	расказаў	+2.891	дарэчы
+3.104	согласен	+5.657	сутак	+2.880	мовы
+3.073	познакомиться	+5.624	памёр	+2.865	реально
+3.052	типа	+5.622	напоминаем	+2.845	украинцев
+3.034	подскажите	+5.613	советуем	+2.821	писал
+3.032	вроде	+5.562	скандуюць	+2.810	расеі
+3.020	гуляем	+5.520	паведамляе	+2.808	чате
+2.958	моему	+5.514	мінскі	+2.761	кремлебот

Figure 11: Top TF-IDF features

Local chats	**Channels**	**Groups**
Hot	SHB	IIB
Send	Youotany	TP
NB	Babaruy	I think
I think	Kesulkyendnya	What
Chryntsa	Lukashenko	Understand
Opshe	Photos	To get out
Consequences	Tsikhanousai	Like
I understand	Tsikhanouskaya	Naogul
Chat	Coronavirus	Info
Info	Ira	Here
News	Coronavirus	I'm watching
Suggest	Psha	No
Good	Ch'tach	Szzopebu
See	Cvk	Laugh
Gme	Belt	Maidan
Pez	Minsk	Belarus
Pause	Tsikhanouskaya	Krynts
I suggest	Babarik	Yipa
Chats	Three percent	News
Chat	BelAZ	Smoke
Bison	MZS	Lulu
Floor	Demonstrators	Then
I'm watching	Berezino	I agree
Typical	Minsk	Breath
I agree	Lukashzenka	Boycott
Pancake	Ant	Goose
No	Akrestsna	It's
Apparently	Accumulated	You
Shog	Lep	Pancake
Selmash	Babarika	Al
Admin	Chytacha	Thu
Insider	Say	Hubka
And	Parade	Right
Private	Detected	You
I will approach	He told	By the way
Agree	Sutak	Iov
Get to know each other	Died	Real
"ITA"	Reminds	Ukrainians
Please help	Recommend	Hiss
Apparently	Whisper	Race
We walk	I tell	Chat

Table 13: Translated Feature Importance

4. TWO-SIDE, COLLECTIVE LEVEL BEHAVIOUR ANALYSIS

In this work, we analyzed a two-sided conflict at a collective level, focusing on the behaviours of the two parties involved. The research focuses specifically on the Russo-Ukrainian War throughout the entire year of 2022 using data from Telegram. Our primary objective is to disentangle the dynamics of propaganda and disinformation dissemination that were spread from both factions. Propaganda is a type of communication that aims to influence or manipulate an audience to accept a desired agenda, often by presenting information in a biased or selective manner, using emotional language and techniques, and avoiding objectivity [Can38]. It is frequently linked to partial or deceptive information and can be employed to shape public opinion for self-serving or harmful intentions [Sta15].

Research Question: In particular, we researched the following question: How do propaganda and misinformation occur during the Russo-Ukrainian War, and how can we identify them? To answer this question, we developed a pipeline for detecting events that are likely targets by propaganda or misinformation using messages in social related to the same events from both parties of a conflict. A high-level idea of the pipeline is shown in Figure 12

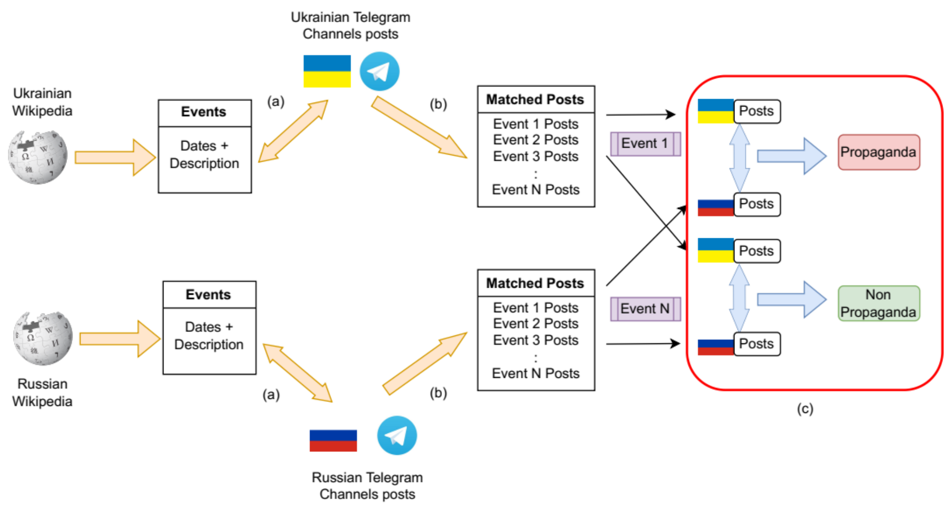


Figure 12: Pipeline: We first filtered events from Russian and Ukrainian Wikipedia pages related to war. Each event consists of dates and description. Using this information, (a) we filtered posts related to each event, which we call as (b) *Matched Posts*. Next, (c) by calculating the similarity score between the Russian and Ukrainian posts, we identify if there exists a propaganda or not.

The rest of the chapter is organized as follows: section 4.2 explains the data collection process of the channel datasets used in the study and the list of external events. In section 4.3, we present a method for assessing the coverage of external events using our Telegram channels dataset and events chronology list. Section 4.4 describes our approach for matching posts to events and identifying related social media posts. Section 4.5 presents our method and results for detecting events targeted by propaganda by finding contradictions between posts of Ukraine and Russia related to the same events.

4.1. Background

Several studies have proposed techniques for detecting propaganda in news items [Vla+19], [Gup+19], [Bar+19]. Such works often employ various AI techniques, ranging from classical machine learning [KKR21] to state-of-the-art NLP techniques, such as embeddings based on words [Ras+21], [Liu+21], the use of transformers [AAO22], as well as on sentence level [Vla+19; CRC19]. Apart from textual-based propaganda detection, there have been works which focused on detecting propaganda techniques in memes [Dim+21]. The state-of-the-art deep-learning-based approaches which are often being employed for propaganda detection could perform very well, but they often lack explainability. To counter it there have been attempts to develop interpretable propaganda detection models, for example for news articles [Yu+21].

It has been observed that sometimes propaganda is latent, often hidden in online content, which appears to be normal [TMM20]. Thus, there have also been efforts to build systems for unmasking propaganda in online news [Bar+19]. Other studies have focused on detecting and classifying online dark visual propaganda [HH19]. Alternatively, in [Liu+21] researchers used attribute-aware word embeddings for depolarizing news articles. Regarding the spreading aspect, there has also been research on understanding the spread of propaganda on social media [Hri+22]. In a similar work, [Cal+20] studied the role of bots specifically for political propaganda on Twitter.

Most of the research around propaganda often involves analysis of only a single language, and that too in English [AAO22]. Some researchers have also explored the use of mixed-code text analysis for detecting propaganda [TMM20] as well as developing cross-lingual propaganda detection models [Wan+20]. There have also been works which have proposed approaches for identifying propaganda in low-resource languages such as in Urdu [KTM20].

Our study differs from previous research by focusing on identifying real-world events that were targeted by propaganda during war times rather than specific messages or other elements of news media. In context of ongoing Russo-Ukrainian war, we specifically study the Telegram messaging platform in original Ukrainian and Russian languages, which are underrepresented in research. We evaluate coverage of external events in our dataset, identify and match social media posts to those events, and compare the posts between Ukraine and Russia to find contradictions and propaganda words. Our framework is aimed to be used on social media platforms to warn people about posts that are likely misleading and targeted by propaganda.

4.2. Dataset Description

Our study involved the collection of posts and metadata from news channels on the Telegram messaging platform that are based in Ukraine and Russia. We focused on Ukraine and Russia only due to the ongoing Russian-Ukrainian war, in which Russia launched a full-scale invasion of Ukraine. By selecting Ukrainian and Russian sources, we aimed to focus on the main players in the conflict and gain insights into their propaganda and misinformation efforts.

Telegram[1] is a cloud-based, cross-platform instant messaging service. A motivation for analyzing Telegram data is that it is the most popular messaging app in both Ukraine and Russia, particularly among the youth [Kos21]. This makes it a valuable source of information for understanding social and political dynamics in these countries. Additionally, a number of studies have shown that Telegram plays a significant role in the spread of information and the shaping of public opinion, particularly in the context of political events and protests [SBS23]. Telegram offers a range of communication tools, including the ability for users to create channels for broadcasting messages to its subscribers.

We collected the data using the official Telegram API[2] and the Telethon[3] Python package. The Telegram API is a set of tools and protocols that allow developers to build applications that can interact with the Telegram platform. Telethon is a Python library for interacting with the Telegram API, which allows developers to easily access and manipulate data from Telegram channels and groups.

We focused on channels of politicians and news media in Ukraine and Russia. We collected two datasets of popular Telegram channels: one focused on Ukrainian channels, and the other focused on Russian channels. These datasets consist of channels belonging to the most popular five politicians and the top five news channels in each country, based on subscribers count as of 1 January 2023. We collected all posts from these channels from 1 February 2022 to 1 January 2023. We used website tgstat[4] to find our channels by different categories and their number of subscribers. Table 14 shows the metadata we collect for each post.

In what follows, we provide a detailed description of the two datasets of Telegram channels collected for this study. In addition, in this section, we also describe a way we collect a list of external events related to the Russo-Ukrainian War.

[1] `https://telegram.org/`

[2] `https://core.telegram.org`

[3] `https://docs.telethon.dev/en/stable/`

[4] `https://tgstat.com/`

Column	Description
post_id	identifier of a post
channel_id	identifier of channel from which post is published
channel_name	channel name from which post is published
post_date	date and time when the post was publish
post_text	text of the post

Table 14: Metadata

4.2.1. Ukrainian dataset

We selected five most popular Telegram channels of politicians (channels with a category "Politics") [5] from Ukraine based on the number of subscribers. As of January 1, 2023, these channels, belonging to well-known politicians, had a total of over 3 million subscribers. The channels are:

1. https://t.me/V_Zelenskiy_official: This channel is run by Ukrainian politician and actor Volodymyr Zelensky, who is known for his role in the television series "Servant of the People" and for being elected as the President of Ukraine in 2019.
2. https://t.me/ASupersharij: This channel is run by Ukrainian journalist Andriy Suprun, and covers news and analysis related to politics, economics, and social issues in Ukraine.
3. https://t.me/Pravda_Gerashchenko: This channel is run by Ukrainian politician and television presenter Iryna Gerashchenko, and covers news and analysis related to politics and current events in Ukraine.
4. https://t.me/vitaliy_klitschko: This channel is run by Ukrainian politician and former professional boxer Vitali Klitschko, who is currently the mayor of Kyiv. The channel covers news and updates related to Klitschko's work as mayor, as well as his views on various issues affecting Ukraine.
5. https://t.me/oleksiihoncharenko: This channel is run by Ukrainian journalist and television presenter Oleksii Honcharenko, and covers news and analysis related to politics and current events in Ukraine.

We then collected five most popular channels that have a Category "News and media" [6]. As of January 1, 2023, these channels had a total of over 5 million subscribers. The channels are:

1. https://t.me/truexanewsua
2. https://t.me/u_now
3. https://t.me/voynareal
4. https://t.me/oko_original

[5] https://uk.tgstat.com/en/tag/ua-politicians
[6] https://uk.tgstat.com/en/news

5. https://t.me/TCH_channel

4.2.2. Russian dataset

Similarly to our approach for the Ukrainian dataset, we collect five channels in Russia of the most popular politicians (based on the subscribers count)[7] and five most popular Russian news channels. The channels of politicians have more than 4 million subscribers as of 1 January 2023 and are the following:

- @RKadyrov_95: This is the official channel of the head of the Chechen Republic, Ramzan Kadyrov.
- @vv_volodin: This is the official channel of the Chairman of the State Duma, Vyacheslav Volodin.
- @MariaVladimirovnaZakharova: This is the official channel of Maria Zakharova, the official representative of the Ministry of Foreign Affairs of the Russian Federation.
- @MedvedevVesti: This is the official channel of the Prime Minister of the Russian Federation, Dmitry Medvedev.
- @pushilindenis: This is the official channel of Denis Pushilin, the Chairman of the People's Council of the self-proclaimed Donetsk People's Republic.

Five most popular news media Telegram channels [8] with more than 5 million subscribers in total, are the following:

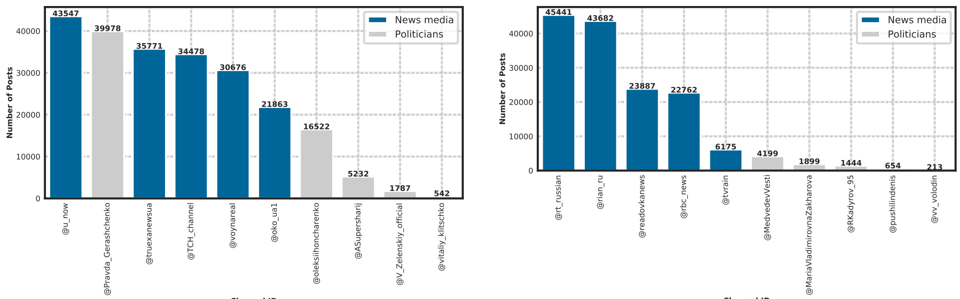
1. https://t.me/rian_ru
2. https://t.me/readovkanews
3. https://t.me/rt_russian
4. https://t.me/tvrain
5. https://t.me/rbc_news

4.2.3. Exploratory data analysis

We collected a total of 380,752 posts from Russian and Ukrainian channels, with 230,396 and 150,356 posts from Ukrainian channels and Russian channels, respectively. Figure 13 shows the contribution of posts per channel. The activity of the channels, as represented by the number of posts per date, is shown in Figure 14 for the combined datasets separately for Ukraine and Russia. As can be seen, most of the contribution comes from news media channels. The most active month for both Ukrainian and Russian channels was March 2022, with 42,527 and 19,300 posts, respectively. This is unsurprising, as it coincides with the escalation of tensions between Russia and Ukraine at the end of February 2022, when Russia began its military aggression against Ukraine. At the same time, the day with the

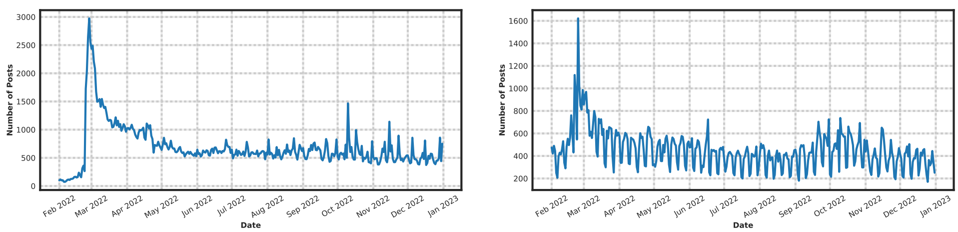
[7] `https://tgstat.ru/en/tag/politicians`
[8] `https://tgstat.ru/en/tag/smi-licensed`

highest number of posts for Ukraine was 27 February 2022, while for Russia 24 February 2022.



(a) (b)

Figure 13: Number of posts per channel in (a) Ukrainian channels and (b) Russian channels and their types



(a) (b)

Figure 14: Post activity in (a) Ukrainian channels and (b) Russian channels

4.2.4. Chronology list with External events

In addition to our collected posts from Telegram, we obtained comprehensive and reliable datasets of external events by referring to the timeline of the 2022 Russian invasion of Ukraine, available in the Russian and Ukrainian languages. More specifically, we collected one chronology list, available in Wikipedia page in Russian language and another one in Ukrainian language [9].

Each list includes detailed descriptions of multiple dates and events that occurred on each of these dates. As of January 1, 2023, there were 233 dates in the Russian version, 21 of which we designated as major dates due to the presence of dedicated Wikipedia pages for the events that happened during this date. These date refer to significant incidents such as the Bucha massacre[10], the Siege of Mar-

[9] https://en.wikipedia.org/wiki/Timeline_of_the_2022_Russian_invasion_of_Ukraine

[10] https://en.wikipedia.org/wiki/Bucha_massacre

iupol[11], the Battle of Kherson[12], etc. Later in the paper, we use the chronology map to match posts from channels to particular events. The Ukrainian version has 281 dates and 23 major dates.

4.2.5. Broader perspective, ethics and competing interests

Our research was conducted according to ethical standards. Specifically, we obtained ethical approval from our university before proceeding with our data collection efforts. Our focus was on collecting data from public Telegram channels freely available to the general public without the need for permission. Importantly, we did not include any private channels in our data collection process. Additionally, we ensured that our dataset did not contain any information about channel subscribers, such as user IDs or other identifiers.

4.3. Coverage

We first perform a quality check on the collected dataset to examine whether the collected dataset covers all the significant events that took place from February 1 2022, to January 1, 2023 (dataset timelines). We employ a metric called coverage, which measures the dataset representation of external (real-world) events.

The main idea of the metrics involves detecting spikes of activity and duration of activity in a dataset, which can serve as a proxy for users' discourse to an event that occurred during spike duration and matching it to the dates of the events from a chronology list. The focus on activity in posts is motivated by previous research showing that external events often trigger increased activity on online social media [MSV21].

More precisely, to calculate the coverage of external events in our collected datasets of Telegram channel posts from Ukraine and Russia, we use a pre-defined chronology of events (defined in section 4.2) with a set of events E and their respective dates D. We identify a set of spikes S in the timeline, with their corresponding duration or timespans T. We define spike as a local maxima by the total number of posts per day between the two nearest days (previous and the next day). We utilised the multiple peak detection technique from signal processing, as we can assume that our timeline of comments is a data in one-dimensinal (1D) vector, where each day gives the number of posts per day. For timespan detection we utilised an algorithm for peak width detection from signal processing with relative height equals to 1. To determine whether a spike covers a given event $e \in E$, we compare the timespan (width) of the spike $t \in T$ with the date of the event $d \in D$. If the timespan of the spike $t \in T$ includes the date of the event d, we consider the event to be covered by the spike if and only if we have a direct mentioned of the event that we extract by proper nouns.

[11] https://en.wikipedia.org/wiki/Siege_of_Mariupol

[12] https://en.wikipedia.org/wiki/Battle_of_Kherson

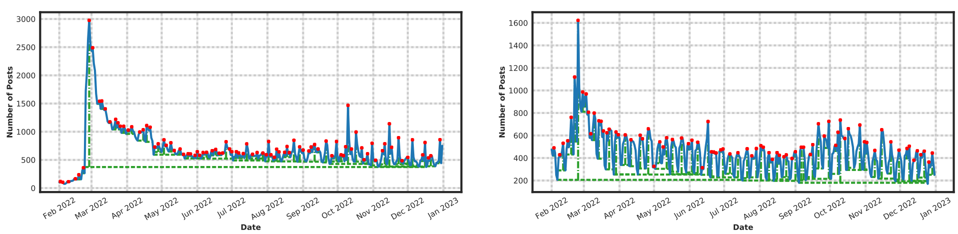
4.3.1. Methodology

To evaluate the coverage of external events in our collected datasets of Telegram channel posts from Ukraine and Russia, we use a pre-defined chronology of events (defined in section 4.2.4) with a set of events E and their respective dates D.

We identify a set of spikes S in the timeline, with their corresponding duration or timespans T. We define spike as a local maxima by the total number of posts per day between the two nearest days (previous and the next day). We utilised the multiple peak detection technique from signal processing, as we can assume that our timeline of comments is a data 1D vector, where each day gives volume per day. For timespan detection we utilised an algorithm for peak width detection from signal processing with relative height equals to 1. To determine whether a spike covers a given event $e \in E$, we compare the timespan (width) of the spike $t \in T$ with the date of the event $d \in D$. If the timespan of the spike $t \in T$ includes the date of the event d, we consider the event to be covered by the spike if and only if we have a direct mentioned of the event event that we extract by proper nouns.

4.3.2. Results

The Figure 15 illustrate the spikes and spikes' timespans. The results showed that Ukrainian channels covered most of the ground truth events, with a coverage of 0.979. Russian channels, on the other hand, have coverage of 0.929. The coverage of major dates is 1 for both sides (we define major dates as dates that have a dedicated page in the Wikipedia).



(a) (b)

Figure 15: Spikes in channels and their lifespan in (a) Ukrainian channels and (b) Russian channels

There are several factors that may have contributed to that observation. Firstly, the nature of the conflict, with Ukraine experiencing a full-scale war, may have received more attention and coverage from Ukrainian channels. Russian news media, on the other hand, may have presented the situation as a smaller-scale operation (special military operation), leading to less coverage of the conflict. It is also possible that government censorship or media control in Russia may have contributed to the lower coverage of external events by Russian news media. A study by TIME [13] found that media in Russia do not offer alternative perspectives to official state views, particularly in relation to conflict situations[14].

4.4. Post-to-Event matching approach

In this section, we introduce a simple yet effective approach for matching posts in datasets to specific events. This algorithm helps to identify sets of posts from Ukrainian and Russian channels that are likely related to a particular event, later enabling us to compare messages from Ukrainian and Russian mass media in pairs to identify similarities and differences (see Section 4.5). The development of this algorithm is motivated by the impracticality of manually examining the large number of daily posts made by channels, as well as the fact that many of these posts are not related to the target events, even if they happened on the same date as they can 1) related to other war events, 2) channel advertisements, or 3) unrelated to war events. We also evaluate the post-to-event matching approach using the help of four volunteers from Ukraine, Russia, and Kazakhstan and report our results.

4.4.1. Methodology

The pipeline involves the following steps:

1. **Step 1:** Firstly, we extract the event date and description of the event from the Chronology list. Next, we determine the event timespan using the methodology presented in the previous section (see Section **??**). Finally, we select only those posts in channels whose time of posting (*post_date*) is between the event date and the last date of the timespan.
2. **Step 2:** Extract keywords from relevant channel posts and the Chronology list's event description. We define keywords to be proper nouns because most of the events are named using geographical locations or proper names. We used a pre-trained named entity recognition (NER) model, which is applied to pairs of event descriptions from Wikipedia and posts in the datasets. To identify proper nouns in texts written in Russian and Ukrainian languages, spaCy models are utilized. In particular, we used *ru_core_news_lg* and *uk_core_news_lg* models for Russian and Ukrainian languages, respectively.
3. **Step 3:** In order to further rank messages according to their similarity to the event description we utilize Jaccard Similarity Coefficient:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

[13] `https://time.com/`

[14] `https://time.com/6151572/russian-media-ukraine-coverage/`

Where A represents the keywords extracted from Wikipedia related to the event description, and B represents the keywords extracted from a post related to this event. Then we select up to the top K messages (sorted by Jaccard coefficient and that are positive), that have as post messages that are related to the event.

4.4.2. Data annotation

To evaluate the reliability of messages assigned to the chronology events selected by our post-to-event matching approach, we selected 2570 for manual inspection (top five posts based on similarity score from Ukrainian dataset per 281 events that belong to the Ukrainian chronology list and top five posts based on similarity score from Russian dataset 233 that belong to the Ukrainian chronology list).

To evaluate the reliability and consistency of the labels assigned to the messages selected by our post-to-event matching approach, we measure inter-annotator agreement using Cohen's kappa. To calculate Cohen's kappa, two annotators independently label the messages as relevant (1) or not relevant (0) to the event. Two scores are reported separately for the Russian and Ukrainian datasets.

4.4.3. Evaluation

We choose to use Precision@k (where k is 5) as our evaluation metric for measuring the performance of our post-to-event matching approach. Precision@k is a commonly used evaluation metric for ranking systems and is defined as the proportion of relevant items among the top-k results. It is formulated as follows:

$$Precision@k = \frac{\text{number of relevant posts in top k}}{k}$$

We choose to use Precision@k because it is a simple and intuitive measure of relevance that is well-suited to our task of identifying only the most relevant messages among a large number of posts. Unlike metrics such as mean reciprocal rank (MRR) and normalized discounted cumulative gain (nDCG), which take into account the ranking of relevant items, which is not important for our task, Precision@k focuses solely on the presence of relevant items in the top-k results. In addition, we measure the Precision@k metric separately for each step of the algorithm. This allows us to analyze the performance of each individual step and assess the impact of incorporating additional information and techniques.

4.4.4. Results

The annotation results are as follows: The Cohen's Kappa score for relevant vs non-relevant posts is 0.83, indicating a high level of agreement between annotators [McH12]. The mean precision@k for the Russian dataset posts to the events is 0.9, meaning that around and Ukrainian dataset posts to the events is 0.88.

4.5. Detecting event contradiction

The final stage of our research involves quantitatively evaluating the extent of contradiction between event representations from Ukraine and Russia. This is achieved by initially obtaining textual representations of a specific event during a particular period separately for both countries. Subsequently, we identify posts from both countries likely to be related to the particular event, using descriptions and dates from a reliable source, such as Wikipedia. In this stage, we will perform a pairwise comparison of the text between Ukraine and Russia by measuring the similarity between each pair of posts. After this, we will calculate the average similarity for each event and rank the events in ascending order. Finally, we say that events with the lowest similarity are likely to contain propaganda.

4.5.1. Methodology

Detecting events that are likely to be targeted by propaganda involves several steps. The first step is to identify posts from Ukraine and Russia related to a specific event. Next, embeddings are extracted for each post using a pre-trained language model such as mBert. The cosine distance is then calculated between each possible pair of posts, one from Ukraine and one from Russia. This distance measurement is a way to compare the similarity of the posts, with a lower distance indicating a higher similarity. We can take the average of the cosine distance and rank the events in descending order by cosine similarity. We can then define events with a score from 1 to 0.5 as highly aligned, from 0.5 to -0.5 as neutrally aligned and events with a score of -0.5 to -1 as highly misaligned.

4.5.2. Results

Figure 17 shows the events and their similarity scores. Our analysis shows that events describing particular war clashes, specifically those containing the word "fight," have a higher similarity to the rest of the events. Conversely, events such as the Bucha massacre, the rocket attack on a shopping centre in Kremenchuk, and the sinking of the ship Moscva were found to have the lowest similarity and alignment among posts on channels from the two countries.

In order to investigate the truthfulness of events reported in Ukrainian and Russian news media with the Wikipedia article description, we extracted embeddings for each event and compared them with the embedding for the Wikipedia event description. For each instance, if the event from the dataset was closer to the Wikipedia event description embedding, it was assigned either yellow or blue color. Yellow indicated that the Ukrainian side was closer to the Wikipedia description, while blue indicated that the Russian side was closer.

The analysis of the events in our dataset revealed that when there was a strong misalignment between the news media reporting and the Wikipedia article description, the Ukrainian side was consistently closer to the reliable source of truth represented by the Wikipedia description. However, in cases where there was a

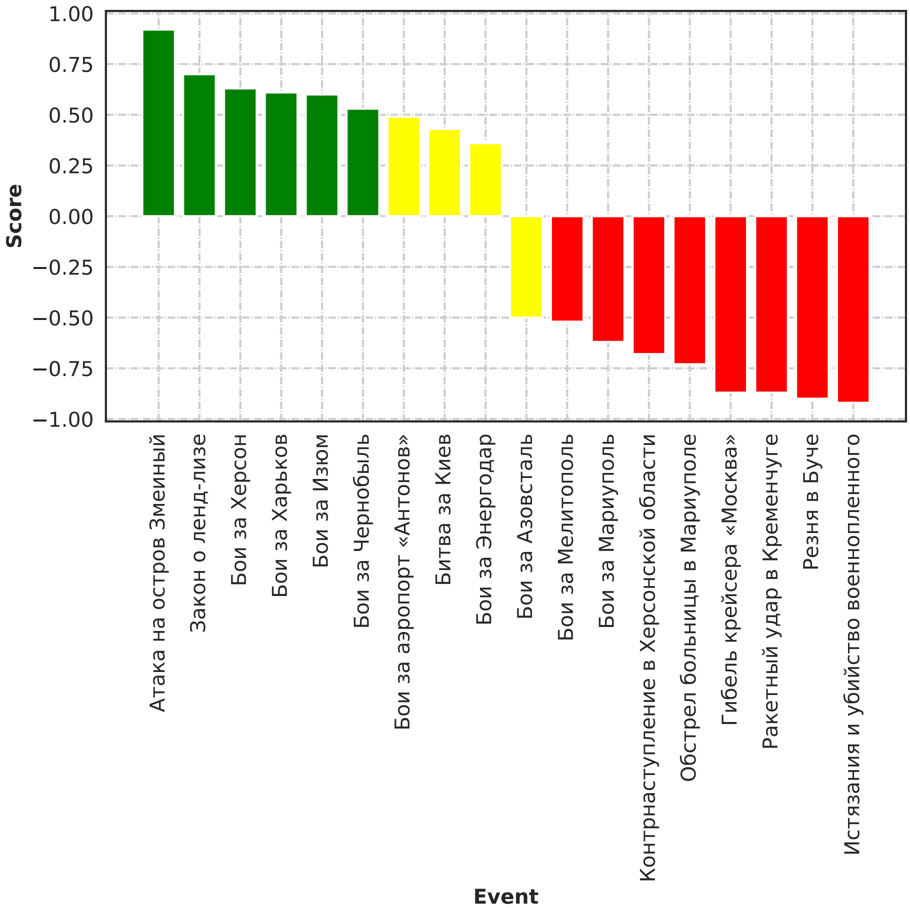


Figure 16: Who is closer to the truth?

strong alignment between the news media reporting and the Wikipedia article description, our analysis showed that the Russian side was sometimes closer to the ground truth.

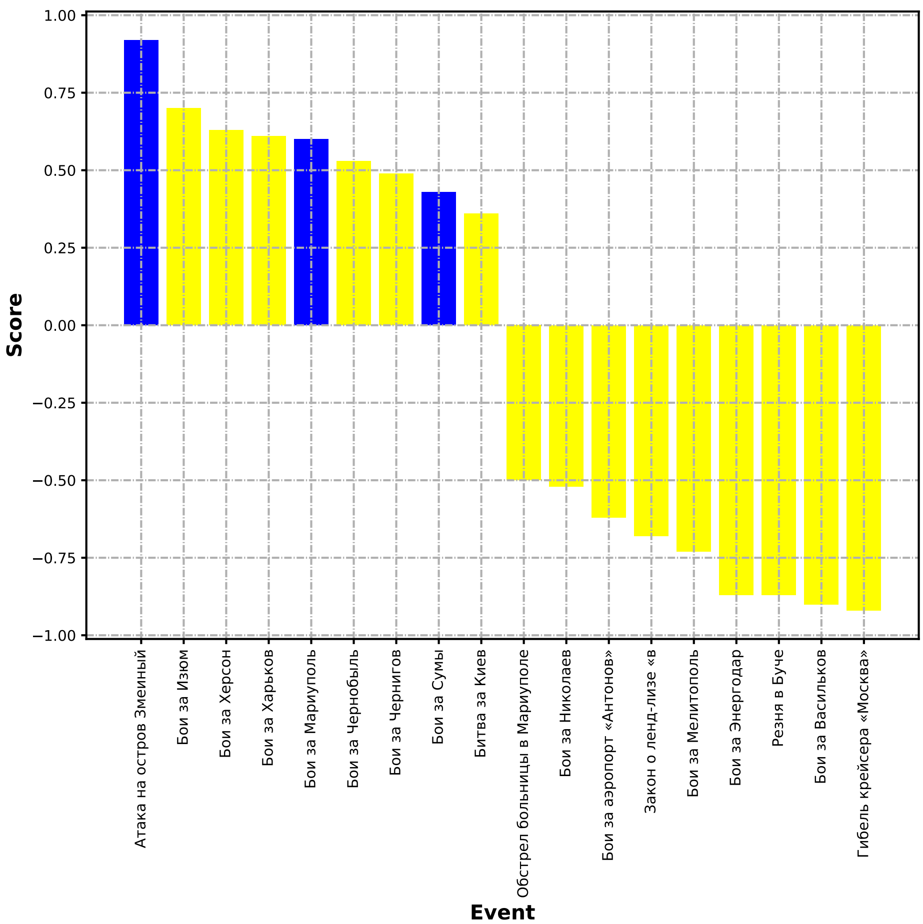


Figure 17: Major events and their similarity scores between Ukraine and Russia

5. CONCLUSION

Computational social science is skewed towards either the English or Latin alphabet while paying little attention to other languages. In this thesis, we used data from social media platforms to study protests and war in CIS countries. In the first work, using Facebook data, we investigated Euromaidan protests which happened in 2014 in Ukraine. In the second work, we analyzed the Belarus protests using Telegram data. In the third work, we studied propaganda using Telegram data on an ongoing Russo-Ukrainian war.

Firstly, we investigated individual changes in language behaviour (instead of simple aggregated data) during the Euromaidan protest. We show that active Ukrainian users changed their language preferences and used the Russian language more often after the end of Euromaidan. By showing this, we provide additional evidence that protesters use language rather strategically depending on the context instead of reacting to an ethnic or national mobilization. We also presented different ways to make sense of our findings. Although we could not provide conclusive modelling of individual behaviour due to the limitations of our data, we were able to propose some data-driven explanations. First, we can rule out the influence of the post language because there was no significant correlation between the languages of posts and comments. Even though the proportion of posts in Russian increased dramatically, active users did not react to it by switching to identical language in their comments. Therefore, we suggest that administrators were not able to nudge the language behaviour of active users.

On the other hand, we observe the appearance of many new users who speak Russian in the data. It seems that active users reacted to new Russian-speaking users by talking with them in Russian, respectively. We also observe that the users who mainly use the Ukrainian language in their comments more often switch to the Russian language than users who mainly use the Russian language and switch to Ukrainian. In other words, even loyal Ukrainian speakers who were active before the end of the Euromaidan are more likely to switch between languages after the end of the protest to react to new users (who often carried conversations in Russian). This finding is in line with the idea that Ukrainian activists use language strategically. They switch between languages depending on circumstances to facilitate communication instead of being nudged by national or ethnic mobilization. Although this explanation has been proposed in the literature [Met+16], our paper is the first to confirm this idea with the longitudinal data. Furthermore, our findings are in line with the results of representative surveys, which show that Ukrainians are more likely to shift their short-term behaviour and identities to reflect their identities rather than modify their identities [PR18b; PRR21]. From the policy perspective, these findings explain why Ukrainians still use the Russian language so often in their daily lives despite the ongoing war with Russia. In the context of online communication, when Ukrainian speakers are exposed to growing content in the Russian language, they are likely to follow the trend. Therefore, one could expect that the new legislation, which requires Ukrainian media websites to post in the Ukrainian language, is likely to have a long-term impact on the increase of the usage of this language. It could be the case that such policy measures can have a more profound effect than ethnic mobilization during political protests or wars.

In the second work, we study online activities during the six months of the protest in Belarus using Telegram data. We collected data from three communication tools (mediums) on Telegram: channels, groups, and chats.

We find that activity in those three mediums was different. Although the protest in Belarus relied on Telegram, protesters used it for different purposes depending on the medium (channels, groups, and chats). For example, users in groups mainly discussed announcements about national-level events. In contrast, local chats discussed local protests or demonstrations in particular neighbourhoods. What topics do users discuss in each medium? We observe that the topics vary by medium. Topics related to coordination were primarily raised in local chats (e.g., location and time of demonstrations), while channels and groups raised rather generic topics (e.g. news about the pandemic or Lukashenko's behaviour). While these findings are not surprising, they show that the online communication during the Belarus protests was well structured. Therefore, one should be careful when studying online communication on Telegram and consider analyzing mediums independently instead of blending them into a single dataset.

We also asked a question of whether users communicate distinctly in different mediums. In simple words, we wanted to understand if there are specific language patterns in each medium that can be easily recognized and predicted. It turns out that our models were able to predict messages only from channels. At the same time, we were not able to differentiate messages from local chats and groups. Our interpretation of this finding is that the administrators of channels used templates for communication, they referred to similar sources and copied similar news, and perhaps were engaged in some coordination. Thus, messages in channels were more homogeneous in their topics and style, and our models were able to recognize them as belonging to the same category. In contrast, people who shared messages in local chats or groups were not homogeneous, they lived in different areas and cared about different (local) events. Respectively, they used some idiosyncratic language styles and references. Therefore, our models were not able to fit these messages into the same category. We believe that this finding is interesting because it shows that the communication from the administrators to broad masses (top-down communication) was well structured and perhaps coordinated, while the horizontal communication between local activists in local chats was more spontaneous and less structured. These findings provide new empirical evidence for the theory of "connective action", which is based on personalized content and is different from classic top-down communication. According to this theory, digital media facilitate "connective action" and influence the core dynamics of the protests [BS12].

In the third work, we investigated the use of propaganda in Telegram, particularly during times of war during Russo-Ukrainian War. We presented a method for evaluating the coverage of external events using our Telegram channels dataset and for matching posts to events and identifying related social media posts. We also presented a method for detecting propaganda by finding contradictions between similar posts. Our results suggest that many events from February to January 2023 were targeted by propaganda to shape public opinion.

6. FUTURE SCOPE

In this thesis, our primary focus has been on analyzing protests either by examining a single platform at a time or by studying a single protest event, with, at most, the inclusion of two parties involved in the conflict. As we move forward, we envision the following directions for our future research:

Multi-Side Analysis: First promising direction for future research is to explore protest movements from a multi-sided perspective at the collective level (while we focus on the two-sided level at most). A notable real-world example of such protests is the *Hong Kong Protests* that took place in 2019. During this period, various opposing groups were involved, including pro-democracy demonstrators, government supporters, and pro-mainland China groups. Multi-Side protests involving multiple opposing groups within a single protest. By analyzing how different sides interact, communicate, and mobilize on social media platforms, we can better understand the dynamics of multi-sided conflicts and their impact on the overall protest landscape.

Social Media Comparison: Another beneficial direction for future work involves conducting a comparative analysis of user behaviour across different social media platforms and messaging apps during protests within a single protest. Unlike our previous works, which only analyzed one platform at a time, we plan to study these conflicts from multiple platforms. We can identify platform-specific trends and their implications on protest dynamics by examining how user engagement, information dissemination, and collective action differ across platforms like Twitter, Facebook, Telegram, and others.

Multi-Conflict Comparison: To enhance the generalizability of findings, future research could explore a multi-conflict comparison approach. This entails analyzing protest movements in different countries that have experienced conflicts or mass demonstrations at various times. For example, comparison of protest movements in Egypt, including the *Egyptian Revolution of 2011*, the *Egyptian Protests of 2019*, and demonstrations in response to government policies. Through analyzing different protest movements, valuable insights can be gained regarding the evolving dynamics of online activism and its role in driving political change within a specific regional context. Findings can contribute to a deeper understanding of the complexities surrounding protest movements and offer guidance for developing effective strategies for digital mobilization and engagement in future demonstrations.

Comparison of Authentic Vs. Inauthentic users: Inauthentic users often use social media platforms to hijack protests by spreading their own agenda. Examples of inauthentic users could be bots, users who create accounts for a very short period. These inauthentic users often forward their agenda by augmenting hate and misinformation. A comparison of inauthentic and authentic (genuine) users in protest settings using stance detection could provide specific agendas from each side during protests.

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SISUKOKKUVÕTE

Veebipõhise sotsiaalmeedia kaasamise uurimine SRÜ riikides protestide, massimeeleavalduste ja sõja ajal

Protestidest ja konfliktidest on saanud mõjukad jõud muutuste esilekutsumiseks ning poliitiliste ja sotsiaalsete maastike kujundamiseks ning seda mitte ainult kohalikul demograafilisel, vaid ka ülemaailmsel tasandil. See on saanud võimalikuks tänu internetile ja veebipõhistele sotsiaalmeedia platvormidele (VSP), mida VSP-ide kasutajad on aktiivselt kasutanud informatsiooni levitamiseks ja koordineerimiseks. Nendeks protestideks on näiteks ühiskondlikud protestid nagu MeToo ja BlackLivesMatter. Samas on olulised ka poliitilised protestid, mis on toimunud kogu maailmas, näiteks araabiamaades, Hongkongis ning Sõltumatute Riikide Ühenduse (CIS) riikides, näiteks Valgevenes ja Ukrainas.

Varem on teadlased uurinud kasutajaid ja nende interaktsioone, et selgitada, kuidas sotsiaalmeedia kasutajad kasutavad digitaalseid platvorme arutelude hõlbustamiseks, tegevuste koordineerimiseks ja plaanide levitamiseks. Need uuringud on siiani kannatanud kahe olulise puuduse all. Esiteks on teadusuuringutes kasutatud peamiselt Twitterit, mida sageli sildistatakse sõnavabaduse eest võitlejaks. Siiski on teatatud, et see ei ole väga populaarne igas maailma osas, näiteks Sõltumatute Riikide Ühenduse (SRÜ) riikides, kus kasutatakse peamiselt alternatiivseid platvorme nagu Facebook ja Telegram. Teiseks on enamik neist uuringutest on tehtud inglise keele andmekogumite abil. Seetõttu puudub endiselt arusaam poliitiliste ja sotsiaalmajanduslike sündmuste ning üksikisikute ja organisatsioonide tegevuse seostest SRÜ riikides.

Nende kahe teaduslünga lahendamiseks on doktoritöö eesmärgiks analüüsida põhjalikult sotsiaalmeediat ja selle aktiivsete kasutajate käitumist oluliste poliitiliste ja sotsiaalmajanduslike sündmuste ajal SRÜ riikides. Analüüsime Twitterile alternatiivseid platvorme, milleks on Facebook ja Telegram. Lisaks, keskendudes peamiselt Valgevenele ja Ukrainale, anname oma analüüsi tulemused mitteingliskeelsete riikide ja nendes elavate kogukondade kohta. Täpsemalt uurime kolme järgmist analüüsitaset:

1. **Ühepoolne, individuaalne tasand.** Sellel tasandil analüüsisime kuidas üksikisikute käitumine konkreetses Facebooki grupis, mis esindab konflikti üht poolt, mõjutasid välised sündmused. Analüüsisime seda Euromaydeni Facebooki lehe abil, mis loodi Ukraina 2014. aastal toimunud Euromaidani revolutsiooni ajal. Andmekogus oli 26 631 postitust ja 1 470 593 kommentaari, mille jättis 124 790 kasutajat 22. novembrist 2013 kuni 31. maini 2014. Täpsemalt vaatlesime aktiivsete kasutajate suhtluskäitumise muutusi grupi lehel enne ja pärast Euromaidani revolutsiooni Ukrainas. Mõõtsime seda muutust analüüsides kasutajate suhtluskeele valikut (postitustes ja kommentaarides). Analüüsi igas etapis kontrollisime oma tulemuste täpsust ning eemaldasime andmetest mitteautentseid kasutajaid, näiteks veebirobo-

tid. Meie uurimus näitas, et kasutajad muutsid oma keelemustreid erinevate poliitilistele ja ajaloolistele tegurite tõttu.

2. **Ühepoolne, kollektiivne tasand.** Teises uuringus analüüsisime konflikti ühe poolega ühinenud isikute käitumist. Täpsemalt keskendusime erinevate meediumite jälgimisele platvormis Telegram, kus Valgevene 2020. aasta protestide ajal infot levitati. Meediumite all peame silmas kanaleid, gruppe ja kohalikke vestlusi Telegramis. Tegime põhjaliku uuringu, et mõista dünaamikaid kõigis kolmes meediumis ning uurisime, kuidas kasutajate tegevus erineb Telegrami erinevates meediumites Valgevene valitsusvastaste protestide ajal 2020. aastal. Kasutades erinevaid NLP tehnikaid, hõlmas meie analüüs inimeste käitumise õppimist Telegramis ja nende huvide muutuste jälgimist.
3. **Kahepoolne, kollektiivne tasand.** Meie analüüsi viimases mõõtmes me teostasime võrdleva uuringu vaadeldes konflikti kahe vastandliku poole organisatsioone ning nende käitumist. Meie eriline fookus oli tegevustel ja strateegiatel, mida kasutavad kõige silmapaistvamad ja mõjukamad massimeedia väljaanded Ukrainas ja Venemaal Venemaa sissetungi ajal Ukrainas aastal 2022. Kogusime kõik uurimisalused postitused kokku 20 kanalilt perioodist 1. veebruar 2022 kuni 1. jaanuar 2023, kus 10 kanalit kuulus Venemaa ja 10 Ukraina poolele. Kummaski 10 kanaligrupis kuulusid 5 mõjuisikutele (näiteks poliitikud ja ajakirjanikud) ning 5 meediale. Eelkõige pakkus meile huvi see, kuidas need kanalid kujundasid propagandapüüdlusi antud konfliktis selleks, et kujundada üksikisikute käitumist. Pakkusime välja ka raamistiku propaganda automaatseks tuvastamiseks sõja ajal.

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I **Ivan Slobozhan**, Tymofii Brik, and Rajesh Sharma. " Differentiable characteristics of Telegram mediums during protests in Belarus 2020." In **Social Network Analysis and Mining** 13, no. 1 (2023): 1-19.

II **Ivan Slobozhan**, Tymofii Brik, and Rajesh Sharma. "Longitudinal change in language behaviour during protests: A case study of Euromaidan in Ukraine." In **Social Network Analysis and Mining** 12, no. 1 (2022): 1-12.

III **Ivan Slobozhan**, Peter Ormosi, and Rajesh Sharma. "Detecting shadow lobbying." In **Social network analysis and mining** 12, no. 1 (2022): 1-11.

IV Pavlo Tertychnyi, **Ivan Slobozhan**, Madis Ollikainen, Marlon Dumas. "Scalable and Imbalance-Resistant Machine Learning Models for Anti-money Laundering: A Two-Layered Approach." In **International Workshop on Enterprise Applications, Markets and Services in the Finance Industry**, pp. 43-58. Springer, Cham, 2020.

V **Ivan Slobozhan**, Peter Ormosi, and Rajesh Sharma. "Which bills are lobbied? Predicting and interpreting lobbying activity in the US." In **International Conference on Big Data Analytics and Knowledge Discovery** (2020), Springer, Cham, 285-300.

VI Artem Mateush, Rajesh Sharma, Marlon Dumas, Veronika Plotnikova, **Ivan Slobozhan**, and Jaan Übi. "Building payment classification models from rules and crowdsourced labels: A case study". In Advanced Information Systems Engineering Workshops: CAiSE 2018 International Workshops, Tallinn, Estonia, June 11-15, 2018, Proceedings 30 (2018) Springer International Publishing

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- Andmeteadus
- Masinõpe
- Sotsiaalvõrgustike analüüs
- Veebipõhiste sotsiaalmeedia platvormide analüüs

Väljaanded

I **Ivan Slobozhan**, Tymofii Brik, and Rajesh Sharma. "Differentiable characteristics of Telegram mediums during protests in Belarus 2020."In **Social Network Analysis and Mining** 13, no. 1 (2023): 1-19.

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