Mapping Twitter Activity in the 2019 Ukrainian Political Landscape

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***Abstract*—Twitter, which was recently renamed to X, has become a critical asset for political discourse and it is widely believed that it has had a substantial influence on the outcome of elections around the world. In this paper, we analyse Twitter activity during the 2019 Ukrainian elections and show that a strong positive support is not a mandatory condition for a positive outcome, while berating the opponent throughout negative Twitter activity is more significant. In the presidential election, Volodymyr Zelensky was considered as an outsider, but his successful campaign took advantage of the negative discourse against Petro Poroshenko. Our analysis also shows that media outlets played an important role as they have kept the anti-Poroshenko discourse active from March 2019 until August 2019 when parliamentary elections were held in Ukraine.**

I. Introduction

Over the past decade, social media platforms, especially X (Twitter) and Facebook, have become increasingly relevant in electoral campaigns around the world. Candidates, parties, journalists, and a steadily increasing share of the public are using Twitter to comment on, interact around, and research public reactions to politics [13]. X, which is still widely referred to as Twitter in the literature and in everyday use, allows for more opinions and displays of emotion than are typically acceptable in traditional news reporting [20].

A plethora of work on social media influence has either focused on identifying automated and bot-like accounts [8], tracked the general Twitter activity during elections [1], [4] (e.g., how many accounts tweeted about certain subject, etc), followed the activity of candidates [16], or looked at content of tweets [22] to track rumours and fake news among others [9], [12]. However, few studies have presented a comprehensive and holistic analysis that helps understanding the use of social media such as Twitter during major political events.

The goal of this paper is to present a more holistic view of Twitter activity pertaining to a major election, focusing on the main candidates during the 2019 Ukrainian elections. Starting with the presidential election in which Volodymyr Zelensky won against Petro Poroshenko end emerges as the new President of Ukraine, we show that the Ukrainian Twitter was dominated by negative Poroshenko discourse (anti-Poroshenko) while discussion around Zelensky was mostly neutral. Thus, our work provides further confirmation the widely belief that a strong positive support online is not mandatory for winning elections.

Our study also investigates the interplay between social media and traditional media or news agencies during the Ukrainian presidential and parliamentary elections. Here, the anti-Poroshenko discourse appears to have been dominated by Ukrainian, Russian and international news agencies, journalists, reporters as well as Russian officials and Ukrainian personalities. However, Zelensky's discourse was limited to local Ukrainian news agencies and journalists.

Some of these media outlets are considered as trust sources within their political group. Moreover, many of these trust sources or anchors act as bridge across political groups. Within anti-Poroshenko group local anchors connect mainly users within the group. Thus, users that had negative Poroshenko discourse exhibit an *echo chamber* behaviour. However, local anchors within Zelensky political group exhibit a limited interaction within their political group, which leads to the spread of the neutral Zelensky discourse.

II. The 2019 Ukrainian Elections

Presidential Election. In 2019, Ukrainians elected new president. The election consisted of two rounds. This political event not only marked the beginning of Zelensky's presidency but also impacted the evolution of events during the last years. While 39 presidential candidates were electable in the first round, only nine of them received more than 1% of the votes and four received more than 10%. Among those were incumbent president *Petro Poroshenko* of the *Petro Poroshenko Bloc* party which was renamed to *European Solidarity* after the election. He came in second with 15.95% of the votes in the first round and lost in the second round with 24.45%. The winner, former actor *Volodymyr Zelensky* of the *Servant of the People* party, named after a TV series in which he played the Ukrainian president, entered the election as a political outsider but obtained 30.24% of the votes in the first and 73.22% in the second round. His campaign was characterized by a strong focus on online channels leveraging his already established popularity [10], [21]. The style has been described as non-agenda ownership, and compared to the 2016 campaign of Donald Trump [24], an evaluation which was disputed by others [14], [18].

Former prime minister *Yulia Tymoshenko* from the *Fatherland* party came in third during the first round with 13.40% of the votes and thus did not take part in the second round. While she was not far behind Poroshenko in the election, we found few tweets referring to her candidacy and the online campaign, at least w.r.t. Twitter, quickly became a contest between the leading two candidates, Zelensky and Poroshenko. Consequently, our analysis focuses on these two candidates.

Parliamentary Dissolution and Election. Originally scheduled in October 2019, the Ukrainian Parliamentary Elections took place three months earlier. During his inauguration the newly elected president Zelensky dissolved the parliament, thus calling for *snap elections*, i.e., early parliamentary elections. They took place on the 21st of July 2019 [23]. The election outcome brought significant changes to the Parliament. Zelensky's party won the majority with 254 seats. Moreover, approximately 80% of the elected candidates were new to the parliament [17].

III. Data Collection and Processing

A. Dataset Collection

We collect and process Twitter data during the presidential and parliamentary elections in Ukraine in 2019 (i.e., from March 8, 2019 to August 31, 2019). Our collection step starts from 151 initial hashtags related to the Ukrainian elections created by foreign policy experts. We use this set to query against the Twitter API and collect (re)tweets. Multiple hashtags can be used on the same (re)tweet and we collected (re)tweets where at least one hashtag matches our list. From the collected data, we extracted all the hashtags, thus extending our initial set. Furthermore, we sanitize these entries by both converting all the hashtags to lower case and removing duplicate entries. Additionally, we search and remove inconsistencies in hashtags like typographical errors and alternative names. For example, we consider *ukrainian* the same as *ukraine*. Table I summarizes the number of collect tweets and retweets during our six month analysis period.

Table I: Initial and final dataset size.

Data	Tweets	Retweets	Accounts
Initial	133418	91338	9872
Final	126052	91338	9233

Our preliminary analysis of the initial set of hashtags revealed that each of the presidential candidates was on average mapped with at most one hashtag. Hence, we choose to include an extra set of 82 hashtags that increase the number of unique hashtags per candidate. Note that we select this additional set based on the frequency of the hashtags within our collected data. Our final list amounts to 227 hashtags (51 non Cyrillic and 176 Cyrillic hashtags).

Next, we considered hashtags that can be linked to any political opinion. We based our selection on a minimum of 4 unique hashtags per candidate. This threshold is based on candidate Tymoshenko having in total, the minimum number of 4 hashtags. This step also rely on foreign policy experts with strong background on Ukrainian political environment. Thus, we considered only 227 (51 non Cyrillic and 176 Cyrillic hashtags) filtered unique hashtags from the 27847 total hashtags, and mapped each re/tweet to them. Doing this, all tweets and retweets using the filtered hashtags list is reduced to 217390 from 9233 unique accounts. Compared to other election like the 2016 U.S. election, where over 20M re/tweets were produced by 2.7M users [3], it is clear that total Twitter activity is far lower in Ukraine.

B. Mapping Hashtags to Political Classes

Our next step is to identify the political significance of hashtags in the tweets. For this purpose, we rely on a set of 227 hashtags carefully selected by Ukrainian experts. We then classified these hashtags based on their contents and political significance. the initial analysis includes Yulia Tymoshenko. Thus, we have three candidates. For each of the candidates, we create three classes: *for the candidate*, *against the candidate*, and just *mentioning the candidate* for a total of nine classes. We group into an additional *Neutral* class tweets that are not mapped to any of the above classes. We then map each of our selected hashtags to one of the nine classes. Note that the classification of hashtags was performed by Ukrainians familiar with the 2019 elections. Most of the hashtags (96%) map to one single class. Table II lists the number (percentage) of hashtags per each class. Note that the numbers do not sum up to 227 since a small number of hashtags fall into multiple categories. A significant number of hashtags are mapped to the *Neutral* class. Breaking down the remaining hashtags per candidate, Figure 1 shows that approximately 18% and 8% of these hashtags are linked to Zelensky and Poroshenko, respectively. Tymoshenko did not reach the second round in the presidential elections. Thus, the low number of Tymoshenko hashtags is most likely a result of the candidate's absence in the second round of the presidential elections. We did not find any hashtags that map to the 'anti-Tymoshenko' class. Thus, we remove this class from our analysis.

Table II: Number (Percentage) of hashtags and accounts per class. A * indicate all political classes related to the candidate.

	Zelensky*	Poroshenko*	Tymoshenko*	Neutral
Hashtags	42 (17.5)	19 (7.9)	4 (1.7)	185 (77.4)
Accounts	3544 (38.4)	6678 (72.3)	413 (4.5)	9045 (97.9)

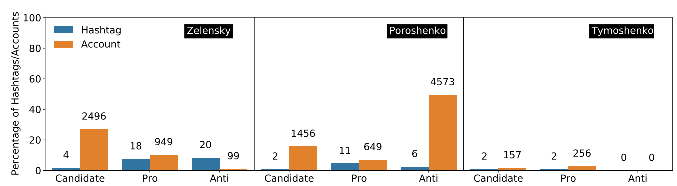


Figure 1: **Percentage (number) of hashtags and accounts per candidate**. Tymoshenko Twitter activity was limited.

C. Tweets versus Retweets

To understand the dynamic of account activity we split the dataset into *original tweets* (which do not have an *original tweet Id*) and retweets. Our dataset is comprised of 58% original tweets and 42% retweets. See Table I) for detailed numbers. We use this classification in analysing account interaction over time and identifying important accounts per political class. Furthermore, we use this distinction to compare the role of different accounts profile in different political classes. Lastly, following the retweet relationship between accounts, we construct a retweet graph to identify interaction between accounts from the same and different political classes. The ratio between tweets and retweets is quite typical for Twitter activity. A large part of the tweets have never been retweeted, and the main interest in political discourse stems from few highly cited sources during the considered period.

D. Account Categories

With some accounts having high tweet and retweet activity, we investigate the importance of these accounts and separate them into two categories: a) accounts that retweet other accounts at a large scale and b) accounts whose original tweets were highly retweeted by other accounts. For this purpose, we manually explored the profile of each of the selected accounts and assigned them to a category. For media accounts we distinguish between local (Ukrainian), Russian, and international new agencies. Similarly, we record activity from local, Russian, or international journalists or reporters [6]. We anonymize the data by replacing personal identifiable information such as username, tweet ID, and account ID by randomly generated ones.

IV. Activity Over Time

In this section, we discuss the Twitter discourses referencing hashtags related to Poroshenko and Zelensky during the presidential and parliamentary elections.

A. Overall Activity

Our analysis shows a stark increase in Twitter activity correlated with each of the two political events. Figure 2a shows the number of tweets and retweets over time. We highlight in grey the period between the first and the second rounds of the presidential election, while the red and black vertical lines represent the Parliament dissolution and new election on May 21, 2019 and July 21, 2019, respectively.

Grouping users according to the candidate they tweeted about reveals that more than 80% (179K) of re/tweets are linked to Poroshenko and Zelensky, and are originated from 60% (6K) of the accounts. Among those, 30% (60K) of re/tweets were linked to Zelensky and 53% (115K) to Poroshenko, respectively. Pro-candidate re/tweet activity is dominated at the rate of 8% (16K) by pro-Zelensky compared to 6% (12K) for pro-Poroshenko. Looking further, from the total number of positive statuses related to both candidates, Zelensky amounts for 56% while the rest is related to Poroshenko. However, anti-Poroshenko dominated anti-candidate Twitter discourse with 34% (74K) of re/tweets compared to 7% (1K) for anti-Zelensky. Narratives related to anti-Poroshenko are more widespread (98% of the negative discourse for both candidates) than the ones related to anti-Zelensky. Thus, Twitter activity is mostly dominated by anti-Poroshenko discourse with some re/tweets including Zelensky.

When looking at the users generating this content we observe that the anti-Poroshenko discourse is dominated by Ukrainian, Russian, and international news agencies, journalists, and reporters, as well as Russian officials and Ukrainian personalities. However, Zelensky's discourse is limited to local Ukrainian news agencies and journalists. Note that, apart from anti-Poroshenko, discourse in the five other political classes was conducted in large part, by a core group composed of the same or similar accounts.

B. Political Account Affiliation

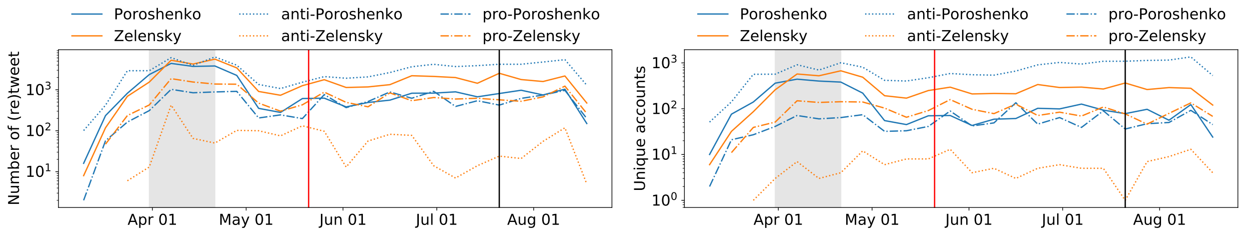
Having seen that accounts participate in different political discussions, we further seek to understand the dynamic of their weekly exchange. Thus, we assign per account the dominant political class related to all the used hashtags per account on a weekly basis. Figure 2b shows the number of accounts assigned to each of the political classes from the selected candidates which confirms that the Twitter discourse was dominated by anti-Poroshenko accounts (see subsection IV-A).

Indeed, with international or Russian news agencies, the activity of anti-Poroshenko account discourse was mostly constant over the span of the data collection. However, most local Ukrainian news outlets only mentioned Zelensky and Poroshenko while the same network of less influential accounts was discussing both pro-Zelensky and pro-Poroshenko. Note that, during the parliamentary election day, the number of accounts related to anti-Zelensky reduced without significantly impacting the number of anti-Zelensky re/tweets. This may indicate a reduction of the activity of end-users accounts and/or new accounts while media accounts maintained high retweet activity on Twitter.

C. Accounts Activity

Ukrainian election Twitter activity is driven by several news agencies and journalists as some accounts appear to maintain the political discourse over the span of the data collection. Therefore, we seek to determine on a weekly basis, new accounts participation to the discourse per class. Figure 3 shows the number of weekly new accounts participating to each class discussion.

Prior the first round of the presidential elections we observe the highest increase in the number of new account that join the election discussion. More than half of new accounts joined the anti-Poroshenko discourse. This anti-Poroshenko discourse activity reduced after the presidential elections but interestingly, the number of new participants to the discussion against Poroshenko increased significantly after the parliament dissolution before almost doubling before the parliament election. Theses new accounts were dominated by a myriad of pro-Ukraine, pro-Nato accounts. The interest in the (neutral) Poroshenko class declined significantly after the presidential elections while interest in the Zelensky topic decreased by a smaller amount. We further compute the overall number of re/tweet per account and find that large part of the accounts have produced less than 10 re/tweets. Thus, most of the activity from the new accounts was apparently limited to a



(a) Unique number of (re)tweets

(b) Unique number of accounts

Figure 2: **Weekly number per political Poroshenko and Zelensky classes (log scale)**. Twitter activity is dominated by accounts re/tweeting about anti-Poroshenko.

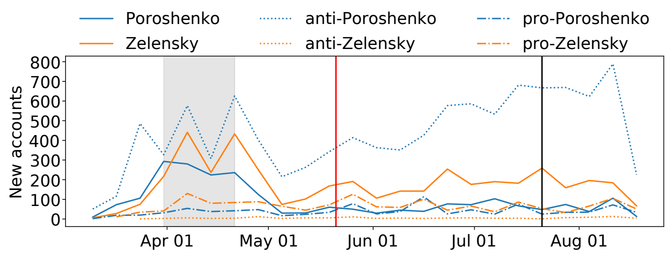


Figure 3: **Contribution of new accounts to the political discourse of Poroskenko and Zelensky**.

one-time or less than 10-times posting or retweeting during the whole period. This confirms our finding that a network composed of a limited number of accounts drive the political discourse, mainly against Poroshenko. Therefore, this network of influential accounts were motivating a variety of accounts to continuously participate in the political discourse.

D. Tweets versus Retweets

We further evaluate the importance of the highly influential account network. To this end, we separate the original tweets from the retweets and plot in Figure 4 the weekly number of accounts posting original tweets and those retweeting. A large part of the tweets were only mentioning any of the candidates. Thus the number of accounts posting anti-candidate discourse was limited while the number of pro-candidate accounts was slightly more important. This indicate that most accounts were cautious in their original tweet while some accounts were positioned as anti-Poroshenko and anti-Zelensky (Figure 4a) .

Focusing on the retweeting activity reveals a significant difference in the anti-candidate retweeting activity. Figure 4b shows that users consistently retweet messages against Poroshenko, while anti-Zelensky retweeting activity is limited. We thus hypothesize that anti-Poroshenko continuous activity was probably maintained by a small network of influential accounts and large number of less influential accounts. Hypothetically, the latter could be bots that are retweeting anti-Poroshenko tweets. Apart from this anti-Poroshenko group, most accounts were also cautious on their retweets. For instance, more accounts retweeted tweets mentioning any of the candidate while a lower number retweeted pro-candidate tweets.

E. (re)Tweets interaction

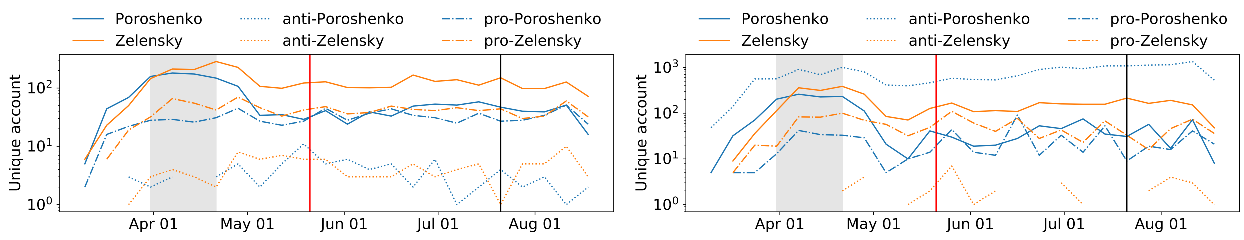
Having seen that potentially anti-Poroshenko discourse is maintained by a small group (possibly consisting of bots), we further seek to analyze the account activity over time. To this end, we separate accounts based on their daily activity into the following four classes: *low*, *medium*, *high*, and *very high*. Figure 5 show the Twitter activity over the time span under observation for the different classes. Each line (x-axis) represents an account; thus the more active accounts, the more data points per line. Accounts with *low* and *medium* activity started their discourse two to three weeks before the elections periods and appear to be active throughout our measurements period. In contrary, accounts with *high* and *very high* have more sporadic intense activity around the presidential and/or parliamentary elections.

With 45% and 31%, a large part of accounts has *low* and *medium* daily activity with a maximum of 1 and 5 re/tweets respectively. Accounts classified as *high* and *very high* represented 14% and 10% of the active accounts on Twitter during the considered period and produced a maximum of 13 and 371 re/tweets respectively. Figure 5 shows tweet activity for the three Zelensky and Poroshenko classes.

Looking further, activity of 67% and 55% of accounts in *low* and *medium* groups was against Poroshenko. This ratio is limited to 32% and 15% for accounts in the *high* and *very high* groups respectively. Moreover, the largest part of accounts in the *high* and *very high* groups was neutral with 67% and 56% respectively, referring the candidate name in their re/tweets. This confirms our intuition that the discourse against Poroshenko mostly relied on a group of accounts having individually limited activity. However, their combined activity maintained the anti-Poroshenko discourse. On the other hand, anti-Zelensky re/tweets are almost nonexistent. Pro-Poroshenko and pro-Zelensky re/tweets are much more balanced, with pro-Poroshenko re/tweets coming more often from *very high* activity accounts.

V. Accounts Interactions

Retweets: We construct the retweets graph from the collected retweets. Each retweet pair is composed of a source and



(a) Tweets

(b) Retweets

Figure 4: **Number of unique accounts tweeting and retweeting for Poroshenko and Zelensky discourses (log scale)**. Zelensky activity was dominated by tweets while anti-Poroshenko discourse was maintain by retweets.

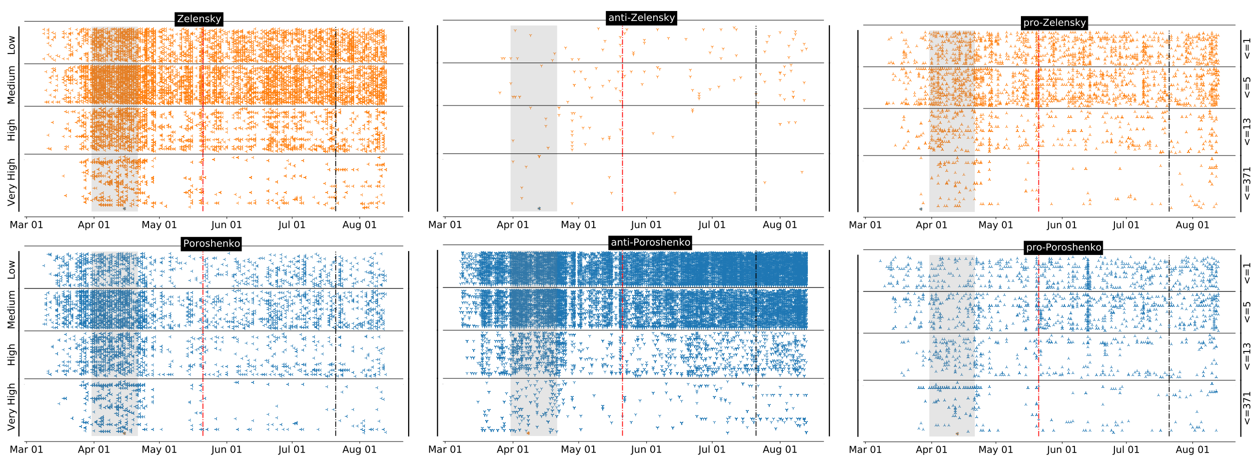


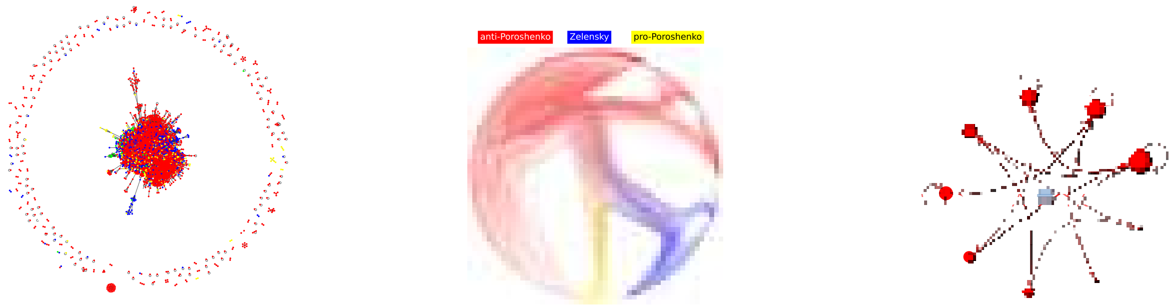
Figure 5: **Twitter activity per candidate classes for Zelensky and Poroshenko**. anti-Poroshenko discourse dominated all four accounts activities groups: low, medium, high and very high.

a target, with the target being the account retweeted and the source being the account retweeting. Note that we colour code each account with its political class (see subsection IV-B).

Figure 6 shows the retweet graph for the two main candidates. Figure 6a shows all accounts involved in the Poroshenko and Zelensky discussion on Twitter, while Figure 6b is the largest connected component (i.e., largest connected accounts thorough retweets). Figure 6c shows the second largest connected component and is limited to the anti-Poroshenko *echo-chamber*. The plot shows a hierarchical edge bundling, where accounts represented as nodes are grouped by political class and adjacency retweets, represented as edges, are bundle together. Hierarchical edge bundling [11] is a widely used technique to decrease the clutter usually observed in complex networks, by organizing nodes (i.e., Twitter accounts) into a circle with edges (retweet) connecting them. Additionally, we emphasise account retweet activity: the more an account is being retweeted, the bigger is its node size on the graph.

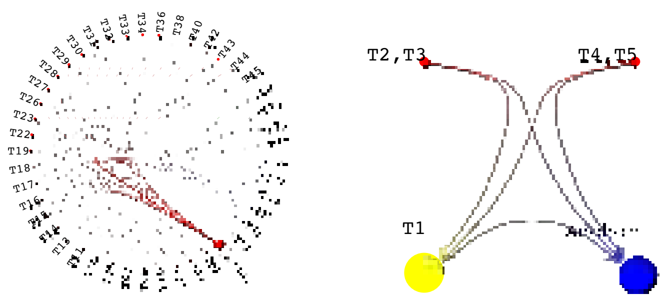
Recall that retweets are dominated by anti-Poroshenko discourse, followed by Zelensky and pro-Poroshenko discourse. Analyzing the retweet graph shows a high retweet activity within anti-Poroshenko class. According to [5], an *echo-chamber* can be characterised by two main dimensions: a) homophily in the interaction networks and 2) bias in the information diffusion towards like-minded peers. Therefore, anti-Poroshenko accounts present an *echo-chamber* behaviour with some accounts playing an *amplifier* role. These accounts tend to amplify or reinforce their anti-Poroshenko campaign by retweeting inside the relatively closed sphere of discourse. This is in line with subsection IV-E, were we show that anti-Poroshenko discourse is maintained by a group of accounts having individually limited activity, but participating together to the anti-Poroshenko discourse (i.e., potential bots). This anti-Poroshenko *echo-chamber* is composed to 91% of accounts whose activity is exclusively limited to the anti-Poroshenko political class. Zelensky and pro-Poroshenko also show *echo-chamber* behaviour, but with significantly fewer members (6% and 3% respectively). Thus, we hypothesize that the reduced impact and importance of their discourse in the retweet activity is a direct consequence of this reduced interaction. Although the spread of Zelensky and pro-Poroshenko is limited we observe that some accounts cross between different political classes. In the following, we refer to such accounts as bridge accounts.

Although large part of account activity is limited within their political class we find that 28% of retweets bridge to a different political classes. Bridge discourse is dominated by exchanges from anti-Poroshenko to Zelensky and from Zelensky to anti-Poroshenko at the rate of 34% and 29% respectively. Anti-Poroshenko bridge accounts tend to be Ukrainian, Russian



(a) All Accounts (b) Largest Component (c) Second Component

Figure 6: **Retweet activity graphs between accounts related to Poroshenko or Zelensky**. Most retweet activities occurred within anti-Poroshenko class while accounts retweeting on Zelensky interact more with other political classes.



(a) Common anchor. (b) Rare anchor.

Figure 7: **Two type of local anchors**. Farm composed of other accounts retweeting an unique anchor is common while retweets chains between anchors and other accounts is rare.

and international news agencies, journalists, reporter as well as Russian official and Ukrainian personalities as describe in subsection IV-A. However, local Ukrainian news agencies and journalists favour Zelensky discourse over any other political classe. Note however, that bridge accounts also participate their local political class discourse.

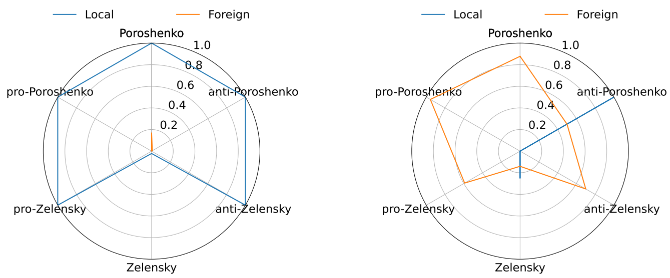
Local Anchors: For each political class, we identify accounts playing an important role within their local class as well as crossing to other political classes. Therefore, we analyse retweet behaviour towards these highly retweeted accounts. For this purpose, we limit our analysis to the top five most retweeted accounts per political class. We use the term local anchors to refer to these top accounts and identify two main retweet patterns. Figure 7 shows the two types of local anchors patterns.

For instance, Figure 7a shows that local anchors are retweeted by a large number of accounts without any apparent link between them. The plot shows that the anchor is the initial author of the tweet, and several accounts retweet the message starting at time $T01$ and ending at $T45$. While there is no retweet between these accounts, we note that these accounts tend to randomly retweet the original tweet. For instance, while the account retweeting at time $T01$ is from the anti-Poroshenko class, the account retweeting the local anchor at time $T02$ is from Zelensky class. This mass retweeting pattern is common and we record that retweets to only 100 unique local anchors represent more than 70% of the retweet activity, with retweets to one Russian local anchor accounting for 10% of the total retweets.

Besides these local anchors being retweet by a farm of accounts, few local anchors participate to retweet chains. Figure 7b shows that the local anchor from Zelensky political class has been retweeted by a pro-Poroshenko account at time $T1$. Then, this pro-Poroshenko account has been retweeted by an anti-Poroshenko account at $T2$, which also retweet the original tweet from Zelensky account at time $T3$; creating a retweet chain. Similar behaviour is observe with another anti-Poroshenko account at time $T4$ and $T5$. This is in line with Zelensky and pro-Poroshenko accounts being limited to local Ukrainian news agencies/journalists. Thus their discourse is limited to the Ukrainian Twitter community with some anti-Poroshenko accounts picking up on interesting tweets to amplify for their international anti-Poroshenko discourse.

Zelensky & anti-Poroshenko: Overall, our analysis shows that Twitter activity during the considered political events is dominated by a high anti-Poroshenko discourse and neutral discussion on Zelensky. Local anchors play an important role in theses activities by acting as bridge between different political classes and/or by being the main source of massive retweets by other accounts from the same political class. To further estimate the role of local anchors and clusters of low influence accounts within and outside of their political class, we further devise two metrics: the *foreign* and *local* affinity of an account. The foreign affinity of an account evaluates the ratio of retweets received from accounts that map to other political classes. Thus, the foreign affinity estimates the popularity of an account towards other political classes. Conversely, the local affinity estimate the popularity of an account tweet or retweet within its own political class. A ratio close to one (zero) indicates a high(low) affinity.

Figure 8 shows the local and foreign affinity for accounts involved in Poroshenko and Zelensky discourse. As expected, local anchors present a high local affinity (Figure 8a). Most local anchors from *pro* and *anti* candidate discourses have a



(a) Top 5 local anchors.

(b) All accounts.

Figure 8: **Poroshenko and Zelensky political class members (median) affinity to local and foreign political classes**. Local anchors have high local affinity. Most accounts are interacting with other political classes, accounts discussing on anti-Poroshenko exhibited an echo-chamber behaviour.

local affinity of 1. However, local anchors within the Zelensky political class exhibit a local affinity of less than 2% which indicates that these local anchors play marginal role in the Zelensky related political discourse. Thus, reducing the spread of Zelensky discourse to a limited number of accounts coming potentially from an *echo chamber*. However, in addition to being critical retweet sources, local anchors within the Poroshenko political class play a notable role as retweet source (bridge accounts) for foreign political classes. Approximately 20% of Poroshenko political class local anchor tweets have been retweeted by foreign political classes accounts, showing that, Zelensky was considered an outsider while Poroshenko as the incumbent president was much more visible internationally.

This trend is also observed when considering all accounts involved on each *pro* and *anti* candidate discourses (see Figure 8b). Accounts within the Poroshenko political class attract more foreign activity then accounts within Zelensky political class. Similarly, pro-Poroshenko discourse is more oriented towards foreign political tweets than pro-Zelensky discourse. Surprisingly though, the anti-Zelensky class exhibits a higher foreign affinity than anti-Poroshenko political class. However, recall that anti-Zelensky discourse is limited to few accounts (see subsection IV-B). Apparently, this limited number of accounts attempted unsuccessfully to interest other political classes to their anti-Zelensky discourse. Indeed, anti-Zelensky discourse is significantly less important compared to other political discourses (see subsection IV-D and subsection IV-E). Conversely, the anti-Poroshenko political class exhibits *echo chamber* behaviour, reducing the impact of foreign discourse: local anchors having high local affinity with the rest of accounts (with local affinity of 1) within the anti-Poroshenko class. While anti-Poroshenko accounts exhibit the highest local affinity, the 25% of local affinity for the limited number of accounts within Zelensky political class confirm the observed *echo chamber* behaviour.

VI. Related Work

During the last decade social media have been heavily used for election campaigns and in many countries Twitter is among the most widely social network for political discourse. Candidates, parties, journalists, and a steadily increasing share of the public are using Twitter to comment on, interact around, and research public reactions to politics [13]. Tumasjan et al. [22] have shown that in the context of the 2009 German federal election Twitter was used extensively for political deliberation and that the mere number of party mentions accurately reflects the election result. Larsson et al. [16] proposed a method to identify different user types based on how high-profile users that utilized the Twitter service during the 2010 Swedish election. In the same vein, Bermingham and Smeaton [2] observed for the 2011 Irish General Election that volume is the single biggest predictive variable followed by inter-party sentiment to capture the voting intentions. Prasetyo and Hauff [7] provide a comprehensive argument for the use of Twitter-based election forecasting in the developing world and show that the most basic Twitter-predictor outperforms the majority of traditional polls, while the best performing predictor outperforms all traditional polls on the national level.

The spread of fake news on social media became a public concern after the 2016 presidential election. Pantti [20] showed for the early stage of the military conflict in Eastern Ukraine as well as to the diplomatic struggle between Ukraine and Russia that Twitter allows for more opinion and displays of emotion than are typically acceptable in traditional news reporting. They demonstrated the coexistence of the traditional media's visualisation of conflict with that driven by social media logic. In this information war, the Eastern Ukrainian conflict was seen in the drastically different narratives about the nature of the conflict: a civil war between the central government and separatist insurgents; a conflict between Ukraine and Russia caused by Russia's economic and political interests; or a proxy war between Russia and the West through which Russia has reacted to the expansion of both EU and NATO [19]. This divided view has persisted after the Russian invasion in 2022.

Kunar et al. [15] found that fake-news spreaders are inclined to spread them fast, so tweets sharing fake-news are more likely to contain hashtags and mentions. Also, the users spreading fake-news are more active by sharing more URLs, mentioning more users, and using more hashtags when compared to users sharing trusted-news.

Matteo et al. [4] focused on information consumption on Twitter by analyzing the interaction patterns of official news sources, fake news sources, politicians, people from the show-biz and many others. They were not able to find any evidence of an organized disinformation Twitter accounts. Moreover, they discover that disinformation accounts (although they have active followers base) have limited reach on Twitter activity during the European parliament election by being ignored by other actors.

VII. Conclusions

In this work, we focused on both the Ukrainian presidential and parliamentary elections that took place in 2019. We studied the evolution of the political discourse through the Twitter lenses. Specifically, we analyzed the Twitter activity that targeted the main Ukrainian presidential candidates: *Zelensky* and *Poroshenko*. We find that the conversation on Twitter was driven by users that have a neutral political discourse regarding Zelensky, but also by users that tweet against Poroshenko. Hence, it is interesting that Zelensky won the elections without strong positive support for his candidacy, at least w.r.t. Twitter.

Focusing on the users, we find that the majority are active for a short period of time and appear to contribute at most 10 tweets or retweets. The anti-Poroshenko discourse appears to be dominated by Ukrainian, Russian and international news agencies, journalists, reporters as well as Russian officials and Ukrainian personalities. However, Zelensky's discourse is limited to local Ukrainian news agencies and journalists. At the same time, new users joined the political discourse prior to the first round of the presidential elections. Users that tweet about Zelensky appear to be more active than the ones that tweet against Poroshenko. We hypothesize that the Zelensky's popularity from his acting career prior to the elections contributed to the high Twitter activity. Not surprisingly, this activity increased during the political events captured by our measurement period.

Going one step further we investigated how users from different political groups interact with other users from their own political group and across different groups. Leveraging the retweeting activity, we find that anti-Poroshenko users retweet mostly within their local group, while Zelensky users' popularity is spread across different political groups. This finding reinforced our hypothesis that Zelensky's popularity is not mainly driven by his political discourse. A closer look shows that the existence of a few Twitter accounts within each political group that play an anchor role within their group. Specifically, these anchors act as bridge across political groups or as source withing their own political group. Within anti-Poroshenko group local anchors connect mainly users within the group. Thus, users that have negative Poroshenko discourse exhibit an echo chamber behaviour. However, local anchors within Zelensky political exhibit a reduced local affinity which directly impacts the echo chamber behaviour spread of the neutral Zelensky discourse.

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