Mapping Twitter Activity in the 2019 Ukrainian Political Landscape

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***Abstract*—Twitter has become a critical asset for political discourse and it is widely believe that it is challenging to any modern election campaign to be successful without it. 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 disqualifying the opponent throughout negative Twitter activity is more significant. While Zelensky was considered as an outsider, his successful campaign took advantage of the negative discourse against Poroshenko, i.e., anti-Poroshenko. Our analysis shows that media outlets played an important role as they have kept the anti-Poroshenko discourse active since March 2019 including the end of the considered period (August 2019).**

I. Introduction

Over the past decade, social media platforms, especially 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 [1].

Unfortunately, groups interested in undermining democracy, spreading fake news, influencing the masses have also exploited the openness and unparalleled reach of these platforms. The widely-believed Russian interference in the US 2016 presidential election [2] and the Facebook-Cambridge Analytica [3] data scandal were arguably major turning points. Indeed, Twitter allows for more opinion and displays of emotion than are typically acceptable in traditional news reporting [4]. For example, the Ukrainian conflict is 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 the European Union (EU) and NATO [5]. Moreover fake-news spreaders are inclined to spread them fast, so tweets sharing fake-news are more likely to contain hashtags, mentions and tend to have more negative sentiment and less positive sentiment [6].

Despite the plethora of work in this area, there is no comprehensive and holistic analysis that helps understanding the use of social media such as Twitter during major political events. Existing work on social media influence, has either focused on identifying automated and bot-like accounts [7], tracked the general Twitter activity during elections [8], [9] (e.g. how many accounts tweeted about certain subject, etc), followed the activity of candidates [10], looked at content of tweets [11] to track rumours and fake news among others [12], [13].

This paper present a more holistic view of Twitter activity pertaining to the two major election candidates during the 2019 Ukrainian elections. Starting with the presidential election from which Volodymyr Zelensky emerged as the winner and 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 reveals that a strong positive support is not a mandatory condition for a positive outcome.

Our study also contribute to underpin the role of media or news agencies during the Ukrainian presidential and parliamentary elections. 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.

Some of these media outlets are considered as trust source within their political group. Moreover, many of these trusted accounts further refer as anchors, act as bridge[1] across political groups. 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 group exhibit a limited interaction within their political group, which leads to the spread of the neural Zelensky discourse.

II. Ukrainian 2019 Elections: Evolution of Events

Presidential Election. In 2019, Ukrainians elected after two rounds a new president. 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

[1] They connect different political groups.

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 [14], [15]. The style has been described as non-agenda ownership, and compared to the 2016 campaign of Donald Trump [16], an evaluation which was disputed by others [17], [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. Although she was not far behind Poroshenko in the election, we collect few tweets referring to this candidate. The online campaign, at least w.r.t. Twitter, quickly became a contest between the leading two candidates, Zelensky and Poroshenko. Consequently, our analysis does not include any more 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 parliamentary thus calling for *snap elections*, i.e., early parliamentary elections, that took place on the 21st of July 2019 [19]. The election outcome brought significant changes to the Parliament. Zelensky's party won the majority with 254 seats in the parliament. Moreover, approximately 80% of the elected candidates were new to the parliament [20].

III. Data Collection and Processing

We use in our study data collected using the Twitter API. Figure 1 illustrates the main steps we take to collect and process the re/tweets.

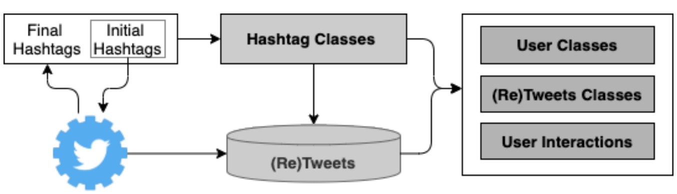


Figure 1: Data collection and processing.

A. Dataset Collection

Figure 1 shows the different steps we used for collecting and processing 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 match our list. However, from the collected data, we extract all the hashtags extending thus our initial set.

Table I: Overview over the sizes of the intermediate and final datasets.

	Raw Data	After hashtag sanitation
Tweets	133418	126052
Retweets	91338	91338
Total statues	224756	217390
Accounts	9872	9233

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*. Furthermore, we identified (re)tweets for which the corresponding hashtags are not comprised in the initial set, and include these in our list of hashtags. Table I summarizes the number of collect tweets and retweets during our six month analysis period.

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

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 (one in Table III and 3 in Table IV in the section A). This step also rely on foreign policy experts with strong background on Ukrainian political environment. Thus, we select an extra set of hashtags. 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. Note that we list all these hashtags in section A. 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 [2], Twitter activity is less important in Ukraine with 217K re/tweets by 9K accounts.

B. Hashtags to Political Classes

A fundamental step to analyze the data 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. For each candidate, we create three classes: *for the candidate*, *against the candidate*, and just *mentioning the candidate* for a total of nine classes. Other tweets are sorted into an additional *Neutral* class. Then we map each of our selected hashtags in one of the devised classes. Note that the classification of hashtags was performed by an Ukrainian 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 2 shows that approximately 18% and 8% of these hashtags are linked to Zelensky and Poroshenko, respectively. Unsurprisingly, we find 1.6% of hashtags map to Tymoshenko. Moreover, we do not map any hashtags to 'anti-Tymoshenko' class and further remove this class from our analysis. Tymoshenko did not reach the second round in the presidential elections. Thus, the low number of Tymoshenko hashtags is most likely correlated with the candidate presence only in the first round of the presidential elections.

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

Class	Hashtags	User Accounts
Neutral	185 (77.41)	9045 (97.96)
Zelensky*	42 (17.57)	3544 (38.37)
Poroshenko*	19 (7.95)	6678 (72.32)
Tymoshenko*	4 (1.68)	413 (4.47)

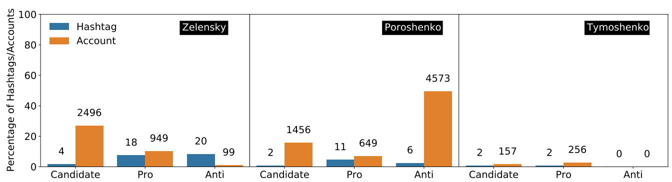


Figure 2: **Percentage (number) of hashtags and accounts per candidate**. Tymoshenko Twitter activity was limited.

C. Tweets versus Retweets

To further understand the dynamic of accounts activity we extract the available *original tweet Id* from the Twitter API. For some messages, however, this information is not available. We consider these messages as *original tweets*. Consequently, messages that have an *original tweet Id* are *retweets*. Using this distinction, we find that our dataset is comprised of 58% of tweets vs. 42% of retweets (see Table I). This approach is helpful while analysing accounts 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 foreign political classes. Although tweets sightly dominated retweets, the ratios are close and is a strong indication of the type of Twitter activity during the considered period: large part of the tweets have been at least retweeted once, which a signal of the interest of the accounts to the political discourse during the considered period. However, some tweets seem to have created no interest.

D. Accounts Categories

With some accounts having high (retweet) activity, we investigate the importance of these accounts: a) accounts highly retweeting other accounts and b) accounts which original tweets were highly retweeted by other accounts. For this purpose, we manually explored the profile of each of the selected accounts and assign them to a category. We distinguish between several media accounts categories: local (Ukrainian), Russian and international new agencies. Similarly, we record activity from local, Russian or international journalists or reporters [21]. Next, 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

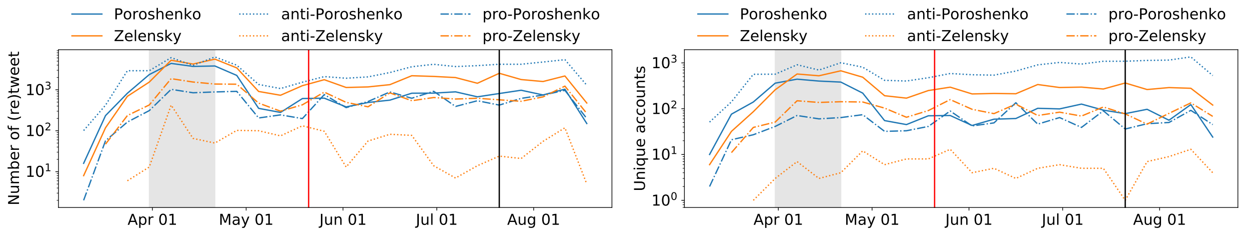
In this section, we discuss the Twitter discourses referencing hashtags related to prominent candidates, i.e., Poroshenko and Zelensky during presidential and parliamentary elections.

A. Overall Activity

Our analysis shows stark increase in Twitter activity correlated with each of the two political events. Figure 3a shows the number of re/tweets 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 (21 May 2019) and the Parliament election (21 July 2019), respectively.

Grouping users according to the candidate they re/twitted about, reveals that more than 80% (179K) of re/tweets are linked to Poroshenko and Zelensky, and are originated by 60% (6K) of accounts. Also, 30% (6K) of re/tweets were linked to Zelensky and 53% (115K) to Poroshenko, respectively. Pro-candidate re/tweets 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 statues 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. Surprisingly, narratives related to anti-Poroshenko are more spread (98% of the negative discourse for both candidates) than the ones related to anti-Zelensky.

Twitter activity is mostly dominated by anti-Poroshenko discourse with some re/tweets including Zelensky. Focusing on the users generating this content shows that the anti-Poroshenko discourse is 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. Note that, apart from anti-Poroshenko, the five other political classes discourses were conducted in large part, by a core group composed of the same or similar accounts.



(a) Unique number of (re)tweets

(b) Unique number of accounts

Figure 3: **Weekly number per political Poroshenko and Zelensky classes (log scale)**. Twitter activity is dominated by accounts re/tweeting about anti-Poroshenko.

B. Political Account Affiliation

With the same network of accounts participating to different political discourse, we 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 3b shows the number of accounts assigned to each of the political classes from the selected candidates. This figure confirms the trend observed in subsection IV-A: Twitter discourse was dominated by anti-Poroshenko accounts while anti-Zelensky topic was less popular.

Indeed, with international or Russian news agencies, the activity of anti-Poroshenko accounts discourse was mostly maintain over the span of the data collection. However, most local Ukrainian news outlets were just mentioning Zelensky and Poroshenko while the same network of less influential accounts where discussing around 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 maintain highly active retweets activity on Twitter.

C. Accounts Activity

Ukrainian election Twitter activity is driven by several news agencies, news reporter or journalist. We also note in subsection IV-B, that some accounts 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 4a shows the number of weekly new accounts participating to each class discussion while Figure 4b shows the distribution of the number of re/tweet per unique account.

Prior the first round of the presidential elections we observe the highest increase in the number of new account that join the election discussion as in Figure 4a. More than half of new accounts were highly interested by anti-Poroshenko discourse. This anti-Poroshenko discourse activity reduce after the presidential elections but strangely, the number of new participants to the discussion against Poroshenko increase significantly after the parliament dissolution before mostly doubling on the parliament election. Theses new accounts were dominated by a myriad or pro-Ukraine, pro-Nato accounts. The interest to Poroshenko was limited to the presidential elections while Zelensky topic interest significantly decrease after the presidential election. Moreover, Figure 4b shows that large part of the accounts have produced less than 10 re/tweets. Thus, most of the new accounts activity were probably limited to a one-time or less than 10-times posting or retweeting during the whole period. This confirms our finding that a network composed of the limited number of same accounts drive the political discourse, mainly against Poroshenko. Therefore, this network of influential accounts were motivating a variety of accounts to continuously participated to any of the political discourse.

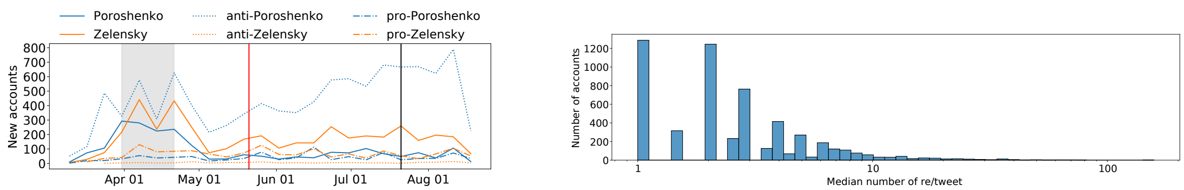
D. Tweets versus Retweets

We further evaluate the importance of this network of highly influential accounts. To this end, we separate the original tweet from retweet and plot in Figure 5 the weekly number of accounts posting original tweets and those retweeting. Large part of tweets were only mentioning any of the candidates. Thus the number of accounts posting anti discourse were very limited while the number of pro accounts where slightly more important. As in Figure 5a, this indicate that most accounts were cautious in their original tweet while limited number of accounts were clearly positioned as anti-Poroshenko and anti-Zelensky.

Focusing on the retweeting activity reveals a significant difference in the anti discourse retweeting activity. Figure 5b shows that users consistently retweet messages against Poroshenko, while anti-Zelensky retweeting activity is limited. We thus hypothesis that anti-Poroshenko continuous activity was probably maintain by a network of few influential accounts and large number of less influential accounts, potentially from a farm of bots retweeting anti-Poroshenko tweets. A part from this anti-Poroshenko bot-farm, 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

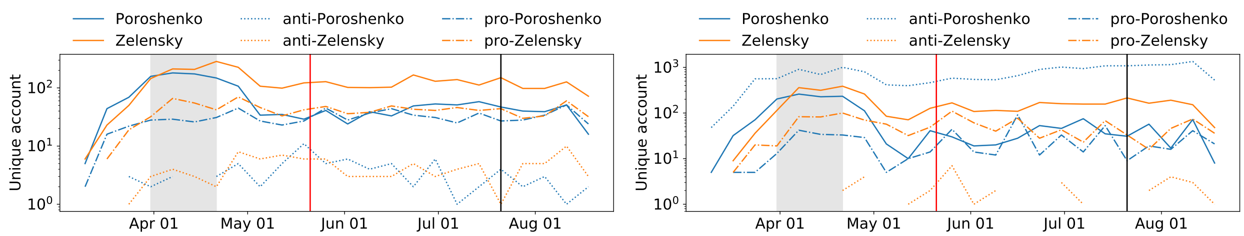
Having seen that potentially anti-Poroshenko discourse is maintain by a farm of bots, we further seek analyze the



(a) New Accounts

(b) Contribution (log scale)

Figure 4: **Contribution of accounts to the political discourse of Poroskenko and Zelensky**. Large number of the users have low (re)tweet activity.



(a) Tweets

(b) Retweets

Figure 5: **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.

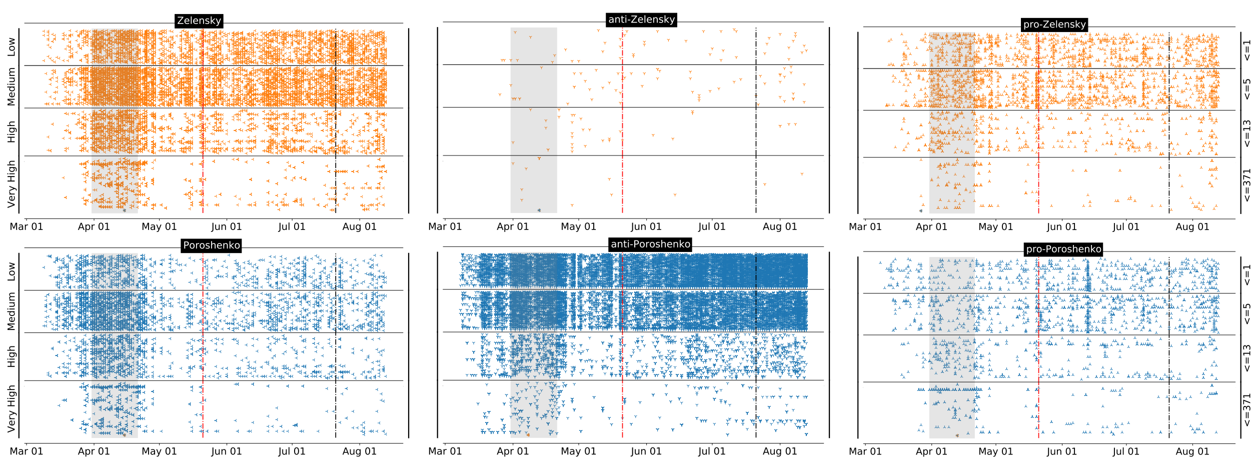


Figure 6: **Twitter activity per candidate classes for Zelensky and Poroshenko**. anti-Poroshenko discourse dominated all four accounts activities groups: low, medium, high and very high.

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 6 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%, large part of accounts have *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. To make individual classes more visible, we show the tweet activity for the three Zelensky and Poroshenko classes in Figure 6.

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 rely on farm of accounts having individually limited activity. However, their combine activity maintain 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

In this section, we investigate how accounts interacted for our selected candidates. Specifically, using the retweets activity we identify and analyze retweets patterns per political class.

A. Retweets

We construct the retweets graph from the retweets collected from the data. Note that we use the full data on the collection period. Each retweet pair is composed of a source and a target, with the target being the account retweeted and the source being the account retweeting. Then, we colour code each account with its political class using approach describe in subsection IV-B.

Figure 7 shows the retweets graph for the considered candidates. Figure 7c shows all accounts involved in Poroshenko and Zelensky discussion on Twitter, while Figure 7a is the largest connected component (i.e., largest connected accounts thorough retweets). Figure 7b is the second largest connected component and is limited to anti-Poroshenko *echo-chamber*. The plot shows an hierarchical edge bundling, where accounts represented as nodes are grouped by political class and adjacency retweet represented as edges are bundle together. Hierarchical edge bundling [22] is well recognized to decrease the clutter usually observed in complex networks, by organizing nodes (i.e., Twitter accounts) into a circle with edges (retweet) connecting between them. Additionally, we emphasise account retweet activity: the more an account is being retweeted, the bigger is it node size on the graph. Note that, we were not able to use the Louvain Method [23] since it relies on non-directed graph while the retweet graph is directed, i.e., source to target.

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 [24], an *echo-chamber* can be characterise by two main dimensions: a) homophily in the interaction networks and 2) bias in the information diffusion toward like-minded peers. Therefore, anti-Pososhenko accounts present an *echo-chamber* behaviour with some accounts playing *amplifier* role. These anti-Poroshenko accounts tend to amplify or reinforce their anti-Poroshenko campaign by retweeting inside the relatively closed anti-Poroshenko discourse. This is in line with subsection IV-E, were we show that anti-Poroshenko discourse is maintain by a farm of potential bots, i.e., accounts having individually limited activity, but participating together to the anti-Poroshenko discourse. This anti-Poroshenko *echo-chamber* is composed at 91% of accounts which activity is exclusively limited to anti-Poroshenko political class. Zelensky and pro-Poroshenko also present *echo-chamber* behaviour, but with significantly less members (6% and 3% respectively). Thus, we hypothesis 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. We further refer to such accounts as as bridge accounts.

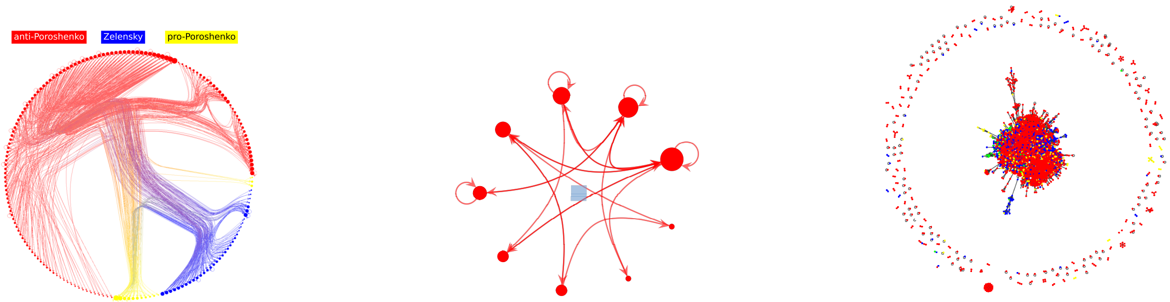
Although large part of accounts activity is limited within their political class we find that 28% of retweets bridge to a foreign political classes. Bridge discourse is dominated by exchanges from anti-Poroshenko to Zelensky and from Zelensky to anti-Poroshenko at the rate of 34% and 29% respectively.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

B. Local Anchors

Per political class, we identify accounts playing important role within their local class and crossing to foreign political class. Therefore, we analyse retweets 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 8 shows the two type of local anchors patterns.

For instance, Figure 8a shows that local anchors are retweeted by a myriad of accounts without any apparent link between them. The plot shows that the anchor is the initial author of the tweet, and several accounts start retweeting this message starting at time $T01$ and ending at $T45$. While there is no retweet between the myriad of accounts, we also record that these accounts tend to randomly retweet the original tweet. For instance, while account retweeting at time $T01$ is from anti-Poroshenko class, 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 8b 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 inline with Zelensky and pro-Poroshenko accounts being limited to local Ukrainian news agencies/journalists. Thus their discourse



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

Figure 7: **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 type. (b) Rare anchor type.

Figure 8: **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.

is limited to Ukrainian Twitter community with some anti-Poroshenko accounts picking up on interesting tweet to amplify for their international anti-Poroshenko discourse.

C. 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 anchor and farm of accounts within and out 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 estimate the popularity of an account towards other political classes. Conversely, the local affinity estimate the popularity of an account re/tweet within its own political class. A ratio close to 1 indicates a high affinity while a ratio close to zero refers to low affinity.

Figure 9 shows the local and foreign affinity for accounts involved in Poroshenko and Zelensky discourse. As expected, local anchors present a high local affinity (Figure 9a). Most local anchors from *pro* and *anti* candidate discourses have a local affinity of 1. However, local anchors within Zelensky political class exhibit a local affinity of less than 2% which indicates that these local anchors play marginal role in Zelensky's political discourse. Thus, reducing the spread of Zelensky discourse to limited number of accounts potentially from an *echo chamber*. However, in addition to being a critical retweets sources, local anchors within Poroshenko political play a notable role as retweets source (bridge accounts) to foreign political classes. Approximately 20% of Poroshenko political class local anchors tweets have been retweeted by foreign political classes accounts. Indeed, Zelensky was considered as an outsider while Poroshenko was the incumbent president.

This trend is also observed while considering all accounts involved on each *pro* and *anti* candidate discourses (see Figure 9b). Accounts within Poroshenko political class strive more foreign activity then accounts within Zelensky political class. Similarly, pro-Poroshenko discourse is more oriented to foreign political classes than pro-Zelensky discourse. Surprisingly, anti-Zelensky class exhibit higher foreign affinity than anti-Poroshenko political class. Recall that anti-Zelensky discourse is limited to few accounts (see subsection IV-B). Therefore, this limited number of accounts attempt 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, anti-Poroshenko political class exhibit *echo chamber* behaviour, reducing the need for foreign discourse: local anchors having high local

(a) Top 5 local anchors.

(b) All accounts.

Figure 9: **Poroshenko and Zelensky political class members (median) affinity to local and foreign political classes**. As expected, local anchors have high local affinity. While most accounts are interacting with other political classes, accounts discussing on anti-Poroshenko exhibited an echo-chamber behaviour.

affinity with the rest of accounts (with local affinity of 1) within 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 several years social media has been heavily used for election campaign. Twitter as most social networks has become a prevalent tool in election campaigns. 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 [1]. Moreover, Twitter is increasingly incorporated in campaign repertoires of traditional parties in an attempt to broadcast their message, candidates or to influence the coverage of campaigns by traditional media. In turn, users who tweet about politics tend not to be representative of underlying populations. Instead, they are more likely to be politically interested, politically partisan, and to participate politically in other ways [1]. [11] have shown that in the context of the 2009 German federal election Twitter is used extensively for political deliberation and that the mere number of party mentions accurately reflects the election result. In [10], a method has been proposed to identify different user types based on how high-end users utilized the Twitter service during the 2010 Swedish election. In the same vein, [25] 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. [26] 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. [4] shown for the military conflict in Eastern Ukraine as well as to the diplomatic wars between Ukraine and Russia, that Twitter allows for more opinion and displays of emotion than are typically acceptable in traditional news reporting. Moreover [6] focused Ukraine, a country where fake news is common, as a case study. They 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. They also observe that in general, Tweets sharing fake-news tend to have more negative sentiment and less positive sentiment.

Grinberg *et al.* shows that cluster of fake news sources shared overlapping audiences on the extreme right, but for people across the political spectrum, most political news exposure still came from mainstream media outlets [12]. They discovered that individuals most likely to engage with fake news sources were conservative leaning, older, and highly engaged with political news. [7] study political bots on Twitter and their influence on the Swedish general election in September 2018. They proposed a classification model that recognizes automated behaviour among Twitter users and were able to identify right-wing Twitter accounts clusters. Russian troll from the Russia's Internet Research Agency (IRA) are widely believed to have tried to interfere with the 2016 U.S. election as well as others elections by running fake accounts on Twitter [13] or propagandising misinformation. This belief has been confirmed by the European Commission which state that the evidence collected revealed a continued and sustained disinformation activity by Russian sources aiming to suppress turnout and influence voter preferences [27]–[29]. Furthermore, for the European Commission, this confirms that the disinformation campaigns deployed by state and non-state actors pose a hybrid threat to the EU. Indeed, many disinformation attempts have occurred: from European Union having Nazi roots [30] to the fact that European Commission is one of the most undemocratic institutions[2][3] or there is no point in voting in the European elections[4]. Other Europe-wide

[2]https://euvsdisinfo.eu/report/european-commission-is-highly-undemocratic

[3]https://euvsdisinfo.eu/report/eu-elections-are-a-sham

[4]https://euvsdisinfo.eu/report/nazis-are-already-in-power-in-latvia-there-is-no-sense-in-voting-in-future-elections

investigation into networks of disinformation resulted in an unprecedented shut down of Facebook pages just before voters head to the polls [31], [32].

Matteo et al. [8] 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. They also shows that there is a strong tendency towards intra-class interaction and that the debate rarely crosses the national borders.

Our study focus on both the Ukrainian presidential and parliamentary elections that took place in 2019. Similar to other studies and reports, we did not infer in our analysis any disinformation Twitter accounts. Our work, however, reveals that a strong positive support is not a mandatory condition in winning an election.

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 Twitter political discourse is driven by users that have a neutral political discourse regarding Zelensky, but also by users that tweet against Poroshenko. Hence, our work reveals that a strong positive support is not a mandatory condition for a positive outcome.

Focusing on the Twitter users, we find that the majority user are active for a short period of time and appear to contribute to the Twitter activity with at most 10 tweets/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 join 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 tweets against Poroshenko. We hypothesize that Zelensky's popularity to his acting career prior to the elections contributes to the high Twitter activity. Not surprisingly, this activity increases during the political events captured by our measurement period.

Taking one step further we seek to understand 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 neural Zelensky discourse.

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Table III: Extracted 51 non Cyrillic Hashtag Classes.

Class	Hashtags
Neutral (44)	coahuila, representation, russia, russianinvasion, elections2019, solicitors, apc, prudhommes, perola, ukraine, ff, email, lawyers, loi, solicitor, syndicat, avocats, tribunal, oposiciones?, salarié, agency, entreprise, input, kyiv, administrativa, lawyer, legaladvice, supremo, krasnopol, online, envivo, eeuu, justice, chartres, travail, class, ukraineunderattack, zik, donbas, elections, donbass, sailors, justicia,russiainvadedukraine
Zelensky (1)	zelensky
pro-Zelensky (2)	Kolomoisky, kolomoyskiy
Poroshenko (1)	poroshenko
pro-Poroshenko (1)	tomos
anti-Poroshenko (1)	stoproshen
Tymoshenko (1)	tymoshenko

Table IV: Extracted 176 unique Cyrillic Hashtag Classes. Note that the same hashtag can be linked to multiple classes.

Class	Hashtags
Neutral (134)	відсіч, аваков, ато, вакарчук, вибори, война, войнанаукраине, всу, выборы, гбр, героямслава, гпу,гриценко, дбр, донбас, донбас..., донбасс, допрос, ес,єс, житомир, зрада, зрада..., зубожіння, израиль, каратели, киев, крым, луганск, медведчук, мова, моряки, нато, нетаниягу, новини, огляд, оос, парламент, пиздец, политика, портнов, президент, реформы, россия, сбу, свобода, список, суд, сша, указ, українареалії, цик, шарий, смешко, украина, зсу, україна, майдан, крим, путін, putin, новости, інавгурація, инаугурация, харків, украине, газ, укроборонпром, рнбо, армія, голос, голосзмін, ихтамнет, церковь, гандзюк, новаполітика, мвф, набу, силаічесть, рада9, аутизм, вакцина, безвиз,гтс, рада, пцу, кір, епіфаній, трибунал, вакцинація, армия, конфликт, раскол, ахметов, верховнарада, кернес, ляшко, госпереворот, жуков, хтозамовивкатюгандзюк, газпром, бойко, дефолт, законпромову, філарет, снбо, лукаш, корь, цру, референдум, оп, хорошковський, диалог, льовочкин, герман, вакул, краснополь, досрочнівибори, гепа, достроковівибори, недоторканість, січ, сакашвілі, русский мир, автокефалия, національнийфронт, гражданская война, ополченка, дрюк, вибори2019, вибори_2019, выборы2019, выборы_2019, війна
Poroshenko (1)	порошенко
pro-Poroshenko (9)	аваков, бпп, президентавпрезиденти, гройсман, майдан, філарет, безвиз, порошенкомійпрезидент, томос
anti-Poroshenko (5)	смешко, силаічесть, госпереворот, сакашвілі, стопрошен
Zelensky (3)	зеленський, зеленский, зеленского
pro-Zelensky (13)	аваков, зе, слуганароду, богдан, коломойський, хомчак, беня, зеправила_життя, труханов, колойський, зробимоцеразом, коломойский, зекоманда
anti-Zelensky (20)	яклоу, думай, стопзе, зеленськийганьба, зекоманда, порохсилакоксмогила, яклоун, зебіл, голосуюнеприколу, стоп_зе_реванш, iamaclown, імпічмент, зeend, госпереворот, аяпредупреждал, зеля, блазень, стопзереванш, стоп_зе, стопреванш
Tymoshenko (1)	батьківщина
pro-Tymoshenko (2)	ахметов, тимошенко

Appendix A
Filtered Hashtags