Evolution of Political Polarization on Slovenian Twitter

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We analyze the evolution of Twitter activities in Slovenia in recent years. We construct networks, with Twitter users as nodes, and retweet relations as edges. We detect communities and influential users in them, and track how they evolve during times of political changes and start of the Covid-19 pandemic. We observe the following: Most of the influential users around which communities emerge are related to politics, the political polarization is increasing, and the right leaning Twitter users are considerably more active.

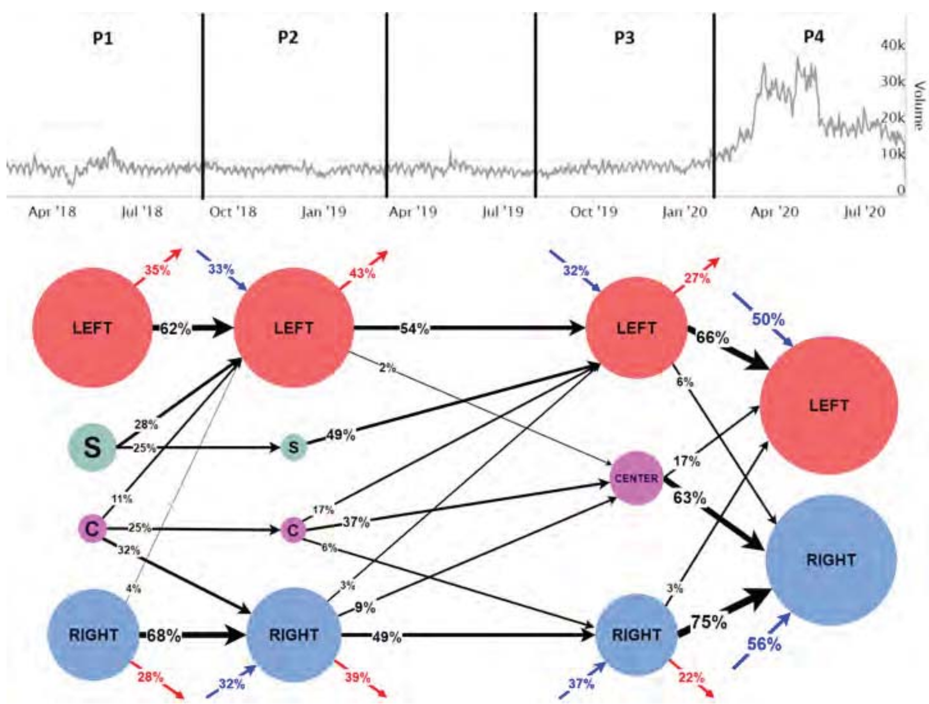

Fig. 1. Volume of tweets (top) and evolution of the top communities (bottom) across the four periods analyzed, P1–P4. Considered are only communities with more than 2% of the Twitter users in each period (S stand for the SPORTS, and C for the CENTER community). Size of a community corresponds to the number of its users. Black arrows show the flow of users between the communities, and percents refer to fractions of the source community. Red arrows indicate users leaving a community, and blue arrows indicate new users (or users from smaller communities) joining a community (shown just for the LEFT and RIGHT communities).

It turns out that the retweet communities very well reflect the actual political alignments. We already demonstrated that political parties and nationality of the members of the European Parliament can be reconstructed solely from their retweet activities [3]. We also showed that there is a correspondence between the co-voting and retweeting in the European Parliament, while higher Twitter activity was observed for the right-wing parties [2]. Also, in the case of Brexit, the Leave proponents showed much higher activity and influence on Twitter than the Remain proponents [4].

We collected most of the tweets from the Slovenian users in recent years with the TweetCat tool [6], built specifically for acquisition of Twitter data for "smaller" languages. For the current work, the collected tweets are split into four 6-months periods corresponding to major political events:

- P1 (Mar. 2018 - Aug. 2018) - government resignation and snap parliamentary elections (on 14 Mar. and 3 Jun. 2018, respectively),
- P2 (Sep. 2018 - Feb. 2019) - left-wing government formation (on 13 Sep. 2018),
- P3 (Aug. 2019 - Jan. 2020) - left-wing government resignation (on 27 Jan. 2020),
- P4 (Feb. 2020 - July 2020) - right-wing government formation (on 13 Mar. 2020) and emergence of the Covid-19 pandemic in Slovenia.

For each period, P1–P4, we detect communities by the Louvain method [1] which maximizes modularity. We identify influential users in terms of the Hirsch index (*h-index*) [5], adapted to Twitter [4]. A user with an index of h has posted h tweets and each of them was retweeted (RT) at least h times: $h\text{-}index(RT) = \max_i \min(RT(i), i)$.

Table 1 shows basic network statistics for the four time periods. If we ignore smaller communities which contain less than 2% of the users, the largest four communities comprise more than 92% of all the users. The communities are labeled as LEFT, SPORTS, CENTER, and RIGHT by their most influential members.

Period	P1	P2	P3	P4
Twitter users (nodes)	8,334	7,952	7,315	9,760
retweeted tweets	155,730	146,806	165,733	410,206
retweets (weighted edges)	448,962	412,434	424,729	1,648,807
communities ($> 1\%$)	6 (95%)	5 (95%)	5 (96%)	2 (96%)
communities ($> 2\%$)	4 (92%)	4 (93%)	3 (93%)	2 (96%)
modularity	0.40	0.38	0.35	0.32
Average *h-index* of the top 20 influencers				
LEFT	15	14	13	27
SPORTS	7	5	/	/
CENTER	12	11	18	/
RIGHT	48	46	43	66

Table 1. The Slovenian retweet networks during periods P1–P4. Size of the networks, the number of communities with more that 1% or 2% of the users with corresponding fractions of all the users covered (top), and average influence of the top 20 users in the largest communities (bottom).

Fig. 1 shows the transitions of the users between the communities across the time periods P1–P4. We observe the dominance of the LEFT and RIGHT communities, and how they eventually absorb the smaller communities (SPORTS is largely absorbed by

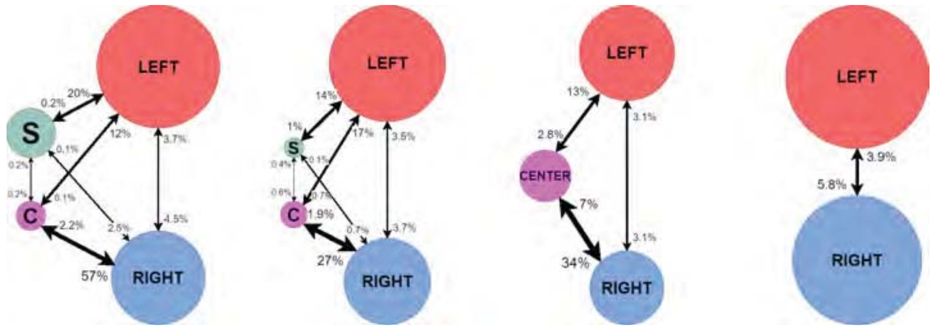

Fig. 2. Inter-community retweeting between the top communities during each of the four periods, P1–P4. Size of a community corresponds to the number of its users, and arrows correspond to fractions of retweets. For example, in P3, 34% of all the retweets by CENTER are from the RIGHT community, and 13% are from LEFT. The rest (53%, not shown) are retweets from the CENTER community itself, i.e., defining it as a community.

LEFT, and CENTER by RIGHT). There is a relatively large fraction of the Twitter users leaving the dominant communities or joint them anew (indicated by the red and blue arrows, respectively). We did not yet exhaustively check the robustness of the Louvain community detection algorithm on this data, but so far there are strong indications that the cores of the communities, in terms of the influential users, remain stable.

Fig. 2 shows the retweeting activity between different communities. CENTER is retweeting more from the RIGHT and is eventually absorbed by the RIGHT. However, CENTER also acts as a link between LEFT and RIGHT (most pronounced in period P3), and this link disappears in period P4. The last period, P4, is characterized not only by an increase in Twitter activities, due to the Covid-19 pandemic, but also by increased political polarization. Our preliminary experiments also indicate that the amount of inappropriate, offensive and violent hate speech is increasing in this recent period.

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