Protest and social media: friendship and communication

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Abstract

Online social networking sites are considered as one of the most influential facilitator of many recent social movements. In this paper we investigate both the dynamics of friendship interactions and the structure of communication in protest-related community. We find that offline actions play insignificant role for the dynamics of the structure of a relatively stable protest online community.

Introduction

For the last few years social media in general and Internet in particular are often considered by journalists or politicians as facilitators of many offline movements with different nature. For example, the protests in Moldova and Iran in 2009, which represent the start of the so-called Twitter-revolutions, began after the fraudulent elections. The wave of uprisings in the Arab world in 2010-2011, which is widely known as Arab Spring, was caused both by disagreement of youth with the political agendas and difficult socio-economic circumstances. Movements in Western countries such as 'Occupy Wall Street' in US, riots in London, movements in Spain, which started during the financial crisis and where protesters demanded other social and economic agendas. Researchers (Gonzalez-Bailon 2011, Lysenko 2012) recently argue that social networking sites played an important role in social movements, because they can be used as an effective tool for information spread, self-organization and mobilization. At the same time, other researchers (Morozov 2012) suggest that the role of social networks in triggering protest activities is limited and, often, overstated. Existing studies predominantly look at the structure of emerging protests communities which actively respond to the offline events and activities.

In this paper we analyze the structure and evolution of stable protest groups, online protest mobilization, and the structure of communication by studying the protests that took place in Russia in 2011-2013. In particular, we analyze how online activities at social network sites such as Facebook are related to offline activities. The protest wave began after the Parliament Elections in December 4, 2011 and continued for more than two years with a several large and small protest demonstrations in Moscow and all over the country. The analysis of protest communities in online social networks can contribute to a growing literature on the determinants of protest movements. As Greene (Greene 2013) outlines, online services play an important role in civil activism and social and political mobilization in Russia: protesters actively used social networking sites to share information about scheduled events and other news. To look into the mechanism of this influence in more details, one needs to understand the structure and dynamics of protest communities and the influence of offline activities on the online environment.

In this paper we use social network analysis to describe both the dynamic structure of friendship ties within the protest Facebook group and communication patterns within Facebook public 'We were on Bolotnaya Square and we'll be back'.

The analysis of communication interactions shows that the key motivation of the participants of online protest communities is self-representation and sharing the emotions and experience. Although, based on group characteristics, it could be expected the discussion of protest activities or protest agenda.Furthermore, there is no homophily effect in the communication network, which is often found in social and information networks. However we indicated the presence of ingroup and outgroup effects which are character for the social system with participants with different characteristics.

Based on the content analysis on both friendship interactions and content-analysis we find that network indices such as nodes' degree centrality, considered as one of the main indicators of the participants activity, do not correlate with the user's contribution to the online community. A lot of participants with high degree centralities avoid posting, commenting, and even liking within the protest group. According to our research, the online protest community moved from the phase of active growth and development into the stable phase. We did not trace the considerable splashes in the number of friendship interactions neither on the offline event nor afterwards. However, for the whole period of observation the density of friendship interactions systematically increased which can be interpreted as the growth of solidarity within an online group.

The structure of the paper is as follows: In the first section we review different approaches which are used for studying the social media, its influence on political participation and offline mobilization. The second section introduces the research hypotheses and the two sets of empirical data on which the analysis is based. A description of gathering data, coding it and creating the social network is given. The third section presents the analysis of the communication network and models used to study it. The fourth section describes the analysis of friendship networks. The fifth section concludes.

Background

Online social networks provide a lot of data for the analysis and scholars from completely different fields use a wide array of methods to study them. Social network analysis remains one of the most widespread technique for the investigation of online communities. According to Lewis (Lewis 2008) by using data directly from online sources researchers avoid interview effects, imperfections in recall and other sources of measurements error that may accompany survey research. In addition, the data collection from online communities is also much easier for such a sensitive issue as protest participation.

Social network analysis was used for studying the structure of different online communities: blogs (Adamic 2005), Questions and Answers forums (Adamic 2008, Stadtfeld 2011, Hsu 2006), massively multiplayer online game (Bakshy 2010, Ducheneaut 2006, Shi 2004), online learning communities (Vaquero 2013, Aviv 2008), recommendation networks (Leskovec 2007), social media (Leskovec 2010, Ugander 2011, Ahn 2007, Mislove 2007), etc. Researchers mostly focus on the following questions.

First, they study the topology of complex online networks, their formation, evolution and dynamics (Kumar 2010, Zhang 2007, Mislove 2008). Sometimes they imply exponential random graph models and stochastic actor-oriented models for the deeper inside in the network structure formation and evolution (Lewis 2012).

Second, they trace differences and regularities between online and offline network structure and dynamics (Backstrom 2006, Leskovec 2008, Kairam 2012).

Third, scholars look at the information propagation over the online networks (Adar 2005, Leskovec 2008, Leskovec 2011). For the recent years there were introduced several models for information epidemics within online social network: cascade model (Leskovec 2007, Kempe 2005, Leskovec 2010), diffusion model (Yang 2010), etc.

In the last few years many papers look at political issues and social media, predominantly focusing on the structure of communications within online protest communities and the structure of links within blog (Adamic 2005, Livne 2011). These papers also show the homophily in blogosphere - the tendency of individuals to create links with similar ones. For example, US bloggers communicate with those people who share their political views. In contrast, Russian bloggers actively communicate both with the same and opposite political preferential (Etling 2010). In these studies researchers investigated the structure of cross-links within blogs, which doesn't answer the question about interaction and communication.

In frames our research we aimed to study the communication network within online Facebook protest groups and identify the patterns of interaction between participants.

Besides the investigation of communication patterns the relevant research question concerns the method to identify the opinion of leaders who have a great impact on the online community audience. Researchers have undertaken a lot of attempts to find the way for the correct identification of the key actors according to their network position (Borgatti 2006, Krackhardt 1990). However the implication of such techniques for the online communities questionable, because links in Facebook or Twitter do not mean the actual friendship. The most adequate interpretation of Facebook friendship link is the channel for the information exchange since Facebook friend receive the updates of each other. To reveal the influence patterns and correlate in with network position and network indexes we identified key actors within online community and revealed their communication patterns.

The interrelations between online and offline environments is a very interesting and actual topic. Although there are a lot of papers, the tracing of such influence is a very difficult and sometimes ambiguous point. The serious influence of offline events and activities on the online environment was identified in works about Canadian and Spain movements (Gonzalez-Bailon 2011, Marcoux2013), but in these cases researches paid attention to the relatively new protest movements which are under construction. In our work we would like to study the influence of offline activity on the relatively stable protest community and uncover some regularities for the stable organization.

Russian protest movement

The first protest meeting was hold in Moscow on December 5, 2011 after the declaration of Russian Central Election Commission about the victory of the pro-government party 'United Russia'. Activists protested against the election results and demanded for the cancellation. Since then the protest activity in Russia multiplied and few big demonstrations were conducted with more than fifty thousand participants. A rather long protest event took place at the beginning of May 2012. Activists formed the 'Occupy movement' which was similar to the 'Occupy Wall Street' in US.

There are few popular social networking sites in Russia. The most popular social media site is the Russian analog of Facebook - Vkontakte. Vkontakte’s monthly audience reaches approximately 50 million users of 12 to 64 years of age in Russia, about half of the country's population of the same age group. The number of Russian Facebook users is significantly lower, with slightly more than 5 million users. Comparatively with Facebook, Vkontakte has a more userfriendly interface and the rules of the social media allow to download movies and songs. However, Facebook played the more important role for the political participation and protests compared to Vkontakte (Reuter 2012), while Vkontakte has a much larger Russian audience than Facebook, the protest community in Facebook was significantly higher and it determined the choose of Facebook for the analysis.

Methodology

We formulated the following hypotheses.

H1: There is homophily within the communication network: people with the similar political views tend to communicate with each other and avoid people with different preferentials.

H2: Opinion leaders within online communities can be distinguished based on the network characteristics.

H3: The community growth has a general timetrend. Besides we can observe the significant jumps before or after offline events.

Data

We have collected two different types of data sets - data about Facebook friendship ties and communication network.

We collected posts and comments from the Facebook group focusing on protest organization “We were on Bolotnaya Square and we will return” about the protests recruitment and mobilization from September 2012 to March 2013. This group was chosen because of its high significance for protest activity.

27 posts and 797 comment were selected.

We coded the author and the recipient of the comment and it established the directed edge from the author of the comment to the destination. We distinguished three types of recipients:

i) It was a specific Facebook user if we can clearly understand the recipient of the message.

ii) We created a special node 'All' and established a direct edge from the author of the comment to it if a person told something for everyone. This artificial node has only in-degree centrality, obviously that its out-degree is 0.

iii) We established a self-loop if a person was talking about his own experience and the message was not addressed to anybody.

Finally we got the weighted directed network.

We also assigned node's attribute according to the attitude towards the group policy. Three attitude types were distinguished: positive, neutral and negative. This characteristics were assigned by four independent researchers. There was a substantial agreement between different coders: the Cohen's Kappa coefficient was 0.53.

We also collected data about friendship interactions between participants in one of the protest groups in the Russian Facebook segment 'Putin must leave'. There were 18 data sets collected from 2 December 2012 to 28 May 2013.

Results and Discussions

Communication network

The communication network has an important characteristic: more than 57% edges within network are self-loops. This can be explained partially by the way of network creation: we assumed an edge as a loop if a person wrote a comment about her own experience and just shared emotions without interaction. So participants of this group prefer monologues over dialogues or collective discussions.

The basic descriptive statistics for the communication network without self-loops presented in Table 1.

Table 1. Descriptive statistics for the communication network

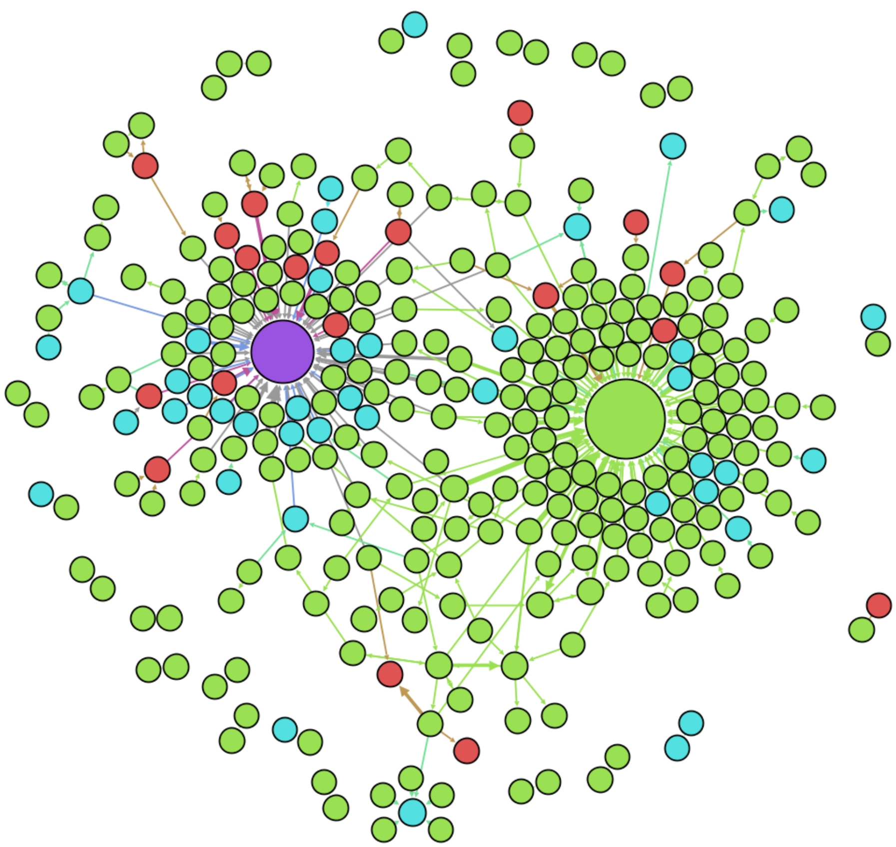
Index	Net	‘All’ free	‘We were…’ free	Both hubs free
Nodes	540	539	539	538
Edges	339	260	218	140
Density	0.0011	0.0009	0.0008	0.0005
Average degree	0.63	0.48	0.40	0.26
Self-loops	455	455	441	411
Reciprocity	0.089	0.115	0.092	0.143
Transitivity	0.005	0.004	0.003	0.050

As can be inferred from the Table 1, the network is very preferential attachment system with two big hubs 'All' and 'We were on Bolotnaya square' which accumulate approximately 60% of all existing links. However the hubs have relatively humble out-degree indexes.

The major part of commentators prefers to address their thoughts to the creator of the group or to all the audience instead of interactions with the peers, although the commentators understand that they will not receive feedback. After the removal of hubs from the network, the system splits into many small clusters and isolates (Pic 1.).

This communication structure can also be considered as an example of creation ingroup and outgroup effects within community. According to Brewer (Brewer 1999) people from the same community with different characteristics (gender, race, social position, etc.) are hostile toward each other. Such effects are also lead to prejustice and stereotypes in both groups.

The ingroup and outgroup effects are well-investigated from the network perspective. As was underlied by Newman, people have a strong tendency to associate with others they perceive as being similar to themselves (Newman 2009), which means the tendency to create cohesive groups with similar actors and remove boundaries with antagonists. This tendency in network science is called homophily or assortative mixing. According to the results of many network researchers tendency of individuals to interact with individuals that share similar political views can be observed in communication networks, including political discussions (Adamic 2005, Livne 2011, Tremayne 2006, Hargittai 2008).



Pic 1. Communication network.

In different online information and social networks the degree of assortativity can also be observed. According to our first hypothesis *H1* we would like to find the homophily within the communication network. The assortativity coefficient is 0,14 which means that people with similar views communicate with each other and avoid interactions with different ones, but the tendency is not very active.

Friendship network

For investigating the friendship interactions within protest community we chose one of the biggest close Facebook protest group 'Putin must leave' (Table 2, Pic. 3). We collected 18 data sets from December 2012 to March 2013 to trace the dynamics of friendship interactions within the group. For data download was used the Facebook application NetVizz (Rieder 2013) which allows to obtain from social network information about members of the group, their location and gender. NetVizz also downloads the information about friendship interactions within the group.

However for our case we did not have enough information and conduced content analysis of group and assigned additional attributes for the group members, based on their political views. There were distinguished two main attributes types: socialists and liberal.

Table 2. Descriptive statistics for the Facebook friendship network

Index	Friendship network
Nodes	2755
Edges	34704
Density	0.009
Average degree	25.2
Clustering coefficient	0.48
Modularity	0.42

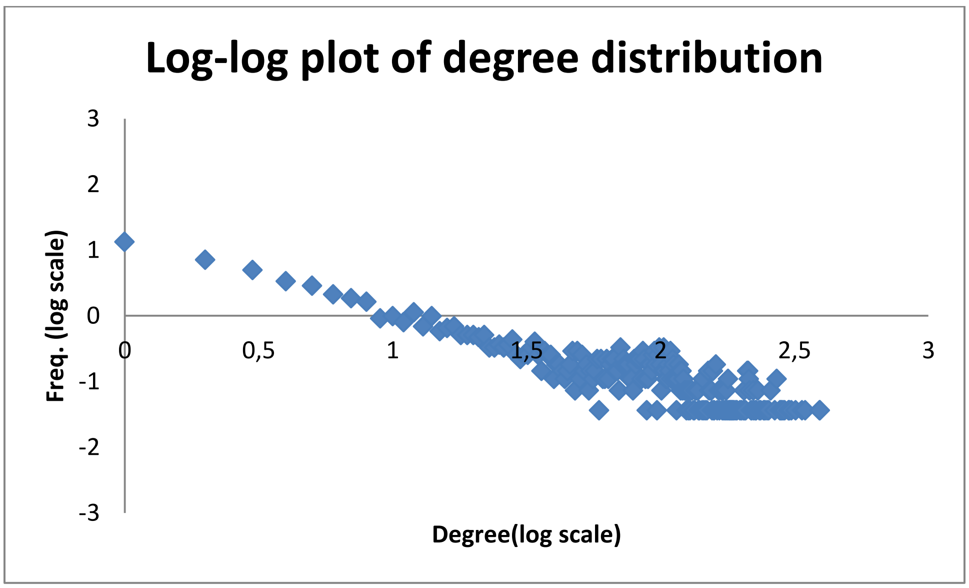
The graph structure of the network reveals few interesting moments. For example, we can distinguish two cores which represent people from different countries. The bigger one is a cluster with Russian and the smallest one is a cluster with people from United States, European Union and other countries. Many of whom are former Russian citizens who wanted to support Russians.

Pic 2. Facebook friendship network

For the partitioning network into clusters we used Louvain method (Blondel 2008) and got a relatively high modularity index. Modularity of a partition is a scalar value between -1 and 1 that measures density of links inside communities as compared to links between communities (Girvan 2002, Newman 2004, Newman 2006). The modularity values between 0.3 and 0.7 indicate strong community structure and higher values are rare at least for social systems (Dinh 2013). This measure for the friendship network shows that there are rather well-distinguished clusters within the community that have a meaningful interpretation.

The biggest cluster (green) represents people who live in Russia and support the left wing of the Russian protest movement, the other big cluster in the Russian core represents people who share the right view. Such segregation shows that people actively add to their Facebook friends those who share their political views. Notably, there was no such evidence in the case of the communication network.

Based on the degree distribution in the friendship network it can be assumed that the preferential attachment network fits the power-law (Barabasi 1999).



Pic 3. Degree distribution for the Facebook friendship network.

There are relatively small amount of users with many friends within the group and a lot of participant with a small number of friends. In the social network it seems reasonable to suppose that individuals who have connections to many others might have more influence, more access to information, or more prestige than those who have fewer connections (Newman 2009). So opinion leaders within the group should have high degrees and actively communicate with other group participants. To verify this hypothesis (H2) we distinguished four sets of random users whose centralities were in intervals from 0 to 10, from 50 to 70, from 110 to 130 and from 180 to 200 respectively and then completed the manual analysis of users' activity within the community.

We traced the number of posts, comments and likes for the posts. It turned out that there are three different types of users based on their activity within the online community: readers, commentators and influencers. Readers are the major part of the group, they just participate in the online community but do not contribute. The degree of centrality of the average reader is very small (0 to 10). He has very few friends within the group. Commentators often like posts and comment on them, but they very seldom post their own posts. Their average degree of centrality is higher compared to the one of the average reader (50 to 70). People with relatively high degrees (110 to 130) activity contribute to the community environment, they post news, photos and comment a lot. So we see a link between the user's activity and it's number of friends within the group to the some point. Surprisingly users with very high degree centralities do not contribute to the online environment at all. Such persons are generally famous civil and political activists who prefer another communication style - they usually post news and comments on their personal Facebook and Twitter pages. Thereby hypothesis *H2* about the possibility to identify the opinion leader based on his degree centrality within Facebook group was not supported in our research.

To find out the correlation between online and offline activities we traced the dynamics of basing network indexes over time and estimated the changes in the structure comparing it with offline events.

The community growth for the six month was about 5% and basing to the result of previous research (Backstrom 2006, Kairam 2012) we can conclude that group 'Putin must leave' doesn't develop over time and it reaches stable level of development. By the way the growth of the density shows the solidarity increasing within the protest group.

According to the many researches of incipient protests, the offline events and actions reflect in community structure (Marcoux 2013). But for the examined online community we didn't trace this effect and hypothesis *H3* about significant changes was rejected. The number of nodes and edges evolved over time without significant changes and jump before or afterward offline events. It seems to be adequate for the pretty stable protest organization which had already formed to the moment of observation.

Conclusion

Social media played an important role in contemporary society, especially in information spread and self-organization. By the way there are a lot of incorrect notions about the structure of communications within online communities and the evolution of ties within such groups.

In this paper we revealed several incorrect points.

At first, as it turned out, the there is ingroup-outgroup effect within protest communication structure. However, people with different political views anyway communicate with each other and we did not fix the clear clusters of liberals or socialists.

Second, we distinguished opinion leaders within the online protest group and revealed that there is no clear correlation between degree centrality and activity. Although researcher assume that actors with high degree centrality are very important members of the social system, our analysis shows that for Facebook network friendship ties mean just the information propagation. Since the research of the influential users should include both social network analysis and analysis of the communication network.

Finally, we did not find the correlation between online activity and offline events for the relatively stable protest movement. Social networks at first stages of the offline activity change significantly, but after some saturation threshold the offline activity does not effect the structure and macro parameters of the online system.

So the role of online social networks in context of facilitator and one of the main tools for the collective action should be examined as well as in structural and communication context paying attention to the dynamics of the social system.

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