Measuring Influencers in Twitter *ad-hoc* Discussions: Active Users vs. Internal Networks in the Discourse on Biryuliovo Bashings in 2013

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Despite disputable possibility of extension of analysis of social relations on Twitter to real life, Twitter discussions are still being under attention of scholars studying structures and meanings of news- and issue-based ad-hoc public discourse. One of the socially relevant aspects of Twitter studies is that of influencers – accounts that produce impact, either inside or outside Twitter. But there is still no agreement in the research community on how to define and measure who is an influencer: either by 'absolute figures' or by network analysis metrics; this issue is even rarely discussed. Politically, today's mediatized public sphere where traditional media play the role of information hubs is highly uneven in terms of access to opinion expression; it privileges institutional players, including political elites, corporations, and media themselves. Hopes that Twitter would provide a more equal space for public deliberation are still not proven well enough. Using web crawling and manual assessment of Twitter ad-hoc discussion on the Biryulyovo bashings of 2013, we show that users who post or even get commented most do not make it to the positions of most 'central' users by network metrics. We also demonstrate that users that rank high by betweenness and pagerank centrality form circles of reciprocal commenting that show the social cleavage wider than the discussion itself.

I. Introduction

By 1990s, it was established in academic literature that mediatized public discussions were uneven in representation of group interest due to several reasons, among which were structural biases of media text, media effects, and unequal representation of newsmakers privileging powerful institutional actors vs. ordinary citizens [1]. This became a factor of growing importance in public decision-making and became studied and theorized. With the emergence of Internet, hopes arose that networked communicative spaces would provide better access of citizens to public discussions [2], which would equalize them more to the existing institutional opinion leaders selected by media serving as gateways / gatekeepers of public agendas [3]. But, as the growing body of research shows that smoothing of disparities online remains a highly disputable issue [4]; moreover, new lines of societal cleavages are drawn in hybrid media environments [5] due to digital divide, diversification of media diets of social groups, and growing tech-based fragmentation of communication arenas.

Recently, a growing area within online democratization studies has looked at *influencers* [6] – platform users with crucial capacities in information dissemination and impact upon other users' opinions. Influencers are viewed as key structural elements of power and impact distribution in networked discussions [7], [8]. Within these studies, Twitter has become a major focus that allowed for a combination of media & public sphere studies with social network analysis (SNA). In these papers, detection and prediction of influencers and their discursive nature has been developing. Among other important aspects, the linkage between the nature of the publics and constellation of influencers [9], [10], [11], [12], [13] have gained substantial space. But it is still unclear whether Twitter as a communicative platform provides for democratization of the influencer status in the so-called *ad-hoc* discussions that rise and fade on individual events of high social importance (like natural disasters or terrorist attacks), as well as on issues with high potential of social polarization.

Twitter studies of influencers may largely be clustered in sub-areas based on understanding of who the influencers are and how to detect them. Thus, there is a division between two concepts of an influencer (based on user activity and user connectivity), as well as a methodological division between the works that measure the power of influencers in absolute figures (tweets, followers, retweets, comments and likes), and those that use network metrics to detect opinion leaders. But practically no attempts have been made to juxtapose these ways of detection of influencers, to see if they produce comparable results. This is, arguably, a significant gap in existing research on influencers in Twitter. Another gap is that, despite the growing volume of studies on Twitter in Euro-Atlantic countries and Middle East, CEE countries, including Russia, remain largely under-researched in this respect [14].

This paper aims at covering these two gaps by collecting and analyzing data on the Twitter discussion around anti-migrant bashings in Biryoliovo (Moscow) in 2013. To do this, we use a specially developed web crawler, collect the discussion bulk based on hashtags and keywords as markers of the trending topic, select metrics of analysis, apply them and juxtapose the user lists by user activity metrics and connectivity metrics (betweenness and pagerank centralities). We manually assess the linked accounts to position them politically.

II. Public Discussions Online and the Figure of Influencer

As we stated above, by the time Internet emerged as a constellation of platform-based public communicative spaces,

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the theory of public sphere and communicative action already argued that public discussions were highly uneven in terms of access to discussion and individual impact of speakers [15]. Institutional speakers naturally gained more power within public deliberation due to its mediatization. Then, media themselves became agenda setters [16], [17], as they create mediated public communication and choose the agents from elites who are given voice. Also, oppressive nature of the majority-oriented public sphere was highly criticized [18], [19], [20], [21], and the role of minority actors in public deliberation was underlined.

With the appearance of computer-mediated communicative spaces online, a wave of hope for a more horizontally-interlinked, equal in access and, thus, more democratic public sphere arose among Western scholarship [4]. But soon this optimism faded away, as, by 2010s, it became clear that not only social [22] but also communicative [23] disparities tend to be reproduced, not diminished, in online communication. Also, new disparities emerge due to 'digital divide' [24], [25] and varying media diets of different social groups and political communities [26], [27]. As put in [12], whether 'Habermas is on Twitter' or not is yet unclear, as the influence of ordinary people on Twitter may still be minimal [28: 31], [4: 192].

Out of this, two questions have emerged, among many others: 1) the substantial one – who become discussion leaders, or influencers, on Twitter, and whether the disparities continue to exist; 2) the methodological one – how we define and detect the influencers, as their detection is measure-dependent.

A. Conceptual limitations in Twitter research on influencers

Of course we see that the limitation of a case study, first of all, lies in the fact that we deal with 'issue publics' [9: 422], [12: 108] – that is, *ad-hoc* publics [11] that gather and dissolve within one heated discussion [10: 74], become affective [13] and thus may not be representative for the 'calm' discussion periods on the same issue. Having this in mind, we nonetheless argue that: 1) this research, being part of a bigger project, will have a chance to test also the 'calm' periods; 2) even if limited in stability of the result, such cases remain relevant for the general public due to the importance of the issues discussed; 3) *ad-hoc* discussions collected within a certain vocabulary have the same constructivist element as any other dataset of media texts due to limitations of indexing and media biases.

Today, use of Twitter for research on public deliberation, including its structural features, is intensely debated among 'Twitter optimists' and 'pessimists'. The former consider Twitter a powerful tool already capable of changing news agendas [29], as well as of creating discussions 'on sub-political' topics [30], [31], even if with limited potential. The latter, though, consider Twitter a depoliticized container of trivial colloquial 'white noise' not capable of producing any meaningful discussion [32] and subjected to slacktivism [33]. But we consider Twitter one of the platforms where 'mass self-publication' [34] may still result into 'self-generated public opinion', as in full-fledged blogs [35]. Moreover, Twitter shows up as the quickest milieu for formation and expression of public sentiment [36], and thus the influencers emerging there may have a chance to cast impact upon later discussions on other platforms, including traditional media. Also, Twitter became especially popular in research uniting SNA and media studies, thanks to availability of software capable of data collection from this platform, openness of data to all users (unlike on other social networking sites where private modes of posting are widely used), and feasibility of tweets for analysis, and our results may be put to a rich research context even if not directly compared to the previous studies.

Another possible limitation of our research stems from the assumption of some scholars that the nature of Twitter as a platform actually privileges certain actors [37] as gatekeepers / gatewatchers [38] or gateways [37: 262], since communication there is based on 'highly skewed distribution of followers and a low rate of reciprocated ties' [37: 263] in user information exchange and interaction; for earlier proofs, see [8], [39], [40]. This makes Twitter similar to more information-sharing network than to an offline social network [37: 264], which, on one hand, undermines the quality of the potential public sphere from the very beginning as it favors information spread rather than discussion, but still suits our purposes, as, by both approaches that we described above, influencers are those who either tweet a lot (and may create strings or waves of retweeting due to that) or engage in a lively discussions with polar opinions represented, commenting and, in their turn, getting retweeted and commented.

Another limitation that rose up very recently is the relation between the influencers and the quality of public sphere in principle – addressed from an unusual, math-based angle. Thus, authors [41] have proven mathematically that, in a group of equally influential interlocutors, 'the group consensus is almost quite a certain result'; this means that 'the latent social influence structure' is the key factor both for 'the persistence of disagreement' and for 'formation of opinions' convergence or consensus' [41: 74]. This, in its turn, means that the issue of 'overt influencers' (e.g. those who tweet most) vs. 'latent influencers' may need to be addressed; we may need to develop new measures to detect the latter and to compare metrics to see which ones fulfill this task better.

B. How to define an influencer

By representing dynamics of the discussion by structured statics, social network analysis (SNA), with limitations, is widely used to detect outstanding users within Twitter discussions. We see three types of divisions in SNA-based research looking for structural definitions of influencers.

First, the conceptual difference is between an influencer who creates a self-oriented 'long tail', like waves of attention and support, and an influencer who links users or groups of users without creating any waves of reposting. In the first case, the influencer is a discussion center and information/innovation disseminator [42: 1261]. In many marketing studies, influencers are celebrity brand advocates [43] who either directly promote a product/brand or help develop loyalty to it. Here, the number of followers, the quantity and regularity of brand-related posting, the intensity of 'waves of support' through liking and sharing are considered key characteristics of an influencer. The research in this area moves today to more longitudinal studies to detect stable patterns of influence based on trust and to model consumer trust networks for marketing purposes. A different understanding of influencer has been developed in academic studies on discussions on social and political issues in social networks. These discussions usually demonstrate social polarization and grouping, and thus it is important to detect not only who is posting a lot but also whether an effective discussion forms at all. Normatively, the efficacy of democratic discussions depends on maximization of such features as openness, inclusiveness, horizontality and individuality [44; 4: Ch. 8], as well as rationality and orientation to consensus between polar opinions, as these features are considered crucial for formation of an effective 'field of discursive connections' [45: 37], or an 'opinion crossroads' as a metaphor for meaningful discussion capable of elaboration of decisions [12]. Structurally, this implies that features like inter-linkage between various clusters in a discussion and number of users involved in commenting and retweeting become the most important. Both approaches, each in its own way, may be viewed as an extension of theory of two-step communication flow in a given community [46]. This 'opinion leader' theory is amplified by the 'influential' theory [47]. Our understanding of an influencer integrates both aspects and considers them interdependent.

Second, a simpler division reshapes the first one: it is more methodological than conceptual. Some works draw a line between activity measures (the number of posts, likes or reposts produced by a user) and connectivity measures. The latter include the number of followers, of likes, shares, and comments received, of users involved into deliberation, but also SNA-based metrics like various types of centrality.

Third, a purely methodological division is between research based on independent absolute figures (N of posts, followers, likes, shares, and comments) and on network-dependent SNA metrics (various types of centrality). In our work, we will use these divisions to more precisely construct the research design.

III. Detecting the Influencers

Existing research in different countries shows that several parameters need to be taken into account and operationalized for detecting the influencers in *ad-hoc* Twitter discussions. These works may be roughly divided into two groups that use different metrics to measuring user impact on Twitter, as stated above.

A. Metrics based on absolute figures

Many of today's research uses network analysis for data collection but measures influence mainly on the micro-level and *in absolute figures*, that is – the researchers count the number of likes, retweets, and replies to a tweet and make conclusions upon these types of data. So far, mixed evidence exists on who, in case of such measurement, is labeled as influencer.

Thus, authors [37] have provided support for the assumption that existed in the early days of social networking sites: that in large online networks such as Twitter traditional gatekeepers, including mass media, 'fade away' (become gateways or at all dissolve as key nodes) giving opportunity for less known actors to attract significant attention to their messages. The study comes to a conclusion that 'the intense activity of individuals with relatively few connections is capable of generating highly replicated messages that contributed to Trending Topics without relying on the activity of user hubs' [37: 260] – that is, 'marketing'-like frequent tweeting may lead to leadership in getting retweeting disregarding whether the reposted tweets are forming a discussion. Also, according to authors [37] the role of media outlets in forming such retweet waves is significantly exaggerated: '[t]heir coverage is widely distributed throughout the environment, but only a small portion of tweets received by ordinary users comes from media outlets' [37: 269]. Here, influencers should be understood as those who pass information to other users. Thus, as stated above, instead of dependence on traditional gatekeepers, both dissemination of information and quality of discussion depend on activity of just several users who produce a lot of retweets and spread a given hashtag ('gatewatchers'), and on the second level of discussion – on mid-range (or 'local-embedded' [42]) 'gateways' of a rather random origin.

But a big stream of recent academic literature opposes this view and argues two other positions.

First, it is institutional users who remain highly influential in how discussions develop. Thus, several studies have proved based on case analysis that Twitter only strengthens the existing hierarchies with mass media and opinion leaders still playing the key role in dissimilation the information [48], [49], [50]. This partly comes from the theoretic understanding of an influencer as a 'prestigious actor whose position is approved by the audience and who initiates more support than criticism [51], and not from the formal network parameters. Anyway, as research on the US and Swedish segments of Twittersphere has demonstrated, one finds among influencers experts and long-established organizations [52], [53]. As authors [14] note, Twitter becomes especially important for people in the situations like social upheavals or natural disasters, and as the authors draw on the following works [54], [55] for this assumption, we see that it is institutional accounts that matter.

Second, most of these researchers underline that among influencers media still play the leading role. The author [54] shows that, by a composite measure named 'mentions' (including original tweets, retweets, mentions and replies), journalists and mainstream media were dominating the top100 accounts in the Twitter coverage of the UK 2011 riots. The author [55], researching on the Twitter discussion on a major earthquake in New Zealand, shows that, in top16 Twitter accounts that got retweeted&commented over 1000 times within the researched period, 11 were institutional – media, authorities 'utilities' (mobile phone operators). Despite the list of top influencers defined this way changes in the immediate aftermath of the tragedy, the list of top influencers remains packed with media and authorities' accounts. Other works cast some light on why this may happen: thus, authors [56] they show that journalists often retweeted their colleagues.

This stream of research provides also allows for speculation on which metrics should be used to detecting and predicting influencers. Here, as authors [42] put it, we again see the difference between 'having a following' and 'being seen as an expert' [42: 1263], which corresponds to our division between 'marketing' and 'political' understanding of influencers, though the metrics the authors but into the two categories may actually apply to both of them. Most of the works (see [37]; for earlier accounts, see [57], [58], [59], [60], [61] share the opinion that the number of retweets is the metric that is sufficient to tell who are the influencers for a given discussion. Moreover, authors [61] demonstrate correlation between the number of followers and the retweet rate of an account, and thus, we seem to be able to construct predictors of influence based on absolute measures. But, as stated above, the number of tweets posted per user must not be overlooked as well, as it produces detectable impact and becomes a mediating factor [62].

B. Metrics from automated network analysis

The demand to detect hidden influencers not evident via frequent posting may lead us to using more fine-grained metrics of network analysis to see whether these metrics produce results different from those on absolute metrics. Classic SNA defines several key metrics for measurement of the most important nodes within a user/webpage network; most of them have already been successfully applied to reconstructing Twitter discussions and finding the influencers, of which the six classic ones include closeness, betweenness centrality, degree centrality, eigenvalue (eigenvector centrality), pagerank centrality, and community ([42], [63] but various other metrics may also be used ([42], [64], [65]. Combinations of metrics [57], [66] as well as author-specific derivatives [67], are also used.

Not to go deep to the discussion of SNA technicalities, we would only state several points that seem relevant for our research. First, absolute figures are network-independent while the network measures are relative and take into account the whole network. Second, this cluster of research on influencers has already produced some results showing that various network parameters naturally produce varying lists of influencers [42]. Third, it is network metrics that may help identify hidden influencers less evident by their absolute-number characteristics. Moreover, the authors [42] state that media remain influencers when measured by indegree and eigenvalue metrics only; in this paper and other research, new groups of influencers join professional media and experts [68]. It is worth knowing whether other basic metrics bring on media as influencers.

C. The task of juxtaposition

Even if the existence of the two streams of academic literature is well-known, only several works combine absolute and automated measures, including those that combine content analysis and network analysis [51], [69], [70].

In previous research, the number of retweets is considered the absolute-figure metric that reveals the influencers. But we argue that, when one detects influencers via the number of retweets, the number of tweets needs to be taken into account. In an ideal equilateral network, a node with a bigger number of posts will have a bigger chance to get noticed and retweeted; this is why we need to check whether the number of posts in real discussions correlates to the metrics that show how important a user is within the discussion graph. From the existing research (see, e.g. [54], [55]) it is not always clear whether the number of posts was assessed, and it remains unclear whether the influencers become such due to the fact that they post important information or just due to the fact that they post a lot. We of course may suggest that media and institutions post valuable information and become influencers due to this, especially in crisis and emergency situations, but even in this case we need to suggest that, of two media oriented to the same audience, the one tweeting more will get a bigger 'tail' of following. Such understanding of influencers has in its core the 'marketing' approach which seems to have an inherent duality: on one hand, those who post a lot and comment other users win the game, but, on the other hand, an influencer is the one who can create a bigger wave of retweets and comments with a possibly smaller effort.

But we also argue that, to detect influencers that help build meaningful discussion, these metrics are not enough; for democratization of public discussion, what is also important is involvement of the maximum number of users into interaction with the given user. We argue that this cannot be detected simply by the number of retweets and comments, but can be assessed by evaluating activity *and* connectivity metrics. Thus, we have the following matrix of metrics (see Table I).

TABLE I. METRICS SELECTED FOR DETECTION OF INFLUENCERS

	Absolute figures	SNA metrics
Activity	Number of original user posts within the discussion (Ntweets)	Number of other users involved into the discussion by the given user, that is, commented or retweeted by the given user, counted based on the number of unilateral interactions (In-Degree)
Connec-tivity	Number of received interactions, that is, retweets and comments combined, by the given user (Nrecom)	1. Number of users involving the given user into the discussion by commenting or retweeting his/her tweets, counted based on the number of unilateral interactions (Out-Degree). 2. Betweenness centrality (BC). 3. Pagerank centrality (PR).

As stated above, we use traditional networks metrics, of which we will focus on two, namely betweenness centrality and pagerank centrality. To our viewpoint, their combination is sufficient to represent an influencer in 'political' terms: betweenness centrality deals with the 'gateway' nature of an influencer capturing both centrality in the discussion and the capacity to link polar 'filter bubbles' [71] inside the discussion space, while pagerank centrality speaks of relative influence within a network by measuring the degree of citation as well as the quality of the citing nodes. This position is supported by a number of other studies [69], [70]. These metrics create 'political' understanding of influencers as effective communication nodes uniting the fragmented discussion.

What we aim to add to the existing knowledge is learning:

1) whether being an influencer in terms of active behavior on Twitter correlates to becoming a discussion center;

2) whether institutional accounts prevail as influencers by both activity and connectivity metrics;
3) whether the lists of top users represent the sides of the conflict, and whether the polarized user accounts are interconnected.

IV. THE BIRYULIOVO BASHINGS AS THE CASE OF SOCIAL AND COMMUNICATIVE POLARIZATION IN RUSSIA

To formulate our research hypotheses more precisely, we also need to take into consideration the context of the case under scrutiny. The relevant aspects include the expectations from the Russian Twittersphere formulated in the existing research and the description of the case and the societal cleavages inside it that help form our expectations of who would be the influencers within the discussion on the case.

Russia, like Eastern Europe [14], remains under-researched in terms of social media and their place in the media system, as well as relations between social and political communities and social media. In particular, research on Russian Twitter is scarce if not non-existent; only a handful of works deserves reviewing. It is even hard to find the data on estimated use of Twitter in Russia; as for August 2015, figures varied from 8 to 11 mln subscribers [72], of which around 50% could be called active users (those who use the platform at least once a month).

In the recent 25 years, the Russian media system has undergone fundamental changes but in many political features it remains rather post-Soviet [73]. One of the specific features of the Russian media today is that the media sphere is structured according to value cleavages and, in its standards and approaches to news framing, follows the division between the post-Soviet mid-urban and cosmopolitan hyper-urban clusters of audience – which, in its turn, in politics expresses itself as the division between systemic and non-systemic political forces [27], [74]. Online, this leads to formation of closed-up communicative milieus known as online echo chambers [75]; thus, Russian Facebook represents an example of anti-establishment echo chamber [74]. Normatively, this brings mixed consequences to the quality of the Russian public sphere: on one hand, echo chambers serve as political mobilization camps, but they also lower the ‘opinion crossroads’ potential.

The existing works on Russian Twitter provide mixed evidence on whether Twitter in Russia can play a role of such an ‘opinion crossroads’, but this evidence is definitely bigger than for Russian Facebook. A research group of Russian Economic School [76] showed that, indeed, the Russian Twitter of 2012 could be perceived as ‘crossroads’ in terms of presence of pro-establishment and oppositional clusters; pro-establishment networks, though, were better organized and more active. Another research [77] finds that of pro- and anti-protest positions in the times of major ‘For fair elections’ protest rallies were practically equally represented on Twitter. These findings were partly supported by Berkman Center for Internet and Society at Harvard [11] which, for 2010-2011, identified mostly topic-oriented clusters in the Russian Twitter. But they identified that, by March 2011, that political clusters included a distinct oppositional one surrounding Garry Kasparov and also ‘patriotic’ clusters around youth movements ‘Nashi’ and ‘Molodaya gvardia’. They, importantly, also noted that nationalists did not form a distinct part of Twitter structure, unlike in the Russian full-fledged blogs. In their other work [89], the Center states that there is a phenomenon of ‘resonant salience’ in Russian Twitter, which refers to a pattern of outbursts of cross-group activity on an event/topic followed by ‘consistent engagement’ of followers later on [78: 13]. Thus, so far, there were no direct research made to identify and describe the influencers in the Russian Twitter discussions.

During two days in October 2013, the case we analyze was in Twitter Trending Topics (as measured by trendinalia.com). This case provides us with expectations as whom to expect as influences in the discussion. The timeline of the case of Biryuliovo anti-migrant bashings includes an (alleged) killing of a Muscovite Egor Sviridov by a phenotypical ‘migrant’, the bashings at a warehouse and its surroundings in Biryuliovo where the alleged killer should have resided and the subsequent street police actions to prevent further violence, several ‘people’s gatherings’ in the area, and arrest of the suspect; the timeline is also surrounded by the statements of federal and Moscow authorities. Thus, important cleavages include those between authorities (federal) and authorities (local); authorities (local/police) and people (bashings participants); people (anti-migrant/nationalists) and people (migrants/pro-migrant/NGOs). Also, we expect high level of media involvement. Whom we expect to see among the influencer users are (in the descending order) media, authorities of both levels, eyewitnesses, NGOs. We do not expect either nationalists or migrants to be highly influential, as stated in previous research [11], [79], [80].

V. RESEARCH HYPOTHESES

We have formulated three hypotheses.

H1. The users that post most become discussion centers: Ntweets significantly correlates to Out-Degree, BC, and PR.

H2. Similarly to previous studies, institutionalized users will dominate over ordinary users by activity and connectivity; but, as it is known from previous research [87; 89], political forces, including pro- and anti-migrant users (like nationalists), will be absent from the lists of both active (Ntweets), attractive (Out-Degree), and ‘central’ (BC/ PR) users’ lists.

H3. Hypothesizing the ‘opinion crossroads’, we expect top users to be neutral in terms of taking sides in the conflict.

VI. METHODOLOGY AND RESEARCH PROCESS

To test the hypotheses, we used vocabulary-based web crawling to collect the data on the discussion and to reconstruct the discussion web graph. To do this, we have developed a focused web crawler [81]. We used our own software to overcome limitations common for openly available API-based analogs, namely the non-availability of archived tweets, limited number of tweets, limited number of requests to the server per second etc. Our web crawler collects all public tweets marked by a keyword/hashtag. Tweets in the friends-only mode were not collected, as we are interested in the public discussion only.

To create the vocabulary, we have first collected relevant keywords and hashtags at trendinalia.com; then we have added several more based on manual snowballing in over 1,000 tweets with the primary vocabulary. The research period chosen was October 1 to 31, 2013, to capture the outburst of the discussion and its long tail. 3734 users with 10715 posts were identified as a result of crawling. One step further in crawling was made to identify those who commented or retweeted the collected tweets; this returned 12042 users.

We have reconstructed the graph of the discussion. The graph was non-directed and had users as nodes, and retweets and comments (and not likes) as edges.

Then we measured the variables from Table I: Ntweets, Nrecom, In-Degree, Out-Degree, BC, and PR; we calculated the values for the users with Ntweets ≥ 10, to include only those users who actively participated in the discussion. We applied the chosen metrics to the graph and got the values for each metric. Then, we have conducted descriptive statistics to see to what extent the suggested metrics correlate. We considered the use of descriptive statistics appropriate in this case, despite we realize that, mathematically, absolute figures and in/out-degree values play a role in formation of centrality of a given user, and thus we expect them to correlate, but the strength of correlation may be telling for our hypotheses. Also, BC and PR may be interpreted as network-dependent, as their values are calculated with regard to other users' values, while In/Out-Degree is based on absolute number of user interaction.

Then, we qualitatively assessed the top lists of users for each metric, to see the patterns of transposition of users from the lists by activity metrics to the lists by connectivity metrics, and those by absolute figures – to those by network metrics. To do so, we assessed the user's self-description, the collected tweets, and the tweets closer to nowadays.

The results are presented below.

VII. Results and discussion

The resulting web graph showed no visible clouds that could be interpreted as echo chambers; thus, even if discussion leaders existed, they were not very evident from the graph. The metrics appeared to be more informative.

H1 proves right only partly (see Table II). We have conducted Spearman rho and have seen that, indeed, in our sample of 180 users with Ntweets$\geq$10, Ntweets positively and significantly correlates with Nrecom (0,459**) and Out-Degree (0,419**) – that is, the more a user posts the more he/she gets retweeted and commented, and the more users do it, though the correlation is not very strong. But Ntweets only very weakly correlates with BC (0,158*) and does not correlate with PR. That is, the relative discussion-specific opinion leaders become those by means other than frequent posting. And this means is posting/commenting to many users (In-Degree), as both BC (0,875**) and PR (0,920**) strongly correlate with In-Degree. Unlike in previous research, it is not Nrecom (which correlates with BC two times weaker and with PR three times weaker than In-Degree) but In-Degree may become a better predictor on who is a deliberative influencer. On Figure 1, while those who get commented a lot (mostly media, marked green) but do not engage in talks do not break through to high BC and PR, those who comment on many other users (mostly non-institutional users, marked orange and blue) get both BC and PR higher. These two groups may be called 'hidden influencers', as they are seen neither by the number of tweets nor by the number of retweets/comments, but they as a group have the key positions in the structure of the web graph.

H2 proves right, but only partly again. If Ntweeet and Nrecom lists are, indeed, full of media and political accounts, in terms of almost full absence of political accounts, only several of them make it to top BC and PR lists. Thus, absolute figures and network metrics produce very different lists, including the institutional status of the users. On the whole, on dominance of institutional users over ordinary people, our hypothesis is largely untrue. Unlike in previous research cases in Western countries, we have found no accounts of federal or Moscow authorities (or their representatives) that would be responsible for handling the bashings – neither among those who tweet most nor among those who get retweeted or have high centrality metrics. Political accounts included one party (though it was the ruling 'United Russia' party), the account by RF Public Chamber, and two accounts by politicians – one oppositional and one pro-establishment. Of institutional accounts, media were present among those who tweet a lot and who get followed, but only four of them (of which two were not among leaders in tweeting) made it to the deliberative center of the discussion, as media were not at all involved into commenting other users (cf. @lifenews_ru: 3265 tweets with comments virtually absent).

For *H3*, we have compared the lists of top20 users by each of the six variables. By that, we have detected several distinct groups of users with stable patterns of user activity vs. connectivity, as well as with similar political stance. The first is a group that we call the 'elite network' (see Figure 1, marked rose). These users are even more hidden, as they neither tweet nor retweet many users; neither get they commented by a lot of them. But in the structure of the graph they play a key role as highly retweeted betweenness centers. They are interlinked via commenting on each other. Without the graph-based measures, we could not have detected them.

Also, Fig. 2 shows that the top users are not neutral towards the discussed issue. If the user list of top tweeters contains many media accounts and eyewitnesses (whose tweets form more or less neutral discourse), top BC and PR lists are vividly divided into two groups, both inter-related: that of nationalists (marked orange) and that of 'angry city dwellers' (marked light orange). The latter are against both migrants and the authorities and demonstrate disappointment and cynicism that resembles neither liberal-oppositional discourse in Russia not that in Europe (where it is largely pro-migrant like, e.g. in Germany). These two groups form the two opposing vectors of the discussion, defining its atmosphere and representing the cleavage between more pro-nationalist mid-urban and big-city cosmopolitan population. They may be called 'networks within a network', and more research is needed to see if these circles are stable outside the discussion on Biryuliovo – or, are they *ad-hoc* just as the discussion itself. This finding would not be possible if we searched by absolute figures only. Thus, we recommend network measurement for describing influencers in *ad-hoc* networked discussions. Based on the combination of metrics, we have shown in Table III five types of influencers.

CONCLUSION

What we have found in this paper clearly reflects our initial notion of two approaches to influencers on Twitter.

First, we have spotted two types of influencers in the discussion on the Biryuliovo bashings. The first comprised mostly media and was clearly 'marketing'-like, as it was based on frequent posting (and low commenting&retweeting) and getting retweeted a lot. But 'deliberative' influencers formed circles of influential users who inter-linked micro-zones of discussion and were cited by other highly-ranked users. The latter effect reminds us of the one discovered in previous research where journalists retweeted by other journalists became a circle of influencers, but in our case no user linked to an institution was actually involved. Our results also adds to the evidence that we need to use SNA metrics, not just simple number of retweets, to detect real influencers.

Second, we have discovered high politicization of the discussion, contrary to expectations; moreover, we have shown that, among the top users by centrality metrics, there were two camps represented, namely the nationalist camp and the one that may be called liberal-critical. It includes users from persons with high level of criticism towards the system to oppositional activists, and this circle seems to be bigger than the nationalist one. This division, on one hand, replicates the overall post-Soviet/cosmopolitan division in the Russian media system [90; 91], but on the other hand it clearly demonstrates that Twitter has a much bigger 'crossroads' potential than other media platforms including social networks like Facebook. We also note that traditional media on Twitter do not perform the 'crossroads' function, as they have low betweenness centrality and, thus, do not gather users around them. But at the same time, on Twitter, unlike in offline world, pro- and anti-establishment media have practically equal following and exposure, which, in a way, adds to the 'crossroads' nature of Russian Twitter. At the same time, we have discovered only one account openly supporting the position of migrant population; this means that the discussion had low deliberative potential in terms of representation of the sides of the conflict.

Third, we definitely need more research on why, in the case of a resonant inter-ethnic crisis, local and national political executives had no place in the discussion. Of course, the simplest explanation would be that local administrations do not tweet; but other explanatory factors may be the traditional low trust to institutions by ordinary Russians as well as low trust to new communicative platforms among local authorities.

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#	Ntweets		Nrecom		In-Degree		Out-Degree		BC		PR	
1	mynameisphilipp	187	ARTEM_KLYUSHIN	3906	BorisALV	112	lifenews_ru	1398	MedvedRu	0,01253	BorisALV	0,00244
2	lifenews_ru	165	lifenews_ru	3265	Antiputja	102	IlyaYashin	505	BorisALV	0,01237	Antiputja	0,00205
3	BorisALV	103	IlyaYashin	1636	mishailv	61	mynameisphilipp	345	rodnyansky	0,00610	Filosof	0,00120
4	White_technolog	97	mynameisphilipp	1403	kp_live	54	polozovs	288	dternovskiy	0,00457	pel13132	0,00109
5	topoprf	89	ruredaktor	729	irynka_korf	52	RT_russian	278	ivanmazurin	0,00404	ivanmazurin	0,00100
6	ruspoker	80	polozovs	625	Sergey_Sergey_G	52	izvestia_ru	256	ForbesRussia	0,00368	Jarilo_	0,00083
7	masfka	76	topoprf	513	MedvedRu	51	belogolovcev	253	mishailv	0,00359	helenascorpion	0,00083
8	volya_naroda	71	dragonforceedg1	464	Jarilo_	50	SvobodaRadio	191	Gavoronok88	0,00354	mishailv	0,00082
9	MetroRussia	69	RT_russian	433	Filosof	50	GraniTweet	179	Elena_Baturyna	0,00340	vvchumanov	0,00081
0	ruvr_ru	67	belogolovcev	371	RTVRU	48	MaloverjanBBC	178	Jarilo	0,00331	CAPITANHZ	0,00081
11	ipotechniy	57	MaloverjanBBC	368	Elena_Baturyna	42	ru_rbc	169	pel13132	0,00322	DerUnabomber	0,00074
12	Mir24TV	55	izvestia_ru	348	ivanmazurin	41	RomanPomych	157	IlyaYashin	0,00317	kp_live	0,00073
13	news_kavkazcen	55	PolitAnimal	336	helenascorpion	39	BorisALV	155	pilodship	0,00310	MedvedRu	0,00071
14	MedvedRu	51	ruvr_ru	307	Natalya_She	36	ARTEM_KLYUSHIN	143	rykov	0,00278	orlovandrey_v	0,00069
15	NoviniRosii	49	SvobodaRadio	297	pel13132	35	rodnyansky	142	roman_primorye	0,00240	RTVRU	0,00067
16	krgzr	48	Andrey_Pr0sto	287	83Mira	35	MetroRussia	141	RTVRU	0,00233	Russkiy83	0,00062
17	Estraniero	45	Moscow_ER	285	AlexSavinovv	35	onlinekpru	138	ruspoker	0,00232	DenYudin	0,00060
18	ciperovich	44	CallmJoker	281	conspirologorg	33	CallmJoker	132	Antiputja	0,00208	maksmms	0,00059
19	urannews	44	dternovskiy	273	DerUnabomber	32	dternovskiy	129	RT_russian	0,00203	AlexSavinovv	0,00058
20	istina	41	ru_rbc	268	VladMatveev	31	Pavel_XII	127	tvrain	0,00197	svetka007	0,00057
…												
23									Sergey_Sergey_G			
28									J7exa			
39									DerUnabomber			
41									vvchumanov		Sergey_Sergey_G	
52											Gavoronok88	
54											J7exa	
66											pilodship	
86											Elena_Baturyna	
112											roman_primorye	
136											tvrain	
149											ForbesRussia	

Fig. 1. The lists of top20 users by the metrics stated in the research; users marked according to their 'strategies' (patterns of appearances in top lists)

#	Ntweets		Nrecom		In-Degree		Out-Degree		BC		PR	
1	mynameisphilipp	187	ARTEM_KLYUSHIN	3906	BorisALV	112	**lifenews_ru**	1398	MedvedRu	0,01253	BorisALV	0,00244
2	**lifenews_ru***	165	**lifenews_ru**	3265	Antiputja	102	IlyaYashin	505	BorisALV	0,01237	Antiputja	0,00205
3	BorisALV	103	IlyaYashin	1636	mishailv	61	mynameisphilipp	345	rodnyansky	0,00610	Filosof	0,00120
4	White_technolog	97	mynameisphilipp	1403	**kp_live**	54	polozovs	288	dternovskiy	0,00457	pel13132	0,00109
5	**topoprf**	89	ruredaktor	729	irynka_korf	52	**RT_russian**	278	ivanmazurin	0,00404	ivanmazurin	0,00100
6	ruspoker	80	polozovs	625	Sergey_Sergey_G	52	**izvestia_ru**	256	**ForbesRussia**	0,00368	Jarilo_	0,00083
7	masfka	76	**topoprf**	513	MedvedRu	51	belogolovcev	253	mishailv	0,00359	helenascorpion	0,00083
8	volya_naroda	71	dragonforceedg1	464	Jarilo_	50	**SvobodaRadio**	191	Gavoronok88	0,00354	mishailv	0,00082
9	**MetroRussia**	69	**RT_russian**	433	Filosof	50	**GraniTweet**	179	Elena_Baturyna	0,00340	vvchumanov	0,00081
0	**ruvr_ru**	67	belogolovcev	371	RTVRU	48	MaloverjanBBC	178	Jarilo_	0,00331	CAPITANHZ	0,00081
11	ipotechniy	57	MaloverjanBBC	368	Elena_Baturyna	42	**ru_rbc**	169	pel13132	0,00322	DerUnabomber	0,00074
12	**Mir24TV**	55	**izvestia_ru**	348	ivanmazurin	41	RomanPomych	157	IlyaYashin	0,00317	**kp_live**	0,00073
13	news_kavkazcen	55	PolitAnimal	336	helenascorpion	39	BorisALV	155	pilodship	0,00310	MedvedRu	0,00071
14	MedvedRu	51	**ruvr_ru**	307	Natalya_She	36	ARTEM_KLYUSHIN	143	rykov	0,00278	orlovandrey_v	0,00069
15	**NoviniRosii**	49	**SvobodaRadio**	297	pel13132	35	rodnyansky	142	roman_primorye	0,00240	RTVRU	0,00067
16	**krgzr**	48	Andrey_Pr0sto	287	83Mira	35	**MetroRussia**	141	RTVRU	0,00233	Russkiy83	0,00062
17	Estraniero	45	**Moscow_ER**	285	AlexSavinovv	35	**onlinekpru**	138	ruspoker	0,00232	DenYudin	0,00060
18	ciperovich	44	CallmJoker	281	conspirologorg	33	CallmJoker	132	Antiputja	0,00208	maksmms	0,00059
19	urannews	44	dternovskiy	273	DerUnabomber	32	dternovskiy	129	**RT_russian**	0,00203	AlexSavinovv	0,00058
20	istina	41	**ru_rbc**	268	VladMatveev	31	Pavel_XII	127	**tvrain**	0,00197	svetka007	0,00057

- pro-migrant accounts
- Nationalist accounts
- accounts supporting nationalist views
- accounts of political institutions or politicians
- personal accounts of users with high liberal-oppositional stance
- personal accounts of users supporting the ruling elite
- media accounts
- accounts of 'Twitter' media - news feeds in Twitter declared 'media'
- accounts of eyewitnesses
- fake/spam accounts
- neutral non-institutional users ('ordinary people')

Note. *Institutional accounts are marked bold.

Fig. 2. The lists of top20 users by the metrics stated in the research; users marked according to their institutional belonging and political stance

TABLE II. SPEARMAN CORRELATIONS FOR THE VARIABLES

Spearman's rho		Ntweets	Nrecom	In-Degree	Out-Degree	BC	PR
Ntweets	Correlation Coefficient	1,000					
	Sig. (2-tailed)	.					
Nrecom	Correlation Coefficient	**,459****	1,000				
	Sig. (2-tailed)	,000	.				
In-Degree	Correlation Coefficient	,088	**,347****	1,000			
	Sig. (2-tailed)	,239	,000	.			
Out-Degree	Correlation Coefficient	**,419****	**,964****	**,351****	1,000		
	Sig. (2-tailed)	,000	,000	,000	.		
BC	Correlation Coefficient	**,158***	**,455****	**,875****	**,479****	1,000	
	Sig. (2-tailed)	,035	,000	,000	,000	.	
PR	Correlation Coefficient	,024	**,297****	**,920****	**,300****	**,846****	1,000
	Sig. (2-tailed)	,752	,000	,000	,000	,000	.

Note. ** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

TABLE III. TYPES OF INFLUENCERS AS BASED ON THEIR METRIC VALUES

	High absolute figures	High SNA metric values
High activity values		
High connectivity values	People's heroes few tweets&retweets comment few users high BC	Elite network few tweets&retweets commented by influential users, high BC Crossroads users few tweets bring waves of comments & high PR