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Salience vs. Commitment:
Dynamics of Political Hashtags in Russian Twitter

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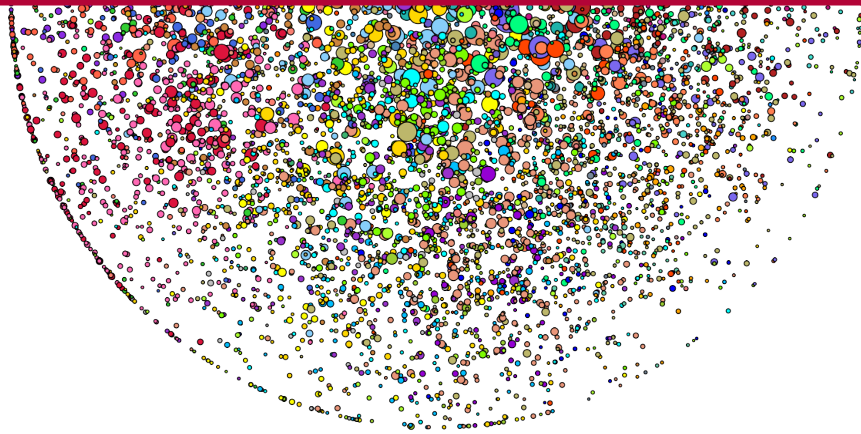

Salience vs. Commitment

Dynamics of Political Hashtags in Russian Twitter

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Abstract

Social media sites like Twitter enable users to engage in the spread of contagious phenomena: everything from information and rumors to social movements and virally marketed products. In particular, Twitter has been observed to function as a platform for political discourse, allowing political movements to spread their message and engage supporters, and also as a platform for information diffusion, allowing everyone from mass media to citizens to reach a wide audience with a critical piece of news. Previous work[1] suggests that different contagious phenomena will display distinct propagation dynamics, and in particular that news will spread differently through a population than other phenomena. We leverage this theory to construct a system for classifying contagious phenomena based on the properties of their propagation dynamics, by combining temporal and network features. Our system, applicable to phenomena in any social media platform or genre, is applied to a dataset of news-related and political hashtags diffusing through the population of Russian Twitter users. Our results show that news-related hashtags have a distinctive pattern of propagation across the spectrum of Russian Twitter users. In contrast, we find that political hashtags display a number of different dynamic signatures corresponding to different politically active sub-communities. Analysis using 'chronotopes' sharpens these findings and reveals an important propagation pattern we call 'resonant salience.'

Keywords: *Social Media; contagion; diffusion; dynamics; political movements; chronotopes*

About this paper

The Berkman Center for Internet & Society at Harvard University, with funding from the MacArthur Foundation, is undertaking a three-year research project to investigate the role of the Internet in Russian society. The study will include a number of interrelated areas of inquiry that contribute to and draw upon the Russian Internet, including the Russian blogosphere, Twitter, and the online media ecology. In addition to investigating a number of core Internet and communications questions, a key goal for the project is to test, refine, and integrate various methodological approaches to the study of the Internet more broadly. More information about the project is available on the Berkman Center Web site: http://cyber.law.harvard.edu.

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1. Introduction

The analysis of contagious phenomena is actively studied both on the theoretical and practical side. Original research in the area included diffusion models based on differential equations[2] as well as sociological work by Mark Granovetter[3] on the rise of social movements in crowds. More recently, models by Watts,[4] Centola and Macy,[5] and others have helped explore the dynamics of contagious phenomena in networked populations.

On the empirical side, Twitter in particular has received a lot of attention from researchers. There are a number of high-level studies of information diffusion on Twitter as well as more specific studies about retweeting information (passing it along through the network) and its effect on diffusion. [6]

The study of political movements in social media is likewise gaining traction in academic research. Theoretical work by Castells has explored recent social movements and their interaction with social media.[7] The intersection of social media, diffusion, and politics is explored in a study by Leskovec, who investigated the spread of string-encoded memes in blogs and news media online before the 2008 U.S. Presidential election.[8] More recently, Wu et al studied the diffusion of news in the Twitter social network and found that different kinds of media (news stories vs. videos, for instance) have distinct propagation patterns.[9]

This work extends research on both the theoretical and practical aspects of contagion diffusion, using an approach that blends temporal and network features to describe key network diffusion patterns. We apply this approach here to a specific context for contagion diffusion: political and news-related hashtags diffusing among the population of Russian-speaking Twitter users between 2007 and 2011. Within this context, we explore the propagation of contagious hashtags in two dimensions: their *dynamics*, the properties of the time series of hashtag use by Twitter users; and their *dispersion*, the distribution of hashtag use across communities within our population of interest. Our analysis of hashtag dispersion presents a methodological advance in the study of contagious phenomena, as it intersects structural methods for breaking down networked populations into communities with studies of diffusion in networks.[10]

We also introduce a method for simultaneously visualizing both the dynamics and dispersion of a particular hashtag. Using this method, we identify hashtag *chronotopes*, or persistent patterns across time and network structure, that may help emerge a taxonomy for contagious phenomena in general, and Twitter hashtags in particular, much as previous efforts have served to taxonomize the behavior of users and communities in social media settings. [11] We anticipate that this method will be useful in future research and in applications involving diffusion in social media.

Our work has several important implications for the study of political and news-related topics in the Russian-speaking Twitter population. We find that users engage with news-related topics in much the same way across the spectrum of Twitter communities, but different communities of users engage in very different ways with political topics. Users belonging to ‘Opposition’ communities that oppose the current political regime in Russia engage with some topics over a long period. In contrast, users belonging to ‘Pro-government’ communities that support the regime engage with topics intensely over a short period of time. Furthermore, we found that topics related to the mainstream government agenda tend to be discussed heavily within one community, whereas topics that are hot-button issues for the opposition tend to be discussed more broadly by the population as a whole. Our results have important implications for the intersection of politics and Twitter in Russia: engagement in political issues is non-uniform across the population, and different communities have distinct patterns of engagement that can help predict their activity in future political events. In light of the Arab Spring uprisings and other events where Twitter became a medium of organizing and enacting political movements,[12] our results have implications for the Russian political climate as a whole and, in principle, for any society in which social media has been enrolled in political action.

The rest of this paper is organized as follows: in section two, we present the theoretical background for our analysis of the dynamics and dispersion of contagious phenomena. In section three, we describe the dataset we use, and in section four, we describe the specific methods we use to analyze the diffusion of hashtags through the Russian-speaking Twitter population. In section five, we describe our results. We conclude with section six, where we give a brief discussion of our results and implications for future research.

2. Background

Given some contagious phenomenon *p*, we consider that *p* has spread to user *u* the first time that *u* engages with *p*. For simplicity, we will measure engagement as mentioning the phenomenon. For news, mentioning is likely a sufficient form of engagement, while for a political movement, stronger evidence of engagement is preferable (contributing money, attending a rally, etc.). However, in social media sites, higher levels of mentioning often correlate with higher levels of engagement (e.g., users tweet about a political rally), while false indicators of engagement are rare: if a user wishes to mention a political movement to disagree with it, she will often not use a tag or specific name referring to that movement, but use a variant of it (e.g., a Twitter user who wants Vladimir Putin out of power may use the tag #Putinout instead of #Putin when tweeting about the prime minister and future Russian president). Therefore, we use the number of first mentions of *p* by users in some social media site as a proxy for the number of users that *p* has spread to.

2.1 Dynamics of Contagious Phenomena

In previous work, Wu et al suggest one possible dimension along which contagious phenomena can be classified: lifespan.[13] Contagious phenomena can either have a short lifespan (news) or long lifespan (videos, popular websites). Contagious phenomena with short lifespans tend to have a sharp peak, when a large number of people mention the phenomenon, but the number of mentions is very small on either side of the peak. In contrast, long-lifespan contagious phenomena tend to grow slowly, with a less pronounced peak of mentions. We were inspired by this measure to create a scale-invariant measure of *Peakedness* for contagious phenomena.[14] First, for a time series of first mentions of a particular contagious phenomenon *p*, we define a peak as a day-long period where total first mentions by day lies two standard deviations above the median first mentions. The specific duration of the peak window and the required deviation can be varied to maximize usefulness for particular kinds of phenomena and for particular social media networks. We use median instead of mean because, due to the skewed distribution of first mentions by day for most contagious phenomena, the mean is over-inflated. Here, the Peakedness of p is the fraction of all first uses that occur during a peak. Contagious phenomena with high Peakedness tend to have volatile temporal dynamics, quickly accumulating many first mentions and just as quickly falling off. Intuitively, news-related hashtags should have the same dynamics, with peaks corresponding to the appearance of newsworthy stories. In contrast, hashtags with low Peakedness tend to have a smooth temporal dynamics, slowly accumulating first mentions over time.

In addition to Peakedness, which measures the broad appeal and salience of a contagious phenomenon, we would like to develop a measure of the staying power of such phenomena – their ability to garner repeat mentions, or build 'commitment' among users. This measure would differentiate between a political movement that is just a fad, and one that accumulates a number of diehard supporters who keep the movement alive. However, in social media sites, the cost in terms of time and effort to mention something for the second or third or tenth time is relatively small; therefore, for our second dimension, we explore two quantities: first, the average number of subsequent mentions (all mentions excluding the first mention of the phenomenon by a user) of a contagious phenomenon among the adopting users; and second, the average time difference (in days) between first and last mention of the phenomenon among the adopting users. While the first measure is relatively easy to inflate by mentioning the phenomenon multiple times in a short period, the second measure indicates long-term commitment to mentioning the phenomenon by a set of users. We call the first measure 'Commitment by Subsequent Uses' and the second measure 'Commitment by Time Range.'

2.2 Dispersion of Contagious Phenomena

In addition to measuring the dynamics of contagious phenomena (the properties of the time series of engagements with a phenomenon), we can measure the dispersion of contagious phenomena (the properties of distribution of a contagious phenomenon throughout a population).

A natural question to consider when examining the dispersion of a contagious phenomenon is whether the phenomenon is confined to a particular community within the population, or diffuses through a number of different communities. Let's assume for a moment that we are studying some population that breaks down into communities, and that for each member of this population, we know what community that member belongs to. Then, for some contagious phenomenon, let's define the Majority Cluster of the phenomenon as the community with the most engaged members at the end of some time period. Finally, we define the Normalized Concentration of the phenomenon as the fraction of engaged users that belong to the Majority Cluster. Phenomena with high Normalized Concentration are confined to just one or two communities, whereas phenomena with low Normalized Concentration are spread across a wide range of communities. Note that, depending on the size of individual communities, Concentration may or may not correlate inversely with popularity.

In addition to Normalized Concentration, we would like to measure some aspect of the connections between the engaged users. For example, it's possible that a contagious phenomenon is widely spread across a number of communities, but diffuses only through strong ties so that the engaged users form a clique.[15] Conversely, it is possible that a contagious phenomenon is confined to a single community, but spreads through weak ties and the engaged users are sparsely interconnected. Therefore, we introduce a measure of Cohesion, which we define as the network density[16] over the subgraph on all users engaged in a particular contagious phenomenon. Contagious phenomena that spread over strongly connected sets of users will have a Cohesion close to one, whereas phenomena that spread over weakly connected sets of users will have a Cohesion close to zero.

3. Data

We use a dataset of over seventy million tweets from Russian users of the Twitter microblogging service, collected between April 2007 and February 2011. This dataset was collected by Devin Gaffney of the Web Ecology Project. For each tweet (post on the service) we collect the user who posted the tweet, the tweet text, and the tweet timestamp. Our dataset contains approximately 475,000 users.

Some of the tweets contain hashtags in their text. These are user-created continuous (no whitespace characters) strings preceded by a '#' sign. Twitter users insert hashtags into the tweet text to identify the topic of the tweet. Twitter allows users to search by hashtag, quickly finding all the recent tweets on a particular topic. Overall, about 55,000 (more than one in ten) users have used at least one hashtag, and approximately 5.8 million (slightly less than one in ten) tweets contain a hashtag. This is comparable to the overall Twitter statistic of about eleven percent of tweets containing a hashtag and suggests that hashtags are a significant, though not ubiquitous, aspect of tweets by Russian users.[17]

The topic a particular hashtag represents can change over time. For example, the hashtag #domodedovo is generally used to identify the topic of the tweet as the Domodedovo airport near Moscow; during the Domodedovo aiport bombing in 2011, the hashtag became associated with the bombing incident specifically, and users searching twitter for #domodedovo could quickly access the latest news, flight information, rescue operations, and hotline numbers.

4. Method

Our first goal was to identify political and news-related hashtags among Russian Twitter users. A set of Subject Matter Experts (SMEs) identified a series of important general news events as well as important topics in the sphere of Russian politics. The topics were chosen to represent four distinct categories of discourse (see Table 1).

Table 1 List of hashtag topics

General News *Salient across Russian society and driven by events*
-The Domodedovo Airport bombing on January 24, 2011 -The Moscow Metro bombing on March 29, 2010 -The forest fires that spread across southern Russia in the summer of 2010
Local News *Salient for specific Russian cities*
-Samara news -Ivanovo news -Moscow news
Opposition Politics *Mainly the focus of activists opposed to the government*
-The attack on the liberal Russian Journalist Oleg Kashin on November 6, 2010. -The movement to protect Khimki forest near Moscow, which the Russian government decided to clear to make way for a new highway between Moscow and St. Petersburg. -The 'Russian Drivers' Movement' protesting the excessive power of Russian police and government officials, characterized by 'blue bucket' demonstrations that mock the sirens on official government vehicles, sometimes vandalizing them.
Pro-government Politics *Mainly the focus of supporters of the Putin regime*
-The March 2009 trial of former Russian businessman Mikhail Khodorkovsky and subsequent political fallout -The Seliger educational forum held annually since 2005. This forum has a youth audience and the presentations and events at it have a strong pro-government theme. -The President Medvedev-led policy of 'modernizing' Russia

In Table 1 and elsewhere in our analysis, 'Opposition' refers to the formal and informal political forces that call for a change to the current political regime in Russia, now led by Vladimir Putin and Dmitry Medvedev, and 'Pro-government' refers to the political forces that support this regime.

Having identified these topics, the SMEs proceeded to collect a set of topic-related hashtags. While there are a number of emerging hashtag directory services,[18] finding the hashtags related to a specific event or phenomenon, especially an event that happened outside of Twitter's narrow search time window (seven days or less, depending on search query), remains a challenging task. The team of SMEs tasked with identifying topic-relevant hashtags examined a month-to-month list of the top 1000 hashtags by mentions that we identified in our dataset. They also reviewed lists of hashtags associated with known opposition and pro-government political Twitter accounts, identified as part of ongoing Berkman Center research on Russian Twitter.[19] In total, the SMEs identified 112 relevant hashtags. We call this set the Bundled hashtags. Some of the Bundled hashtags are directly related to the topics above, e.g., the hashtag #metro29 is directly related to the Moscow Metro bombing, others are tangentially related, e.g., the hashtag #ryazan refers to a city where the forest fires took place.

For reference, we also collected a subset of the 500 most popular hashtags (by number of users who used the hashtag) in the dataset. This subset provided us with a baseline for comparing the Bundled hashtags along the dimensions of propagation dynamics listed in Section II.

Finally, we identified a 'core' of about 10,000 users from our dataset and performed attentive clustering on that core to split it into a number of non-overlapping communities, using the methodology described in Kelly et al.[20] The clustering method we used assigns each user to a single cluster in the core. We identified 49 distinct clusters of various sizes and memberships. As in previous work,[21] we combine these clusters further into a smaller number of zones or groups based on topical similarity. However, in this work we are particularly interested in how hashtags spread through political vs. non-political communities, so we use a more politics-focused set of cluster groups, found in Table 2.

Table 2 Cluster Groups

Local clusters represent groups of users who tweet about local issues in particular towns, e.g., Samara and Ivanovo
Tech/News clusters that represent groups of users who talk about tech-related topics (smartphones, computer systems, software) as well as news across a broad topic range.
Opposition clusters that represent groups of users who oppose the current political regime
Pro-government clusters that represent groups of users who support the current political regime
Instrumental clusters that represent groups of users who post spam content or are professional online marketers
Social clusters that represent groups of users who are interested in social events (parties, concerts) as well as social media.

5. Results

We begin by comparing the 112 Bundled hashtags to our baseline dataset of the top 500 hashtags. Figure 1 shows a plot of Peakedness vs. Commitment by time range for the Bundled hashtags as red dots, and the top 500 hashtags as black dots.

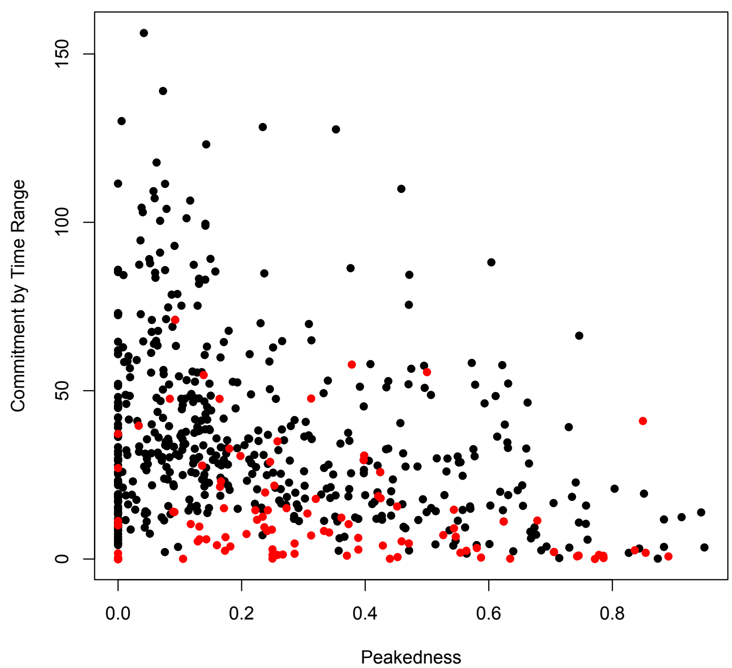


Figure 1 Peakedness vs. Commitment by Time Range for two sets of hashtags

As we can see, news- and politically-related hashtags display a generally lower level of Commitment by Rime Range than the top 500 hashtags at the same level of Peakedness. Some of the top 500 hashtags have extreme levels of Commitment, up to 150 days. Hashtags with the highest levels of Commitment are of several sorts, which notably include regional/location tags, tags for particular sports, religion tags (e.g., 'Catholic,' 'Jewish'), tags for particular news outlets, and general tags related to investing and financial markets. Intuitively, all of these are topics that might engage a stable set of users over a long time. We also compared the Commitment by Subsequent Uses vs. Peakedness for top 500 and Bundled hashtags and found the same qualitative pattern as in Figure 1.

5.1 Dynamics of Contagious Phenomena

Next, we analyze measures of the dynamics of contagious phenomena, namely, Peakedness, Commitment by Time Range, and Commitment by Subsequent Uses. We plot Peakedness for the bundled hashtags against both levels of Commitment: subsequent uses (Figure 2a) and time range (Figure 2b). This allowed us to focus on the distribution within politically relevant tags.

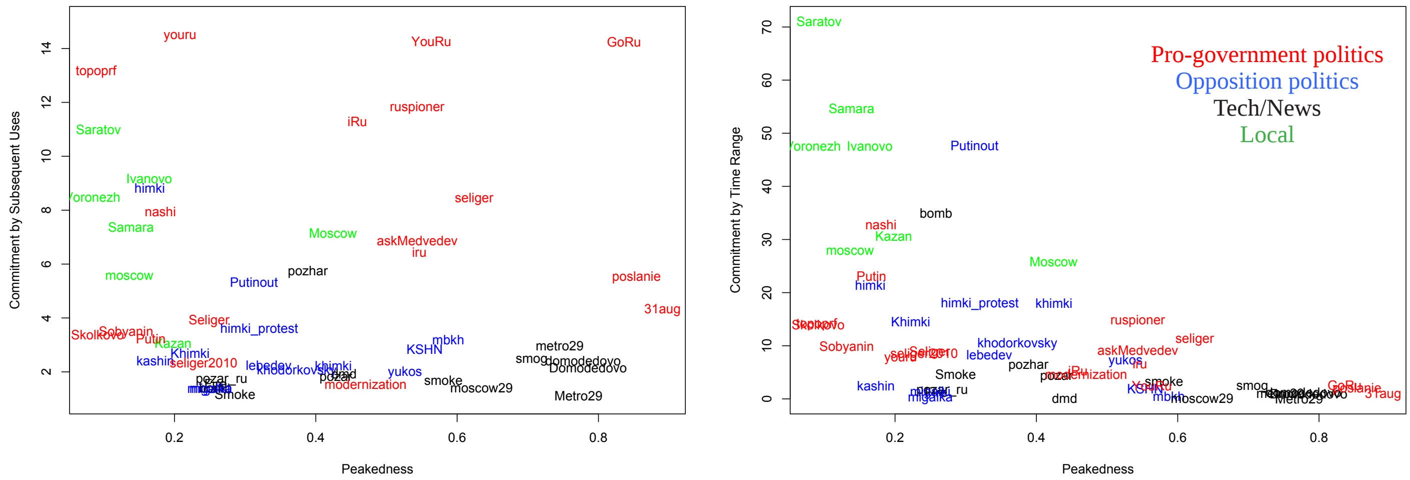


Figure 2 Peakedness vs. Commitment by Subsequent Uses(a) and Commitment by Time Range(b) for news-related and Political hashtags. Color indicates hashtag topic.

In Figure 2a, we see several distinct regions of the distribution. On the bottom right, hashtags with high Peakedness and low Commitment by Subsequent Uses are all directly related to salient news events such as the airport and metro bombings (#Domodedovo, #explosion, #metro29, #Moscow29).

On the bottom left, hashtags with low Peakedness and low Commitment by Subsequent Uses are generally not very popular. Some of them are very generic (#moscow, #metro), and some just never had a peak nor became adopted by a committed user base. Some of these are tags that are similar to popular tags, but reflect less-used variations.

On the top left, hashtags with low Peakedness and high Commitment by Subsequent Uses are all regional hashtags (with the exception of the Nashi hashtag that refers to a pro-government political youth movement in Russia). These regional hashtags were tangentially related to the forest fires events, but their main use is likely in talking about local affairs, hence the high commitment of a few users.

Finally, on the top right, we have a number of hashtags with both high Peakedness and high Commitment by Subsequent Uses. These tend to be pro-government political hashtags (#iRu and #GoRu are both related to Medvedev's policy of modernization while #ruspioner and #seliger are both related to the Seliger youth camp). This observation suggests that pro-government political hashtags have some event (such as the Seliger camp) that is linked to a sudden burst of popularity, but subsequent to that event, users continue to include the hashtag in their tweets. This suggests that pro-government political hashtags may have 'staying power' in the Russian twitter community. Alternatively, or in combination with this, a committed set of users may use the pro-government hashtag both before and after the event, perhaps in an organizational or mobilizing capacity.

In contrast, we present Figure 2b. One can find some of the same clustering seen in Figure 2a (news on the bottom right, regional hashtags on the top left), but the top right group dominated by pro-government hashtags has moved down, indicating that these hashtags do not have staying power over long periods of time: they may be mentioned multiple times, but in a relatively short time range around the peak (days or weeks, not months). In contrast, the hashtags on the top right in Figure 2b are the regional hashtag #Moscow and the political hashtag #Putinout (referring to the anti-Putin movement). It's important to note that #Putinout in particular has relatively long temporal staying power (an average of 50 days between first and last mention by a user in the dataset) but relatively short staying power by mentions (an average of less than six subsequent mentions).

For reference, we present Figure 3, which shows a distribution across the nine topics identified in section 3, of median number of mentions per day by hashtag within each topic. Within each subgraph, the x axis is median number of mentions per day and the y axis is the number of hashtags that fall under that topic and have that many median mentions per day. Again, we use median instead of mean because for skewed data means tend to be inflated. Figure 3 shows, predictably, that news-related hashtags tend to have the most median mentions per day, whereas for other topics few hashtags have more than ten median mentions per day.

Figure 3 Distribution of median mentions per day by topic

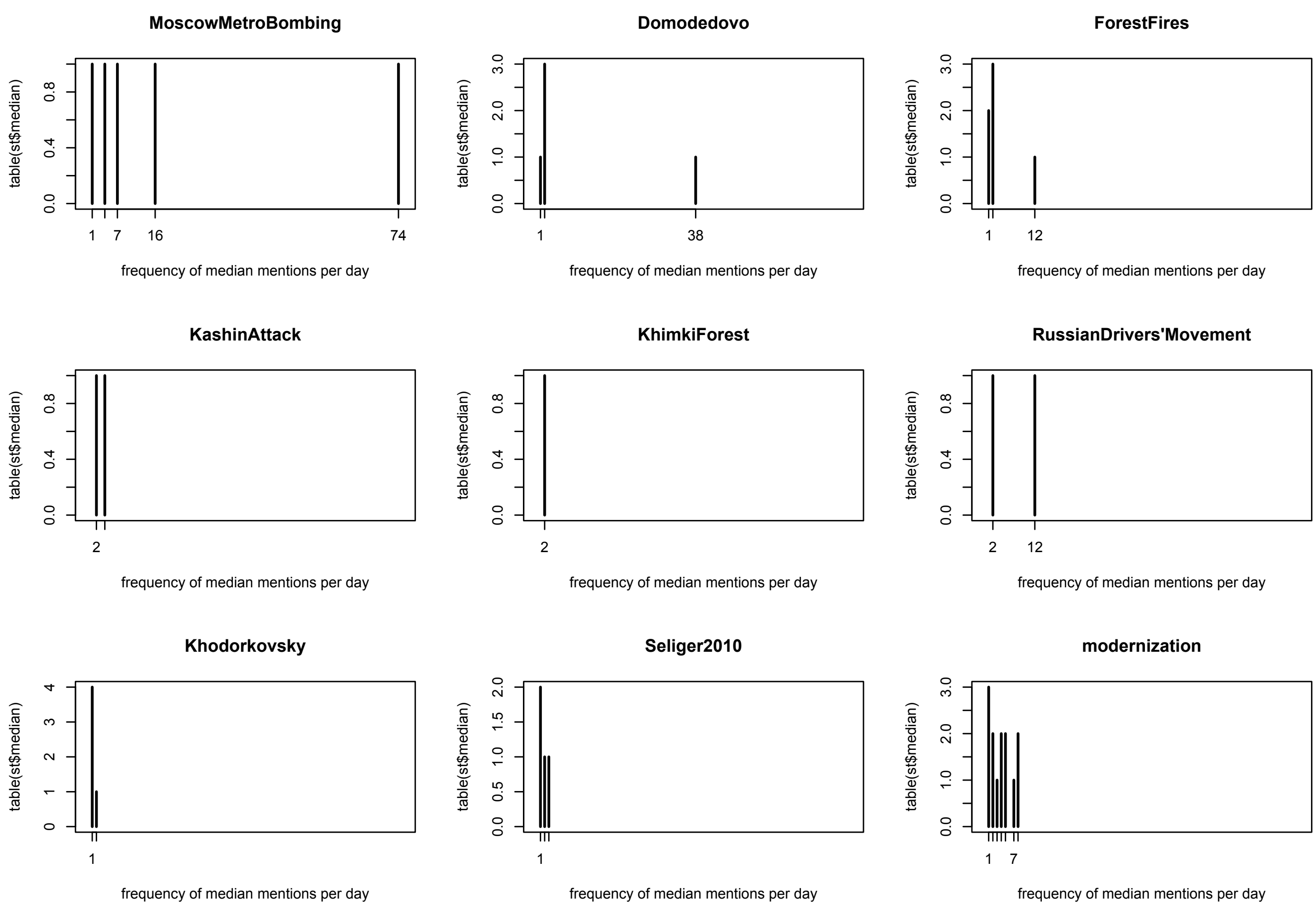
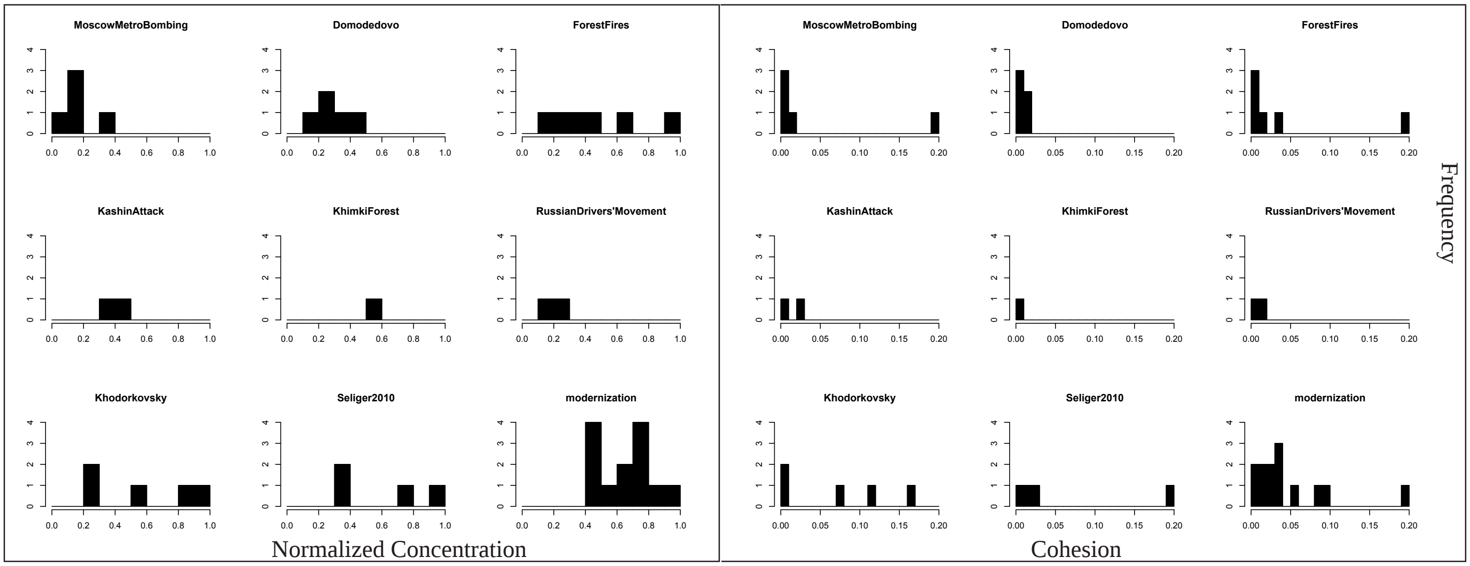


Figure 4 Distribution of mention-weighted Normalized Concentration by topic (a) and clustering coefficient by topic (b)



5.2 Dispersion of Contagious Phenomena

We analyze measures of dispersion of hashtags across the 'core' set of Twitter users as defined in Section 2. In Figure 4(a), we plot the distribution across nine topics of Normalized Concentration by hashtag within each topic. Comparing across all nine topics allows us to see distinctive patterns: the *minimum* Concentration among pro-government hashtags in the Seliger and modernization topics is between .3 and .4. In contrast, the *maximum* Concentration among opposition hashtags in the Kashin and Russian Drivers' Movement topics, is between .4 and .5. Pro-government hashtags are on the whole more concentrated within one cluster than opposition hashtags. Hashtags related to news events, such as the Moscow Metro Bombing and the Domodedovo attack, tend to be diffuse, which is in line with the intuition that major news events tend to engage the population as a whole rather than specific communities.

In Figure 4(b), we plot the distribution across nine topics of Cohesion by hashtag within each topic. For ease of visualizing, we cut off the distribution plots at .2 and assign all hashtags with Cohesion > .2 a value of .2. Again, there is a contrast between opposition hashtags, which have extremely small Cohesion of .03 and below, and some pro-government hashtags (especially those in the Seliger and modernization topics), that have the much higher Cohesion of .10-.30. Curiously, a few news-related hashtags have very high Cohesion, which suggests that some news-related hashtags may spread through strong ties, an interesting contrast to previous work.[22]

5.3 An In-depth Look at Contagion Dynamics: Hashtag Chronotopes

The previous sections provide a high-level analysis of hashtag diffusion among the Russian-speaking Twitter community, both from the temporal and the spatial (network) perspective. However, this analysis necessarily leaves out the idiosyncracies of individual hashtags, which we explore in more detail now.

Detailed analysis of individual contagious phenomena permits us to cross the dimensions of dynamics (loosely, temporal properties) and dispersion (loosely, spatial properties) of the latter. Therefore, we can construct spatiotemporal analyses of contagious phenomena, such as hashtags, and discover patterns in their diffusion across time and space. We borrow terminology from M.M. Bakhtin to call such patterns the *chronotopes* of the hashtags.[23] A chronotope is simply a pattern that persists across a spatiotemporal context, originally used in literary theory to describe genres or tropes.

In order to discover hashtag chronotopes, we visualize the diffusion of individual hashtags both across different communities and across time. First, we select a particular hashtag and bin the set of engagements of Twitter users with this hashtag by day. Next, for each day, we break down the volume of engagements for that day by cluster group. Finally, we create a grid where columns correspond to cluster groups and rows correspond to days. We fill each row-column cell of the grid with a color corresponding to the cluster group. We give a cue to the volume of engagements corresponding to a particular cell via the brightness of the color: the brighter the cell, the more engagements with a hashtag on that day from that cluster group. Black cells correspond to days when a particular cluster group has no engagements with the hashtag.

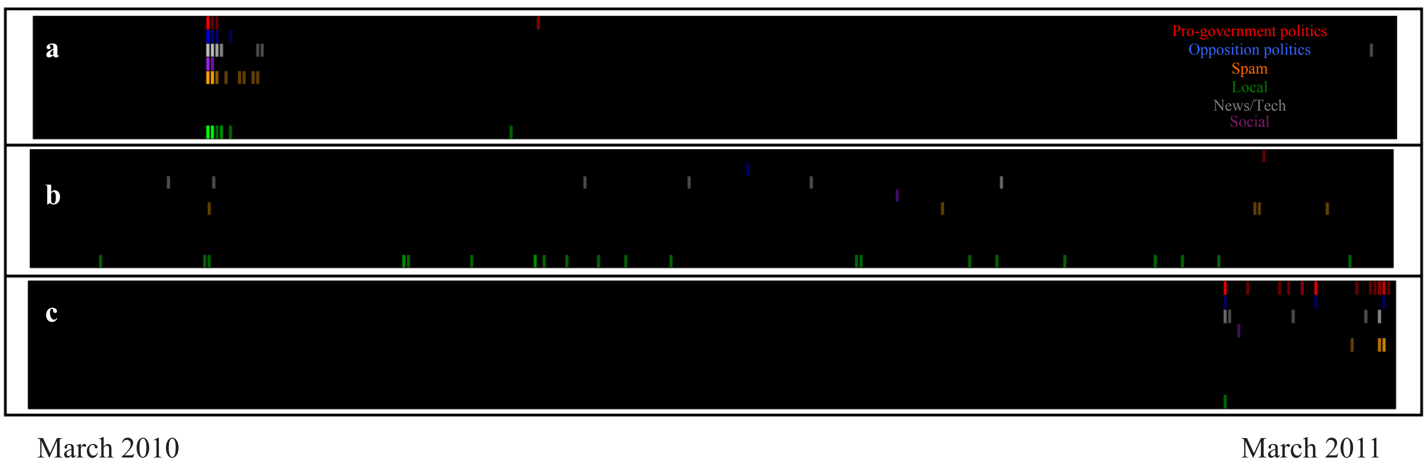


Figure 5 Chronotopes of the #metro29 (a), #samara (b), and #iRu (c) hashtags. Color indicates cluster group, color brightness indicates volume of engagements

Figure 5 shows three such visualizations: the #metro29 hashtag related to the Moscow Metro bombings on March 29, 2010; the #samara hashtag related to the Russian city of Samara; and the #iRu hashtag, related to President Dmitri Medvedev's policy of modernizing Russia. These three visualizations display three distinctive patterns across space and time: #metro29, in Figure 5(a) has a 'salience' chronotope, with engagements across the spectrum of cluster groups during the week around March 29. In contrast, #samara in Figure 5(b) has a 'resonance' chronotope, with consistent engagements from the local cluster group, presumably residents of Samara talking about their city. Finally, #iRu in Figure 5(c) has a 'resonant salience' chronotope, with an initial cross-group burst of activity in late November, 2010 (around the time of Medvevev's announcement of his new policies), followed by consistent engagements from the Pro-Government cluster group over the next month. Note that Figure 5 does not contrast with Figure 2, which suggests that pro-government hashtags have low staying power, but instead presents a more subtle picture: the cluster group of pro-government users remains active in the #iRu hashtag over the course of a month, but, as Figure 2(b) indicates, individuals within that cluster rarely carry on with adoptions for more than 5 days. We can hypothesize that there is a high turnover of users of the #iRu hashtag, with new enthusiasts coming in even as the original adopters lose interest in the topic.

6. Discussion

This work aims to explore the behavior of contagious phenomena in social media, using hashtags spreading throughout the Russian-speaking Twitter community as a case study for developing generalized approaches. We approached the analysis of these phenomena from three angles: dynamics, dispersion, and low-level analysis.

The analysis of hashtag dynamics indicates that there are two primary patterns in the use of political hashtags: salience, in which events drive adoption across the network broadly; and resonance, in which small sets of network actors sustain use of a hashtag over long periods of time. We captured these patterns with two metrics of hashtag dynamics: Peakedness captured salience whereas the two different measures of Commitment captured resonance. In Russian Twitter, news-related hashtags demonstrate the first pattern, and hashtags strongly associated with a particular region or topic often display the second. In between are the political hashtags, which sometimes display a third pattern, *resonant salience* – salience (to varying degrees) among many combined with commitment by adopters within particular communities.

Furthermore, an important difference between our two measures of Commitment reveal subtle differences in hybrid patterns featuring resonance with some adopters and salience among many. When we measure Commitment by Subsequent Uses, we find that pro-government hashtags enjoy both high levels of Peakedness and a large number of subsequent uses. However, when we switch to Commitment by Time Range, we find that pro-government hashtags have the same or even lower levels of loyalty than opposition hashtags. This is a telling observation: pro-government hashtags inspire a lot of active discussion after they are first mentioned, but interest in the same fades quickly over time. Opposition hashtags may inspire less interest at first, but some of them (such as #Putinout and #himki) display high levels of staying power.

Analysis of the dispersion of hashtags in the Russian Twitter user base presents another important observation. While patterns of individual hashtags vary, on the whole pro-government hashtags tend to be much more concentrated in a particular cluster than either opposition or news-related hashtags. Furthermore, networks of users who engage with pro-government hashtags tend to be more densely interconnected than networks of users who engage with other hashtags. Earlier work on simple and complex contagions suggests that information, including news, should spread quickly throughout a network, and therefore it is unsurprising that news-related hashtags are diffuse.[24] Of more interest is the difference between pro-government and opposition hashtags. It is not clear whether pro-government hashtags generally have a higher threshold of engagement than opposition hashtags,[25] or whether an ‘echo chamber’ of the same users consistently engages with pro-government hashtags that are of little interest to the rest of the community. In fact, both factors may be at play: pro-government hashtags may have a relatively high threshold of engagement for the broader population of Russian users of Twitter, but a relatively low threshold of engagement for Twitter users who support Putin's regime. This scenario would explain the observed pattern that pro-government hashtags readily spread through a few clusters of loyal Putin followers but fail to diffuse beyond these clusters.

Finally, the low-level analysis of hashtag chronotopes further illustrates the patterns of salience and resonance discovered in our analysis of hashtag dynamics, including the intriguing new pattern, or chronotope, of resonant salience. Chronotope analysis is especially useful for detecting resonant salience, wherein a particular topic initially engages a number of users across cluster group boundaries, and subsequently one or more of these groups continue engagement with the issue for a long period of time. We see this in the #iRu hashtag example, which initially garnered broad engagement from Russian-speaking Twitter users (presumably, as they were talking about the president's announcement of the modernization policy), and subsequently occupied the attention of users in the Pro-Government cluster group. The latter maintain their focus on the issue of modernization, possibly to support or discuss the president's policies, even as the rest of the community has moved on.

Our analysis presents a high-level perspective on dynamic activity in the Russian-speaking Twitter community. Just as previous work constructs a cyber-geographic map of social media communities in Russia,[26] so our work builds towards a *cyber-dynamic* map of the same communities that describes the behavior of contagious phenomena in the latter, over time. The addition of time as a dimension allows us to identify novel patterns of behavior in social media. For instance, hashtags such as #Putinout or #iRu may be used by committed political groups over a long period of time, but also demonstrate one or more moments of rapid diffusion. It is possible that grassroots political groups might use such hashtags as a means of raising awareness or attempting to mobilize the public to participate in a noteworthy, salient event, such as a pro-government demonstration, large protest march, or public confrontation with the authorities. The approach demonstrated here supports detection of complex and hybrid patterns of diffusion of contagious phenomena in social media, a promising direction for further study.

Endnotes

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