# 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, and apply our system to a dataset of news-related and political hashtags diffusing through the population of Russian users of Twitter. Our results show that news-related hashtags have distinctive propagation dynamics, but that political hashtags have many different dynamic signatures.**

***Keywords-Social Media; contagion; diffusion; dynamics; political movements***

## I. 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 on 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 [6,1] as well as more specific studies about retweeting information (passing it along through the network) and its effect on diffusion [7, 8].

The study of political movements in social media is likewise gaining traction in academic research. Theoretical work by Castells [9] has explored recent empirical social movements and their interaction with social media. The intersection of social media, diffusion, and politics is explored in a study by Leskovec [10], who investigated the spread of string-encoded memes in blogs and news media online before the 2008 US Presidential election.

## II. 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, he 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 President Putin out of power may use the tag #Putinout instead of #Putin when tweeting about the Russian President). Therefore, we use the number of mentions of *p* by users in some social media site as a proxy for the number of engagements with *p* by those same users.

Previous work[1] already suggests one possible dimension along which contagious phenomena can be classified: lifespan. Contagious phenomena can either have a short lifespan (news) or long lifespan (videos, popular websites). Contagious phenomena with a short lifespan tend to have a sharp peak, when a large number of people mention the phenomenon, but the number of mentions is very small on each 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[1]. First, for a time series of first mentions of a particular contagious phenomenon *p*, we identify a peak as a day-long period where total first mentions by day lies two standard deviations above the median first mentions. 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. Then, the Peakedness of *p* is the fraction of all first uses that occur

[1] We also experimented with Wu et al's lifespan measure and found it gave similar results, but it is not scale-invariant as is peakedness.)

during a peak. Contagious phenomena with high Peakedness tend to have a very 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 of a contagious phenomenon, we would like to classify such phenomena based on their staying power – 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.

## III. DATA

We use a dataset of over fifty million tweets from Russian users of the Twitter microblogging service, collected between April 2007 and February 2011. For each tweet (post on the service) we collect the user who posted the tweet, the tweet text, and the tweet timestamp.

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.

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, 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.

## IV. 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 three distinct categories of discourse:

- 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
    - Forest fires that spread across southern Russia in the summer of 2010
- Opposition Politics, mainly the focus of activists opposed to the government:
    - Attack on the liberal Russian Journalist Oleg Kashin on November 6, 2010
    - The movement to protect Khimki forest near Moscow, which the Putin 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
    - 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 Medvedev-led policy of "modernizing" Russia

In the current analysis, "opposition" refers to the 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 events and topics, the SMEs then did manual Google and Twitter searches to identify hashtags related to each. They also reviewed lists of hashtags associated with certain clusters of known opposition and pro-government political Twitter accounts, identified as part of other Berkman Center research on Russian Twitter. These hashtags could be directly related to the events (e.g. the hashtag #domodedovo is directly related to the Domodedovo airport bombing) or tangentially related to them (e.g. the hashtag #ryazan refers to a city where the forest fires took

place). In total, the SMEs identified 112 relevant hashtags. We call this set the Bundled hashtags.

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 the theory section. Figure 1 shows a comparison of the top 500 hashtags (black dots) to the 112 Bundled hashtags(red dots). The x axis is Peakedness, the y axis is Commitment (by time range).

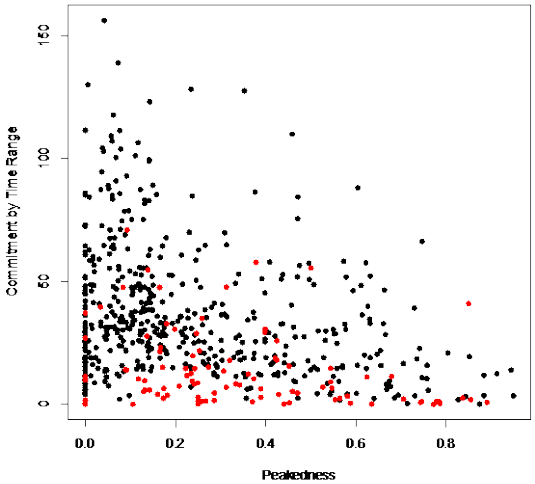


Figure 1. Peakedness vs. Commitment by Time Range across two sets of Hashtags

As we can see, news- and politically-related hashtags display a generally lower level of Commitment by time 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.

Next, we plotted Peakedness for the Bundled hashtags against both levels of Commitment: subsequent uses (Figure 2) and time range (Figure 3). This allowed us to focus on the distribution within politically relevant tags.

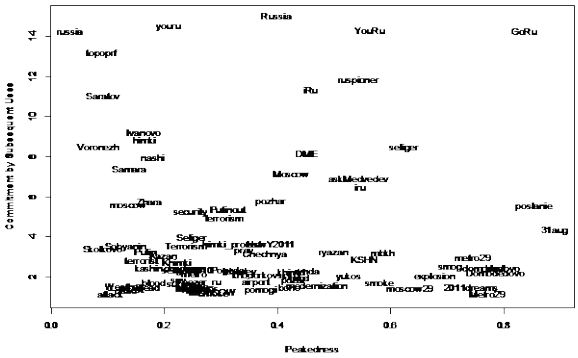


Figure 2. Peakedness vs. Commitment by Subsequent Uses for Bundled Hashtags

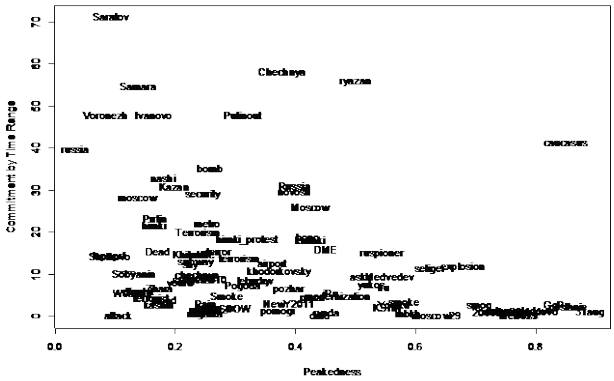


Figure 3. Peakedness vs. Commitment by Time Range for Bundled Hashtags

In Figure 2, 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 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 prior to, and after, the event, perhaps in an organizational or mobilizing capacity.

In contrast, we present Figure 3. One can find some of the same clustering seen in Figure 2 (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 temporal 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 3 are "hot-button" issues such as Chechnya and Caucasus (referring to the war-torn Caucasus region of Russia) and #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).

## V. DISCUSSION

Exploration of Peakedness and the two measures of Commitment indicates that there are two primary patterns in the use of political hashtags: salience, in which events drive adoption across the network broadly; and commitment, in which small sets of network actors sustain use of a hashtag over long periods of time. In Russian Twitter, news-related hashtags demonstrate the first pattern, and hashtags strongly associated with a particular part of the political spectrum (such as opposition or pro-government) often display the second. This intuitively makes sense.

However, the clear difference between the two commitment metrics with respect to some pro-government hashtags points toward another type of pattern, which features both commitment by some adopters and salience among many. With this group of hashtags, we see strong peakedness, with adoption spreading very quickly across the network at a particular point in time, but then continued use on subsequent days by one or more small groups of users. We could refer to this pattern as "resonant salience," since it appears that such hashtags enjoy a rapid rise to widespread popularity, but then become a focus of sustained discussion among one or more committed communities as interest quickly fades among others.

As shown in Figure 3, however, the duration of this topical resonance is limited when compared to the level of commitment enjoyed by tags related to regions, sports, news outlets, and the like. It is easy to imagine, however, that there might be some hashtags which are used by committed political groups over a long period of time, and that might also demonstrate one or moments of rapid diffusion. For instance, a grass roots political group might use a hashtag representing one of its target issues as a means of raising awareness or attempting to mobilize the public. If it were then successful in creating a noteworthy event, such as a large protest march or public confrontation with authorities, the tag might enjoy a peaked moment of salience, as well perhaps as some resonant follow-on discourse among key interested groups. Detection of more complex and hybrid patterns such as these would require development of additional metrics, and is a promising direction for further study.

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