Evidence for echo chamber and disagreement effects in the political activity of Twitter users

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Abstract

Online social networks have emerged as a significant platform for political discourse. In this paper we investigate what affects the level of participation of users in the political discussion. Specifically, are users more likely to be active when they are surrounded by like-minded individuals, or, alternatively, when their environment is heterogeneous, and so their messages might be carried to people with differing views.

To answer this question, we analyzed the activity of approximately 400,000 twitter users who expressed explicit support for one of the presidential candidates of the 2012 US presidential election. We quantified the level of political activity (PA) of users by the fraction of political tweets in their posts, and analyzed the relationship between PA and measures of the users political environment. These measures were designed to assess the likemindedness, e.g., the fraction of users with similar political views, of their virtual and geographic environments.

Our results showed that the dependence of PA on likemindedness of the virtual environment is independent of political affiliation. This dependence has a dominant maximum that occurs when political opinions of users virtual peers are evenly split. This peak is inline with the disagreement theory that states that user’s political activity is invigorated by the disagreement with their peers.

The effect of likemindedness in the geographical environment on PA differs significantly between Democratic and Republican users. PA of Democratic users is almost independent of their geographical environment, whereas PA of Republican users is significantly higher in predominantly Republican areas. The latter is a manifestation of the echo chamber effect.

Therefore, our results demonstrate that participation in political discourse on social networks is a product of both echo chamber effects and effects of disagreement, and is dependent on both social and geographic environments.

Introduction

In the recent years, online social networks have emerged as a significant platform for discussion and dissemination of political information. For example, 2011 Pew surveys (Smith 2011) found that 22% of adult Internet users participated in political campaigns through at least one of the major social media platforms (Twitter, Facebook, Myspace) during the 2010 US elections. Similarly, (Rainie et al. 2012) found that, in year 2012, 34% of social network users posted their own thoughts on political or social issues, and 38% of users “liked” and reposted political posts of others.

This increasing importance of social media and the relative convenience of its analysis attracted attention from academic researchers. Among the questions that have been investigated are: prediction of future election results (e.g., (Gayo-Avello, Metaxas, and Mustafaraj 2011)), finding users whose opinion on a certain subject is influential (Barbieri, Bonchi, and Manco 2012; Weng et al. 2010), and leveraging anonymized web search queries to analyze and visualize political issues (Weber, Garimella, and Borra 2012).

In this paper we analyze social factors associated with the level of participation of users in the political discussion. Two complementing theories were suggested in the scientific literature to explain the interaction between likemindedness of ones’ social environment and of the level of political activity:

- **Echo chamber effect.** In (Stinchcombe 2010), the author shows that people tend to look for cognitive comfort by discussing their opinions with like-minded people. Their opinions are thus echoed and reinforced by their social peers; creating an echo chamber effect. In the context of the web, the echo chamber effect is achieved when people follow blogs and news sources that do not challenge their political opinions. This theory predicts that people in comforting environments such as echo chambers will exhibit an increased level of political activity.

- **Disagreement effect.** A large body of political-science literature (Nir 2011; Pattie and Johnston 2009; Mutz 2006; Moy and Gastil 2006) explores the effect that disagreement, i.e., having political opinions different from a persons’ (non-virtual) social peers, has on their political activity. In (Nir 2011), the author shows that dis-
In this paper we test the presence and the relative importance of these two effects in political discussions in Twitter. We also test a conjecture that likemindedness of both the virtual (web) environment and the physical (geographical) environment have effect on a user’s level of political activity.

**Methods**

In this paper we analyze data from Twitter - a micro-blogging service that allows users to post short “tweets” and to receive tweets made by other users by “following” their blogs, thus creating a social network of blogs. Our data extraction technique largely follows methods from (Dyagilev and Yom-Tov 2013). We begin by identifying a large population Twitter users that expressed explicit support for Barack Obama or Mitt Romney during the 2012 US Presidential election. In what follows, we alternatively refer to these users as Democrats and Republicans, respectively.

To do so, we looked for specific highly-partisan hashtags (a single word preceded by “#” sign, listed in Table 1) among the tweets made in the 10 days following Election Day. We picked this method over other existing methods (e.g., (Pennacchiotti and Popescu 2011; Conover et al. 2011; O’Banion and Birnbaum 2013)) because of ease of its implementation and accuracy (above 95%) that is higher than in other solutions. The simplicity and the higher accuracy of our method come at the expense of a smaller recall than that of other existing methods. However, the obtained user population was large enough for meaningful analysis.

As in (Dyagilev and Yom-Tov 2013), we found a total of 372,769 Democratic users and 22,902 Republican users. We let $U$ denote the set of all users.

We then extracted all tweets published by users in $U$ during the three months period between Aug. 1st and Nov. 15th 2012. This interval includes tweets published, roughly, three months before the election day (Nov. 6th) and ten days after it.

Overall, there were 55,740,001 tweets. As in (Dyagilev and Yom-Tov 2013), we used hashtags such as “#election2012” (see Table 2 for the complete list) to extract a subset of 465,842 tweets on political issues.

Given the number of political and non-political tweets made by each user, we are able to calculate their political activity

| Affiliation | Used hash-tags |
|-------------|---------------|
| Pro Obama   | #voteobama, #obama2012, #goobama, #obamabiden, #guardthechange, #4moreyears, #forward, #forwardwithobama, #obamaforpresident, #goobama |
| Pro Romney  | #romenryryan2012, #voteromneyryan, #voteromney, #benghazi, #nobama, #imwithmitt, #americascomebackteam, #fireobama, #teamprolife, #gogop |

Table 1: List of hashtags used for identification of the political affiliation of users.

| List of hashtags: |
|-------------------|
| All hashtags from Table 1: #tcot, #election2012, #gop, #romney, #obama, #elections, #president |

Table 2: List of hashtags used to identify political tweets.

(PO), which is quantified as the fraction of political tweets among their posts.

We next inferred the edges of the social graph that connects users in $U$. There are several commonly used proxies for the social connections between Twitter users. For instance, one approach is to assume that there exits a directed edge from user A to user B if user A follows user B’s blog. Another approach is to define an edge from user A to user B if user A “retweeted” at least two of user B’s posts. We choose the latter approach as it indicates a stronger connection between users. Namely, user A is more than just reading user B’s blog, user A also engages in discussion with user B. We refer to corresponding social network over users in $U$ as the Retweet-network. We keep the terms “follower” and “followed” to describe the relationship between users in the Retweet-network.

The likemindedness of users that follow the considered user (read their blog) is dubbed follower-LM and is quantified as the fraction of user’s followers that share their choice of a candidate. Similarly, we define followed-LM as the fraction of people followed by the user that share their choice of a candidate. We note that this separation between followers and followees is meaningful since only 12.5% of edges in Retweet-network are reciprocated.

Finally, we identified a small subset $U_{GEO}$ of users in $U$ with enough geo-spatial information to identify counties they reside in. To this end, we began by extracting a larger subset of users that provided their geographical location (in terms of GPS coordinates) in at least two of their tweets. For each such user, we calculated their average location by taking the mean value of GPS coordinates. In order for this average location to be representative, we discarded all users with the maximal distance between user’s locations greater than 50 kilometers. We further discarded all users with the average location outside of the United States. The remaining subset $U_{GEO}$ contains a total of 1,083 Republican users and 18,475 Democratic users. For each user in $U_{GEO}$ we
use their average location to identify the county this user resides in and obtain the official voting record for this county. Given this information we are able to calculate the likemindedness of user’s geographical environment (geographical-LM), which quantified as voting share of user’s party in their county.

**Results**

We begin by analyzing the relationship between the average PA and the likemindedness of their virtual social environment, i.e., the followed-LM and the follower-LM. We found that both these relationships are independent of the political affiliation of the considered user.

Figure 1 depicts the dependence of the average level of political activity on the likemindedness of the blogs read by the considered user, i.e., average PA vs. followed-LM. We observe three pronounce maxima in this function: a dominant peak and two secondary peaks of similar magnitude. The dominant peak is obtained for the values of followed-LM between 0.3 to 0.7, which corresponds to the disagreement effect. The first secondary peak is obtained for the values followed-LM greater than 0.9, which corresponds to the echo chamber effect. Finally, there exists an additional secondary peak for the small (less than 0.2) values of the followed-LM. The magnitude of this peak is significantly lower than that of the dominant peak, which is inline with the disagreement effect (Nir 2011).

Figure 2 depicts the dependence of the average level of political activity on the likemindedness of users that read posts of the considered user, i.e., average PA vs. follower-LM. Here, we observe two maxima. Again, the dominant peak corresponds to the disagreement effect and obtained for the values of follower-LM between 0.3 to 0.7. There also exists a peak for the small (less than 0.2) values of the followed-LM. However, there is no evidence for the echo chamber effect.

Finally, we analyze the relationship between the average PA and geographical-LM. The results are depicted on Figure 3. In contrast to the dependence of average PA on follower-LM and followed-LM, the dependence of PA on geographical-LM differs for Democratic and Republican users. We have found that PA of a Democratic user is almost unaffected by likemindedness of his geographical environment, except for a small spike for the high levels of geographical-LM (echo chamber effect). The average PA of a Republican user exhibits high activity in predominantly Republican counties (strong echo chamber effect), attenuation for the low values of the geographical-LM (disagreement effect), and a secondary peak of activity for the intermediate values of geographical-LM (disagreement effect). This is in contrast to the dependence of likemindedness of the virtual environment, where disagreement has a more dominant effect.

**Discussion**

In this paper we analyzed the connection between user’s level of political activity on Twitter (PA) and the likemindedness of its virtual (follower-LM, followed-LM) and geographical environments (geographical-LM). Specifically, we focused on the presence of the echo chamber and the disagreement effects.

We showed that user’s PA as a function of both follower-LM and followed-LM is independent of user’s political affiliation. Both of these curves have a dominant maximum for
the intermediate values of likemindedness, which is inline with the disagreement effect. The dependence of average PA on followed-LM also has a secondary maximum for the high levels of followed-LM, which corresponds to the echo chamber effect. The relationship between the average PA and follower-LM does not manifestate the echo chamber effect. Dependence of PA on both follower-LM and followed-LM have an additional peak for small values of likemindedness. The PA in this peak is relatively small, which is inline with the disagreement effect.

In contrast to the dependence of PA on follower-LM and followed-LM, the dependence of PA on geographical-LM differs for Democratic and Republican users. We have found that PA of a Democratic user is almost unaffected by likemindedness of his geographical environment. However, PA of a Republican user grows significantly in predominantly Republican counties, i.e., counties with large values of geographical-LM. The latter effect can be attributed to the echo chamber effect.

We thus conclude that the level of political activity of the Twitter users correlated with likemindedness of both their geographical environment and their virtual environment. The exact form of correlation manifestates the echo chamber phenomenon and the phenomenon of disagreement.

The main limitation of our approach is in the selection of users for our analysis. Specifically, we ignored users that are politically active but did not express explicit support for neither of the presidential candidates of the 2012 US presidential election. This obviously introduced a bias to our measurements of user’s follower-LM and followed-LM.

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