2018 Internet, Politics, and Policy (IPP) Conference

Oxford Internet Institute, University of Oxford

Online pre-election campaign by polls and likes

K. Tsyganova, D. Tsyganov
Saint-Petersburg State University,
e-mails: k.tsyganova@spbu.ru, d.tsyganov@spbu.ru

Abstract

Online social networks change the way we receive information, including information about political campaigns. Each major event in the world is followed by a wave of opinions and discussions found on different social networking sites. Internet activism is a new way to achieve public engagement in different social and political spheres.

In this paper, we are interested in the online pre-election campaign for the Russian presidential election on March 18th 2018.

Information and misinformation, unlimited access yet presence of echo-chambers, all coexist in online social networking platforms. It is challenging to understand mechanisms surrounding online election campaigns and to trace the tendencies that form public opinion.

Our analysis indicates clusters of groups and pages that unite each candidates' supporters. These clusters may be used to explain online voting behavior. In this research, we examined the effect of selective exposure in VK online communities during the pre–election debates. The high modularity in political online VK communities makes them susceptible to selective exposure.

Keywords

online campaign, online social networks, online groups, “likes”, selective exposure, clusters, modularity, polarization

Introduction

It is hard not to reflect on what we have learned during the last couple of years about the new way of election campaigns. Years of 2016-2018 were marked with major political events - US presidential election, Brexit and Russian presidential election. As the result, many researchers are interested in determining if social media may influence people's voting behavior as well as identifying main factors that make some individuals more or less susceptive to disinformation campaigns in social media.

Social media sites give us a great opportunity to share views and beliefs on a variety of topics with a very large online audience in real-time. The use of social media has become especially important during political campaigns and debates (Lilleker & Vedel, 2013). Many researchers agree that social media platforms are effective informational and communication tool, but the exact role of this powerful tool is still under research.

In light of the upcoming Presidential election in Russia, scheduled for March 18, 2018, political pundits, journalists and researchers are starting to ask similar questions about the role of social media in the country's election. Elections are considered as the foundation of the democracy. Russian presidential elections use the popular vote system, where each vote has an equal weight, to decide the outcome. In this study, we examined how social media sites are used by supporters of presidential candidates and the opposition. Tension in Russian society is high, and the year 2017 was marked with several social protests against the current government. Many of them were organized on the popular social media site called VKontakte (VK). The social media platform chosen for this study is VK based on its popularity - all political parties and the opposition use it for their pre-election campaigns.

The groups' formation is an essential part of social networking sites. Groups' membership and page subscriptions are crucial factors for information dissemination. Despite the almost unlimited possibilities, offered by social networks, in obtaining a variety of information from different sources, people tend to limit themselves to certain groups and pages, leaning towards particular points of view. Why people choose a particular group or page and will it lead to an opinion formation - this is the challenge we are going to address in this paper.

For our study we have selected 6 groups related to upcoming presidential election in Russia 2018. Within a month before the election, we chosen three most popular posts from each group's wall, based on the number of "likes". For each post we have collected profiles of "likers", including their subscriptions to other pages. We have also collected 11 public online polls, dedicated to the upcoming presidential elections, published on different groups' walls in VK.

What is peculiar about selected polls results is that they all show a relatively high popularity of Pavel Grudinin (Communist Party), comparing to the other candidates, including the current president Vladimir Putin. For example, several online polls show Grudinin rating as high as 68% comparing to Putin's 17% (See Appendix A for details). This is in contradiction to the pre-election surveys, provided by several official agencies (FOM, VTsIOM, Levada Center), which show Grudinin's rating around 6% and Putin's at or above 60%.Could the online polls, discussed above, be yet another example of a misinformation, spreading via so called "echo chambers".

The collected data includes two main datasets:

- "Likers" profiles and their page subscriptions from popular political posts
- Online polls, including profiles of users who voted and their page subscriptions

Well established homophily theory stated that that people tend to become friends with one who is similar to them. In our study we are interested in how being part of one group leads to the formation of a similar opinion among all the group members. We found that people who favor same groups for news consumption, have predictable political activity. For example, users with similar page subscriptions are likely to vote online for a particular presidential candidate.

People choose groups based on their interests, in search for information, to consume news, and, during political campaigns, to support preferred political views. This paper will shed a light on how particular view or political position can be examined by analyzing what content user likes and to what pages user have a subscription to.

Literature Review

We will begin by providing an overview of the recent studies related to elections and the challenge to understand what role the internet and in particular social networking sites play in this realm. We performed a review of relevant publications and not only those discussing online campaigns, but also which focus on the theory of selective exposure. Additionally, we reviewed the works that illustrate the feature of "Likes" as a simple action that indicates an actor attitude toward a particular subject on online platforms.

Previous research on political participation has covered many aspects of citizens' involvement, but have a lack of attention toward the microcontexts in which citizens are embedded (Knoke, D., 1990).

With the availability of data provided by social media we can analyze group formations and relationships with real-world behavior from different angles. Evidence of similarity traces in a study of clusters assumes that if a connection exists between members of a group, they have a closer ties. Clustering of ideological types in online social networks was examined by Gaines et al., 2009

The question of how online participation affects human behavior was studied by other authors. For example, Bond et.al., 2012 examined how the influence of directly sent messages affect users real-world voting behavior. They found that close friends of users were also affected by these messages, and it is assumed that the users most likely had real-world connections with the friends. This allows the researchers to assume that social networks can be a strong catalyst for certain social shifts because face-to-face communication is also influenced by social network activity.

Some researchers are concerned with the tendency to generalize results (Miller et.al., 2016) and suggest to be more specific about each case study. Miller proposed two new theories in the global and homogeneous space: polymedia and scalable sociality. Polymedia means that we consider different media not in themselves, but in terms of their correlation in the life of the user. Scalable sociality shows how the space between private and public was established on social media.

The theory of selective exposure relies on the assumption that humans have tendency to seek information that will not be in conflict with their mentality. The study of selective exposure recently has received renewed research attention (Stroud, 2017).

Some studies focus on studying friendship ties as being a type of selection people make. In particular these studies examine the role of friendship ties and common interest. Lewis et. al. (2012) writes about the relationship of selection and influence and the effects they have as being one of the largest questions to be set on solving in social science. In a study Lewis et. al. (2012) looked at college students on Facebook and the effects of friendship ties. One of the findings was that students who share tastes in music and movies increase their chances of becoming online friends.

As our area of interest lies in political campaigns we analyzed literature that is connected to this area. Many researchers recognize the important role social media plays during recent election campaigns. A study by Vicario at al., (2017) that is relevant to our paper, investigates the use of Facebook during Brexit in the UK debate. They address news consumption and determine two distinct communities of news outlets. There are several researches, that study the effect of “fake-news” and targeted advertisement on popular social media sites like Twitter and Facebook, especially in the context of the 2016 Brexit referendum in the UK and the 2016 Presidential election in the US. Role of the internet in 2008 U.S. elections is focus for the researchers (Smith & Rainie).

Researches indicate, that the risk of information polarization is high (Guess et al., 2018), since people prefer congenial information, including political news, and online “echo-chambers”, and they also indicate that these may lead to a misinformation.

Schmidt et. al. (2017) explore news consumption on Facebook on a global scale and created a model of selective exposure to reproduce the observed connectivity patterns.

While these works provide a great deal of research about power of social media and news consumption they do not cover analysis of the way online groups form and how the decision to join a specific group effects users political position.

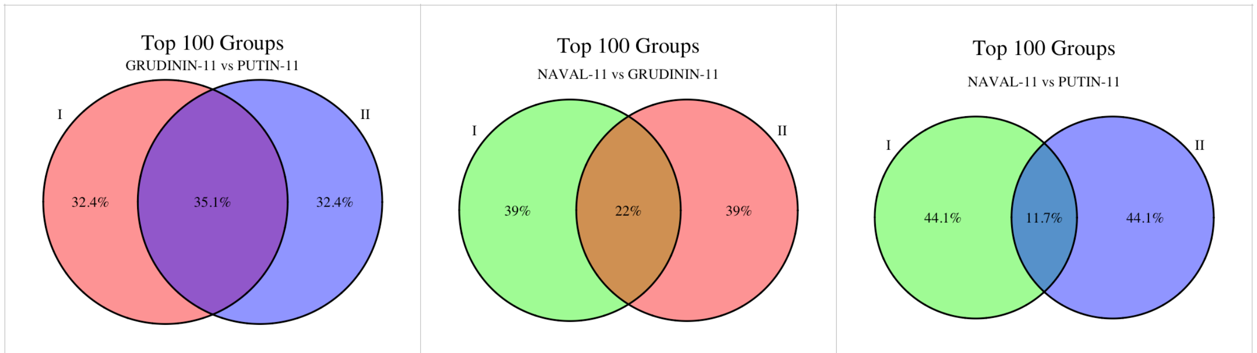
In our study, we are interested to investigate the role of the “like” feature and it's correlation for the group formation. The power of a “like” was the subject of several recent studies. Some researches indicated that “likes” can be used to predict race, sexual orientation, and political views (Kosinski et al., 2013). We will look into how likes help to detect the formation of clusters in certain groups and the effects it has on other online activities.

Method

The primary data that was collected for this study is the activity on VK: including “likes” left on public social media posts and public polls published on VK groups’ walls. For this study we have selected public groups and pages on VK that can be divided into three categories: supporting the current president (Putin), supporting the competing candidates (Grudinin, Communist Party), and the opposition (Navalni). Navalni's presidential candidature was rejected by Central Election Committee, but he is regarded as one of the most vocal opponents of the current government.

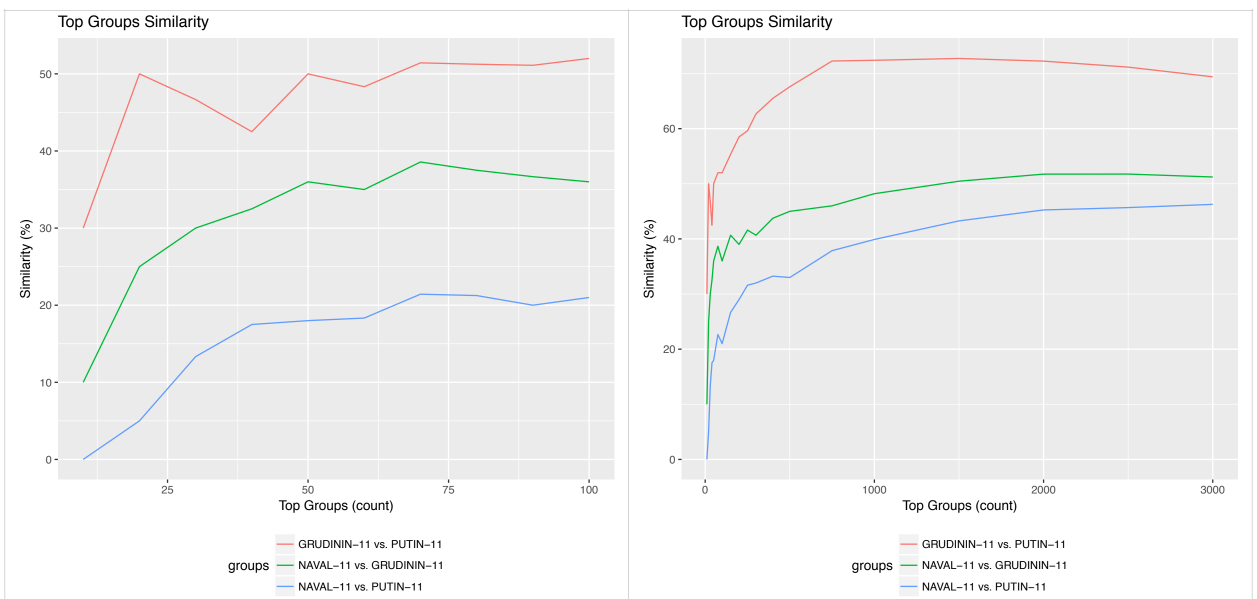
To achieve the first goal of the study, which is to identify the clusters of communities with discrete political affiliations, we have collected profiles of users who “liked” most popular posts from 6 communities, with clear indication of their political association (by the names and the description) with three different candidates: A. Navalni, P. Grudinin and V.Putin. In each community we picked three most popular posts by the number of “likers”. For each “liker” we have collected subscriptions to other online communities (pages) and combined them, forming three sets of pages. The pages in each group were sorted in decreasing order by the number of subscribers among “likers”.

Simple comparative analyses shows that we can identify different collections of pages in each set. Pic. 1 shows the pairwise comparison of top 100 pages from each set and the overlap does not exceed 35.1%



Pic. 1 Pairwise comparison of top 100 pages from Group 1, Post 1 of each candidate. The highest overlap is between Putin and Grudinin pages, at 35.1%, the lowest - between Putin and Naval pages at 11.7%

It is interesting to see if the difference between candidates pages sets will disappear if we start increasing the number of top pages. For this test, we gradually increased top pages count and calculated “similarity” index, which is the percentage of common pages in pairwise set comparison, where 0% indicates absence of similarity and 100% – a complete match. The result of similarity test is shown on Pic. 2. The similarity reaches its maximum at the count range between 900 and 2000 top pages and then plateaus, or even declines. The highest similarity is detected between Putin and Grudinin pages (67%), and the lowest is between Putin and Navalni pages (43%).



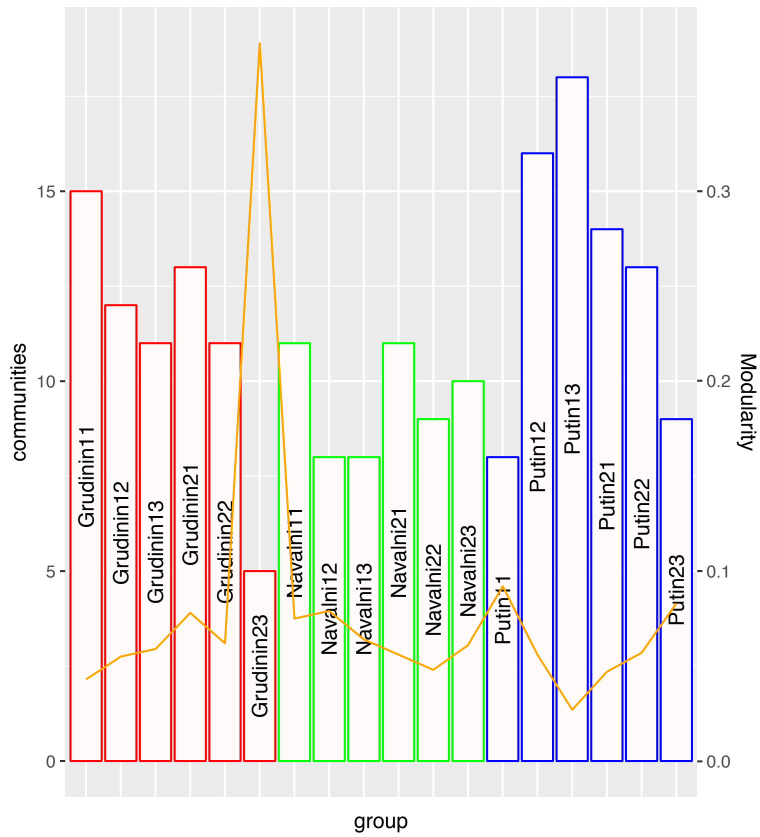
Pic. 2 Pages “similarity” index for top 100 and 3000 pages from Group 1, Post 1 of each candidate. The highest similarity is between sets of Putin and Grudinin at 67% around top 900 pages, and the lowest similarity is between Putin and Navalni at 43% around top 3000 pages.

Community Detection

Considering the differences in the sets of candidate pages, we should expect that there will be unique clusters of pages as the indication of user polarization. Users association with such clusters via subscription can be viewed as participation in so called “echo-chambers” where similar political and ideological views are exchanged and amplified. We performed a community detection algorithm test on the top 100 pages from each set of pages to identify such polarized clusters.

Each set of pages and users can be represented as a bipartite graph B=(P,U,E), where P=(pi| i=1…Np) is a set of pages, and U=(uj| j=1…Nu) is a set of users. P and U are disjoint and independent sets of vertices of network B. E=(eij| i=1…Np, j=1…Nu) is an edge between sets P and U, and **eij** exists (is 1 in the matrix representation) when user **uj** is subscribed to page **pi**, and does not exist (is 0) otherwise. To perform cluster analyses of pages we projected an original two-mode graph onto weighted undirected one-mode graph G=(P,E), where P=(pi| i=1…Np) is a set of vertices, representing pages, and E=(eij| i=1…Np, j=1…Np) is a set of weighted edges between vertices P. The **eij** weight was deduced from the number of users, subscribed to both pages **pi** and **pj**.

For the community detection we used algorithm described in Vincent D Blondel et all (2008), with resolution algorithm described in R. Lambiotte et all (2009). Setting the resolution parameter at 0.7 and using weights, the applied algorithm successfully detected number of communities, between 5 and 18, with consistent positive modularity index (See the test summary on Pic. 3).



Pic. 3 Community detection algorithm summary: number of communities detected and modularity index. The label indicates group and post from which top 100 pages is taken. For example Grudinin11 - is group 1, post 1 for Grudinin, etc.

We carefully analyzed and classified all clusters. Each cluster was assign to the one of the following categories:

1. News
2. Political candidate support
3. Movies and culture
4. Educational
5. Patriotic
6. Cooking and recipes
7. Beauty
8. Humor
9. Other

We have combined clusters in News category and Political candidate support category for each candidate in separate sets: Navalni set - 50 pages, Putin set - 54 pages and Grudinin set - 77 pages. These sets were used for the following test.

Election Polls Test of Independence

Online polls is a more direct way for people to express their support for a candidate. Our second research question was: can the results of online public polls be explained by selective exposure. For this test we have collected the results of 11 online polls, with user (voters) profiles and their page subscriptions. The hypothesis can be stated as follows:

Ho: The result of a user's vote is independent from his page subscriptions
Ha: The result of a user's vote depends on his page subscriptions

To test this hypotheses, we performed a Chi-square Test of Independence on two categorical variables - user's vote for a particular candidate and user's affiliation (via page subscription) with online communities, similar to the communities of supporters for three candidates: Navalni, Putin and Grudinin. Users' votes were taken from the poll results. To find the user affiliation, we compared user's page subscriptions with the unique sets we has discovered in the clusterization test. We have assigned to each user an affiliation variable, based on the maximum overlap with one of the sets: Navalni set, Putin set and Grudinin set. If there is no overlap, or in the case of a tie, we assigned the user to Neutral category. The results of Chi-square Test of Independent shown in Appendix A, tables 1 - 9. The p-values for all test were far less then alpha 0.05, giving that, we can reject the **Ho** hypotheses and conclude that users voting decision and their page subscriptions are dependent. In addition, we have calculated Cramer's V Strength Test, included with the Chi-square test results. For most tests, Cramer's V is above 0.5, indicating strong correlation between users voting and users group subscriptions. To illustrate the cell-by-cell contributions to the Chi-square test results, we included plots of Residual for each cell (see Appendix A, Pic. 4 - 11). The size of the circle on the Residual plots indicates cell's contribution to the Chi-square value — cells with the large circle contribute the most. The color of the circle indicates the sign – dark blue is positive and dark red is negative. The Residual plots are consistent from test to test and can be used as an indication of an opinion of users from different affiliation to the candidates on online vote lists.

Conclusions

One of the significant factors in the formation of political preferences is the involvement in communities on social networks. This study reveals how the examination of a seemingly simple feature of “Likes", leads to insights about relations between social network communities. Our findings indicate that VK users have the tendency to select particular sets of groups and subscribe to particular pages of interest, based on their political and social preferences.

The comparison of each candidate’s supporters’ page subscriptions shows noticeable differences and indicates the presence of a unique ecosystem of pages in each community.

The community detection algorithm identified clusters of pages for each ecosystem. We classified each cluster and assigned it to categories: News, Candidate Supporters, Movies, Culture and etc. The largest difference was found in clusters of the categories News and Candidate Supporters.

With the use of aforementioned page clusters, we have assigned each user, participating in online pre–election polls, to a distinct group. The Chi-square test of independence and Cramer’s V test show that the voter page subscription and his vote are dependent and highly correlated.

Our study shows that online user actions, such as likes or votes, can be explained with the users group subscriptions. We showed, by indirect comparison, that users, subscribed to similar page clusters, will likely support the same candidate.

This approach may be applied to different, not just political, aspects of online user actions. It also may be used in development of models, predicting online user behavior.

References

Adamic, L., & Glance, N. (2005). The political blogo- sphere and the 2004 U.S. election: Divided they blog.

Bond, R., Fariss , C., Kramer, A., Marlow, C., Settle, J., Fowler, J. (2012). A 61-million-person experiment in social influence and political mobilization

Brian J. Gaines & Jeffery J. Mondak (2009). Typing Together? Clustering of Ideological Types in Online Social Networks, Journal of Information Technology & Politics, 6:3-4, 216-231

Carron-Arthur, B., et al., Describing the distribution of engagement in an Internet support group by post frequency: A comparison of the 90-9-1 Principle and..., (2014), http://dx.doi.org/10.1016/j.invent.2014.09.003

Dalton, R. J. (2006). Citizen Politics. Public Opinion and Political Parties in Advanced Industrial Democracies. Washington (DC): CQ Press.

David A. Huffaker. The impact of group attributes on communication activity and shared language in online communities. First Monday, Volume 16, Number 4 - 4 April 2011 http://firstmonday.org/ojs/index.php/fm/article/view/3450/2856

Del Vicario, M., Zollo, F., Cardelli, G., Scala, A., Quattrociocchi, W. (2017). Mapping social dynamics on Facebook: The Brexit debate. Social Networks (50), 6-16

Farrell, H. (2012). The consequences of the internet for politics. Annual Review of Political Science, 15, 35-52.

Foucault Welles, B., Vashevko, A., Bennett, N., & Contractor, N. (2014). Dynamic Models of Communication in an Online Friendship Network. Communication Methods and Measures, 8(4), 223– 243. http://doi.org/10.1080/19312458.2014.967843

Guess, A., Nyhan, B., Reifler, J. (2018). Selective Exposure to Misinformation: Evidence from the consumption of fake news during the 2016 U.S. presidential campaign.

Huckfeldt, R. & Sprague, J. Citizens, Politics, and Social Communication: Information and Influence in an Election Campaign (Cambridge Univ. Press, 1995)

Kosinski, M., Stillwell, D., Graepel, T. Digital records of behavior expose personal traits Proceedings of the National Academy of Sciences Apr 2013, 110 (15) 5802-5805; DOI: 10.1073/pnas.1218772110

Krueger, B. S. (2002). Assessing the Potential of Internet Political Participation in the United States. American Politics Research, 30(5), 476-498.

Lazarsfeld, P. F., Berelson, B., & Gaudet, H. (1968 [1944]). The people's choice, 3rd ed. New York: Columbia Univer- sity Press.

Lilleker, D.G., & Vedel, T. (2013). The Internet in campaigns and elections. In Oxford Handbook of Internet Studies, ed. W.H. Dutton. Oxford: Oxford University Press, 401'420.

Putnam, R. (2000). Bowling alone: The collapse and revival of American community. New York: Simon and Schuster.

Stroud, N.J., (2017). Selective Exposure Theories. In Oxford Handook of Political Communication, ed. K. Kenski, K.H. Jamieson

Tolbert, C. J., & McNeal, R. S. (2003). Unraveling the effects of the Internet on political participation? Political Research Quarterly, 56, 175–185.

Viswanath, B., Mislove, A., Cha, M., Gummedi,K. (2009) On the Evolution of User Interaction in Facebook

Chun, H., Kwak, H., Eom, -H Y., Ahn, Y-Y .,Moon, S. and Jeong, H Online Social Networks: Sheer Volume vs Social Interaction. In Proc. of IMC, 2008.

Vincent D Blondel, Jean-Loup Guillaume, Renaud Lambiotte, Etienne Lefebvre, Fast unfolding of communities in large networks, in Journal of Statistical Mechanics: Theory and Experiment 2008 (10), P1000

R. Lambiotte, J.-C. Delvenne, M. Barahona Laplacian Dynamics and Multiscale Modular Structure in Networks 2009

Appendix A

	Navalni	Grudinin	Putin	Neutral
Сергей Бабурин	19 [11.29] (2.29)	16 [22.83] (-1.43)	10 [8.34] (0.58)	13 [15.54] (-0.65)
Павел Грудинин	1061 [1236.33] (-4.99)	2994 [2499.78] (9.88)	706 [912.86] (-6.85)	1590 [1702.02] (-2.72)
Владимир Жириновский	49 [74.75] (-2.98)	124 [151.14] (-2.21)	87 [55.19] (4.28)	124 [102.91] (2.08)
Владимир Путин	76 [220.56] (-9.73)	326 [445.95] (-5.68)	403 [162.85] (18.82)	328 [303.64] (1.4)
Ксения Собчак	249 [194.67] (3.89)	239 [393.6] (-7.79)	115 [143.74] (-2.4)	397 [267.99] (7.88)
Максим Сурайкин	10 [7.79] (0.79)	9 [15.74] (-1.7)	6 [5.75] (0.1)	15 [10.72] (1.31)
Борис Титов	21 [10.32] (3.33)	12 [20.86] (-1.94)	7 [7.62] (-0.22)	13 [14.2] (-0.32)
Григорий Явлинский	384 [113.3] (25.43)	59 [229.08] (-11.24)	46 [83.65] (-4.12)	93 [155.97] (-5.04)
X-squared	1683.7773626211			
df	21			
p-value	0			
CramersV	0.725			
Table 1.	Poll 1 Chi-square test results. **actual** [**expected**] (**residual**)			

	Navalni	Grudinin	Putin	Neutral
Владимир Жириновский (ЛДПР)	21 [22.53] (-0.32)	44 [75.41] (-3.62)	37 [19.35] (4.01)	52 [36.71] (2.52)
Григорий Явлинский (ЯБЛОКО)	20 [5.56] (6.13)	5 [18.61] (-3.15)	4 [4.78] (-0.36)	9 [9.06] (-0.02)
Павел Грудинин (КПРФ)	659 [657.05] (0.08)	2334 [2199.75] (2.86)	463 [564.55] (-4.27)	1036 [1070.65] (-1.06)
Екатерина Гордон (Партия «Добрых дел»)	7 [4.68] (1.07)	12 [15.67] (-0.93)	1 [4.02] (-1.51)	12 [7.63] (1.58)
Борис Титов (Партия РОСТА)	8 [3.22] (2.67)	3 [10.77] (-2.37)	4 [2.76] (0.74)	7 [5.24] (0.77)
Михаил Козлов (Партия Социальной Защиты)	1 [0.88] (0.13)	3 [2.94] (0.04)	0 [0.75] (-0.87)	2 [1.43] (0.48)
Максим Сурайкин (Коммунисты России)	5 [2.05] (2.06)	4 [6.86] (-1.09)	2 [1.76] (0.18)	3 [3.34] (-0.18)
Владимир Путин	32 [57.05] (-3.32)	116 [190.98] (-5.43)	136 [49.02] (12.42)	106 [92.95] (1.35)
X-squared	334.628327369445			
df	21			
p-value	0			
CramersV	0.442			
Table 2.	Poll 2 Chi-square test results. **actual** [**expected**] (**residual**)			

	Navalni	Grudinin	Putin	Neutral
Жириновский	88 [115.44] (-2.55)	293 [313.3] (-1.15)	178 [135.18] (3.68)	328 [323.07] (0.27)
Грудинин	1460 [1297.2] (4.52)	4325 [3520.51] (13.56)	1147 [1518.98] (-9.54)	3035 [3630.3] (-9.88)
Титов	83 [210.71] (-8.8)	248 [571.86] (-13.54)	80 [246.74] (-10.61)	1208 [589.69] (25.46)
Путин	341 [578] (-9.86)	1239 [1568.63] (-8.32)	1235 [676.81] (21.46)	1626 [1617.56] (0.21)
кто-то другой	391 [161.65] (18.04)	308 [438.69] (-6.24)	127 [189.28] (-4.53)	416 [452.38] (-1.71)
X-squared	2450.88133365459			
df	12			
p-value	0			
CramersV	0.636			
Table 3.	Poll 3 Chi-square test results. **actual** [**expected**] (**residual**)			

	Navalni	Grudinin	Putin	Neutral
В.В. Путин (Самовыдвижение)	539 [1120.42] (-17.37)	2172 [2564.71] (-7.75)	2029 [1049.78] (30.22)	2687 [2692.09] (-0.1)
В.В. Жириновский (ЛДПР)	199 [298.25] (-5.75)	666 [682.7] (-0.64)	332 [279.44] (3.14)	780 [716.61] (2.37)
П.Н. Грудинин (КПРФ)	3160 [3600.22] (-7.34)	9295 [8241.12] (11.61)	2674 [3373.23] (-12.04)	8736 [8650.44] (0.92)
А.А. Навальный (Самовыдвижение)	1593 [543.99] (44.98)	790 [1245.23] (-12.9)	224 [509.69] (-12.65)	999 [1307.08] (-8.52)
К.А. Собчак (Самовыдвижение)	314 [242.13] (4.62)	365 [554.24] (-8.04)	180 [226.86] (-3.11)	746 [581.77] (6.81)
X-squared	4222.59885901978			
df	12			
p-value	0			
CramersV	0.574			
Table 4.	Poll 4 Chi-square test results. **actual** [**expected**] (**residual**)			

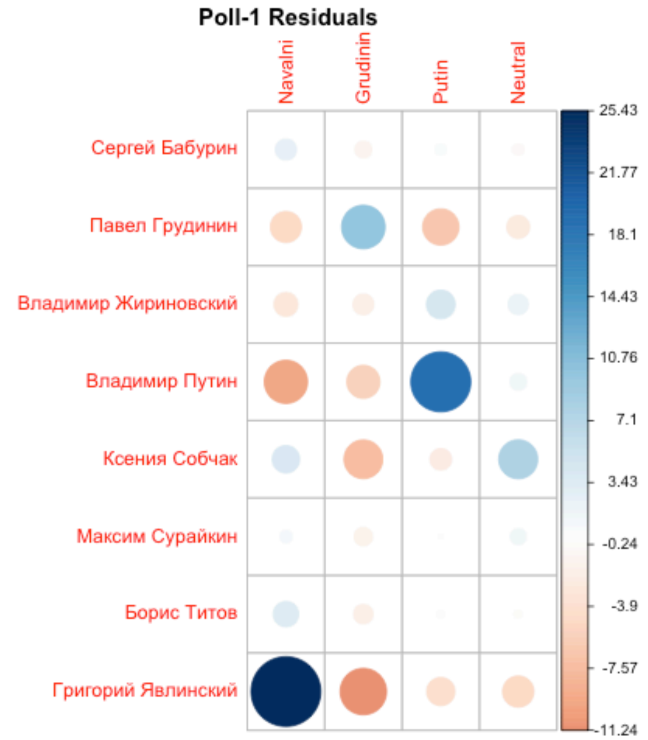
	Navalni	Grudinin	Putin	Neutral
Путин Владимир Владимирович	332 [499.67] (-7.5)	981 [1252.86] (-7.68)	885 [457.93] (19.96)	1170 [1157.54] (0.37)
Волынец Ирина Владимировна	21 [18.1] (0.68)	31 [45.38] (-2.13)	19 [16.59] (0.59)	51 [41.93] (1.4)
Жириновский Владимир Вольфович	71 [83.97] (-1.42)	194 [210.55] (-1.14)	98 [76.96] (2.4)	203 [194.53] (0.61)
Собчак Ксения Анатольевна	174 [137.38] (3.12)	271 [344.46] (-3.96)	112 [125.9] (-1.24)	369 [318.26] (2.84)
Грудинин Павел Николаевич	1880 [1786.22] (2.22)	4899 [4478.74] (6.28)	1209 [1637.02] (-10.58)	4052 [4138.01] (-1.34)
Бабурин Сергей Николаевич	13 [10.83] (0.66)	23 [27.16] (-0.8)	11 [9.93] (0.34)	26 [25.09] (0.18)
Явлинский Григорий Алексеевич	40 [15.43] (6.26)	19 [38.69] (-3.17)	5 [14.14] (-2.43)	40 [35.74] (0.71)
Михайлов Владимир Викторович	9 [5.49] (1.5)	10 [13.76] (-1.01)	6 [5.03] (0.43)	12 [12.72] (-0.2)
Титов Борис Юрьевич	34 [16.91] (4.15)	26 [42.41] (-2.52)	14 [15.5] (-0.38)	40 [39.18] (0.13)
X-squared	807.60584927769			
df	24			
p-value	0			
CramersV	0.374			
Table 5.	Poll 6 Chi-square test results. **actual** [**expected**] (**residual**)			

	Navalni	Grudinin	Putin	Neutral
Жириновский	85 [129.17] (-3.89)	276 [319.32] (-2.42)	182 [131.76] (4.38)	336 [298.75] (2.16)
Грудинин	1747 [1705.91] (0.99)	4966 [4217.34] (11.53)	1388 [1740.19] (-8.44)	3508 [3945.57] (-6.97)
Путин	177 [418.65] (-11.81)	761 [1034.99] (-8.52)	863 [427.06] (21.09)	1048 [968.29] (2.56)
Явлинский	44 [19.54] (5.53)	20 [48.32] (-4.07)	22 [19.94] (0.46)	47 [45.2] (0.27)
Собчак	245 [279.49] (-2.06)	474 [690.96] (-8.25)	208 [285.11] (-4.57)	975 [646.44] (12.92)
Сурайкин	11 [10.14] (0.27)	17 [25.07] (-1.61)	11 [10.34] (0.2)	30 [23.45] (1.35)
Титов	13 [12.78] (0.06)	18 [31.61] (-2.42)	20 [13.04] (1.93)	36 [29.57] (1.18)
Бабурин	13 [11.61] (0.41)	18 [28.7] (-2)	20 [11.84] (2.37)	28 [26.85] (0.22)
я их не выбираю	452 [199.7] (17.85)	340 [493.7] (-6.92)	129 [203.71] (-5.23)	438 [461.89] (-1.11)
X-squared	1690.34001704151			
df	24			
p-value	0			
CramersV	0.517			
Table 6.	Poll 7 Chi-square test results. **actual** [**expected**] (**residual**)			

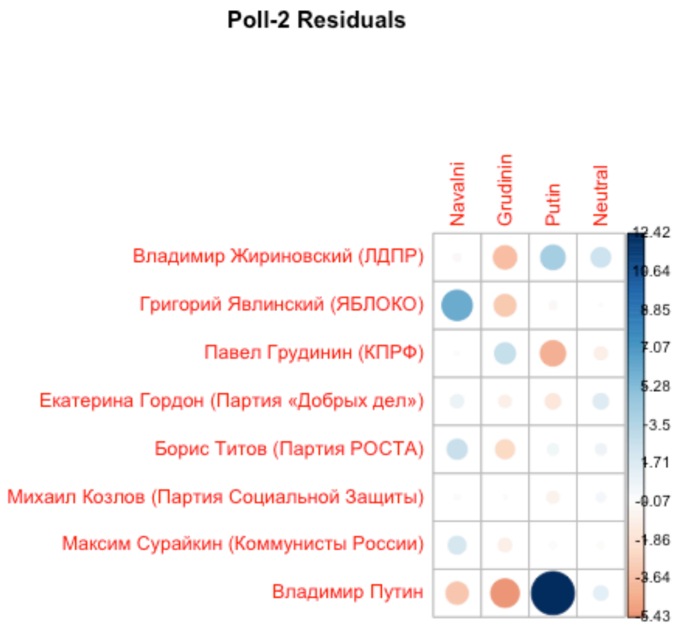
	Navalni	Grudinin	Putin	Neutral
Павел Грудинин	1710 [1647.67] (1.54)	5517 [4070.23] (22.68)	1244 [2273.41] (-21.59)	2257 [2736.68] (-9.17)
Владимир Путин	423 [1131.01] (-21.05)	2110 [2793.92] (-12.94)	3093 [1560.54] (38.79)	1738 [1878.53] (-3.24)
Владимир Жириновский	169 [354.02] (-9.83)	547 [874.52] (-11.08)	388 [488.46] (-4.55)	1201 [588] (25.28)
Ксения Собчак	227 [123.33] (9.34)	251 [304.66] (-3.07)	124 [170.17] (-3.54)	201 [204.84] (-0.27)
Григорий Явлинский	111 [37.78] (11.91)	39 [93.33] (-5.62)	31 [52.13] (-2.93)	65 [62.75] (0.28)
Борис Титов	55 [22.58] (6.82)	36 [55.77] (-2.65)	25 [31.15] (-1.1)	31 [37.5] (-1.06)
Не пойду на выборы.	1260 [638.61] (24.59)	1270 [1577.56] (-7.74)	552 [881.14] (-11.09)	1076 [1060.69] (0.47)
X-squared	5206.96705609228			
df	18			
p-value	0			
CramersV	0.779			
Table 7.	Poll 8 Chi-square test results. **actual** [**expected**] (**residual**)			

	Navalni	Grudinin	Putin	Neutral
Владимир Путин	555 [1648.55] (-26.93)	3269 [5092] (-25.55)	6485 [3847.6] (42.52)	3340 [3060.85] (5.05)
Павел Грудинин	2202 [1846.27] (8.28)	8030 [5702.71] (30.82)	1931 [4309.07] (-36.23)	3123 [3427.95] (-5.21)
Владимир Жириновский	179 [251.47] (-4.57)	720 [776.73] (-2.04)	713 [586.91] (5.2)	470 [466.9] (0.14)
Сергей Бабурин	21 [16.79] (1.03)	46 [51.86] (-0.81)	42 [39.18] (0.45)	30 [31.17] (-0.21)
Григорий Явлинский	55 [20.65] (7.56)	34 [63.79] (-3.73)	32 [48.2] (-2.33)	50 [38.35] (1.88)
Максим Сурайкин	10 [13.04] (-0.84)	39 [40.29] (-0.2)	43 [30.44] (2.28)	16 [24.22] (-1.67)
Ксения Собчак	186 [91.55] (9.87)	226 [282.79] (-3.38)	154 [213.68] (-4.08)	192 [169.98] (1.69)
Борис Титов	34 [18.48] (3.61)	53 [57.08] (-0.54)	32 [43.13] (-1.69)	34 [34.31] (-0.05)
Не пойду на выборы...	1196 [531.2] (28.84)	1291 [1640.75] (-8.63)	926 [1239.78] (-8.91)	985 [986.27] (-0.04)
X-squared	6842.57051014378			
df	24			
p-value	0			
CramersV	0.747			
Table 8.	Poll 9 Chi-square test results. **actual** [**expected**] (**residual**)			

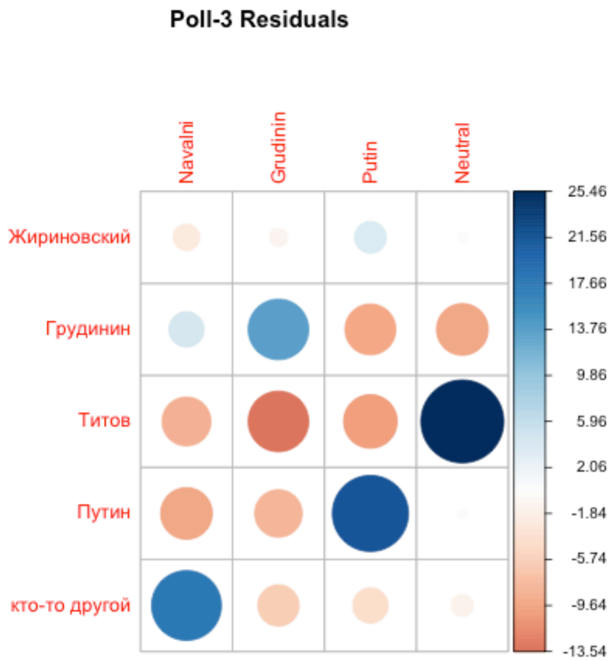
	Navalni	Grudinin	Putin	Neutral
Бабурин	288 [279.06] (0.54)	17 [29.94] (-2.36)	10 [11.17] (-0.35)	34 [28.83] (0.96)
Грудинин	6163 [8074.25] (-21.27)	2175 [866.2] (44.47)	509 [323.26] (10.33)	1251 [834.29] (14.43)
Жириновский	569 [774] (-7.37)	162 [83.03] (8.67)	104 [30.99] (13.12)	133 [79.98] (5.93)
Путин	2934 [4020.33] (-17.13)	754 [431.3] (15.54)	601 [160.96] (34.68)	739 [415.41] (15.88)
Собчак	3256 [3335.09] (-1.37)	311 [357.78] (-2.47)	150 [133.52] (1.43)	454 [344.61] (5.89)
Сурайкин	244 [228.68] (1.01)	18 [24.53] (-1.32)	7 [9.16] (-0.71)	17 [23.63] (-1.36)
Титов	599 [546.12] (2.26)	20 [58.59] (-5.04)	10 [21.86] (-2.54)	54 [56.43] (-0.32)
Явлинский	1027 [914.73] (3.71)	45 [98.13] (-5.36)	9 [36.62] (-4.56)	63 [94.52] (-3.24)
Испорчу бюллетень	3199 [2900.91] (5.53)	164 [311.21] (-8.34)	75 [116.14] (-3.82)	190 [299.74] (-6.34)
Не пойду на выборы	23733 [20938.83] (19.31)	841 [2246.29] (-29.65)	207 [838.31] (-21.8)	1406 [2163.56] (-16.29
X-squared	7386.98270688638			
df	27			
p-value	0			
CramersV	0.649			
Table 9.	Poll 11 Chi-square test results. **actual** [**expected**] (**residual**)			



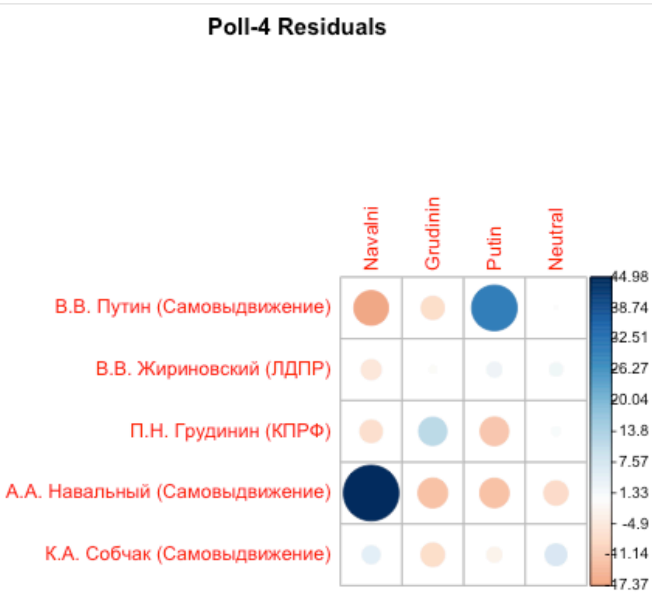
Pic. 4 Poll 1 Residual.



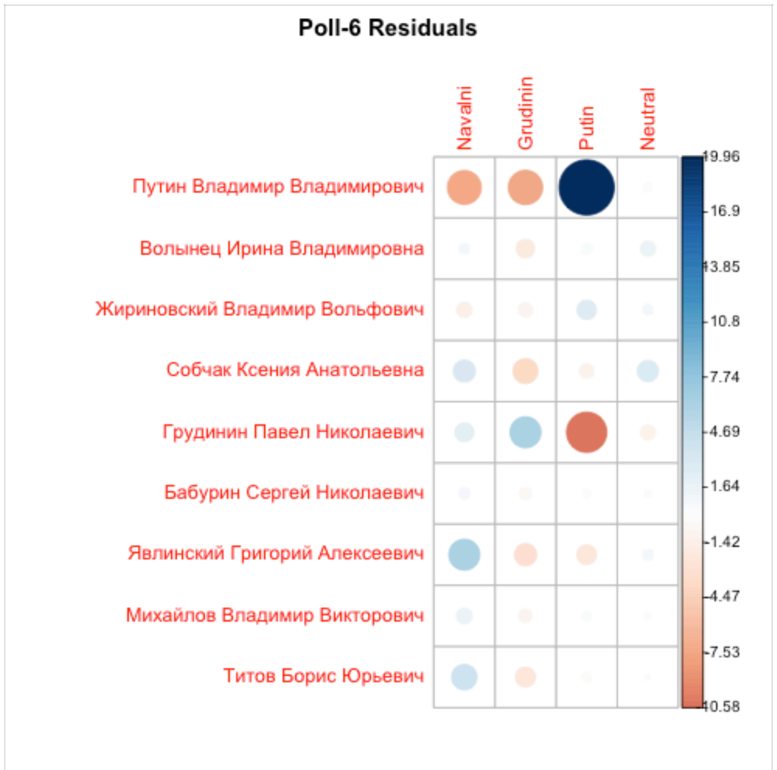
Pic. 5 Poll 2 Residual.



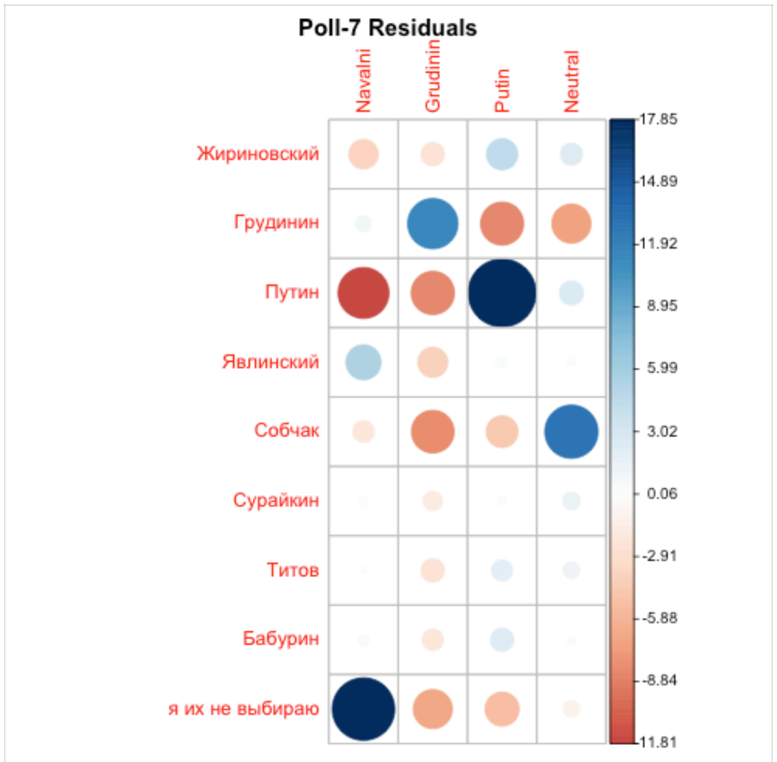
Pic. 6 Poll 3 Residual.



Pic. 7 Poll 4 Residual.

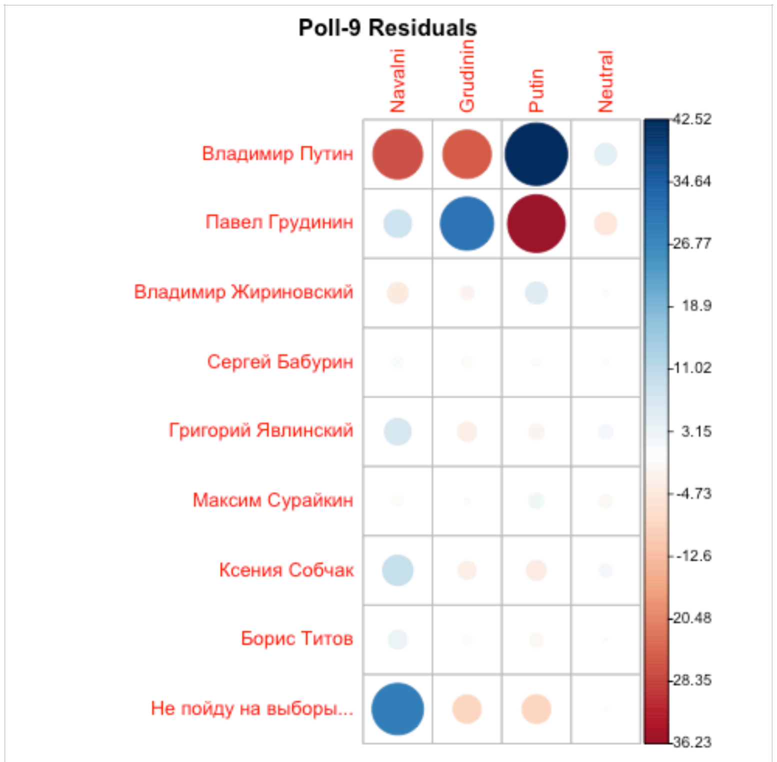


Pic. 8 Poll 6 Residual.



Pic. 9 Poll 7 Residual.

Pic. 10 Poll 8 Residual.



Pic. 11 Poll 9 Residual.