Echo chambers vs opinion crossroads in news consumption on social media

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Abstract.
Social media are often conceived as a mechanism of echo-chamber formation. In this paper we show that in the Russian context this effect is limited. Specifically, we show that audiences of media channels represented in the leading Russian social network VK, as well as their activities, significantly overlap. The audience of the oppositional TV channel is connected with the mainstream media through acceptable mediators such as a neutral business channel. We show this with the data from the VK pages of twelve leading Russian media channels and seven millions users.

Keywords: social media, social network analysis, TV, echo-chamber.

1 Introduction and related work.

Nowadays, the process of information gathering and sharing by media consumers has become simpler than it ever was in the world history. As a result, media audiences can seemingly easily obtain and compare different types of information from different sources.

Despite this, some research has found that social media force users to select social and political content which is not too different from their views (Colleoni, 2014), this phenomenon being known as *echo chamber effect*. It refers to users' inclination to select sources of information with similar orientation and to avoid sources with different slants and even agendas. Festinger (1954) explains echo chambers in terms of cognitive dissonance and selective exposure theories. Likewise, Colleoni (2014) claims that people experience positive feelings when they obtain information that supports their opinion and stress when they get different points of views.

The hypothesis about the echo chamber effect facilitated by social media is supported in (Adamic & Glance 2005, Conover et al., 2011, Guerra et al., 2013). Both studies show that social media users tend to link with alters with similar views – an effect also termed *homophily* if this attachment occurs voluntarily (McPherson et al., 2001). Adamic (Adamic & Glance 2005) and Guerra with colleagues (Guerra et al., 2013) provide the evidence of left-right communities with very little mutual contacts.

Likewise, a Facebook research (Bakhshi et al 2015) finds that individuals' choices play a greater role than algorithmic ranking in limiting users' exposure to cross-cutting content. At the same time, this research finds that Facebook users do get exposed to some discordant content and have some heterogeneous friends.

More detailed research finds that homophily levels vary depending on message content and style, as well as across social groups (Barberá et al 2015; Liao et al 2014). Thus, lower homophily was observed for non-political and moderately discordant content and among users with high accuracy motives. A study of the Russian blogosphere (Etling et al 2010) found it to be very connected across all political clusters and very dissimilar to the bi-polar American structure described in Adamic and Glance (2005). The situation opposite to the echo chamber effect has been termed "*national conversation*" (Barberá et al 2015) and "*opinion crossroads*" (Bodrunova et al 2015) and is the main alternative theory to explain online political landscapes.

In this study, we seek to test the echo chamber effect in news-related behavior in the largest Russian social networking site VK based on five different measures. Namely, we seek to determine how news consumption on the VK pages of the twelve leading TV channels overlaps in terms of common subscribers, likers, commenters and likes on comments. If individual TV channels or politically homogeneous groups of channels have unique sets of users that do not overlap with other channels or groups of channels, the echo chamber effect hypothesis will hold. If otherwise, the opinion crossroads hypothesis will be more plausible.

2 Data

We perform our analysis on a dataset from VK social networking site (vk.com, a replica of Facebook in terms of its functionality) that has more than 450 millions accounts. We select twelve key Russian media outlets that have the most visible presence in VK, and they happen to be ten TV channels, one news agency and one media organization that is both. We consider only channels with pronounced political agenda. In terms of political landscape, Russia is now divided into a conservative pro-government majority, and an oppositional minority that is mostly liberal, with both "liberal" and "conservative" having different meanings than usually in the "West". Accordingly, we find that only TV Rain is oppositional and liberal (which is why it was deprived of its air frequency and now is an entirely Internet TV channel). RBC is a business channel that tries to keep objective and politically neutral. All the rest may be classified as pro-government. RT was initially an English language TV aimed only at international audience, before it started producing Russian language content in VK in 2017.

For each VK page belonging to a channel we have collected the following information: the lists of users who follow the page, as well as those who have at least once reposted a page's post, or commented on one, or liked either a page's post or a comment to a page's post. The overall dataset embraces the period of one year (2017) and consists of 7,323,983 users. Descriptive statistics for each channel is in Table 1. Such dataset gives us an option to consider different forms of individual participation, both active (reposting, liking and commenting) and passive (following the pages).

After collection, user data were disconnected from their VK IDs and thus anonymized.

Table 1. User activity and subscribers distribution over media pages in VK.

Media outlet	Page audience	Number of comments	Number of reposts	Number of likes to posts	Number of likes to comments
RIA Novosti	2001980	36161	37742	182270	54649
Channel 1	1559147	10654	14145	64612	17887
RT	1001380	26729	15172	74828	36590
RBC	590878	5611	17513	69230	9107
Rain	373963	9360	9327	41647	15305
NTV	299177	5162	6572	23903	7017
Vesti	267568	7752	6856	27572	10639
Channel 5	91809	3248	3919	13461	3537
Russia 1	87573	6203	6349	20153	6846
Kultura	43155	384	2519	6387	464
Mir	23005	227	704	2312	146
TVC	9274	135	255	772	83

Descriptive statistics shows that TV channels are unevenly represented in VK. Some TV channels (Channel 1 or RT) have more than one million subscribers, while other (TVC, Mir or Kultura) have only several thousands.

3 Methods and Results

A database with information about users and their interactions with the channels' pages can be viewed as an adjacency matrix of two-mode (or affiliation) network with two different types of nodes: social network users and public pages. To investigate the structure of channels' similarity in terms of their audiences, we project such two-mode networks into one-mode page-page social networks. As the result we obtain five full weighted graphs with 12 nodes and 66 ties each where the weight of a tie indicates, respectively, the number of subscribers, content sharers, commenters, post likers, or comment likers shared by a given pair of pages. The strength of the ties varies from 0.1% to 5%.

3.1 Relation between different types of overlaps between channels

Theoretically, any two channels may overlap in some aspects (e.g. likes), but not in others (e.g. subscribers). To check this assumption, we test whether the structures of our five networks are correlated. For this, we perform quadratic assignment procedure (QAP-test) (Krackhardt, 1988; Simpson, 2001) that allows to correlate sets of non-independent observations (Table 2). The empirical estimates show that the different networks are significantly interconnected (correlation is in range 0.84-0.98) which means that if any two channels overlap in one aspect they will also tend to overlap in all others with similar strength.

Table 2. Correlations between the five types of networks according to QAP-test .

	Co-membership	Reposts	Comments	Likes	Likes to comments
Co-membership	-	0.89***	0.84**	0.90***	0.85***
Reposts		-	0.92**	0.96***	0.91***
Comments			-	0.94***	0.98***
Likes				-	0.91*
Likes to comments					-

*- p-value < 0.05, ** - p-value <0.01, *** - p-value<0.001

3.2 Communities of the most overlapping media channels.

We use Jaccard index to calculate the strength of pairwise intra-channel overlap, while we perform community detection to find clusters of the most overlapping channels. Jaccard index is calculated as the number of common elements in a pair of sets divided by the total number of unique elements in both sets. It is thus sensitive to the difference in the sizes of the compared sets, which is why we, instead of looking at its highest absolute values, find the most similar (overlapping) pair for each channel. First, we confirm the results of the QAP test finding out that such a pair is the same across all or most aspects (likes, shares etc.) for each given channel: Channel 1 and TVC – 3/5, Mir – 4/5, others except Kultura – 5/5. Kultura's similarity pattern is inconsistent. Second, when measured by the sum of Jaccard indices across all aspects, the most similar pair is nearly always much more similar to the given channel than all the rest. An exception is Channel 1 which overlaps with NTV nearly as strongly as it does with its most similar pair (RT). By pointing an arrow from each given channel (except Kultura) to its most overlapping pair we obtain the following scheme:

1. [Rain ↔RBC]
2. [RIA Novosti ↔ RT] ← Channel 1
3. [Channel 5 → NTV ⟶ Vesti ↔ Russia 1]
4. [TVC ↔ Mir]

We thus observe two closed dyads, as well as a dyad and a quartet linked by Channel 1 for which we also show its second strongest link. When other second strongest links are added, more ties emerge between neighboring lines, but never between lines 1&3, 2&4 or 1&4 (Kultura gets linked to lines 3 and 4). Also, mean values of Jaccard index are low in all networks (0.016-0.022, max=0.1) which indicates overall modest level of audience intersection. Before interpreting these results, we report the results of community detection performed with Louvain algorithm for weighted networks (Blondel et al., 2008). The cells in Table 3 contain labels of the clusters detected in each of five networks. If the labels for different social networks are the same, it means that these two channels are from the same clusters in both social networks.

We see that, first and foremost, cluster structure is weakly expressed (modularity values are: co-membership network 0,14; comments and likes networks 0,1; reposts and likes on comments networks 0,08). At the same time, cluster composition is relatively stable across different networks, except that a third cluster occurs in comments and in likes to comments networks (Fig.1), but again with the same set of members.

Table 3. Clusters of the most overlapping media channels in VK.

Channel	Subscribers	Reposts	Comments	Likes to posts	Likes to comments
RIA Novosti	1	1	1	1	1
Rain	1	1	1	1	1
Mir	2	2	3	2	3
Vesti	2	2	2	2	2
Russia 1	2	2	2	2	2
RBC	1	1	1	1	1
Channel 1	1	2	2	2	2
NTV	2	2	2	2	2
Channel 5	2	2	2	2	2
RT	1	1	1	1	1
Kultura	2	2	3	2	3
TVC	2	2	3	2	3

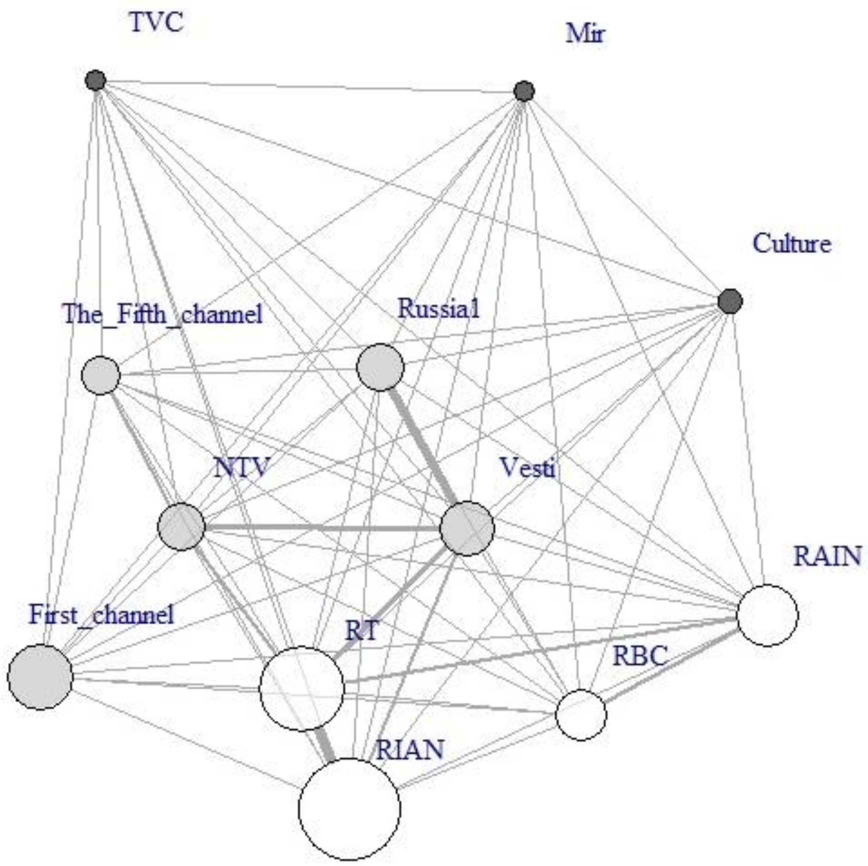

Fig. 1. Community structure of the likes to comments network projection. The size of the node is proportional to the number of likes to the comments of the corresponding channel. Same colored nodes are from the same cluster. The strength of the tie is proportional to the number of users who liked comments on both channels.

4 Discussion and conclusion

In this paper we investigate the overlap of news consumption between the leading media channels represented in VK social network and try to relate those overlaps with media political stances. A difficulty of this research is that media political stances are not as easily defined in Russia as they are e.g. in the US. Nevertheless, it is obvious that oppositional Rain is reliably connected to RBC that tries to serve business audience irrespective of its political views. The two channels that emerge as the nearest neighbours of Rain and RBC are RIA Novosti and RT. Although internationally the latter is associated with the Russian propaganda, together with the first two it follows the objective-looking style of Western hard news, while RIA Novosti might exploit its lasting reputation of formerly independent news agency. Anyway, both link the oppositional Rain and the neutral RBC to the mainstream pro-government media which, in turn, are linked to the marginally present TVC (Moscow city channel), Mir (formerly CIS inter-state channel) and Kultura (official educational channel). By no means Rain is the most isolated channel being in the middle of the list (sorted by mean Jaccard index) even when controlled for the channel's audience size.

To reliably judge the strength of echo chamber effect in Russia, it would be best to compare it to an obviously polarized "golden standard" case, but no such case is available. But even without it we can claim, based on the observed levels of modularity and Jaccard index, that all channels are modestly, but relatively evenly interconnected which is why opinion crossroads theory looks a most plausible approach to describe the Russian case. It does not resemble the bi-polar structure found in US, perhaps, because of the extremely uneven sizes of the oppositional and the pro-government political communities. Minority status may stimulate Rain audience to be more integrated into the mainstream discussion through acceptable mediators. Further research into comment content is needed to determine whether opinion exchange between different political groups does take place, and on what media pages - oppositional or mainstream or both.

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