Binary Separation Index for Echo Chamber Effect Measuring

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***Abstract*—In this paper, we develop a new metric to measure the echo chamber effect in online social networks for a particular topic. Unlike previous approaches, our one does not require the knowledge of users' opinions towards the fixed issue. Once information sources that spread relevant content in a social network are determined as well as their positions, our metric generates a value unambiguously. Changing from null to one, it increases as long as the level of informational separateness is on the rise. We discuss the problem of the metric calculation in the case of the social network Vkontakte. Considering attitude towards the Russian government as a topic, after empirical data processing we obtain the value of 0.802 that evidences the sufficiently high level of information separation among Vkontakte users.**

Keywords—online social networks, echo chamber, information dissemination

I. Introduction

The term "echo chamber" is used to describe the situation when an individual (not necessary a user) is embedded in an information network in such a way that information they get coincide with their views. Such phenomenon is suggested to draw on the theory of confirmation bias or selective exposure theory that states individuals prefer to receive messages containing opinions similar to their own, avoiding any contradictions with their prior positions [1], [2]. Another point of view is that one should consider the similarity between persons themselves rather than between a recipient and a message. In that context, we can highlight two mechanisms [3]: (i) people prefer to be influenced by individuals with similar views – symbolic interactionism theory [4]; (ii) ties between individuals tend to appear between those have some similar traits, e.g. age, religion, sex, etc. – so-called homophily phenomenon [5], [6].

Existing theoretical studies argue that in the case an individual is in an echo chamber, their position becomes stronger reducing a probability to reach a consensus concerning corresponding issues [3], [7]–[12].

In essence, the echo chamber effect (as well as the homophily one) has received a lot of attention because of online social networks such as Twitter or Facebook as they have emphasized it as well as given scholars an opportunity to deal with it by processing a large amount of open-data [6], [13]. It is worthy to note that many studies in this field deal with political issues. A remarkable number of papers is devoted to exploring the situation in U.S. political domain that can be reduced to the following couple of alternatives: Republicans and Democrats [6], [13]–[17]. Nonetheless, the echo chamber effect in some other countries has also been investigated [13].

To capture such systems, a combination of machine learning and social network analysis is usually employed. For example, it is essential to retrieve the social graph from the online data and understand the ways information appears and spreads through a network. Besides, one should label users according to their political preferences. However, such tasks cannot be resolved without some inevitable steps of simplification. A common problem here is to determine users' political preferences carefully. For example, considering U.S. political landscape in general and users' preferences towards the most appropriate candidate for the Presidency in particular, it is usually assumed that users follow the politician in social media for whom they are going to vote [15]. The more reliable approach is to deal with those individuals have made their political position public-available (for example, by taking part in open opinion polls or filling corresponding information on their online pages) [14].

In this paper, we propose an approach to measure the echo chamber effect that avoids the abovementioned problem. Namely, we develop a function that for a given online social network and a fixed topic generates a number between null and one: the higher number indicates the greater level of information separateness. A significant feature of our metric is that it does not require information concerning users' political views. All we need is to determine the set of accounts who disseminate information in the network and their political positions. Existing studies argue that such a task can be resolved by means of machine learning techniques since information spreaders are usually convenient objects for classification as these accounts contain the sufficient level of relevant information that can be used by a classification model to make a forecast [18], [19].

In what follows, we call the metric by Binary Separation Index (BSI). A sufficient restriction of the version of BSI presented in this paper is that it requires ideological space to be binary.

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Trying to fill the gap in the field related to the echo chamber phenomenon where there is a lack of studies devoted to the Russian political domain, we concentrate entirely on the Russian political landscape and the prevalent Russian online social network Vkontakte.

II. Binary Separation Index

In this Section, we formulate the main axioms that the measure we want to develop have to admit and propose BSI as the function that is appropriate here.

Let us fix an online social network and two sets of information sources in this network without intersections: I_1 and I_2.

Definition 1. A user $i \notin I_1 \cup I_2$ is considered to be connected with an information sources $j \in I_1 \cup I_2$ if it gets the information from this source directly or even indirectly (i.e., via reposts).

Here we consider only those users who are not information spreaders. That is to say, our primary concerns are with the ordinary users – information recipients.

Let us denote the set of users connected with the information sources from $I_1 \cup I_2$ by U. In turn, the sets of those users who are connected only with I_1 or I_2 information sources we denote by U_1 and U_2 correspondingly. Additionally, we make use of the following notations: $\alpha = |U1| / |U|$, $\beta = |U1| / |U|$. One can easily obtain that $\alpha + \beta \leqslant 1$.

We introduce the set of axioms a function should satisfy in order to be considered as BSI. To do it, we confine ourselves to the two-variable functions $f(\alpha,\beta)$ with the convex compact domain $\alpha \geqslant 0, \beta \geqslant 0, \alpha + \beta \leqslant 1$.

Axiom 1. $f(\alpha,\beta) = 0$ if and only if $\alpha * \beta = 0$.

That is, if at least one set of information spreaders has no connected recipients, then the level of information separateness is the lowest.

Axiom 2. $f(\alpha,\beta) = 1$ if and only if $\alpha = \beta = 0{,}5$.

It means that the highest level of separateness is reached when U1 and U2 are clusters with the similar and the highest possible cardinal numbers.

Axiom 3. $f(\alpha,\beta) = f(\beta, \alpha)$ for any α and β.

Axiom 3 stands for the symmetry of information sources of different positions from the perspective of our analysis. Finally, Axiom 4 represents the heuristic that if we fix the nonzero number of individuals connected only with, say, accounts from I_1, and if the number of individuals connected with $I_1 \cup I_2$ information sources increases only because of new users connected solely to I_2 information sources, then $f(\alpha,\beta)$ has to increase.

Axiom 4. For a given $\beta \neq 0$ it is satisfied that $f(\alpha_2,\beta) > f(\alpha_1, \beta)$ if $\alpha_2 > \alpha_1$. Similarly, for a given $\alpha \neq 0$ if $\beta_2 > \beta_1$ then $f(\alpha,\beta_2) > f(\alpha,\beta_1)$.

The following statement is true.

Collocation 1. The function $f(\alpha,\beta) = 4*\alpha*\beta$ satisfies Axioms 1-4.

Hereafter, we use the function $f(\alpha,\beta) = 4*\alpha*\beta$ as BSI.

III. BSI Calculation Methodology

Here we discuss main problems regarding BSI obtaining from the unstructured Vkontakte data.

First of all, it is essential to posit an opinion space. As we have mentioned, BSI requires binary opinions. In this paper, we consider the following opposite positions in the Russian political landscape: Russian Government backers and non-systemic opposition supporters. Then we have to build two lists of corresponding information sources. Only *public pages* (or, simply, *publics* – a special kind of accounts in Vkontakte dedicated to information propagation) are used to develop the lists. For simplicity, we reduce the difference between selective exposure and symbolic interactionism assuming that information spreaders disseminate ideologically homogenous content.

To select necessary publics from the wide variety of those in Vkontakte, the following steps are performed. We collect the balanced dataset of users with known political preferences towards the stated ideological space and then use them as "anchors." Namely, we extract public pages these users are subscribed to, encode them using dummy-encoding [15], [20], fit the logit classifier to the encoded and labeled data (without preprocessing them by PCA or other dimensionality reduction techniques), and then retrieve coefficients that fitted classifier assigns to the features. Because of our feature space formalization strategy, each public is associated with a particular value which sign is determined according to the following assumption.

Assumption 1. If selective exposure appears to be and we label government backers by ones and non-systemic opposition supporters by zeros before the model training step, positive values should stand for the publics that generate government-favored content, and negative values should represent publics that disseminate information with oppositional ideas. The higher are absolute values of the coefficients, the more importance corresponding publics have in the classification task.

Therefore, we find the publics having the greatest values of regression's coefficients and label them according to their signs. All computations are performed in the Anaconda Python 3.6 environment. To call the logit model, we use the scikit-learn library. Hyperparameters of the model are adjusted through 5-fold cross-validation, the metric named AUC ROC evaluates the quality of classification tasks. Noteworthy, we reach the value of 0.931 (which is considered to be a high performance rate) when select L2-regularization with the coefficient C = 0.1. 'Saga' algorithm solves the optimization problem.

Finally, we choose 32 publics whose values are significantly higher than the rest ones' coefficients and label them according to Assumption 1.

TABLE I. DIFFERENT BSI CALCULATIONS

Configuration of Definition 2	BSI	10 Random Decompositions	Number of Engaged Users' Accounts
Only subscribers	0.797	Mean=0.667 Std=0.042	11725175
Subscribers + users who have made at least one action	0.801	Mean=0.667 Std=0.042	11828444
Full version	0.802	Mean=0.657 Std=0.041	12093562

The outcome is checked manually. Surprisingly, there are no mistakes, all the chosen information sources are relevant (in essence, all publics we get are dedicated to either mass media or politically oriented issues) and their labels are placed correctly.

Then we detalize Definition 1 trying to adopt it to Vkontakte functionality.

Definition 2. A user is connected with a public if at least one of the following options are satisfied:

1) The user is subscribed to this public;
2) The user has made some activity (like, posts, reposts, comments) to the posts belonging to the public;
3) The users has a friend who has made a repost from this public.

The approach presented in Definition 2 seems to cover approximately all possible ties between users and publics that can be detected by open-data processing.

We calculate BSI by means of VK API methods using the Anaconda Python 3.6 environment again. For each of the 32 publics we find:

1) Its subscribers.
2) The posts that were published on its wall in the time span [t – three Months, t – three Days], where t is the day of data downloading.

Each post is processed, users who have liked, commented or reposted them are identified. Additionally, we collect the friends of those users who have made reposts from a given public.

There are some limitations we face through this algorithm:

1) From August 2018, it is impossible to retrieve reposters – users who have reposted given post – via VK API procedures. To avoid this restriction, we apply the following heuristic: since the act of reposting is accompanied by liking, it would be profitable to find reposters by detecting the walls of those users have liked the posts in a given public.
2) Of course, a user may take away the like that has appeared after reposting and make himself hidden for our algorithm.
3) Additionally, users may deny access to their walls – such users are also neglected in our research.

All data we use are processed in de-identified form, so we do not break the information privacy law.

We obtain BSI for three different configurations of Definition 2: (i) in the first case only those users are suggested to be connected with a public who are subscribed to it; (ii) in the second one we add to this list users who have made actions on public's posts; (iii) the third configuration is the prior version of Definition 2. Besides, 10 random decompositions of the full public list of 32 accounts into two sets are included in the analysis. Thus, we aim to detect the ambiguous situation carefully when there are no intersections between users connected with different publics (even in the case publics belong to the same side).

IV. RESULTS AND DISCUSSION

The results we obtain are depicted in Table 1.

Such results indicate that there is a high level of political information separateness in the Russian domain. Noteworthy, when we form two lists of publics from the whole set of 32 ones randomly, it decreases BSI significantly. It means that there are many intersections between audiences of publics of similar political positions.

Surprisingly, three configurations of BSI that we have obtained for the rational partitioning do not differ strongly: there is small growth. In contrast, for randomly generated sets BSI reduces slightly if we consider broader approaches to establish connections between information spreaders and recipients. In essence, for BSI calculating (if we keep working within Definition 2 paradigm) we can confine ourselves to the extraction of publics' subscribers omitting other types of connecting.

Nonetheless, some simplifications are involved in obtaining the results from Table 1: for example, we do not consider all possible information spreaders neglecting group pages and users' accounts. Hence, BSI we obtain in this paper is the function of two sets of publics rather than the fixed social network. Besides, Definition 2 does not reflect all the possible types of information receiving by users: i.e., it would be fruitful to consider clever news feed that sorts the content a user get in Vkontakte according to a smart algorithm [14]. In our oncoming studies, we try to resolve these problems.

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