

Short communication

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Bifurcation of public opinion created by social media algorithms

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Abstract. The *purpose* of this work is to consider the possibility of nonlinear influence of social media algorithms to the users opinions. A social media inherent algorithm of information ranging interacts with the user inherent bias and that increases the positive feedback loop. The result of this interaction is receiving by the user the only one side of an opinion and the user loses the very possibility to receive the opposite information. The conditions for the society polarization by means of a social media are investigated. *Methods.* In this paper, a model of users opinions dynamics was studied. There are two types of user's strategy was considered: strategy 1, when a user puts "like" on information with proximity to his own view, but differed in any direction; strategy 2, when a user puts "like" on information along his own view, but more strict. *Results.* It was shown that for strategy 1 the society comes to a consensus, but for strategy 2 the society polarizes to the two opposite views. Considering the mixed society, where both strategies are used, it was found that the bifurcation to the society polarization appears when there are more than 40% of people using strategy 2. *Conclusion.* The inherent algorithms of social media, which are created to adapt in coming information to the user's interests, creates or amplifies the bias of the user's opinion and locks the user in an information chamber of only one type. That effect is substantially created by the social media algorithm itself. Thus interaction of users within a social media may increase the polarization of a society more than if they would communicate offline.

Keywords: cognitive science, opinion dynamics, nonlinearity, nonlinear systems, social science.

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Introduction

The active use of social Internet networks (VKontakte, Facebook, Youtube, Twitter) increases the influence of information from social networks compared to information received from other sources (live communication, books, television). This increases the relevance of research on the influence of social networks on the formation of opinions in society using modeling (see the overview of models in [1]). The influence of a social network on people's opinions is nonlinear. On the one hand, users themselves determine from which sources to receive information in accordance with their views — establish connections in the social network with those who share their views [2]. On the other hand, there is a polarization of opinions in society. These poles as sources of information contribute to the formation of opinion attractors with corresponding nonlinear dynamics, in some cases having fractal features [3]. The very interaction of a person with the information received from the social network is also nonlinear — information is perceived through the prism of emotions [4]. Receiving information contrary to a person's opinion can cause aggravation of his own position [5].

The content of information from social networks depends not only on a person's choice of posts to read and videos to watch. It also depends on the choice of posts that are offered by the social network itself (in the "feed" from "friends", in "recommended videos"). The social network has a built-in "ranking algorithm" of posts and videos, which determines what information will be offered to a particular user. Ranking algorithms are a trade secret, but the general principles are observable and known to specialists in the promotion of posts on the social network. Setting a "like" by the user leads to the fact that he is further more likely to be offered: 1) information from the same author to whom he put a "like"; 2) sources that were positively evaluated by those people who also put a "like" on this post — there is a channeling of the information supply and the entry of a person into a certain audience. This means that a person who has positively evaluated some information will continue to receive information with similar content and will not receive opposite information on this topic. Thus, a positive feedback generated by the algorithm of the social network may occur. Such an algorithm of the social network can contribute to the aggravation of a person's opinion, while the chances of a change of opinion are reduced. In this regard, nonlinear effects of the influence of social network algorithms on people's opinions are possible. To test this hypothesis, we conducted a model study.

1. Methodology

Let's consider some topic in which each person can hold some position between two extreme values. These may be views on moral dilemmas (for example, attitudes towards abortion — to allow or prohibit) or attitudes towards political parties — a lot of research has been devoted to analyzing the dynamics of opinions of US residents towards elections between Republicans and Democrats, or between conservatives and liberals. Let's denote the extreme positions as 1 ("yes", "for") and 0 ("no", "against"). In addition to his own position, a person has connections in a social network with other users who broadcast their views. The connection with the source of information can be described by a number from 0 (does not perceive this source, there is no incoming connection) to 1 (constantly perceives this source of information) — we will get a matrix W of connections between them for a group of users. We will use the [6] model based on Durkheim theory — a person's opinion shifts to perceived information:

$$Opi_n(t+1) = Opi_n(t) + a \left(\frac{\sum_{k=1}^N W_{n,k} * Opi_k(t)}{\sum_{k=1}^N W_{n,k}} - Opi_n(t) \right), \quad (1)$$

Here Opi_n — the opinion of a person n on this topic (a real number from 0 — "no/against", to 1 — "yes/for"). N — the number of people in society, they are also sources and recipients of information. Information links $W_{n,k}$ with other users of the social network or information channels of the social network determine whose information a person receives. The formula means that a person's opinion is gradually approaching the opinion of those with whom he is connected in the social network (whom he reads), and the rate of change of opinion is determined by the parameter a .

1.1. Strategy 1. In the [6] model, which is based on Durkheim's theory, it is assumed that a person strengthens his incoming socio-informational connections with those who are close to his position (strategy 1):

$$W_{n,k}(t+1) = W_{n,k}(t) + b \left(e^{-c*|Opi_n(t)-Pik(t)|} - W_{n,k}(t) \right), \quad (2)$$

where the parameter b determines the rate of change of connections, the coefficient $c = 10$.

In such a model, the absolute closeness of opinions is significant — for example, who is “a little for” ($Opi_n = 0.6$) will strengthen the connection more with someone who is “a little against” ($Opi_k = 0.4$; the difference is 0.2) than with someone who is clearly “for” ($Opi_k = 1$; difference 0.4). This seems implausible, since it assumes that a person easily changes his views.

1.2. Strategy 2. We can assume another strategy in which a person is inclined to choose those who reinforce his current opinion (strategy 2):

$$W_{n,k}(t + 1) = W_{n,k}(t) + b(d - W_{n,k}(t)), \quad (3)$$

In the strategy 2: $d = 1$ if $Pi_k(t) > Pi_n(t) > 0.5$ or $Pi_k(t) < Pi_n(t) < 0.5$; otherwise $d = 0$. Let's consider a society in which there are people using the 1 and 2 strategies, and analyze how the increase in the number of people using the 2 strategy affects the dynamics of opinions in the context of a possible conflict of opinions. Denote $N2$ the percentage of people who use the strategy 2 (the rest — strategy 1). With $N2 = 0$, we have a classic Durkheim case.

1.3. Strategy 3. You can also consider a softer strategy 3: having a certain intention “for” ($Opi_n > 0.5$) or “against” ($Opi_n < 0.5$), a person prefers to put “likes” on information that is in the same vein ($Opi_k < 0.5$ or $Opi_k > 0.5$, respectively), and reduces the connection with sources of opposing views (3). In the strategy 3: $d = 1$ if $Pi_k(t), Pi_n(t) > 0.5$ or $Pi_k(t), Pi_n(t) < 0.5$; otherwise $d = 0$.

1.4. Method parameters. The calculation of the final histogram of the simulation results was carried out by averaging over 50 iterations, each with 100 steps of exchanging opinions and changing relationships. The initial distribution of opinions $Opi_n(1)$ is random (Fig. 1, a). A society of 100 people was considered ($N = 100$). The rate of change of opinions $a = 0.1$. The dynamics of the model was studied by varying the parameter b from 0.1 to 0.9.

2. Results

2.1. Final distributions of opinions. The 1 strategy model shows that for any values of a and b , society averages its starting discrepancies (see Fig. 1, a) in opinions and comes to a single average consensus (Fig. 1, b). In the case of the 2 strategy, opinions are polarized (Fig. 1, c). It is expressed the more strongly the larger the parameter b , which reflects the influence of the algorithm of the social network. Similarly, in the strategy 3 there is also a division of society into two camps, but less strong (Fig. 1, d).

2.2. Dynamics of opinion formation. The results for $b = 0.5$ are presented separately below. In this case, the rate of change of connections is only 5 times higher than the rate of change of opinions $b = 0.1$. This seems to be a rather “soft” option, since the rate of change of connections in the social network is very high — it is enough to watch one video or put a “like” and the ranking algorithm itself enters a person into a certain audience, regardless of whether the person has managed to change his position. Therefore, the rate of change of connections imposed by the social network b can be assumed to be even greater relative to the rate of change of opinions a . We are considering exactly the beginning of the user's acquaintance with a certain topic — when the algorithm of the social network has not yet detected the user's views and has not yet determined which audience to include him in his attitude to this topic. When a user already has experience interacting on a social network with content on this topic, he is already inscribed in a certain audience regarding this topic. Therefore, his single estimates no longer have such a value and this shows the nonlinearity — the first actions of the user when perceiving the content have more weight than the subsequent ones.

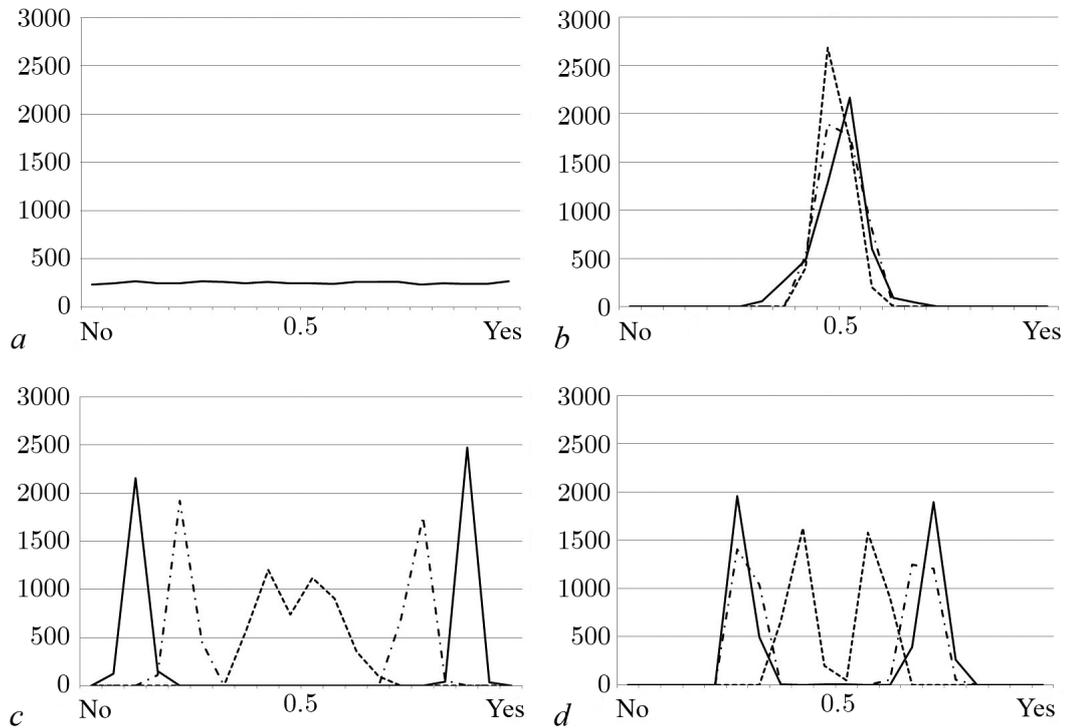


Fig. 1. Opinions histograms obtained in the model. An opinion is shown on the horizontal axis (“yes” towards right side, “no” towards left side). The vertical axis represents the number of user having that opinion. *a* — Start distribution. *b* — Result of the strategy 1. *c* — Result of the strategy 2. *d* — Result of the strategy 3. The polarization of opinions is increasing with parameter *b*: $b = 0.9$ — solid line, $b = 0.5$ — dashed-dotted line, $b = 0.1$ — dotted line

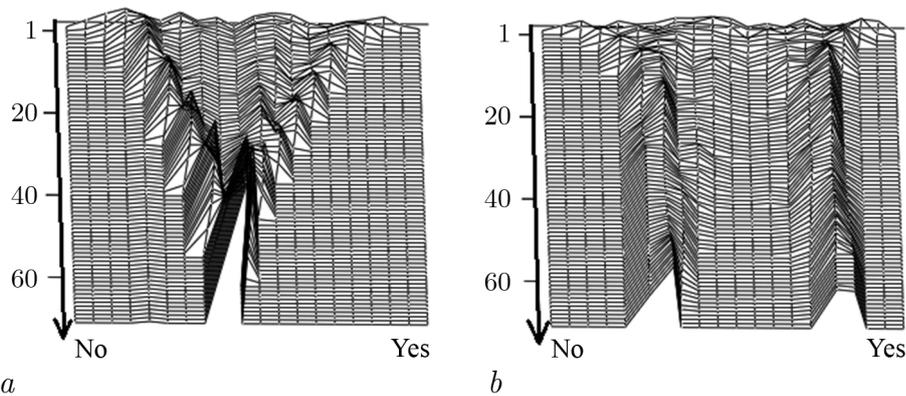


Fig. 2. Dynamics of opinions in the model. Horizontal axis represents opinions (“yes” towards right side, “no” towards left side). A column height represents the number of people having this opinion. Vertical axis represents the model time steps (increasing down). *a* — Strategy 1, $N_2 = 0\%$. The society comes to a consensus. *b* — $N_2 = 40\%$. There a polarization appears

Examples of the dynamics of opinion formation in a mixed society are shown in Fig. 2. If everyone uses only the strategy 1 ($N_2 = 0\%$), then the society comes to a single average consensus (Fig. 2, left). If 40% of people in society use the strategy 2 ($N_2 = 40\%$) and only 60% of the strategy 1, then the results are different. Society is divided into two groups of people who tend to have opposite views (Fig. 2, on the right).

2.3. Mixed society. The results for different values of N_2 (the proportion of people using the strategy 2) are shown in Fig. 3. At low values of N_2 (from 0% to 10%), society comes to a consensus. With the growth of N_2 to 35%, the consensus disintegrates and society has a wide variety of views. With a further increase of N_2 from 40% or more — the society is divided into two distinct groups that have different positions.

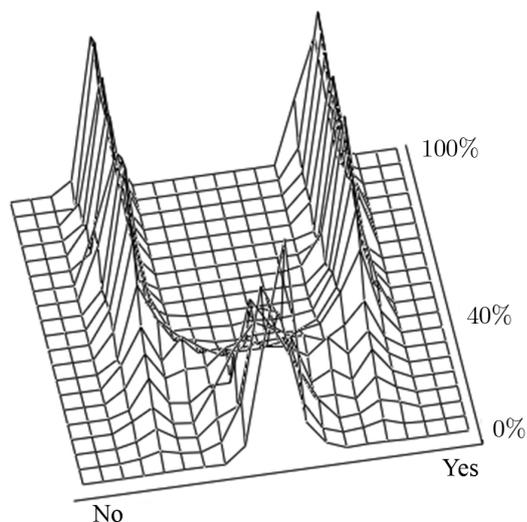


Fig. 3. Opinions histograms obtained in the model depending on the percentage of people having strategy 2 (vertical axis on the right). Horizontal axis represents opinions (“yes” towards right side, “no” towards left side). A column height represents the number of people having this opinion. When the percent of people using strategy 2 increases above 40% the socium divides to two groups with opposite views

Conclusion

The influence of modern social network algorithms on the receipt of information by users can lead to the division of society into two camps and contribute to the creation of a social conflict of opinions. Such a conflict arises if there is a large percentage of people in society who tend to positively evaluate the information corresponding to their views. In the considered model, it was found that with an increase in the proportion of such people from 40% or more, bifurcation occurs — society is divided into two distinct groups that have opposite positions. This is relevant if the society initially has an even distribution of opinions. The results show that the algorithms of social networks can increase the polarization of opinions in society, as they rigidly channel the information received by a person based on his current opinion. This phenomenon is amplified by the social network due to the fact that the rate of changes in information connections (b in the model) in the social network significantly exceeds the rate of change of opinion (a in the model). Thus, the growing popularity of social networks, in which the owners have built-in algorithms for ranking information based on user interests, contributes to the strengthening of positive feedback and generates significant nonlinear dynamics in the positions of society, forms the polarization of society into two parts even from a uniform distribution.

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