MODELS OF EPIDEMIC PROCESSES IN SOCIAL NETWORKS: METHODOLOGICAL SUPPORT

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Abstract

In this paper, the micro models of processes infection with the social networks users content as well as users in the process of two contents conflicting have been substantiated. The methodological support is suggested for epidemic risk analysis of social networks. The methodological approach is based on the probabilistic representation of the user's infection process, where its different states takes place during the content perception. For the assessment of the values of the transition probabilities between these states, the results of statistical studies obtained for networks were used: communication, media-content exchange, reviews and insights, group discussions, authors' accounts, social book markings, according to interests. Moreover, the topics of content were taken into account: music, food, scenery, people, goods, restaurant, tickets, stocks, health, nuclear weapons, war, business, society, cooperation, etc. In addition, there was a recalculation in conditional probabilities when considering the problem of collision of competing contents, including the specifics of social network analysis from the point of view of risk assessment of the spreading the destructive content and the user's chances to perceive positive information. This approach actually considers the situations being relevant to network confrontation when there is a collision of competing contents in the network, and their diffusion takes place under influence of the conditional probabilities of the network vertex transition into one or other state of perception of

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these contents. In this regard, the models taking into account the loss and retention of immunity in relation to the impacted contents were considered. At the same time, the model of contents confrontation offered in the paper is arising from the capabilities of multiple states of network vertex. For this purpose, the appropriate analytical expressions for conditional probabilities of transition from the state to the state of network user have been obtained. To discuss the possible practical application of the proposed methodology, this paper considers the analytical assessment of risks and chances of content diffusion in the network this approach is based on the weighting of the network elements, where their specific traffics are logically used, easily computed from these publicly available social networks. The weighted sets of infected and other vertices characterize in this case the results of the epidemic process at its different stages. The corresponding analytic expressions are also suggested for the case of several contents collision in a network.

Keywords: Social network, epidemic, micromodels of the epidemic process, microfractal.

I. Introduction

When Developing a Micro Model of the Epidemic Process, it is Required to Define the Conditions under which this Model can Function

1. The time in the model is discrete. The unit of time is one iteration. The time countdown starts at zero, and each discrete should cover the period of the vertex's transition from one state to another. This condition allows us to leave out without consideration all the transitional processes within the discrete limits.
2. The modelling network is stationary, that is, has a fixed set of vertices and links between them, the strength of which is also fixed. There cannot be closed clusters in a network, because in this case the vertices of this cluster will not participate in the epidemic process.
3. At the initial moment of time, the probability parameters of the network infection are formed according to the statistics. All vertices are divided into types that define their state in the infection process.

For further calculations we will use the notion of fractal. Fractal is a mathematical set that consists of parts having a self-similarity property [20]. Thus, micro elements of the model that are specific to the entire process can be identified. In fact, microfractal displays the epidemic behavior of a specific vertex. You can think of microfractal as a graph for which the vertices are the state of the epidemic process, and the edges are the probability of transferring from one state to another. In particular, it is possible to say that macrofractal is a probabilistic model of the infection process.

Taking into Account, it is Appropriate to use in Microfractal the Model of a Single Infection of the User:

1. Familiarity with the content for the purpose of its analysis for later use. Here the user is in the neutral state with respect to the content but is theoretically susceptible to its subject-matter (state $S$).
2. A stage where the user positively perceives the content (the state of latent infection E) or remains indifferent to it, that is, it is in the original state S.
3. Further, from state E the user can pass into other states: immunized, acquired on its own (state M) or through moderation (status A); the state when it becomes the distributor of the infection (state I). This allows the user to remain in the E state.
4. In the case of I-state, it should be noted that not all infected users remain in it. Some of them, under the action of internal (loss of serviceability) and external (troubleshooting by moderator) factors, can transit to the R state, which is characterized by the temporary nonviability of the user's individual resource.

II. Model Building Methodology

Let’s imagine it as a graph, the vertices of which are the network vertex (user) states described above, and its arcs are the probability of transitions into those states.

From here, the distribution per subsets of the network under epidemic states, will be as follows:

- |S| - the potency of sets of susceptible vertices S;
- |E| - the potency of sets of vertices in the latent phase E;
- |I| - the potency of sets of infected vertices I;
- |R| - the potency of sets of inactive vertices R;
- |M| - the potency of sets of immunized vertices M;
- |A| - the potency of sets of vertices recovered with the help of administrator A.

Then the micro-fractal of the epidemic process will take the form presented in Fig. 1.

![Micro-fractal of the epidemic process](image)

**Fig. 1:** Micro-fractal of the epidemic process

The above reasonings allows building the probabilistic model (Fig. 1) in the form of a graph that outlines the start of the epidemic process where $P_{AM}$, $P_I$, $P_R$, and $P_E$ - the probabilities of occurrence of respective transitions.
The studies of social networks to determine the probabilities of state transition of the epidemic process are known. Analysis of these sources allows us to summarize these probabilities according to topics of discussion in Tables 1-7.

### Table 1: Communication networks

| Topics     | $P_I$       | $P_E$       | $P_R$       | $P_M$       |
|------------|-------------|-------------|-------------|-------------|
| Cats       | $5.98 \cdot 10^{-2}$ | $4.33 \cdot 10^{-3}$ | $2.68 \cdot 10^{-2}$ | $9.49 \cdot 10^{-6}$ |
| Music      | $3.36 \cdot 10^{-2}$ | $1.34 \cdot 10^{-3}$ | $4.98 \cdot 10^{-2}$ | $6.43 \cdot 10^{-6}$ |
| Food       | $3.43 \cdot 10^{-2}$ | $1.53 \cdot 10^{-3}$ | $8.23 \cdot 10^{-2}$ | $5.47 \cdot 10^{-6}$ |
| Open flights | $3.27 \cdot 10^{-2}$ | $8.09 \cdot 10^{-5}$ | $2.71 \cdot 10^{-2}$ | $1.54 \cdot 10^{-6}$ |

Communication networks are the class with the largest number of users. It follows a low probability of infection for users, as shown in Table 1. The probability of infection is of the same order as the probability of deletion. This means that the site administration is sufficiently good at keeping track of the destructive content of the network and timely blocks the users who distribute it. The probability of immunization is very small order, which indicates a low capacity to evaluate information critically.

### Table 2: Media share networks

| Topics   | $P_I$ | $P_E$ | $P_R$ | $P_M$ |
|----------|-------|-------|-------|-------|
| Landscape | 0.081 | 0.127 | 0.0061 | 0.00771 |
| Battle   | 0.313 | 0.0575 | 0.0278 | 0.0472 |
| People   | 0.33 | 0.0783 | 0.1037 | 0.119 |
| Album    | 0.171 | 0.6319 | 0.6203 | 0.0724 |
| Genre    | 0.136 | 0.1314 | 0.0094 | 0.0369 |

The analysis of Table 2 shows that in networks to share media contents, the probability of latent infection is greater or commensurable with the probability of infection. This means that users more likely browse the content than distribute it.

### Table 3: Feedback and review networks

| Topics   | $P_I$ | $P_E$ | $P_R$ | $P_M$ |
|----------|-------|-------|-------|-------|
| Goods    | 0.1794 | 0.099 | 0.501 | 0.00924 |
| Restaurant | 0.1266 | 0.045 | 0.453 | 0.0087 |
| Tickets  | 0.152 | 0.083 | 0.428 | 0.0081 |
| Place    | 0.19992 | 0.1494 | 0.402 | 0.0076 |
| Low price | 0.1082 | 0.083 | 0.209 | 0.0415 |
Feedback and review networks (Table 3 analysis) have a high, compared to others, probability to be deleted, which may reach 0.5. This means that almost every second user who distributes destructive content will be found out by the site administration. Other transition probabilities are also relatively high in the background of all other types of social networks.

### Table 4: Discussion forums

| Topics         | $P_I$  | $P_E$  | $P_R$  | $P_M$  |
|----------------|--------|--------|--------|--------|
| Stock price    | 0.6798 | 0.0045 | 0.6198 | 0.1226 |
| Sales          | 0.7270 | 0.0081 | 0.6320 | 0.1388 |
| Low price      | 0.7506 | 0.0059 | 0.7262 | 0.1419 |
| Convenience    | 0.7914 | 0.0078 | 0.6433 | 0.1230 |
| Health protection | 0.7677 | 0.0065 | 0.7190 | 0.1361 |
| Labour Code    | 0.7433 | 0.0088 | 0.7510 | 0.1324 |

In networks for collective discussions (analysis of Table 4), the probabilities of infection and deletion are high (more than 0.5-0.6). This is because each user has the right to speak out in a forum or blog and his reasonings will be used in repost, on the upside and the downside. However, users of the networks of collective discussions do not accept obtrusive content, so the probability of deletion is also high.

### Table 5: Social publishing platforms

| Topics         | $P_I$  | $P_E$  | $P_R$  | $P_M$  |
|----------------|--------|--------|--------|--------|
| Nuclear weapons| 0.0062 | 0.9500 | 0.4379 | 0.0034 |
| War in Iraq    | 0.0180 | 0.9115 | 0.4739 | 0.2565 |
| Health protection | 0.0039 | 0.5696 | 0.5761 | 0.2995 |
| Barack Obama   | 0.0034 | 0.2212 | 0.7929 | 0.0937 |
| John McCain    | 0.0076 | 0.8078 | 0.7190 | 0.2232 |

From the analysis of the social publishing platforms (Table 5), you can see that there is a high probability of latent infection. Obviously, this is due to the fact that the user interested in any content after finding himself on the site already has the need to read it. However, if it is unacceptable for him, it will leave the site and may not return (the probability of deletion is high).

### Table 6: Social bookmarks

| Topics         | $P_I$  | $P_E$  | $P_R$  | $P_M$  |
|----------------|--------|--------|--------|--------|
| Development    | 0.267  | 0.082  | 0.055  | 0.102  |
| Open resources | 0.192  | 0.026  | 0.052  | 0.032  |
| Article        | 0.134  | 0.014  | 0.055  | 0.014  |

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The analysis of Tables 6 and 7 leads to the conclusion that social bookmarks networks and networks of interests are likely to be of comparable.

III. Results of the Proposed Methodology Application

The aforesaid micromodel refers to the mono situation in which one content is distributed on the network. However, there is usually a second (even alternative) content which is the norm of network confrontation. Here it is necessary to consider the probability of transitions for different types of content. For example, you can analyze Table 8 for the Facebook network.

Table 8: The probability of transitions for the Facebook network

| Categories | Probabilities $P_i$ |
|------------|---------------------|
| Policy     | $\cong 24\times10^{-3}$ |
| Science    | $\cong 24\times10^{-7}$ |

Table 8 shows that for different topical headings, the probabilities of infection by content is also different, confirming the inevitability of the epidemic processes confrontation. In this regard, the following versions of the epidemic process model can be identified:

1. During the epidemic process, the vertex can accept and distribute only one content, and therefore can be only in one state.
2. In course of epidemic process, a vertex can accept and distribute multiple contents, and therefore be in more than one state.

It should be noted that the time in the models should be discrete, and each discrete should cover the period of the vertex transition from one state to another. This condition allows us to leave out without consideration all the transitional processes and operate them within the specified discrete limits.

We do not consider the case when the considered susceptible vertex has one incidental infected vertex since it is a probabilistic model of the epidemic process for mono-situation discussed above. The confrontation takes place provided that the considered vertex is affected by several vertices emitting different content.
Let's consider the first scenario for confrontation of two types of content. The receptive vertex \( S \) is affected by the adjacent vertices with infections \( I_1 \) and \( I_2 \) (Fig. 2). The actions take place not jointly and independently, so the vertex transits into state \( E_1 \) or \( E_2 \) with probabilities \( P_{E_1} \) or \( P_{E_2} \). The further transition to the immunized state \( AM_1 \) or \( AM_2 \) is out of interest. Let's pay attention on the vertex in the state \( E_1 \). On the one hand, it continues its transition to a state of infection, that is in \( I_1 \), on the other hand, it is still being infected \( I_2 \) and trying to transit into \( E_2 \).

![Fig. 2: Contents confrontation model with the same vertex state](image)

It is appropriate to speak about conditional probability of \( [20] \) \( P(E_1|E_2) \). Since the disjoint dependent events take place, the probability of vertex infection \( I_2 \), provided that it is in latent state after infection \( I_1 \), will be equal to:

\[
P(E_1|E_2) = P(E_2)(1 - P(E_1)),
\]

\[
P(E_2|E_1) = P(E_1)(1 - P(E_2)).
\]

If the vertex being in the state \( E_1 \) transits to state \( E_2 \), the confrontation will continue according to the scenario indicated above. If the vertex being in the state \( E_1 \), transits to state \( I_1 \) then there are again conditional probabilities. The infection \( I_2 \) is still trying to take possession of a vertex to transit it into the state \( E_2 \), provided that it is already infected with infection \( I_1 \):

\[
P(I_1|E_2) = P(E_2)(1 - P(I_1)),
\]

\[
P(I_2|E_1) = P(E_1)(1 - P(I_2)).
\]
Such a confrontation will continue until all the adjacent vertices become infected with the same infection, or the affected vertex becomes immunized or inactive.

Let's consider the second option. In this case, the joint events take place, that is, one vertex can be infected by two infections at the same time (Fig. 3). When two infected vertices with infections $I_1$ and $I_2$ affecting the susceptible vertex in the $S$ state, it can transit into latent states: $E_1$ with probability $P_{E_1}$, $E_2$ with probability $P_{E_2}$, $E_1E_2$ with probability $P_{E_1E_2} = P_{E_1} \cdot P_{E_2}$ according to theorem on the product of probabilities.

Transitions to immunized states and inactive states are not considered. Transitions from states $E_1$ and $E_2$ are possible in the state of their joint latent being in one vertex, or in the state of infection of one vertex and the latent state of another. Then only the joint infection remains.

In this case, it is difficult to talk about confrontation. Here, rather, there is a neutrality. Such a scenario is much easier to consider as a model, but increase in the number of states and transitions complicate the process of modeling.

![Fig. 3: Contents confrontation model with the probability of vertex several states](image)

Network immunization also requires analysis. There are two possible situations: A vertex immunized against one infection, faced with another infection, loses immunity and becomes vulnerable to both infections.
1. A vertex immunized against one infection when faced with another infection remains immuned against the first infection. The second approach once again increases the number of states and transitions.

Let's consider these situations. Let the vertex is immunized against the infection $I_1$ (Fig. 4), then, with the exposure to infection $I_2$, it will lose its immunity and again becomes susceptible to infection $I_1$. This option is only possible if the vertex is in one state. If the vertex that lost immunity $AM_1$ has an adjacent vertex with the infection $I_1$, then the scenario of confrontation presented in Fig. 2 takes place. If we are dealing with a case where immunity is retained (Fig. 5), confrontation should be forgotten. However, a vertex can have immunity against one infection but at the same time to become the source of the other one which is more complicated from the point of view of modeling. In addition, the vertex may not become the source and be immunized against both infections, either become inactive and go to R state.

![Diagram](image)

**Fig. 4:** Model with loss of immunity
IV. Discussion of Results in the Context of Practical Risk-Analysis of Social Networks

Since the negative content is considered, it is logical to take as a risk the normalized value of the summarized specific traffic $\delta$ of the sets $|E|$, $|I|$, $|R|$.

$$\overline{Risk} = \delta(|E|) + \delta(|I|) + \delta(|R|).$$

Accordingly, the chance can be expressed as:

$$\overline{Chance} = 1 - \overline{Risk}.$$

On the other hand, the chance is the sum of specific traffics of susceptible and immunized vertices:

$$\overline{Chance} = \delta(|S|) + \delta(|AM|).$$

Obviously, the above estimates are weighted because they take into account the weights of the network vertices participating in the process. However, it must be kept in mind that these are the expected estimates because they are derived from the possibilities of transit from one state to another. In this case, the chance and risk are calculated at each step of the diffusion predictable process of content.

The above analysis considers the destructive content. Otherwise (when positive content is distributed), the chance and risk will swap.

It is interesting to note that the sum of chances and risks is an invariant specified by the accuracy of representative sample from the network. Thus, in the case where
during sampling 5% loss of traffic is considered acceptable, the above invariant will be 0.95.

When competing content is considered, when assessing the chance and risk, the summation should be performed according to vertices sets, the state of which is defined in relation to the specific content. For example, for two competing content: $K_1$ and $K_2$ can be written:

$$\overline{\text{Chance}}(K_1) = \delta [\overline{E}(K_1)] + \delta [\overline{I}(K_1)]$$

and

$$\overline{\text{Chance}}(K_2) = \delta [\overline{E}(K_2)] + \delta [\overline{I}(K_2)].$$

A prediction of the relative attraction of content in network will be composed of

$$\overline{\text{Chance}}(K_1) - \overline{\text{Chance}}(K_2)$$

at each step of the modeling process.

The last expression describes the dominance of the "adepts" overall weight of one of the content being considered. If only "preachers" of content are of interest in the network, then similar comparative analysis should be carried out using a difference

$$\delta [\overline{I}(K_1)] - \delta [\overline{I}(K_2)],$$

which also characterizes the chances of further spreading the competing contents.

All evaluations considered, indicate the expected share of traffic controlled by the adherents of the traffic being distributed in the analyzed network. Thus, the weighted centre of the vertices (according to specific traffic) proved to be a very universal and productive criterion from the point of view of comparative analysis.

The suggested technique can be used effectively to explore the content diffusion processes in course of networked information confrontation.

Given the software provided, the suggested methodologies can be considered as the developing an approach for evaluation and managing the risk of epidemic processes in social networks.

In this regard, the best practice of in sphere of discrete modeling of information processes will prove to be useful. The matter is that the traditional tools of fill diffusion modeling in network structures, widely used to describe medical and biological epidemics, due to its analogue nature, has almost exhausted its capabilities, leaving many issues. They were particularly evident when modeling epidemic processes of social networks where the discrete nature of user states (infected, latent, immunized, etc.) clearly requires the resolution of the following contradictions between:

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practical necessity of taking into account the frequently used reposting of the destructive content and the impossibility to describe this phenomenon in analog models;

-the pressing need of modeling of network attacks by destructive content distributed both in the network space (multiple sources) and over time (asynchronous injection), and the principled un readiness of traditional tools to analyze the situation;

-the current need to change (manage the protection) the parameters (probability and so on) of the network at a certain modeling step and the inability of analog models to do it;

-the real need to take into account the weights (importance) of users in the epidemic process and the orientation of traditional modeling to un weighted networks;

-the objective need to model the processes of collision with the competing contents in the network vertices corresponding to its users, and the conceptual impossibility of such situation description by means of analog models.

In this regard, the objective is the creation of discrete modeling tools (mathematical and software) of the content distribution processes in heterogeneous information networks, solving the above indicated contradictions in the interests of a more adequate forecasting of these processes development in conditions of the growing network confrontation.

To Achieve this Goal it is Required to Solve the Following Tasks

1. The formation of information support, including topological features (users incidence and the strength of their relationships) of the analyzed network, the value of inter-element traffic, and the users probability to transit from one state to another when exposed on them by the contents of different subject matter.

2. Creation of models and techniques to infect users with content, as well as content diffusion on the network taking into account the heterogeneity of its elements, including during collisions of competing content at the network vertexes.

3. Algorithmic and software implementation of the developed mathematical software on the prospective platforms including the creation of mobile applications oriented on wide audience of virtual space.

At the same time, it must be understood that the estimated tools have a dual purpose, as it will allow not only to predict the popularity (chance) of the distribution of constructive content, but also to assess the danger (risks) of the epidemics of destructive content.

Generally speaking, at the modeling start, the user must initially determine the social network or social networks class that suits his interests. Their classification is known, and the current statistics data on the topology and the "communication strength" in such networks are publicly published. It is this data that provides the basis for building the aforementioned matrices used in discrete models of the content distribution process in networks. The user is also able to determine (for example, by expertise) and preset the probabilistic parameters of the content. Next, based on the
matrix of weighted centrality and on the assumption of its own access capabilities, he must select the network vertices to which the content will be delivered. Using the suggested tools, the user can quickly predict the expected susceptibility of the network to the content distributed by it, which gives hope for the wide popularity of this software complex and its successful commercialization.

Conventionally, this project can be called "calculator for networking success". It focuses on predictive modeling of content distribution in social networks, and a good prognosis is already a half of success. Assessing the chances of the generated content perception by the network structure, the network user measures the capabilities of his smart product. The author's ambitions can be successfully implemented through social network services. However, the cost portion is mostly concentrated in the area of generating quality content, and the main purpose of modern user (in the broad sense) is self-actualization through the conquest of popularity in the network. He is willing to make numerous attempts to achieve this goal and the "calculator for networking success" can be a useful aid in reducing the number of such attempts.

The considered software complex can be used to model the destructive content distribution in the network, that is, the assessment of the network resistance to epidemics in the context of its security. However, it is applicable to both the negative (destructive) content and to the positive content. It depends on the user's intent who generates the content. And the more skillful the product, the more advantage or damage it will bring the networks and its society. Thus, the proposed product has a strong pronounced dual purpose: analysis of the distribution processes of malicious content in the network (probabilistic risk assessment); modeling of network perception of positive content (probabilistic chance assessment).

The most Widespread use of the Proposed Product is Seen in Solving the Second Task, Namely in the Social Networks where

- there is a huge number (millions and billions) of potential product consumers in the person of social networks users;
- the sustained motivation of these users to gain network success as a result of the widespread and effective perception of the independently generated (authoring) content distributed in the network of interest.

Alas, the space of social networks has become the scene of a fierce struggle for the right to govern mass consciousness, and this stress once again the relevance, scientific and practical significance of the expected results in assessing the risks and chances that arise in this case, and informational management of them in the interests of sustainable development of the mankind.

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