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Improving the Quality of a Viral Video Marketing Campaign with a Predictive Model

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Abstract

Objectives: The article deals with one of the modern methods of marketing communication that is viral marketing. Users of social networks act both as target audience and distributors (recipients) of viral videos. **Methods:** The synergetic approach should be applied in the research, which makes determination and clear formalization of a viral video campaign almost impossible. The author's propose to classify the users into three basic groups: active, interested and passive. The proportion of these types of recipients in the network determines the efficiency and quality of the viral video campaign. The iteration method should be used to establish ranges of the acceptable values. **Findings:** The article presents a formalized model of a social network consumer that takes into account the non-linear nature of the virus development. The authors define the ranges for the parameters of the proposed activity (watching videos, sending videos, comments, likes, deletion). The article proposes ways to evaluate communication media activity, the latter represented by social networks. The classification of social networks operating in the Runet was conducted after the criteria of thematic content and popularity according to search queries. The authors considered the most popular networks and estimated their communication activities according to the concentration of various types of network users. The experimental part of the article identifies the target group and the efficiency of a predictive model of the viral video campaign. **Improvements/Novelty:** It is planned to create the predictive model of the viral video life cycle with focus on days where the activity occurred in the communication medium and the range of the criteria for each group of users.

Keywords: Improving the Viral Campaign Management, Internet Marketing, Marketing, Predictive Model, Social Networks, Viral Marketing

1. Introduction:

Modern reality is increasingly making a person to use the Internet more actively in all areas of life. By present moment more than 60% of Russia's population is Internet users. In addition to that, one can witness a growing popularity of mobile Internet, social networking sites and various applications. All the above, in general, makes life easier for people, increases its speed, saves time and gives us the information we need quickly. However, it also reduces people's ability to cope with stress.

That is why finding efficient communication Internet marketing tools that can attract consumers and promote products and services becomes such an urgent task. Employers are actively looking for the spots their audience frequent, and that is online.

Thus, to solve the above problem, first, it is necessary to develop a predictive model that could improve the quality of a viral video marketing campaign. This will allow businesses that use viral marketing to predict its development and the impact on the consumer. The value of this model mainly stems from the fact that it enables a better visualization of possible management response to the virus, allowing further prediction of goods promotion, indicating the potential the virus has for marketing and brand image.

However, despite the growing popularity of viral videos in recent years, there has been practically no evidence-based study on the opportunities of their application that would consider this phenomenon both from theoretical and practical points of view. In addition, the absence of viral content management tools leads to a

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reduction in the quality of marketing communications in the Internet and undermines the potential of their long-term use.

The hypothesis of the study implies determination of the specific features of the viral marketing application compared to other marketing tools of online communications and the development of a method to build a predictive model of a viral video marketing campaign that would boost the quality and positive impact on the brand image. This approach involves the study of the virus in the context of a synergistic approach as a self-organizing system in the conditions of uncertainty.

To assess the current state of the viral campaign we proposed classifying the consumers and identifying the basis of social networking. The findings lay foundations for the development of strategic and tactical management decisions for the development of a viral video campaign by means of mathematical modeling techniques used to construct a predictive model of viral videos development. The following model is to become the basis for management decisions.

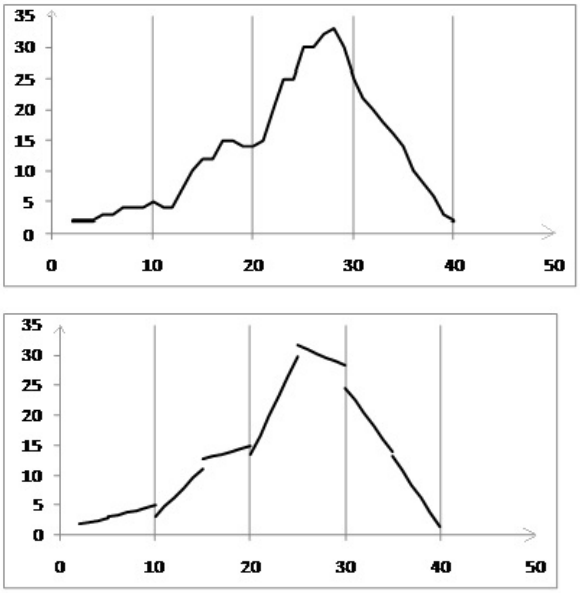


Figure 1. The Piecewise Linear Function of Vtime (Days) based on Linear Regression.

The effectiveness of marketing communications is considered in[1-4]. Russian researchers[5-9] paid more attention to practical aspects of the Internet use for the development of marketing. Theories of Internet marketing planning can be found in the works by some international researchers[10-12]. Viral marketing was studied in [3,13-15]. The synergetic approach to the organization of economic systems is considered by [16-17]. Synergetic concepts of systems and structures acting as the multi-level basis for self-organization mechanisms can be found in[18-22].

Despite the detailed study of the issues related to Internet marketing and the organization of effective online marketing communication, some theoretical and practical aspects of viral video campaign marketing have not been studied properly; these include specific features of management and prediction.

In addition to that, there is a need for systematization of a wide range of scientific and practical views on the applications of a synergistic approach to the development of marketing in the Internet.

Both incompleteness of theoretical research and the practical need for additional studies justify the choice of the purpose and objectives of this study.

2. Methodology:

The development and implementation of a marketing viral campaign depends on many factors. Since a viral video as a controlled object should be considered as a self-developing system operating in the unstable environment, it seems viable to apply the synergetic approach to its study, which makes determination and clear formalization of a viral video campaign almost impossible.

This fact is used as an argument when researchers state that it is impossible to assess the effectiveness of viral videos on the stage of development, and even during the implementation stage. Indeed, if we draw on such statistical characteristics of videos as the number of views and unique users, the only controlled variable would be the users, and that is only at the stage of video seeding during the initial mailing of links to users. There is a popular assumption that here one deals with the principle of the sales funnel, and to make the viral campaign most efficient one needs the highest possible seeding.

We believe that this is not so, and the effectiveness of viral content can be predicted at stage following the seeding. In this case, the assessment of both the current state of the virus and the future prediction must be based on previous statistics, which is accumulated in a special V (views) data array from the first days of the "life" of the virus.

However, one cannot simply draw trend lines according to mathematical extrapolation models based on the statistics for the previous period as in its life cycle the

virus passes many bifurcation points, which dramatically changes the vector of its development from growth to extinction, and vice versa. In this regard, one can draw trend lines based on a linear filtering, when the development of the virus can be divided into sections in which the virus developed evenly. A linear dependence V on time is estimated for the latest reporting period, which interpolates the raw data, while the inclination of this line demonstrates the growth, decline or stability of views during this time interval. According to the dependence $y = kx + b$, where the dependent variable is represented by the views V, and the independent – by the days, the continuous function given in the V tabular array is divided into a piece wise linear function (Figure 1).

The inclination of the line is determined by k coefficient of the equation $y = kx + b$. It is k coefficient that indicates the current status of the virus. For a more detailed description of this approach, see article[23].

When testing this method, we registered similar trends in the viral video campaigns development in the same social networks acting as communication medium of the virus, regardless of the video content. This led us to the conclusion that a predictive model of the viral life cycle can be built prior to its launch in the network, as long as it is based on the parameters of the user social network.

Schematically, all users can be divided into three categories: active, passive and interested.

- An active user is characterized by such actions as opening the link received, reviewing of a video, writing comments, and further sharing the video.
- An interested user just opens the link to view the video, watches it and deletes it after that.
- A passive user, at best, would open a link, without watching the video, or most often will simply mark the letter as spam without reading it.

The proportion of various types and primarily the number of active users at the initial stage of the life cycle defines the communication medium of the social network, and that is the reason why a virus develops in some social networks and dies in others.

- Therefore to build a predictive model for assessing a viral video campaign, one should:
- Classify the user by identifying the parameters of his activity according to the videos viewed online;
- Detail the classification of users by setting a range of parameter values of the activity;
- Form the basis of social networks according to thematic criteria and popularity;
- Select approaches for the social network formalization;
- Develop a prediction method based on the location (a specific social network) and the number (source link) of the seeding.

Due to the fact that the main way of spreading viral videos is forwarding them from one user to another in personal messages, we need to determine what the individual is likely to do upon obtaining a link to the video. A set of these actions will be the parameters of the user's activity.

The object "user" can be characterized by the following parameters:

1. Opening the link, that is clicking through from the link received to the video hosting, whereas opening a link does not mean that it will be viewed, because when a user sees what kind of information it is, he may simply leave, even without starting to watch it. We will index this parameter as X_1, which can take the values 0 or 1, corresponding to "the video opened" or "the video not opened". If $X_1 = 0$, we can firmly define the user as a passive one, who does not take part in the propagation of the virus.
2. Viewing the video; this parameter relates to the overall time, because the user can return to the link and see it several times, which will prove that he is active or interested. The parameter is indexed as X_2, taking values from a_2 to b_2 within Y_2 days.
3. Sharing the video is the main parameter in terms of the virus propagation, since only this will allow attracting new users and starting an avalanche viral campaign if the concentration of active users is high. Like parameter X_2, parameter X_3 has a range of changes from a_3 to b_3 which shows how many people the user will forward a link within Y_3 days.
4. Writing a comment – a dummy variable indicating whether the user has commended or not. In this case, we ignore the possible "messaging" under the video and define this parameter as the occurrence of even a single comment X_4, which takes values from 0 to 1.
5. Giving Likes – a parameter similar to the previous one, but dealing with likes and not comments.

6. Deleting a link, which denotes the user firmly disliked the video, this may also involve deleting links after watching the video (X_6=0; X_2=1) and deleting a link without opening (X_6=0; X_1=0).

Thus, in general terms the user is formalized as the set of variables X_i that take value in the specified range $[a_i, b_i]$. The proposed model has 8 variables (Table 1). The model is universal and can be expanded with other parameters.

Table 1. The Formalized Model of a Social Network User

Parameter	Variable	Lowest Value	Highest Value
Opening the link	X_1	0	1
Viewing the video	X_2	a_2	b_2
Days of viewing	Y_2	Ya_2	Yb_2
Share the video	X_3	a_3	b_3
Days of sharing	Y_3	Ya_3	Yb_3
A comment	X_4	0	1
Giving Likes	X_5	0	1
Deleting links	X_6	0	1

A detailed user classification will include 7 types:

1. Super Active.
2. Active, type 1.
3. Active, type 2.
4. Interested, type 1.
5. Interested, type 2.
6. Passive.
7. Super passive.

The formalization of differences in their response to the video link is presented in Table 2. Limit values of variables X_1 and X_2represent the hypothesis of this study that stems from the expert assessment of the authors and experts from advertising and market research agencies. In the future, the values presented will be tested and will require multi-iterative adjustments based on the comparison of results obtained after building a predictive model and receiving the experimental results.

ParametervaluesY_2andY_3 areestimatedas5 days (Ya_2=Yb_2=5; Ya_3=Yb_3=5), as the research conducted by the authors shows that for users of social networks such as Instagram, VKontakte , Odnoklassniki, Facebook the average time during which people review a video and share it is 5 days. Besides, according to this study, users write comments and give likes to the video when viewing it for the first time, thus it does not seem really viable to extend these parameters.

Table 2. Classification of Social Networks Users after Formalized Parameters of Response to a Link to the Video Content

User type	Actions
Super Active	Opens a link, watches, shares and reviews the video, gives a like, and writes a comment.
Active, type 1	Opens a link, watches, shares and reviews the video, gives a like.
Active, type 2	Opens a link, watches the video, and gives a like.
Interested, type 1	Opens a link, watches a video.
Interested, type 2	Opens a link, watches a video, and deletes the link after watching.
Passive	Opens a link
Super passive	Deletes a link without opening it.

User type	X_1	X_2		Y_2	X_3		Y_3	X_4	X_5	X_6
		a_2	b_2		a_3	b_3				
Super Active	1	3	5	5	2	4	5	1	1	0
Active, type 1	1	1	3	5	1	2	5	0	1	0
Active, type 2	1	1	2	5	0	0	5	0	1	0
Interested, type 1	1	1	1	5	0	0	5	0	0	0
Interested, type 2	1	1	1	5	0	0	5	0	0	1
Passive	1	1	1	5	0	0	5	0	0	1
Super passive	0	0	0	5	0	0	5	0	0	1

How then the seven types of users considered above will be able to identify the communication medium of the spreading virus?

Firstly, it is proposed to select the communication medium of seeding according to the maximum concentration of the target audience. In this case, social networks are the most suitable option, since it is where the users can group themselves according to their interests and the level of requirements and, as a consequence, they are a set of non-passive consumers.

It is proposed to classify social networks according to the proportion of the considered seven types of users (Table 3), while estimation of the share of each type of users may be performed by polling the audience in each social network.

Table 3. The Formalization of Social Networks According to the Proportion of the Users Types

User type	Social networkA	Social networkB	Social network C
Super Active	5%	3%	2%
Active, type 1	7%	4%	5%
Active, type 2	8%	9%	10%
Interested, type 1	15%	12%	12%
Interested, type 2	10%	20%	16%
Passive	20%	25%	25%
Super passive	35%	27%	30%
TOTAL:	100%	100%	100%

It is also proposed to conduct the polling as on-line survey, and the user should be invited to join the survey via a private message. The number of unanswered messages provides information on passive and super passive users in this network. The questionnaire should consist of 4 sets of questions:

1. The first part allows determining overall user activity on the Internet, his preferences and social networks used.

2. The second part provides information on the action the user takes after receiving a link from a contact the user knows in person.

3. The third part describes the reaction of the user to the links received from somebody the user has met only online.

4. The fourth part determines the user's action to a link received from a stranger.

The last three parts of the questionnaire should support or refute the hypothesis of a different reaction to the video from both known and unknown users.

Describing the types of users, their specific parameters and approaches to initialization of the communication medium of the virus, one should consider the algorithm and the example of the predictive model of the viral life cycle. To illustrate an example, let us consider a situation when the social network is composed of 10% super active users, 30% of interested, type 1, and 60% of passive users. The seeding is 10 links (N).

Step 1. Estimating the number of users of each type.

N x10% - 1 super active user;

N x30% - 3 interested users;

Nx60% - 6 passive users.

Step 2. Evaluate each user according to the given parameter ranges. Initiation of parameters X_2 and X_3 is carried out with random numbers ranging from $a_2$tob$_2$for X_2 and from$a_3$tob$_3$ for X_3. At the same time we complete the matrix of users' actions according to days, where columns from 1 to 5 represent days (since we stated the variables Y_2 andY_3equal 5). Examples of the distribution of random views and video sharing are presented in Tables 4, 5.

Table 4. Matrix of Views (Distribution X2)

Type	X_2	Day 1	Day 2	Day 3	Day 4	Day 5
Active	4	1		1	1	1
Interested	1		1			
Interested	1			1		
Interested	1	1				
Passive	1			1		
Passive	1		1			
Passive	1					1
Passive	1				1	
Passive	1			1		
Passive	1	1				
Total:		3	-	-	-	-

Table 5. Matrix of Video Sharing (Distribution X3)

Type	X_3	Day 1	Day 2	Day 3	Day 4	Day 5
Active	3		1	1	1	

Interested	2	1				1
Interested	1			1		
Interested	2		1		1	
Passive	0					
Passive	0					
Passive	0					
Passive	0					
Passive	0					
Passive	0					
TOTAL:		**1**	-	-	-	-

Step 3. Let us estimate the number of new users after the sum of cells of the first column; this is number N_1 where index 1 shows the day of generation.

The matrix of video sharing is the main generating tool, as it allows us to determine how many new people are infected with a virus. In the example it is $N_1 = 1$.

Step 4. Repeating the algorithm from step 1, where $N = N_1$.

This 1 new user randomly refers to one of the types of users described in the communication medium. In this example, with a probability of 10% this will be a super active user; 20% – an interested one, and 60% – a passive user, then the already existing matrix increases to the number of new users, and the cells that are responsible for videos views and sharing are filled. Next, the sum of the second column is calculated, and new values are obtained (views, sharing, likes, comments, etc.), after which the body of the loop repeats itself. In the present case the virus finally "dies" on day 15 (Figure 2).

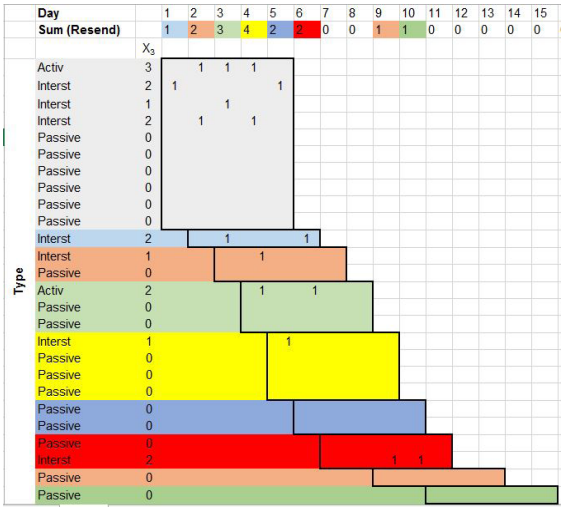


Figure 2. An Example of a Predictive Model Whenseeding10 Links in the Passive Communications Medium.

The top two rows represent the number of newly initiated users in time. The lower matrices provide details on how, according to the procedure, new users are estimated, how many of them belong to active, interested and passive types. Data calculation according to X_3 is the crucial one as it identifies new users, which later provides the relevant information for the matrices dealing with the views, comments, likes, and deleting links.

The proposed method can form the basis for an information system where the operator will choose a social network according to the target audience and introduce the initial seeding value, receive the predicted statistics of views, unique users and assess the effectiveness of the viral video at each stage. Naturally, one first needs to collect the data on each social network, determine the proportion of each user group. The iteration method should be used to establish ranges of acceptable values for the parameters of each user type and to verify the resulting model.

3. Results and Discussion

The practical implementation of the proposed method requires analyzing social networks for further classification by subject matter and popularity among users. These two criteria are chosen as the key ones when selecting the communication medium of seeding.

Having conducted the content analysis in the Runet, we identified 176 social networks of various levels (Table 7). Definitely, the most popular and "multifarious" arethe popular sites such as VKontakte , Odnoklassniki, Facebook and Instagram (Table 6).

These four social networks, being the most popular sites, were selected for study aimed at determining the proportion of various types of users and adaptation of the proposed methodology.

The study was conducted from April to May 2016, with 200 respondents participating in it. The survey results were processed using SPSS statistical package. The main data of the general sample are presented in the diagrams (Figures 3, 4, 5).

Here we should note another important feature – the amount of time the Internet users spend online: a little more than 50% of respondents said they spend more than 5 hours. About 30% said it was 3.5 hours and less than 20% spend online less than 3 hours.

Since the main way of viral video spreading is one user sharing it with another one through personal messages, it is necessary to determine how the users react when they

Table 6. The Most Popular Social Networks According to the Search Statistics Analysis

Name	Site	Yandexsearch statistics (thousand)	Googlesearch statistics (thousand)	Average (thousand)
VKontakte	https://vk.com	5 500	37 200	21 350
Facebook	https://www.facebook.com	2 500	3 760 000	1 881 250
Odnoklassniki	http://odnoklassniki.ru	92 000	101 000	96 500
Instagram	https://www.instagram.com	660	68 000	34 330

Table 7. Classification of Social Networks According To the Thematic Areas and Search Statistics

Social network type	Total	Name	Site	Yandex search statistics	Google search statistics	Average
Cars	5	Drom	www.drom.ru	800 000	823 000	811 500
		Drive2	www.drive2.ru	260 000	301 000	280 500
		Bike Post	http://bikepost.ru	1 700	1 000	1 350
Activists	1	Remember About	http://pomnipro.ru	7 000	90	3 545
Anonymous	3	Nekto	http://nekto.me	7 500	9 900	8 700
		Cheloveche	http://cheloveche.ru	3 000	390	1 695
		Unface	http://unface.me	100	320	210
Charity	2	Planeta	https://planeta.ru	43 000	165 000	104 000
		myYearbook	http://myyearbook.ru	30	405	218
Blogs	5	LiveJournal	http://www.livejournal.com	260 000	165 000	212 500
		QIP	http://qip.ru	114 000	74 000	188 000
		Blogger	http://www.blogger.com	21 000	4 090	12 545
Most popular	3	VKontakte	https://vk.com	5 500 000	37 200 000	21 350 000
		Facebook	https://www.facebook.com	2 500 000	3 760 000 000	1 881 250 000
		Google+	https://plus.google.com	18 000	2 240 000	1 129 000
Wiki	1	Cyclopedia	http://cyclowiki.org	1 300	720	1 010
Women	13	Babyblog	https://www.babyblog.ru	135 000	201 000	168 000
		A Cook	http://www.povarenok.ru	88 000	27 100	57 550
		Mothers' Country	http://www.stranamam.ru	86 000	74 000	80 000
Restricted	5	E-xecutive	http://www.e-xecutive.ru	600	590	595
		GosBuk	http://www.gosbook.ru	200	140	170
		Parlamentary Portal	http://portal.parlament.gov.ru	96	0	48
Education	10	Grade book	https://dnevnik.ru	6 100 000	1 500 000	3 800 000
		Nsportal	http://nsportal.ru	33 500	18 100	25 800
		Busuu	https://www.busuu.com/ru/	5 000	165 000	85 000
Games	8	Gamer	http://gamer.ru	4 300	368 000	186 150
		GameXP	http://www.gamexp.ru	3 700	4 400	4 050
		Tagged	http://tagged.com	10 000	4 900	7 450

Hobbies	1	On the Alert	http://nacheku.ru	2 800	0	1 400
Art	6	Revision	http://revision.ru	12 000	110 000	61 000
		Unknown Master	http://neizvestniy-geniy.ru	8 000	5 400	6 700
		Gallerix	http://gallerix.ru	3 000	22 200	12 600
IT	3	Habrahabr	https://habrahabr.ru	10 000	33 100	21 550
		My Live Page	http://mylivepage.ru	2 000	10	1 005
		MatroNet	http://mylivepage.ru	30	90	60
Book lovers	8	Poetry	http://www.stihi.ru	150 000	110 000	130 000
		Beezona	http://beesona.ru	75 600	170	37 885
		Reading room	http://chitalnya.ru	17 000	1 300	9 150
Metallurgists	2	Precious Metals	http://drugmetal.ru	150 000	1 600	75 800
		i-Think	http://drugmetal.ru	400	33 100	16 750
Microblogs	2	Twitter	https://twitter.com	300 000	83 100 000	41 700 000
		Tumblr	https://www.tumblr.com	150 000	166 000	158 000
Mobile	3	Spaces	http://spaces.spaces.ru	192 000	224 000	208 000
		Foursquare	https://ru.foursquare.com	5 500	550 000	277 750
		Galaxy	http://javagala.ru	2 300	1 830	2 065
Music	4	Last.fm	http://last.fm	13 500	246 000	129 750
		Ikra	http://ikra.tv	320	12 100	6 210
		Myband	http://myband.ru	50	1 300	675
News	6	New Russia	http://newrussia.org	320 000	590	160 295
		Russia.ru	http://russia.ru	45 000	1 900	23 450
		Newsland	http://newsland.com	15 000	18 100	16 550
Learning	3	Ask me!	http://sprashivai.ru	1 300 000	246 000	773 000
		Ask.fm	https://ask.fm	73 800	6 120 000	3 096 900
		Educators	http://metodisty.ru	1 400	590	995
Communication	26	Small World	http://mirtesen.ru	52 000	60 500	56 250
		Flirchi	https://flirchi.ru	51 000	74 000	62 500
		Among Friends	http://vkrugudruzei.ru	26 000	14 800	20 400
Teenagers	4	Girlfriends	http://podruzhki.ru	706	3 600	2 153
		Stardoll	http://www.stardoll.com/ru	500	748	624
		ClassNet	http://www.classnet.ru	40	3 600	1 840
Professional	11	LinkedIn	https://ru.linkedin.com	64 000	30 400	47 200
		Business World	http://delovoymir.biz	12 000	880	6 440
		Law	http://zakon.ru	11 000	33 100	22 050
Travel	6	eNeighbors	http://www.esosedi.ru	670	320	495
		GEOID	http://geoid.ru	350	9 900	5 125
		I'm a Piligrim	http://yapiligrim.ru	81	140	111
Regional	8	Classmates	http://odnoklassniki.ru	92 000 000	101 000 000	96 500
		E1	http://e1.ru	150 000	301 000	225 500
		My World	http://my.mail.ru	50 000	1 830 000	940 000

Religion	2	Resurrection	http://www.vosocial.com	230	22 200	11 215
		Cross.tv	http://cross.tv	135	1 300	718
Family	4	MyHeritage	https://www.myheritage.com	4 700	90 500	47 600
		Sosedi.ru	http://sosedi.ru	3 200	14 800	9 000
		Geni	https://www.geni.com	2 000	90 500	46 250
Fishing	3	Fion	http://fion.ru	4 300	14 800	47 400
		Fish-hook	http://www.fish-hook.ru	100	12 100	6 100
		F. Guide	http://www.fgids.com	11	0	6
Sport	4	RusBody	http://rusbody.com	320	480	400
		Rusfan.ru	http://rusfan.ru	30	10	20
		DISSP	http://dissp.com	17	90	54
Students	1	StudiVZ	http://www.studivz.net	100	60 500	30 300
Finance	1	Financial Social Network	http://webtransfer-finance.com	206	20	113
Photo	8	Photocountry	https://fotostrana.ru	1 400 000	2 740 000	2 070 000
		Instagram	https://www.instagram.com	660 000	68 000 000	364 000
		Fotki	http://www.fotki.com/Russia/ru	15 000	22 200	18 600
Shopping	4	Reviewer	http://otzovik.com	130 000	49 500	35 900
		Flamp	http://flamp.ru	3 100	12 100	7 600
		Potrebiteli.ru	http://potrebiteli.ru	440	20	230

receive links from personal acquaintances, people they know only online or strangers.

The research proved that almost all users will open a link received from personal acquaintances, a smaller share of them will watch a video. Unfortunately, only a small part of those who opened and viewed the video will share it. However, even few forwarded links will allow spreading information.

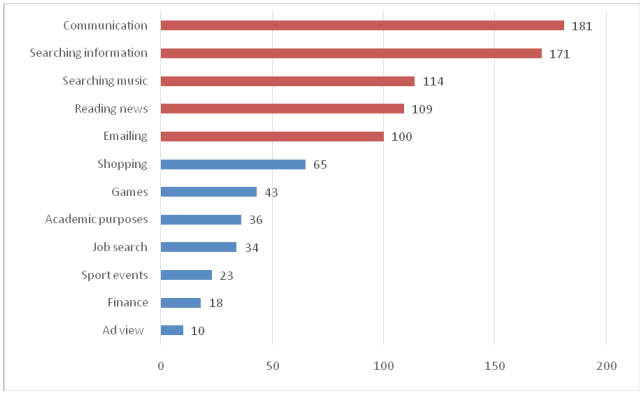


Figure 3. What do you use the Internet for?

When analyzing the users' response to the video links received from friends they know only online, the proportion of those opening the link and viewing the video was almost the same, however, the number of those who deleted a link without opening it was higher. This is a big drawback of viral videos "seeding", since it not only impossible to spread the information; moreover, it is not accessed where it was "seeded". In other words, the video will neither be shared nor viewed. The number of those forwarding the video will be much smaller than in the previous case, but even in this situation the viral video will continue to spread, quite slowly though.

Definitely, the answers to the questionnaire submitted mostly came from active and interested users. To estimate the number of passive users, we calculated the number of blank questionnaires (unanswered ones); in this case there were 158 of them.

These figures could be distributed among the social networks according to the proportion of registered users in the poll:

- Facebook – 195 people;
- Odnoklassniki – 99 people;
- Facebook –77 people;
- Instagram – 130 people.

Hence, the percentage of social networks was:

- VKontakte – 195/200 = 99.5%;
- Odnoklassniki– 99/200 = 49.5%;
- Facebook –77/200 = 38.5%;
- Instagram– 130/200 = 65%.

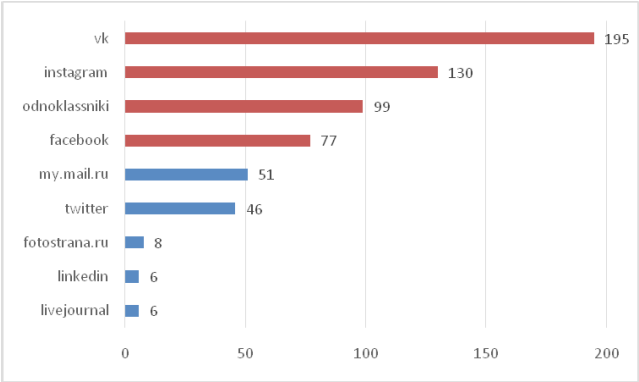


Figure 4. What social networks do you use?

Therefore, the absolute (estimated number) of passive and super passive users for each network will amount to:

- VKontakte - 99.5% * 158 ≈ 157 people;
- Odnoklassniki - 49.5% * 158 ≈ 78 people;
- Facebook - 38.5% * 158 = ≈ 61 people;
- Instagram - 65% * 158 ≈ 103 people.

To determine other types of users we used the SPSS mathematic and statistical tool; absolute figures reflecting the numbers of users classified into different categories are shown in Tables 8–11.

Table 8. Communication Activity of VKontakte Social Network

User type	From a personal acquaintance		From an online acquaintance		From a stranger	
Super Active	0	0%	0	0%	0	0%
Active, type 1	7	2%	1	0%	0	0%
Active, type 2	16	5%	14	4%	5	2%
Interested, type 1	100	32%	89	29%	50	16%
Interested, type 2	5	2%	4	1%	3	1%
Passive	27	9%	26	8%	18	6%
Super passive	157	50%	178	57%	236	76%

Table 9. Communication Activity of Odnoklassniki Social Network

User type	From a personal acquaintance		From an online acquaintance		From a stranger	
Super Active	0	0%	0	0%	0	0%
Active, type 1	6	4%	1	1%	0	0%
Active, type 2	9	6%	13	8%	5	3%
Interested, type 1	50	32%	41	26%	28	18%
Interested, type 2	0	0%	0	0%	0	0%
Passive	13	8%	13	8%	0	0%
Super passive	78	50%	88	56%	123	79%

Table 10. Communication Activity of Facebook Social Network

User type	From a personal acquaintance		From an online acquaintance		From a stranger	
Super Active	0	0%	0	0%	0	0%
Active, type 1	4	3%	0	0%	0	0%
Active, type 2	6	5%	8	7%	4	3%
Interested, type 1	37	31%	34	29%	20	17%
Interested, type 2	0	0%	0	0%	0	0%
Passive	10	8%	8	7%	9	8%
Super passive	61	52%	68	58%	85	72%

Table 11. Communication Activity of Instagram Social Network

User type	From a personal acquaintance		From an online acquaintance		From a stranger	
Super Active	0	0%	0	0%	0	0%
Active, type 1	6	3%	1	0%	0	0%
Active, type 2	12	6%	8	4%	3	1%

Interested, type 1	64	31%	60	29%	31	15%
Interested, type 2	0	0%	0	0%	0	0%
Passive	20	10%	17	8%	12	6%
Super passive	103	50%	119	58%	159	78%

We can see that after receiving a link from different contacts, the proportion of users types in the network can vary considerably. In this case, we can consider the communication activity for each type of links separately, for example, to improve the quality of seeding; one can e-mail it, firstly contacting the future recipients of the virus personally, thereby greatly enhancing the efficiency of its distribution. Or to share it between personal friends, which will enable to maximize the viral processes.

To find the common features for all networks, one can calculate the integral indicators after the proportion of the different types of users by introducing the correction factors of 0.2 for links from personal acquaintances, 0.3 for links from their online friends, and 0.5 for links from strangers. Having applied this approach, we obtained the following results (Table 12).

Table 12. Formalization of social networks according to the proportion of users types

	Instagram	Facebook	Ok	Vk
Super Active	0.0%	0.0%	0.0%	0%
Active, type 1	0.6%	0.6%	1.1%	0%
Active, type 2	2.9%	4.6%	5.1%	3%
Interested, type 1	22.4%	23.4%	23.2%	23%
Interested, type 2	0.0%	0.0%	0.0%	1%
Passive	7.4%	7.7%	4.0%	7%
Super passive	66.4%	63.8%	66.3%	65%

To test the predictive method, as part of the experiment we launched a series of viral video on the subject of the historical quest, by viewing which users could participate in the real treasure hunt with a prize hidden in a particular area. To do this, one had to solve a series of tasks described in the videos. As of October 25, 2016 four clips were launched and we collected statistics from two social networking sites VKontakte and Odnoklassniki, as well as the statistics from youtube video hosting.

It should be said that the statistics on the video views for each site is calculated independently and does not repeat the YouTube analytics:

Videos are available at the following links:

YouTube.com:

- Promo https://youtu.be/BWDsMOOK734
- Vikhlyaika https://youtu.be/sC1KDwWYrOQ
- Sampur https://youtu.be/I_2cE2JUpBs
- Kipets https://youtu.be/tlZpd3L-cF8

Odnoklassniki:

- Promo https://ok.ru/video/10432483614
- Vikhlyaika https://ok.ru/video/29189083571
- Sampur https://ok.ru/video/31401120179
- Kipets https://ok.ru/video/34414203315

VKontakte :

- Promo https://vk.com/video21562551_456239024Vikhlyaika
- https://vk.com/video-23707587_456239017Sampur
- https://vk.com/video21562551_456239031Kipets
- https://vk.com/video21562551_456239037

Statistics for each video including the total time in the network, views, likes is presented in Table 13.

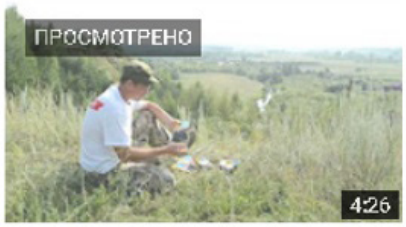
4. Conclusions:

The experiment clearly shows the highest activity in Odnoklassniki network, which slightly correlates with the data in Table 12 where the integral values of the proportion of active and interested users were higher than in VKontakte network.

The first conclusion one can jump at is that the proposed method is inappropriate and that the research on the communication medium was not conducted in the right manner, or that the impact of the video content in its life cycle is different. However, it is not so!

In this case we deal with a very important fact, fully confirming the initial hypothesis that it is the proportion of active users on the network that determines the quality of the viral video campaign.

Table 13

		OK	VK	YouTube	Total:
Promo 	days	42	73	74	
	views	305	84	281	**670**
	likes	6	4	6	**16**
Vikhlyaika 	days	51	52	67	
	views	266	73	197	**536**
	likes	14	9	4	**27**
Sampur 	days	42	47	48	
	views	320	70	241	**631**
	likes	18	4	7	**29**
Kipets 	days	29	22	29	
	views	1048	37	160	**1245**
	likes	72	3	3	78

The videos uploaded in VKontakte network and on YouTube were part of the project that also included creation of special groups "Life Quest of Tambov State Technical University" at vk.com/questtstu and "Tourism Quest" at youtube.com/UCA9OynTfJ1HRKc3qaxvjS9Q. At the same time, there was no seeding of the virus itself, since virtually all views came from users who just dropped there by accident (Table 12). In Odnoklassnikithe video was posted on his page by a person with many friends and an active user of the social network,and all reposts were made by personal acquaintances (Table 9, Column 1).

Table 14. Comparison of Experimental Communication Platforms

User type	**OK** *Among personal acquaintances*	**VK** *Integral calculation*
Super Active	0%	0%
Active, type 1	4%	0%
Active, type 2	6%	3%
Interested, type 1	32%	23%
Interested, type 2	0%	1%

Passive	8%	7%
Super passive	50%	65%

In fact, VKontakte and Odnoklassniki networks should be compared according to the following parameters (Table 14) that would explain the results.

The experiment allowed us to verify the coefficients of the activity of each user group. For that purpose in the future we are planning to create the predictive model of the viral video life cycle with focus on days where the activity occurred in the communication medium and the range of the criteria for each group of users. The results are compared with experimental data obtained when launching a viral video in the same medium with the same seeding.

Coefficients are adjusted; while the use of the regression model in a few iterations enables to compare the predictive model and the experimental results. At this stage, using the experimental data, one can carry out multi-iterative verification.

The proposed predictive model allows planning a viral campaign at the development stage and to determine the volume of the initial seeding and a set of social networks, where the seeding should be carried out. The target group for the model is mainly small and medium-sized businesses.

Each target group can have the following areas where the findings can be applied.

Small and medium-sized businesses, operating in the field of B2C: analysis of the current marketing campaign, independent development of the viral video campaign and prediction of its efficiency at the initial stage will allow reducing marketing costs and, as a result, reallocating the resources and improving the quality of the communication policy.

Advertising agencies and agencies dealing with promotion of goods and services: explaining the customers the costs of viral video campaigns development, assessment of the effectiveness of this work, the ability to offer customers a variety of options for promotion and to demonstrate the resulting effects on the project approval stage.

Marketing directors of retail networks: development of viral marketing programs for segmented groups of goods with pre-determined efficiency.

Students of economics at the second and third tiers of higher education: obtaining theoretical and practical skills in the development and planning of modern forms of marketing on-line communications, design of predictive multi-criteria tasks of unstable self-developing systems which include viral videos.

The teachers of various economics courses: methodological tools for teaching such subjects as marketing, marketing communications, marketing information systems, etc.

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