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Human behavior in online social systems

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Abstract. We present and study data concerning human behavior in four online social systems: (i) an Internet community of friends of over 10^7 people, (ii) a music community website with over 10^6 users, (iii) a gamers' community server with over 5×10^6 users and (iv) a booklovers' website with over 2.5×10^5 users. The purpose of those systems is different; however, their properties are very similar. We have found that the distribution of human activity (e.g., the sum of books read or songs played) has the form of a power law. Moreover, the relationship between human activity and time has a power-law form, too. We present a simple interest-driven model of the evolution of such systems which explains the emergence of two scaling regimes.

PACS. 89.75.Fb Structures and organization in complex systems – 89.65.Ef Social organizations; anthropology – 89.75.Da Systems obeying scaling laws

1 Introduction

In recent years investigations of complex systems have attracted the physics community's great interest, e.g., it has been discovered that the structure of various biological, technical, economical and social systems has the form of complex networks with common properties [1]. The advent of modern database technology has greatly advanced the statistical study of social systems. The vastness of the available data sets makes this field suitable for the techniques of statistical physics [2,3]. Progress in information technology makes it possible to investigate the structure of social networks of interpersonal interactions maintained over the Internet. E-mail networks [4], blog networks [5] and web-based social networks of artificial communities [6] are examples of such networks. All users of such systems can add, by mutual consent, other people to their databases of friends. However, their activity is not restricted to maintaining social contacts. They can, depending on the system, write blog posts, play games, listen to songs, etc.

The aim of this work is to present a data set describing human behavior in four different social systems and to introduce a simple model of the evolution of such systems. The first one is a large social network of an Internet community (Skyrock), which consists of 10^7 individuals. The Skyrock project started in 2002 at `www.skyrock.com`. Since then, it has grown into a social phenomenon well-known mainly among French-speaking Internet users. Each user of Skyrock can write a blog with an unlimited number of posts, which others can comment on.

The second system under investigation is LastFM – a music community server or, to be more precise, its part known as the Audioscrobbler project which was launched in 2002. Like in the other systems discussed here, there is one server connected to the Internet, on which user accounts are registered. There are about 1×10^6 users of this system. Its special plug-in, an important part of the system, is installed into a music player application (e.g., winamp) It sends information about every song played by users to the Audioscrobbler server. Data thus gathered are used to find users with similar music tastes: people with similar tastes in music and who listen to the same songs are presented and recommended to users who can see this information on their personalized website via a web browser. People with similar taste in music can meet one another and make friends (mutual consent is required) and/or gather in groups (according to music genre, favorite performers, etc.). The users' activity can be calculated by the number of songs played over time.

The third system described in this paper is a booklovers' system Shelfari. Shelfari is a website server similar to LastFm. Users can create accounts obtaining in this way their personalized website where they can create virtual shelves with books which they enjoy. The system recommends users to one another according to similar tastes and books read, it shows other people's opinions about various books, and makes it possible to create or join groups.

The fourth system under investigation is XFire. It is a gamers' community program similar toInternet chat systems integrated with almost all popular computer games. People who are playing a game do not need to

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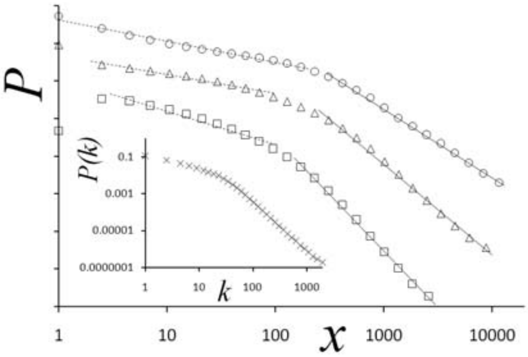

Fig. 1. Results for SkyRock in double logarithmic scale. Probability $P(x)$ that an individual writes x posts in a blog (squares) or a user's blog will be x times commented on (triangles) or visited (circles). The data sets are vertically offset. In the inset the degree distribution is shown.

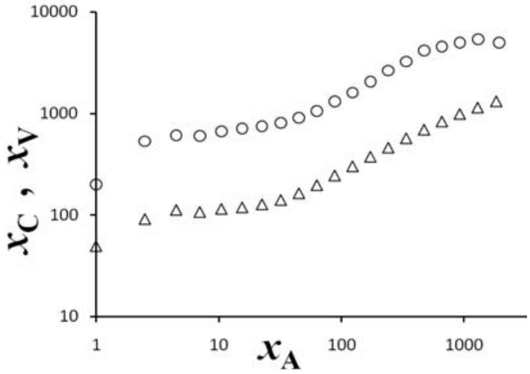

Fig. 2. Relationship between the number of posts x_A and the average number of visits x_V (circles) and the relationship between x_A and the average number of comments x_C (triangles). The size of errors bars is smaller than the size of marks.

quit it to chat with people who are doing something else at that moment because XFire makes it possible to talk inside games via a special chat window. People who like to play computer games use this application to maintain contact with other players even when they are not playing any game or are playing two games at the same time. XFire gives each user their own web space with their statistics (i.e., overall time played, list of friends). Information about overall playing time can be considered an indicator of human activity.

The paper is organized as follows. In the next section we describe basic measures for all systems under investigation. Next, in Section 3 we investigate the evolution of human behavior in time. A mathematical model describing the evolution of the systems under investigation is presented in Section 4. All conclusions are presented in Section 5. The properties of online social networks are presented in reference [7].

2 Statistical properties

Data on human activity in a web-service are registered in its database. At the time of this study SkyRock had 9 823 234 users. Each user can write their own blog. In this electronic diary they can post an unlimited number of posts. The probability that a user has written x_A posts is shown in Figure 1 (the parameters of power-law distributions were computed with maximum likelihood estimation [8]; in other cases least-squares fitting was used). The graph shows a power-law regime $P(x_A) \sim x_A^{-\alpha_A}$ with $\alpha_{A1} = 0.89$ for low x_A and $\alpha_{A2} = 3.1$ for high x_A. All users can comment on articles posted by others. The probability that a blog has been commented on x_C times is shown in Figure 1. The results can be approximated with a power law with the value of the exponent $\alpha_{C1} = 0.5$ for a low number of comments and $\alpha_{C2} = 2.4$. The database registers the number of visits, too. The probability that a blog has been visited x_V times can be approximated with the power law (see Fig. 1). Like in previous cases the exponent can have two different values: $\alpha_{V1} = 0.6$ for a low number of visits and $\alpha_{V2} = 1.8$ for a high one x_V. To compare the goodness of fit for power-law distribution and more general models, $P_1(x) \sim x^{\beta-1}e^{-\lambda x^{\beta}}$ and $P_2(x) \sim e^{-\lambda x}(x-x_0)^{-\beta}$, the likelihood ratio test was used [8]. These models include cutoffs and saturation, hence can be fitted to all data. The basic idea behind the likelihood ratio test is to compute the likelihood of our data in two competing distributions. The one with the higher likelihood is then the better fit. For large values of x the power-law distribution fits better than P_1 and P_2, with one exception: for the distribution of the number of visits the P_2 fits better (however only in the case of large values of x; for low values of x power-law fits better).

In all cases there are two scaling regimes. They result from the presence of two groups of users in the system. The first group consists of typical users, who have written a low number of posts and whose blogs are rarely visited or commented on. The other group is much smaller. Its members have written a large number of posts. Other users find those posts interesting; therefore, they often visit and comment on them. These blogs are often written by celebrities (e.g., actors, singers), thus they attract much more interest than ordinary users' blogs. The correlations between the number of posts x_A, the average number of visits and the average number of comments are shown in Figure 2. x_C and x_V are positively correlated with x_A. Moreover, the number of comments and the number of visits increases faster for high values of x_A than for low values of x_A. This means that the greater the number of posts in the blog, the greater the interest it attracts. The number of visits is much greater than the number of comments, because it is impossible to add a comment without reading the blog and users usually read posts, rather than write comments.

All users of SkyRock can add, by mutual consent, other people to their databases of friends. In this way undirected friendship network is formed (the properties of online social networks are presented in Ref. [7]). It should be noted that in the case of the degree distribution there are two scaling regimes, too (see inset in Fig. 1). Such a behavior is often observed in web-services whose basic aim is to

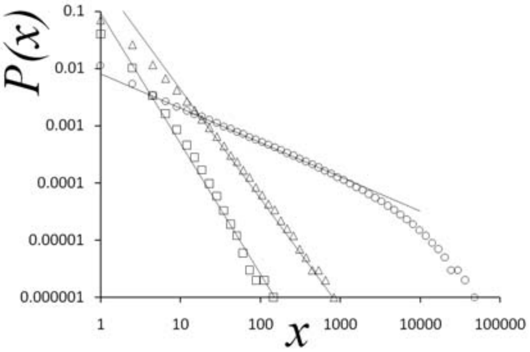

Fig. 3. Probability that a user of the LastFM web-service has listened to x songs (circles) or created x journals (squares) or sent x posts (triangles). The results can be fitted to the power-law (solid lines), with the values of exponents 0.7, 2 and 1.8 for songs, journals and posts, respectively.

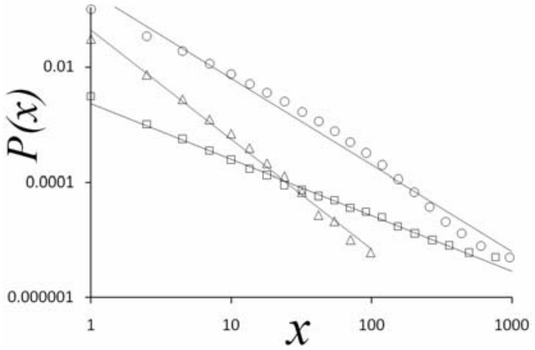

Fig. 4. Probability that a user of the Shelfari web-service has read x books (circles) or written x tags (squares) or written x opinions (triangles). The results can be fitted to the power-law (solid lines), with the values of exponents 1.6, 1 and 1.8 for books, tags and opinions, respectively.

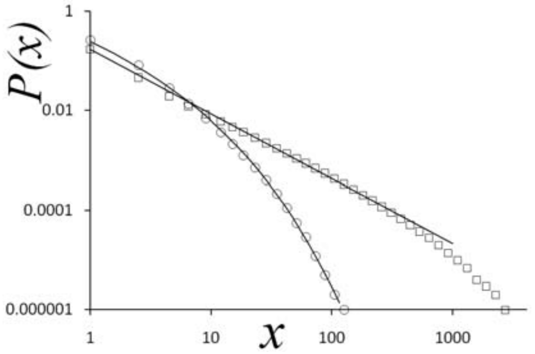

Fig. 5. Probability that a user of the XFire web-service has played x games (circles) or how long they have played them (squares). The results can be fitted to the power-law (solid line) with the value of the exponent 1.4. The number of games a user has played decreases as a stretched exponential $P(x_G) \sim x^{\beta-1}e^{-\lambda x^{\beta}}$ with $\beta = 0.4$ and $\lambda = 1.4$.

facilitate interpersonal interactions between its users [6,9]. A double scaling law is also observed in the case of an empirical distribution of the number of connections of words in the Word Web [10,11].

LastFM was investigated next. We analyzed data on 1 192 118 users. A user's basic activity in the web-service can be calculated on the basis the number of played songs x_S. The distribution of the probability that a user has listened to x_S songs is shown in Figure 3. In a wide range of values of x_S ($x_S < 10^4$), the graph shows a power-law regime $P(x_s) \sim x_S^{-\alpha_S}$ with the value of the exponent $\alpha_S = 0.7$. Each user can write an unlimited number of journals x_J in the web-service. The probability that a user has written x_J journals can be approximated with a power-law relationship with exponent $\alpha_J = 2$ (see Fig. 3). The website contains additional services such as discussion forums. The probability that a user has written x_P posts in a forum is shown in Figure 3. The relationship can be approximated with the power law with the value of the exponent $\alpha_P = 1.8$.

The third system described in this paper is the booklovers' system Shelfari with 253 967 users. Shelfari is a social cataloging website where users can catalog, tag or review books. They can build virtual bookshelves consisting of the titles they have read. The probability that a user has read x_B books is shown with a power-law regime with the value of the exponent $\alpha_B = 1.6$ (see Fig. 4). Similarly the probability that a user has written x_O opinions or x_T tags follows the power law with the value of the exponents $\alpha_O = 1.8$ and α_T slightly higher than one($\alpha_T = 1.01$), respectively.

The fourth system under investigation is XFire (5 241 578 users). XFire's database logs what games users play and how long they play them. The probability that a user devotes x_H h to playing games can be approximated with the power law with the value of the exponent $\alpha_H = 1.4$ (see Fig. 5). The number of games a user has played decreases as a stretched exponential $P(x_G) \sim x^{\beta-1}e^{-\lambda x^{\beta}}$ with $\beta = 0.4$ and $\lambda = 1.4$. This is a discrepancy in the results observed in various web-services (cf. Fig. 4). This is so because playing a game can be much more time-consuming than reading a book, e.g., MMORPGs can take a few years.

3 Time evolution

Online communities offer a great opportunity to investigate human dynamics [12,13], because so much information about individuals is registered in databases. To analyze to what extent people are interested in using a web-service over time, we studied the creation date and the last login date registered in a database. The lifespan of an individual T_L is defined as the number of days from the time the individual was added to the database (i.e., a user account was created) to the date of the last logging in, i.e., to the last activity of the user in the system. It should be noted that such definition of a lifespan makes it possible to eliminate the influence of users who drop out of the system.

In all systems the time development of the parameters describing a user's behavior in the social

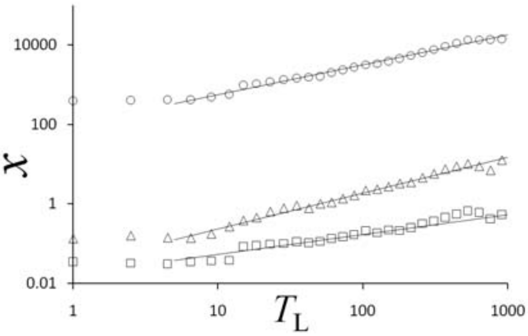

Fig. 6. Time development of the number of songs (circles) or journals (squares) or posts (triangles) for LastFM users. The results can be fitted to the power-law (solid lines), with the values of exponents 0.75 ($R^2 = 0.98$), 0.55 ($R^2 = 0.95$) and 0.9 ($R^2 = 0.96$) for songs, journals and posts, respectively.

system can be approximated with the relationship $x(T_L) \approx T_L^\beta$ with $\beta \leq 1$ (the results for LastFM and Shelfari are shown in Figs. 6 and 7, respectively). The more time-demanding an activity, the slower the increase in time, e.g., the number of read books increases more slowly than the number of written opinions (see Fig. 7). It should be noted that such a power-law relationship between the degree of a node and time has been found in other systems [9,14].

In the case of Skyrock and XFire the value of the exponent β equals 1, the number of blog posts and the number of hours devoted to playing games increases linearly with time. This indicates that the users of those systems devote daily, on average, the same amount of time to their activity (e.g., they write one blog post every day). A value of the exponent lower than one indicates that users lose interest in using web-services over time. Their activity in those systems becomes less and less important for them.

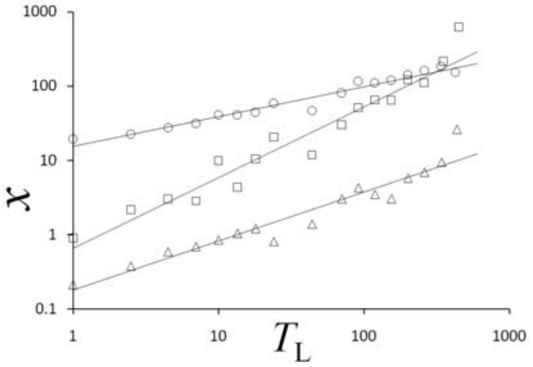

Fig. 7. Time development of the number of books (circles) or tags (squares) or opinions (triangles) for Shelfari users. The results can be fitted to the power-law (solid lines), with the values of exponents 0.4 ($R^2 = 0.95$), 0.95 ($R^2 = 0.94$) and 0.7 ($R^2 = 0.92$) for books, tags and opinions, respectively.

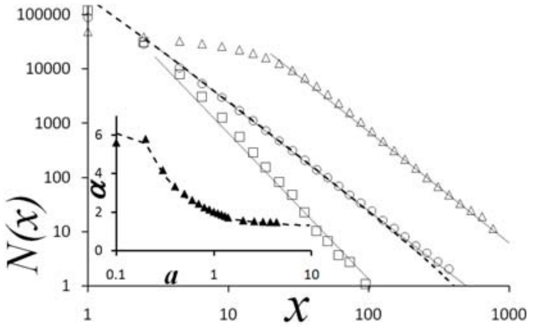

Fig. 8. Results of numerical simulations for $a = 1$, $b = 0.0005$ (squares), $a = 0.5$, $b = 0.0005$ (circles) and $a = 1$, $b = 0.01$ (triangles). The results can be fitted to the power-law $N(x) \sim x^{-\alpha}$(solid lines), with the values of exponents 1.9, 2.8 and 2.0 for circles, squares and triangles, respectively. The relationship between the value of the exponent α and the value of the parameter a is shown in the inset. Dashed lines show results of analytical calculations.

4 Mathematical models

We present a simple mathematical model of the evolution of online systems. Each individual is described with two parameters: x denotes a user's activity (e.g., the number of read books) and t – the number of time steps since creation. In each time step n new users are added to the system with $x = 0$ and $t = 0$. Next, in the same time step the value of x of all users increases with certain probability. It is more likely that a user who has read ten books will read another one, than a user who has read only one book (the probability that a frequently visited blog will be visited again is high; this is an adaptation of the well-know *the rich get richer* principle [1]). On the other hand, users with greater lifespan T_L are less active (see Sect. 3). Therefore, we assume that the probability that x will increase by one is proportional to x and inversely proportional to t:

$$p(x,t) = a\frac{x}{t} + b \tag{1}$$

(we assume that $p = b$ for $t = 0$). The results of numerical simulations are shown in Figure 8. The value of the parameter n was $n = 10^3$ and the time of simulation was $t_{max} = 10^3$ time steps long , one time step corresponded to one day. In this way the size of the system (10^6 individuals) and the time it existed (10^3 days, i.e., almost three years) were similar to the values observed in the other systems under investigation. The results of numerical simulations can be approximated with a power-law relationship $N(x) \approx x^{-\alpha}$. The value of α decreases with an increase in a (see inset in Fig. 8 for $b = 0.0005$). The value of the parameter b slightly influences the value of the exponent α (α increases with an increase in b). However, for high enough b there are two scaling regimes. In systems like Skyrock there are two groups with different behaviors. For most users the probability that x will increase is low but for high t do not change over time ($p(x,t) \approx b$). In the second group (which is much smaller) users are very active (high x) but the probability that x will increase considerably depends on time ($p(x,t) \approx a\frac{x}{t}$). Therefore, the value of $N(x)$ decreases faster in the second group (see Fig. 8 and cf. Fig. 1).

The approximation of the $N(x)$ relationship can be calculated analytically using the following equation:

$$N(x)=n\sum_{t=0}^{t_{max}}P(x,t) \qquad (2)$$

where $P(x,t)$ is the probability that a user is active x after t time steps and t_{max} is the duration of the system. According to equation (1) the value of probability $P(x,t)$ for $x\geq 1$ can be calculated using the following master equation:

$$P(x,t+1)=P(x,t)+p(x-1,t)P(x-1,t)-p(x,t)P(x,t). \qquad (3)$$

Knowing that the value x cannot be greater than t we can write:

$$\sum_{x=0}^{t}P(x,t)=1. \qquad (4)$$

Introducing the relationship $R(x,t)=p(x,t)P(x,t)$ we can write equation (3) in the following form:

$$P(x,t+1)-P(x,t)=R(x-1,t)-R(x,t). \qquad (5)$$

The above equation can be rewritten using continuum x,t approximation:

$$\frac{dP(x,t)}{dt}=-\frac{dR(x,t)}{dx}. \qquad (6)$$

Knowing that $P(x,t)=\frac{R(x,t)}{p(x,t)}$ we can write equation (6) in the following form:

$$\frac{dR(x,t)}{dt}\left(\frac{ax}{t}+b\right)+R(x,t)\frac{ax}{t^2}=-\frac{dR(x,t)}{dx}\left(\frac{ax}{t}+b\right)^2. \qquad (7)$$

After calculations in which the approximation $b\approx 0$ is used, we obtain:

$$R(x,t)=-t\frac{R(x,t)}{dt}-ax\frac{R(x,t)}{dx} \qquad (8)$$

hence $R(x,t)\sim t^{-1}x^{-\frac{1}{a}}$. Next we can calculate the form of the probability $P(x,t)$:

$$P(x,t)\sim\frac{1}{ax+bt}x^{-\frac{1}{a}}. \qquad (9)$$

Next, by using the condition (4) and equations (2), (9) the form of $N(x)$ distribution can be calculated. The analytical solution for $N(x)$ (dashed lines) is compared with the results of numerical simulations in Figure 8. The value of the exponent α was computed with maximum likelihood estimation [8]. The results obtained analytically agree well with the numerical results. Having the distribution $P(x,t)$ (Eq. (9)) we can calculate the time development of average value of x. The results are shown in Figure 9. For large enough values of a the relationship can be fitted to the power-law. Note that time t is defined as a number of steps (days) from an individual creation to the end of simulation, therefore these results can not be compared with results from Section 3, where the relationship $x(T_L)$ is shown.

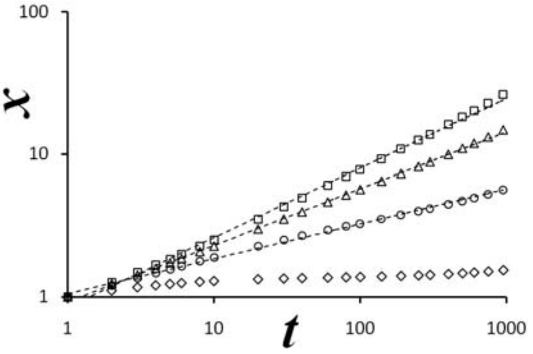

Fig. 9. Time development of the activity of an individual for $b=0.0005$ and $a=2;1.5;1.01;0.5$ from top to bottom, respectively. For large enough a the results can be fitted to the power-law (dashed lines), with the values of exponents 0.49 ($a=2$), 0.4 ($a=1.5$) and 0.25 ($a=1.01$).

The aforementioned explanation of $N(x)$ evolution is very simple, e.g., it does not take into account that a user can stop logging in (in most online systems the distribution of life span T_L has a power-law [9,14] or exponential [15] form), and fail to reproduce the relationship $x(t)\sim t^{\beta}$ with $\beta<1$ observed in a real system. In our model x increases linearly over time, thus $\beta=1$. This is so because for most active individuals $p(x,t)\approx$ const. $(x\sim t)$. When $\frac{x}{t}$ starts to decrease the value of $p(x,t)$ also decreases. The decrease in $p(x,t)$ is very rapid and an individual quickly becomes inactive, because $p(x,t)$ is very low. Note that in our system the lifespan of an individual is defined as the number of time steps between the creation of an individual to the last activity in the system. Therefore, we present a model which can explain the emergence of a power-law relationship by using an approach similar to interest-driven models [13]. Contrary to Barabási model of human dynamics [12] the interest-driven models are much less explored. However many real-world human activities, which are mainly driven by personal interests, could be well explained by such models [13].

We assume that every day humans execute their list of tasks (they read books, write blog posts, etc.) and each task is assigned a priority parameter ($p_r\in[0,1]$) [16–19]. The probability that a task will be executed equals this priority p_r; therefore, $p_r\in[0,1]$ and the increase in x is proportional to this priority, i.e., $\frac{dx}{dt}=cp_r(t)$. However, priorities of tasks can change in time. We assume that the change in p_r is proportional to its current value and depends on initial priority p_{r0} and time. The more important the task (the higher the value of initial priority p_{r0}), the lower the probability that individuals will abandon executing that task. After some time individuals become used to executing the task and execute it by force of habit. The longer the duration of an activity, the more difficult it is to give it up (the decrease in the value of priority is lower). Moreover, a growing network of online friends [7] encourages users to invest their time in the system. In extreme cases an addiction can be developed, especially in the case of MMORPGs [21]. Therefore, we assume that the equation describing the time evolution of the value of priority has the form:

$$\frac{dp_r}{dt} = -(1 - p_{r0})\frac{p_r}{t}. \tag{10}$$

We assume that the change in p_r is proportional to its current value, because p_r cannot take values lower than zero. After calculations we obtain:

$$p_r = p_{r0}t^{-(1-p_{r0})}. \tag{11}$$

Knowing the relationship between priority and time we can calculate the time development of the parameters describing the user's behavior in the social system:

$$x(t) = ct^{p_{r0}} \tag{12}$$

where the parameter c controls the rate of task execution. The value of c depends on the type of activity (e.g., it is easier to listen to five songs than read five books) and the user's attitude to this type activity (e.g., users can write posts in their blogs once a week or once a day and for both groups of users the priority p_r of this task can be the same). The assumption that all users have the same value of the parameter c or initial priority p_{r0} is unrealistic in real systems (the activity of users in online social system can depend on such characteristics as age or gender [20]). For example, in the case of Skyrock there are two different groups: users with a very high value of initial priority $p_{r0} \approx 1$ but a low value of c (thus $p_x \approx$ const., cf. previous model), and very active users (high c) who, in contrast, quickly lose interest in using web-services ($p_{r0} < 1$). Without knowledge of the real distribution of c and p_{r0}, it is impossible to successfully integrate both models (at this moment such data are unavailable). However, the model presented here makes better understanding of the problem possible.

5 Conclusions and future work

We have shown that users' behavior in different social systems does not differ much: the distributions of parameters describing users' activity x in the system have the form of the power law. The value of an exponent depends on the type of activity. Similar behavior is observed in the activity of individual agents in online auctions (the distribution of the total number of bids placed by the same agent follows the form of the power law [22]), in the activity of 24×10^7 users of the Microsoft Messenger instant-messaging system (the number of logins per user follows the form of the power law [23]) and in the number of posts per blog (the data set of 45×10^3 blogs was analyzed) [24].

We have investigated the relationship between x and time. In none of the systems did the power-law relationship have values of exponents greater than one. This indicates that in most cases users lose interest in their activity in online systems over time and become less and less active. The power-law form of distributions and time development of users in the systems under investigation and other results [9,12,14] indicate that such a scaling law is common in human dynamics and should be taken into account in models of the evolution of social systems [25,26] and of human activity. Moreover, it was recently found that the heavy-tailed distribution of the intercontact times between susceptible and infected individuals has a significant influence on the spreading of computer viruses [27]. We suggest that our results concerning human behavior can have a significant influence on the dynamic phenomena in complex networks [28] (e.g., rumor propagation or opinion formation [29]).

We have presented a simple model of the evolution of a social system. The model has two parameters: the first one allows tuning the value of the exponent of power-law distribution. For high enough values of the second parameter, two scaling regimes emerge in the system.

The time development of a user's activity in an online social system is explained with the second model presented in our work. A decrease in the value of priority assigned to a task leads to a power-law relationship between x and time observed in all systems under investigation. The value of an exponent equals the initial value of the priority of the task.

In future studies we will explore other online systems in order to compare their properties with those already investigated. Of further interest would be an improvement of the model of evolution of an online social system. Such a model should explain time development of users' activity, emergence of a power-law distribution of parameters describing a user's activity and a distribution of lifespan (T_L) observed in real social systems.

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