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Quantitative analysis of bloggers' collective behavior powered by emotions

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Abstract. Large-scale data resulting from users' online interactions provide the ultimate source of information to study emergent social phenomena on the Web. From individual actions of users to observable collective behaviors, different mechanisms involving emotions expressed in the posted text play a role. Here we combine approaches of statistical physics with machine-learning methods of text analysis to study the emergence of emotional behavior among Web users. Mapping the high-resolution data from digg.com onto bipartite networks of users and their comments onto posted stories, we identify user communities centered around certain popular posts and determine emotional contents of the related comments by the emotion classifier developed for this type of text. Applied over different time periods, this framework reveals strong correlations between the excess of negative emotions and the evolution of communities. We observe avalanches of emotional comments exhibiting significant self-organized critical behavior and temporal correlations. To explore the robustness of these critical states, we design a network-automaton model on realistic network connections and several control parameters, which can be inferred from the dataset. Dissemination of emotions by a small fraction of very active users appears to critically tune the collective states.

Keywords: self-organized criticality (theory), scaling in socio-economic systems, online dynamics

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1. Introduction

Online social interactions among users of different Web portals, which are mediated by the posted material (text on blogs, pictures, movies, etc), or via direct exchange of messages on friendship networks, represent a prominent way of human communication. It has been recognized recently [1, 2] that the unsupervised online interactions, involving ever larger numbers of users through the self-organized dynamics, may lead to new social phenomena on the Web. Understanding the emergent collective behavior of users thus appears as one of the central topics of the contemporary science of the Web, besides the structure and security issues [2, 3].

The role of emotions known in conventional social contacts has been increasingly perceived in the Web-based communications. The empirical analysis of sentiment and mood, and opinion mining through user-generated textual data are currently developing research fields [4]–[6]. Different dimensions of the emotional state, i.e., arousal, valence and dominance of an individual user, can be measured in the laboratory [6]. The amount of emotions expressed in a written text and transferred from/to a user have been studied [7, 6]. On the other hand, methods are devised to measure group emotional states and public mood, for example, related to a given event [8, 9]. However, the emergence of the collective emotional states from the actions of individual users over time is a nonlinear dynamical process that has not been well understood.

Physics and computer science research of the Web have been independently developing their own methodologies and goals. For instance, large efforts in computer science are devoted to improve the algorithms to retrieve information and sentiment from written text [10, 7]. Different methods have been developed for social sciences to analyze particular phenomena [11]–[13], whereas physics research is chiefly focused on the underlying processes from the perspective of complex dynamical systems [14]–[17]. The quantitative approaches are based on the network representations and application of graph theory (for a recent review see [18]).

Here we use the theory of complex networks and the methods of statistical physics of self-organized dynamical phenomena, which we combine with recent developments in computer science focused towards the emotion contents of the text, and study the emergence of collective emotional states among Web users. This combined research framework offers new insight into the genesis and structure of the collective emotional states, as the states with self-organized critical features depending on several control parameters. At the same time it introduces a set of quantitative measures and parameters which characterize users' behavior and can be inferred from the information embedded in the original data. For further understanding of the observed collective states, we design a network-automaton model on the realistic network structure, within which we tune the control parameters of the dynamics and monitor their effects.

The organization of this paper is as follows. In section 2 we explain our methodology and the structure collected data needed for the quantitative analysis of this type. In section 3 we define the quantities necessary to characterize the collective emotional states of users and perform the systematic analysis of the data to determine these quantities. In section 4 the network-automaton model is introduced and its parameters estimated from the empirical data. The results of simulations are presented. Finally, a short summary and conclusions are given in section 5. Some related technical details are given in the appendix.

2. Data structure and methodology

Fine structure of the data is required for this type of analysis. Specifically, we consider a large dataset collected from *digg.com*, which has desired structure and English text for automated classification, as described in the appendix. Typically, a user posts a story by providing a link to other media and offering a short description. Then all users may read the story as well as already existing comments, and post their own comments, digg (approve) or bury (disapprove) the story. Each user has a unique ID. Every action of a user is registered with high temporal resolution and clearly attributed to the post (main story) and/or to a given comment on that story. Our data also contain full text of all comments. Similar microscopic dynamics, i.e. user posting a comment on a post or on a comment related to a post, is found in most of the blogs. However, information regarding comment-on-comment, which is relevant for our analysis, is not often recorded, see [16, 17] for the analysis of blogs.

Developing an emotion classifier, which is based on machine-learning methods [19] and trained on a large dataset of blog texts (see more details in the appendix), we determine the emotional content of each comment in our dataset. In particular, a probability is determined for each text to be classified first as either subjective, i.e. having emotional content, or otherwise objective. Then the subjective texts are further classified for containing either negative or positive emotional content. Owing to the high resolution of our data, we are able to study quantitatively the temporal evolution of connected events and determine how the emotions expressed in users' comments affect it. Here we are particularly interested in the collective dynamical effects that emerge through the actions of individual users. For this purpose we select a subset consisting of popular posts with

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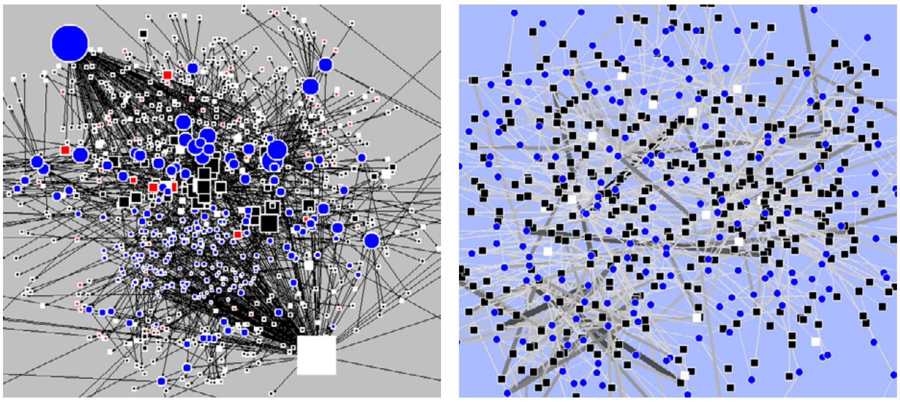

Figure 1. (Left) One-post bipartite network of users—bullets and comments—squares marked by the emotional contents: red—positive, black—negative, white—neutral. Outgoing links point from a user node to nodes representing its comments. While each user has an incoming link from the original post-node, some users also have an incoming link from a comment node on which they made a comment. Size of nodes are plotted proportionally to their out-degree. (Right) Part of a weighted bipartite network with users (bullets) and posts (squares). The widths of links are given by the number of comments of the user to the post. Color of the post-node indicates overall emotional content of all comments on that post.

the number of comments over 100 (see supplementary material available at stacks.iop.org/JSTAT/2011/P02005/mmedia for other measures of popularity). From these popular posts we then select those posts on which more than 50% of all comments represent comment-on-comment actions. The reduced dataset, here termed discussion-driven-Diggs (ddDiggs), consists of $N_P = 3984$ stories on which $N_C = 917\,708$ comments are written by $N_U = 82\,201$ users.

Mapping the data onto a bipartite network is a first step in our methodology. Two partition nodes are user nodes and posts-and-comments nodes, respectively. The resulting network is thus given by $N = N_P + N_C + N_U$ nodes. By definition, a link may occur only between nodes of different partitions. Thus these bipartite networks represent accurately the post-mediated interactions between the Web users. (Note that the post-mediated communication makes the networks of blog users essentially different from the familiar social networks on the Web, such as MySpace or Facebook, where users interact directly with each other.) We keep information about the direction of the actions, specifically, a link $i_P \to j_U$ indicates that user j reads the post i, while $j_U \to k_C$ indicates that the user j writes the comment k. In the data each comment has an ID that clearly attributes it with a given post (original story). The emotional content $e \in [0, -1, +1]$ of the text appears as a property of each post-and-comment node. Figure 1 (left) shows an example of the accurate data mapping onto a directed bipartite network: it represents a network of one popular post from our dataset. In this graph each link indicates a single reading–writing action. Note two types of well-connected nodes: the main post (white square visible in the lower part) and a user-hub (circle node visible in the upper left part of the network), which indicates a very active user on that post.

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Mapping of the entire dataset results in a very large network. For different purposes, however, one can suitably reduce the network size. For instance, a monopartite projection on user-partition can be made, using the number of common posts per pair of users as a link [16]. For the purpose of this work, we keep the bipartite representation while we compress the network to obtain a weighted bipartite network of the size $N = N_P + N_U$, consisting of all popular posts and users attached to them. The weight W_{ij} of a link is then given by the number of comments of the user i on the post j. A part of such a network from our ddDiggs data is shown in figure 1 (right). These networks exhibit very rich topology and interesting mixing patterns [20, 16] (see also [21, 22] for similar networks constructed from the data of music and movie users). In particular, they have scale-free structure of links both in user-and post-partitions. The distributions of the common number of users per pair of posts and the common number of posts per pair of users also exhibit a power-law behavior [20]. For the purpose of this work we are mostly interested in the community structure of these networks, as discussed below.

Based on the network representation and information about the emotional contents of the texts and the action times, here we perform quantitative analysis of the data, in order to identify users' collective behavior. Specifically, we determine:

- *Community structure* on the weighted bipartite networks, where a community consists of users and certain posts which are connecting them. Emotional contents of the comments by users in these communities are analyzed;
- *Temporal patterns of user actions* for each individual user and for the detected user communities; correlations between the evolution of a community with the emotional contents of the comments is monitored over time;
- *Avalanches of (emotional) comments*, defined as sequences of comments of a given emotion which are mutually connected over the network and within a small time bin $t_{\mathrm{bin}} = 5$ min.

3. Empirical data analysis

3.1. User communities and emotions

Time sequence of user activity on all posts, i.e. the number of comments within a small time bin $t_{\mathrm{bin}} = 5$ min is followed within the entire time period available in the dataset. Similarly, the time series of the number of emotional comments, $n_{\mathrm{e}}(t)$, and the number of negative/positive emotion comments, $n_{\pm}(t)$, is determined. An example is shown in figure 2 (top): zoom of the initial part of the time series is shown, indicating bursts (avalanches) in the number of comments (further analysis of the avalanches is given below in figures 4 and 3(f)). The occurrence of increased activity over a large period of time suggests possible formation of a user community around some posts. In this example, the intensive activity with avalanches of comments lasted over 2153 h, followed by reduced activity with sporadic events for another 1076 h.

Such communities can be accurately identified in the underlying network by different methods [23]–[25]. Here we use the method based on the eigenvalue spectral analysis

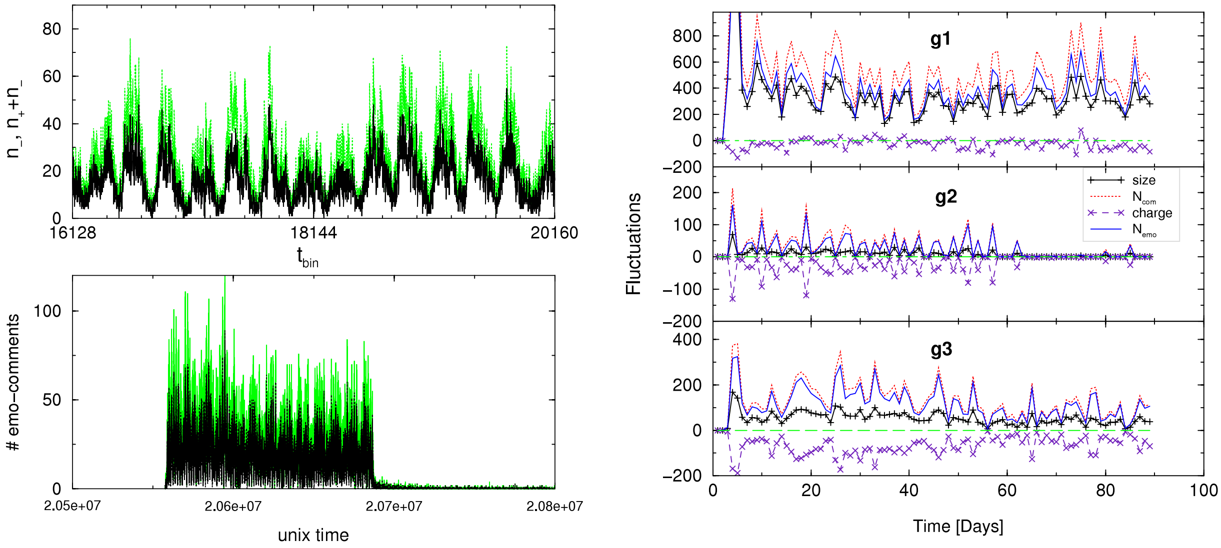

Figure 2. (Left) Time series of the emotional comments—pale, and the comments classified as carrying negative emotions—black, in the popular digg stories, plotted against unix time from the original data. Zoomed part of the time series corresponding to a two week period is shown in the upper panel against number of time bins, each bin $t_{\rm bin} = 5$ min. (Right) Temporal fluctuations of the size, the number of comments, and the number and the charge of emotional comments of three user communities g1, g2 and g3, described in the text.

of the Laplacian operator [26, 27], which is related to the symmetrical weighted network $\{W_{ij}\}$:

$$\mathscr{L}_{ij} = \delta_{ij} - \frac{W_{ij}}{\sqrt{\ell_i \ell_j}}; \qquad \ell_i = \sum_j W_{ij}, \tag{1}$$

and ℓ_i represents the strength of node i. Bipartitivity and weighted links with scale-free distributions of weights and high clustering coefficients of the projected monopartite user networks are among the features of these networks that may limit the performance of the classical methods for the community structure analysis [23]. For these reasons, the spectral analysis and weighted maximum-likelihood methods [28] are used here to determine the community structure on suitably reduced network sizes, as discussed below.

As described in detail in [27], the existence of communities in a network is visualized by the branched structure in the scatter plot of the eigenvectors corresponding to the lowest nonzero eigenvalues of the Laplacian. The situation shown in figure 3(a) is for the user-projected network of our dataset of popular diggs. In this case W_{ij} represents the number of common posts per pair of users. Users with strengths $\ell_i > 100$ are kept, thus reducing the number of users to $N_U = 4918$. Branches indicating three large communities are visible. By identifying the nodes' indices within a branch, we obtain the list of users belonging to a community that the branch represents. In order to unravel what posts (and comments) keep a given community of users together, here we perform the spectral analysis of the weighted bipartite network, where the matrix elements W_{ij} represent the number of comments of a user i to post j. Adding $N_P = 3984$ popular posts to which the above

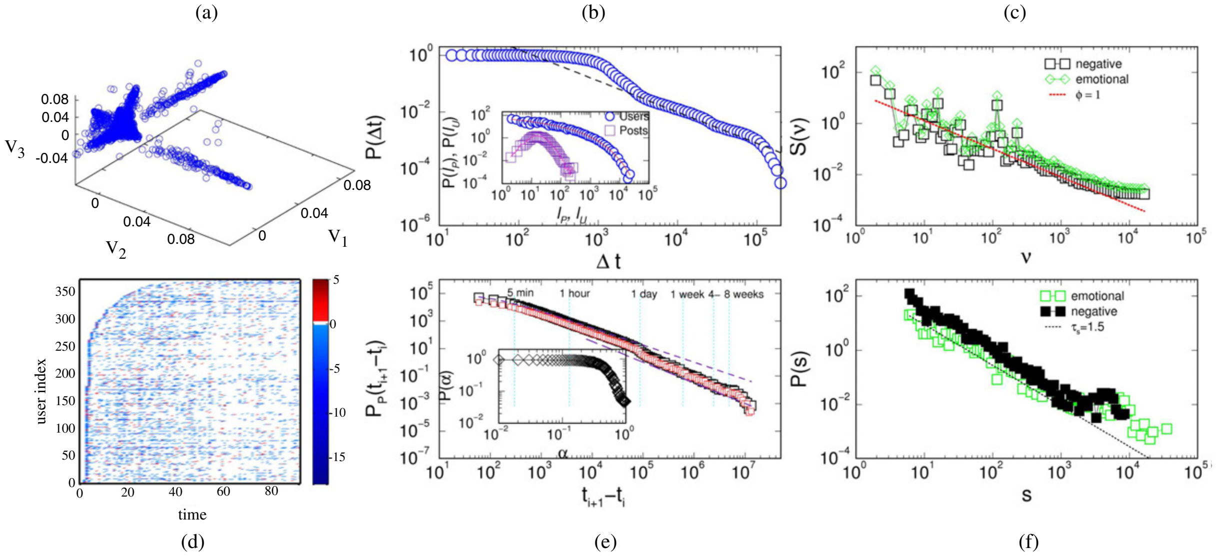

Figure 3. (a) Scatter plot of the eigenvectors corresponding to three lowest nonzero eigenvalues of the Laplacian in equation (1) indicating occurrence of user communities on popular diggs. (b) Distribution of time delay Δt between two consecutive user actions, averaged over all users on ddDiggs. Inset: distribution of strength ℓ_U, ℓ_P for user and post-nodes on the weighted bipartite network, part of which is shown in figure 1 right. (c) Power spectrum of the time series in figure 2 top, with all emotional comments—pale, and comments classified as negative—black. (d) Activity pattern of a user community, color indicates charge of all comments by a user within time bin of 12 h; (e) distribution of the delay between the emotional actions of users to a given post, averaged over all posts. Inset: Distribution of the probability α for a user to post a negative comment. (f) Distribution of the size of avalanches with negative—black and all emotional comments—pale, obtained from the same dataset as (c). (Log-binning with the base $b = 1.1$ is used for the distributions in figures (b), (c), (e) and (f).)

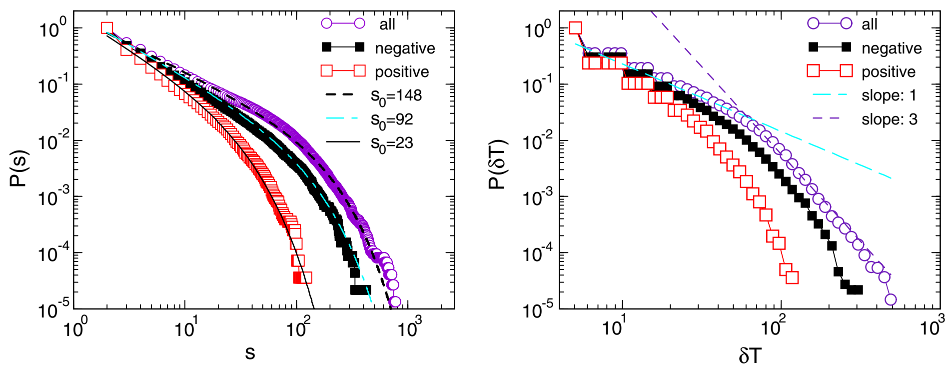

Figure 4. Cumulative distribution of avalanche size $P(s)$, and inactivity time $P(\delta T)$ between avalanches of comments observed at individual posts, bisected post-by-post from the network of ddDiggs. The cases with comments of positive and negative emotional content are shown separately.

set of users are connected, we have a weighted bipartite network of $N = N_U + N_P = 8902$ nodes, where we look for the community structure. In this way we identify the list of user- and post-nodes belonging to a community. For each identified community we then select from the original data all comments on the posts made by the users in that community, together with their time of appearance and the emotional contents. In the weighted bipartite network of ddDiggs described above, we identified three communities (g1, g2, g3), which can be well separated from each other. The largest community g1, part of which is shown in figure 1 (right), contains 5671 nodes (2249 posts and 3322 users). The group g2 has 236 nodes (108 posts and 128 users), and 948 nodes (587 posts and 361 users) are identified in g3.

3.2. Temporal patterns of user behavior

The actual evolution of an identified community can be retrieved from the data related to it. The procedure—network mapping, community structure finding and identifying the active users within the community—is repeatedly applied for successive time periods of one day throughout the dataset.

Comparative analysis of the fluctuations in the number of different users (size) of the communities identified in our ddDiggs dataset is shown in figure 2 (bottom) with the time interval of one day. Also shown are the fluctuations in the number of all comments and the 'charge' of emotional comments $Q(t) \equiv n_+(t) - n_-(t)$, where $n_+(t)$ and $n_-(t)$ stand for the number of comments of all users in that community on a given day that are classified as positive and negative, respectively. It is remarkable that the increase in the number of users is closely correlated with the excess of the negative comments (critique) on the posts. In the supporting material (available at stacks.iop.org/JSTAT/2011/P02005/mmedia) we give several snapshots of the networks, indicating the evolution stages of one of these communities.

Further analysis of the time series reveals long-range correlations in the number of emotional comments over time. In particular, the power spectrum of the type $S(\nu) \sim 1/\nu$ is found, both for the number of all emotional comments and the number of comments with negative emotion of the time series from figure 2 (left). The power-spectrum plots are shown in figure 3(c). The pronounced peaks, which are superimposed onto the overall $\sim 1/\nu$ law, correspond to daily and weakly periodicities of user activity, which can be easily seen in the zoomed part of the time series in figure 2 (left). (Note that the spectrum may be randomized if a so-called 'digg-time' scale [29] is considered instead of the natural time.)

User activities on posted text exhibit robust features, which can be characterized by several quantities shown in figures 3(b)–(e). Specifically, the pattern of a user's activity represents a fractal set along the time axis, with the intervals Δt between two consecutive actions obeying a power-law distribution. In figure 3(b) the histogram $P(\Delta t)$ averaged over all users in ddDiggs is shown. Consequently, the number of comments of a user within a given time bin is varying, which is shown graphically in the color plot in figure 3(d). The color code represents the charge of the emotional comments made by a given user within a 12 h time bin. Different users are marked by the indices along the y axis and ordered by the time of first appearance in the dataset. Occurrence of the diagonal stripes indicates the activity that involves new users potentially related with the same story.

(Note that mutually connected comments are accurately determined using the network representation, as discussed below.) Another power-law dependence is found in the delay time $t_i - t_0$ of comments made by any one of the users to a given post, measured relative to its posting time t_0 [16, 30]. In view of the emotional comments on a given post, in the present study it is interesting to consider the delay $\delta t \equiv t_{i+1} - t_i$ between two emotional comments. The histograms for the case of negative (positive) comments from our dataset is given in figure 3(e), averaged over all posts in the dataset. Both distributions have a power-law tail with the slope $\sim$1.5 for the delay time in the range $\delta t \in [24\ \mathrm{h}, 8\ \mathrm{wk}]$ and a smaller slope $\sim$1.25 for $\delta t \in [5\ \mathrm{min}, 24\ \mathrm{h}]$, indicated by dashed lines. However, differences and a larger frequency of negative comments is found in the domain $\delta t \lesssim 5$ min.

Occurrence of heavy-tail distributions in human activity patterns was shown in several other empirical data [30]–[32]. The origin of the observed power laws and universality of human dynamics have been modeled within priority-queuing theory [30, 31, 33] or assuming that other mechanisms (natural cycles, repetition processes and changing communication needs) play a role [32]. Within our research framework, owing to the bipartitivity of the network representation of human dynamics on diggs and blogs and having additional features of user's comments—their emotional contents—we have expanded zoo of the delay-reaction distributions and with them related scaling exponents. Remarkably, when the emotional contents are taken into account, the variety of distributions that can be defined still exhibit power-law dependences, with different exponents. The role of emotional contents in the underlying mechanisms of human reactions remains to be studied within appropriate approaches.

3.3. Structure of the emergent critical states

The observed correlations in the time series are indicative of bursting events, which are familiar to self-organized dynamical systems. In our case an avalanche represents a sequence of comments, i.e. a comment triggering more comments within a small time bin t_{bin}, and so on, until the activity eventually stops. In analogy to complex systems such as earthquakes [34, 35] or Barkhausen noise [36], the avalanches can be readily determined from the measured time series, like the one shown in figure 2 (left). Specifically, putting a baseline on the level of random noise, an avalanche encloses the connected portion of the signal above the baseline. Thus the size of an avalanche in our case is given by the number of comments enclosed between two consecutive intersections of the corresponding signal with the baseline. The distribution of sizes of such avalanches is shown in figure 3(f), determined from the signal of emotional comments from figure 2 (left). A power law with the slope $\tau_s \simeq 1.5$ is found over two decades.

The scale invariance of avalanches is a signature of self-organizing critical (SOC) states [37, 38] in dynamical systems. Typically, a truncated power-law distribution of the avalanche sizes

$$P(s) \sim s^{-\tau_s} \exp(-s/s_0) \tag{2}$$

and other quantities pertinent to the dynamics [39, 40, 36] can be measured before a natural cutoff s_0, depending on the system size. The related measures, for instance the distribution of temporal distance between consecutive avalanches, $P(\delta T)$, also exhibits a power-law dependence, as found in the earthquake dynamics [34, 35].

Here we give evidence that the SOC states may occur in the events at individual posts in our dataset. We analyze avalanches on each post by bisecting post-by-post from the rest of the network. (Note that the network cannot be fully separated into a network of single posts, because a number of users are active at several posts!) The results of the cumulative distributions of the avalanche sizes, $P(s)$, averaged over all 3984 posts, are shown in figure 4. The distributions for avalanches of different emotional contents are fitted with equation (2) with different exponents ($\tau_s \in [1.0, 1.2]$) and cutoffs. On the single-post networks we can also identify the quiescence times between consecutive avalanches: the distributions, $P(\delta T)$, are also shown in figure 4. It should be stressed that, besides the natural cutoff sizes, these avalanches are additionally truncated by the single-post network sizes. Nevertheless, they can be fitted by the expression (2), indicating the self-organized dynamics at single-post level. For comparison, the differential distribution of the avalanche sizes in figure 3(f), which refers to the simultaneous activity on all posts, shows a power-law decay over an extended range of sizes and an excessive number of very large avalanches (supercriticality). Note that these data are logarithmically binned for better vision. A histogram with binned data superimposed onto original data is given in the supplementary material (available at stacks.iop.org/JSTAT/2011/P02005/mmedia): a large fraction of the avalanches is found in the tail region, giving rise to the bump in the distributions.

The existence of different attractors inherent to the dynamics [40, 41] or coalescence of simultaneously driven events [42, 43] may result in non-universal scaling exponents, which depend on a parameter. Relevance of the conservation laws is still an open question [44]. The situation is even more complex for the dynamics on networks. Nevertheless, the SOC states have been identified in different processes on networks [45]–[47]. In order to understand the origin of the critical states in the empirical data of ddDiggs, and their dependence on the user behavior, in the following we design a cellular-automaton-type model on the weighted post–user network, within which we simulate the dynamics, identify the realistic parameters governing the dynamics and explore their effects by varying them.

4. Modeling avalanche dynamics on popular posts

The microscopic dynamics on blogs, i.e. a user posting a comment, triggering more users for their actions, etc, can be formulated in terms of update rules and constraints, which affect the course of the process and thus the emergent global states. A minimal set of control parameters governing the dynamics with the emotional comments is described below and extracted from our empirical data of ddDiggs. Specifically:

- *User-delay* Δt to posted material, extracted from the data is given by a power-law tailed distribution $P(\Delta t)$ in figure 3(b), with the slope $\tau_\Delta \approx 1$ above the threshold time $\Delta_0 \sim 300$ min.
- *User tendency to post a negative comment*, measured by the probability α, inferred from the data as a fraction of negative comments among all comments by a given user. Averaged over all users in the dataset, the distribution $P(\alpha)$ is given in the inset to figure 3(e).
- *Post strength* ℓ_{iP} is a topological measure uniquely defined on our weighted bipartite networks as a sum of all weights of its links, i.e. the number of users linked to it with

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multiplicity of their comments. Thus it is a measure of attractiveness (relevance) of the posted material. Histograms of the strengths of posts and users in our dataset are given in the inset to figure 3(b).

- *User dissemination probability* λ is a measure of contingency of bloggers' activity. It is deduced from the empirical data as the average fraction of the users who are active more than once/at different posts within a small time bin ($t_{\rm bin} = 5$ min). In the model we vary this parameter, as explained below.
- *Network structures* mapped from the real data at various instances of time underlying the evolution of connected events. Here we use the weighted bipartite network, representing the g1 community of the ddDiggs data, figure 1 (right).

Within the network-automaton model these parameters are implemented as follows: first, the weighted bipartite network is constructed from the selected data and given time interval. To each post on that network we associate its actual strength ℓ_{iP}, and to each user a (quenched) probability α taken from the actual distribution $P(\alpha)$. A well-connected user is selected to start the dynamics by posting a comment on one of its linked posts. The lists of active users and exposed posts are initiated.

Then at each time step all users linked along the network to the currently exposed posts are prompted for action. A prompted user takes its delay time Δt from the distribution $P(\Delta t)$ of the actual dataset. Only the users who got $\Delta t \le t_{\rm bin}$ are considered as active within this time step and may comment on one of the exposed posts along their network links. The posted comment is considered as negative with the probability α associated with that user, otherwise equal probability applies for the positive and objective comment. With the probability λ each active user may make an additional comment to any one of its linked (including unexposed) posts. The post strength is reduced by one with each received comment. Commented posts are added to the list of currently exposed posts. In the next time step the activity starts again from the updated list of exposed posts, and so on. Note that the activity can stop when: (a) no user is active, i.e. due to long delay time $\Delta t > t_{\rm bin}$; (b) the strength of the targeted post is exhausted; (c) no network links occur between currently active areas. Therefore, in contrast to simpler sandpile dynamics, in our model the avalanche cutoffs may depend not only on the network size but also on certain features of the nodes and the links.

In the simulations presented here we vary the parameter λ while the rest of the parameters are kept at their values inferred from the considered dataset, as described above. The resulting avalanches of all comments and of the positive/negative comments are identified. The distributions of the avalanche size and duration are shown in figure 5 for different values of the dissemination parameter λ.

The simulation results, averaged over several initial points, show that the power-law distributions (2) of the avalanche size occur for the critical value of the dissemination, $\lambda = \lambda_{\rm c} \sim 2.1 \times 10^{-4}$, for this particular dataset, whereas varying the parameter λ in the simulations appears to have major effects on the bursting process. Specifically, the power law becomes dominated by the cutoff for $\lambda < \lambda_{\rm c}$, indicating a subcritical behavior. Conversely, when $\lambda > \lambda_{\rm c}$, we observe an excess of large avalanches, compatible with supercriticality. Therefore, our simulations support the conclusion that contagious behavior of some users may lead to supercritical avalanches, observed in the empirical data.

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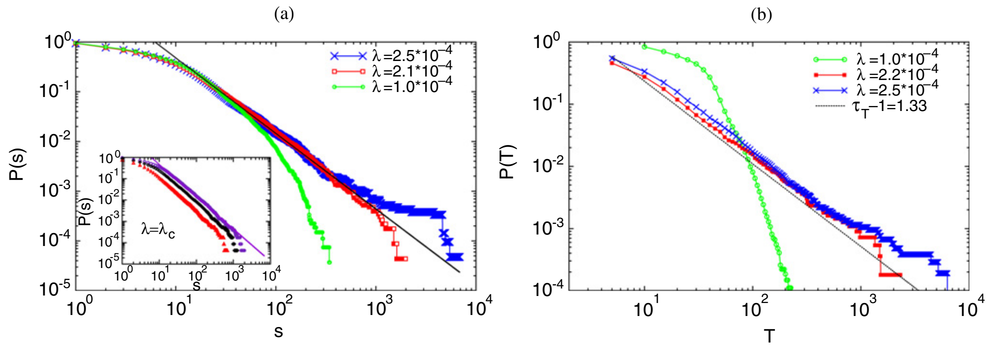

Figure 5. Cumulative distributions of the size (a) and duration (b) of avalanches of emotional comments simulated within the network-automaton model for varied dissemination parameter λ. Fixed parameters for the network structure, post strengths and user inclination towards negative comments and delay actions are determined from the ddDiggs dataset, as explained above. Inset: the distribution $P(s)$ for all avalanches, and for avalanches of positive and negative comments for a critical value of the dissemination parameter $\lambda = \lambda_c$.

The critical behavior at $\lambda = \lambda_c$ has been confirmed by several other measures. The slopes of the distributions of size and duration, shown in figure 5, are $\tau_s - 1 \approx 1.5$ and $\tau_T \approx 1.33$, respectively. The critical behavior persists, but with changed scaling exponents, when the other control parameters are varied. In particular, assuming the distribution of user delay as $P(\Delta t) \sim \exp(-\Delta t/T_0)$ leads to the power-law avalanches with the slopes τ_s and τ_T depending on the parameter T_0. The results are shown in the supporting material (available at stacks.iop.org/JSTAT/2011/P02005/mmedia).

In summary, our simulations within the network-automaton model confirm that the observed scaling in the empirical data can be attributed to the self-organizing dynamics of users at individual posts and within wider networks with user communities. These self-organized states, however, can be considerably altered by varying the contagious behavior of users, which is measured by the parameter λ in the model. Swinging through a critical point at $\lambda = \lambda_c$, the collective states with emotional avalanches thus can be identified as having supercritical, critical or subcritical features. Note that in the empirical data the actual value of the parameter λ is not fixed but varies over time and communities considered. Our simulations and the quoted critical value for λ_c are obtained on the bipartite network representing the largest community g1 of ddDiggs, as described above. A different value for λ_c is found, for instance, when the network-automaton is simulated on the bipartite network of popular blogs [17]. In the supplementary material we give the distribution $P(\lambda)$ of the values for λ that we determined in the empirical dataset of ddDiggs. It shows that the values of λ above the theoretical critical value λ_c can be found with a large probability in this data, which is compatible with the prevalence of supercritical avalanches.

5. Conclusions

We have analyzed a large dataset with discussion-driven comments on digg stories from *digg.com* as a complex dynamical system with the emergent collective behavior of users.

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With the appropriate bipartite network mappings of the dynamical data and using the methods and theoretical concepts of statistical physics combined with computer science methods for text analysis, we have performed a quantitative study of the empirical data to:

- Demonstrate how the social communities emerge with users interlinked via their comments over some popular stories;
- Reveal that an important part of the driving mechanisms is rooted in the emotional actions of the users, overwhelmed by negative emotions (critiques);
- Show that the bursting events with users' emotional comments exhibit significant self-organization with the collective critical states.

The collective behavior of users in the empirical data of ddDiggs has been identified via several quantitative measures, which can be defined within the theory of complex dynamical systems and self-organized criticality. These are: (a) topologically distinguished user communities on the network made by the dynamics of user actions—commenting on each other's posts-and-comments; (b) with fine time resolution identified chains of actions (emotional comments) in terms of connected avalanches. For these avalanches we determine several quantities to characterize their SOC structure, both on the entire bipartite network and for the truncated avalanches on single-post networks. The distributions of size and duration, and inter-avalanche times are determined for the avalanches. (c) The $1/\nu$ type of power spectrum, characterizing the long-range temporal correlations, with superimposed circadian, daily and weekly cycles, was found for both the emotional comments time series and for all comments of a community time series.

Properties of the emergent collective states can be captured within a network-automaton model, where the real network structure and the parameters native to the studied dataset are taken. (Note that the term 'model' is often used for data modeling in computer science, e.g. [48, 49]. In contrast, here we designed a theoretical model by anticipating the dynamical rules and simulating the emergent states of the system.) Despite several open theoretical problems related with the self-organized criticality on networks, the observed critical states appear to be quite robust when the parameters of user behavior are varied within the model. However, they are prone to overreaction with supercritical emotional avalanches triggered by a small fraction of very active users, who disseminate activity (and emotions) over different posts.

Within our approach, the activities and related emotions of every user and of the identified user communities are traced in time and over the emerging network of their connections. In view of the complex dynamical systems, the statistical indicators of the collective states and the numerical values of the parameters governing the dynamics of cybercommunities are readily extracted from the empirical data. Due to the automated text analysis, the emotional contents of the user comments are the subject of the precision of the emotion classifier (described in the appendix). However, it should be noted that these processes lead to broad distributions and the scale invariance of the emotional avalanches, as revealed by our analysis. Therefore, we expect that such robust behavior may persist, although the balance between the emotional/neutral contents and the scaling exponents may change with the classifier precision.

For the generality of our approach, it should be stressed that the networks considered in our approach represent precise mappings of the dynamics of user actions, and not social 'fun networks', that can also be constructed from the same diggs data [50] (available at stacks.iop.org/JSTAT/2011/P02005/mmedia). Fun networks appear to have different structures (details of some community structures are given in the supplementary material). For instance, considering the structure of the fun relationships within the 4918 users in the ddDiggs community structure analyzed above, we find that 3620 users have no fun relationship (are disconnected) with other users in this set. The remaining cluster exhibits three communities (see supplementary material), which mainly contain users from the g1 group studied above. Our methodology applies also to the user dynamics on blogs, where different network structures and values of the control parameters can be identified [17]. On the other hand, different training of the emotion classifier (due to short texts) is necessary for Twitter data, whereas the dynamics of communications on the social networks (MySpace, Facebook) requires different approaches both in the data analysis and theoretical modeling.

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Appendix

Data collection. The Digg dataset was collected through the website's publicly available API[3], which allows programmers to directly access the data stored at its servers, such as stories, comments, user profiles, etc. The dataset is comprised of a complete crawl spanning the months February, March and April 2009. It contains 1195 808 stories, 1646 153 individual comments and 877 841 active users (including those who only digg a story). Among these we find 305 247 users who posted or commented on a story at least once within this dataset. More information can be found in [51]. The dataset is freely available for scientific research.

Emotion classifier. The emotion classifier is based on a supervised machine-learning approach, according to which a general inductive process initially learns the characteristics of a class during a training phase, by observing the properties of a number of pre-classified documents, and applies the acquired knowledge to determine the best category for new, unseen documents [10]. Specifically, it represents an implementation of the hierarchical language model (h-LM) classifier [52, 53], according to which a comment is initially classified as objective or subjective and, in the latter case, as positive or negative. The h-LM classifier was trained on the BLOGS06 dataset [54], which is a uncompressed 148 GB crawl of approximately 100 000 blogs, a subset of which has been annotated by human assessors regarding whether they contain factual information or positive/negative opinions about specific entities, such as people, companies, films, etc. Because the resulting training dataset is uneven, the probability thresholds for both classification tasks were optimized on a small subset of humanly annotated Digg comments, in a fashion similar to [19]. Performance of the classifier has been tested (see [19], which also describes the

[3] http://apidoc.digg.com/.

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experimental set-up and the training process). The actual performance (using 'accuracy' as the metric) of the LM classifier is 70.12% for positive/negative classification and 69.7% for objective/subjective classification.

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