Can human-like Bots control collective mood: agent-based simulations of online chats

Bosiljka Tadić¹,³ and Milovan Šuvakov¹,²

¹ Department of Theoretical Physics, Jožef Stefan Institute, Box 3000, SI-1001 Ljubljana, Slovenia
² Institute of Physics, University of Belgrade, Pregrevica 117, Belgrade, Serbia
E-mail: bosiljka.tadic@ijs.si and suvakov@gemail.com

Received 10 May 2013
Accepted 19 September 2013
Published 17 October 2013

Abstract. Using an agent-based modeling approach, in this paper, we study self-organized dynamics of interacting agents in the presence of chat Bots. Different Bots with tunable ‘human-like’ attributes, which exchange emotional messages with agents, are considered, and the collective emotional behavior of agents is quantitatively analyzed. In particular, using detrended fractal analysis we determine persistent fluctuations and temporal correlations in time series of agent activity and statistics of avalanches carrying emotional messages of agents when Bots favoring positive/negative affects are active. We determine the impact of Bots and identify parameters that can modulate that impact. Our analysis suggests that, by these measures, the emotional Bots induce collective emotion among interacting agents by suitably altering the fractal characteristics of the underlying stochastic process. Positive emotion Bots are slightly more effective than negative emotion Bots. Moreover, Bots which periodically alternate between positive and negative emotion can enhance fluctuations in the system, leading to avalanches of agent messages that are reminiscent of self-organized critical states.

Keywords: interacting agent models, scaling in socio-economic systems, socio-economic networks, stochastic processes
1. Introduction

Understanding and potentially controlling human behavior in online communication systems are of paramount importance not only from a technical point of view—for providing intelligent user-adapted services—but also due to raised awareness of the intricate connections between online and offline social behaviors. The underlying social processes on various online communication systems differ from each other owing to their characteristic time scales, rules and constraints for user-to-user contacts. However, a number of robust features of the online social dynamics across many scales are being discovered, for example, by using quantitative methods of statistical physics and graph theory [1]–[3].

Recently, analysis of empirical data from Internet Relay Chat (IRC) revealed that the self-organized dynamics of emotional messages exchanged between users may lead to social networking and recognizable collective behaviors. In particular, empirical data from the Ubuntu chat channel\(^4\) has been analyzed as a complex dynamical system [4, 5]. It has been recognized that long-term associations among users occur as a specific kind of online social network, in which both the type of messages exchanged in user-to-user communications and their emotional content play a role [4]. Apart from human users, different types of web Bots are often available on the channel, for example, to provide information (in terms of ready messages) in response to user requests. Technically, chat Bots with different features can be implemented\(^5\). In the current technological developments, it is tempting to use chat Bots as mood modifiers in online chat systems [6, 7], although their potential to promote collective effects are currently not well understood. From the practical point of view, recent developments in the quantitative investigation of emotions [8, 9] and methods of

\(^4\) www.ubuntu.com.

\(^5\) www.cleverbot.com/; http://iii.ru.
emotion detection from a written text [10, 11], the emotion of the added Bot in a chat channel can be quantitatively defined. A practical implementation, i.e., creating the body of the messages which involve a specified emotion, is also technically feasible [7, 12]. On the other hand, mechanisms that Bots can utilize to achieve their goals, as well as quantitative measures of a Bot’s impact on users, depending on the properties of the Bot and the actual parameters of the system, make part of the problem more difficult. Owing to the self-organized dynamics and appearance of a network of connections, we assume that the particular actions of a Bot may propagate on that network and affect the course of these nonlinear processes, thus possibly altering the global state of the system. However, a complete understanding of the mechanisms calls for appropriate theoretical modeling and analysis.

In this work, we use agent-based modeling to study self-organization in the dynamics of chats that Bots may utilize to shape the collective mood of users. We propose a model in which the emotional agents [13, 14], representing users, interact among each other and with a Bot of specified characteristics. The Bots that we introduce have several features which make them qualitatively similar with other agents. Specifically, Bots are inclined to direct communications, they can be picked up by agents for conversation, and they have emotional states that correspond to a commonly recognized emotion, according to Russell’s model of affects [8]. Moreover, following the universal picture of human dynamics on the web with a characteristic delay of action (interactivity time) [15]–[17], our Bots also assume a nontrivial interactivity time $\Delta t_B$ for their actions. Note that, apart from these ‘human-like’ attributes, the Bots follow some action rules which differ from ordinary agents (see details in section 2.2).

The dynamics of agent chats consists of exchanging emotional messages on a network, which itself evolves by these chats. By performing numerical simulations of the model for a specified set of control parameters which are inferred from an empirical chat system, we are able to examine the influence of an emotional Bot on a realistic chat channel. To characterize Bot’s impact, we compute several quantitative measures of collective agent behavior. Specifically, we determine persistence in the time series of emotional messages by detrended fractal analysis. Further indicators of collective dynamics are determined from the power spectral density of these time series and the avalanches of emotional messages. Then we demonstrate how these quantitative measures are changed when a Bot of given emotional function is added to the system and identify the parameters that can adjust the Bot performance. We consider Bots with positive and negative emotional impacts as well as Bots that can alternate between specified emotional states. We compare the effectiveness of these Bots by quantifying their impact on agents, and examine the nature of the collective states that they provoke among the agents.

In section 2 we describe the model and provide details of the numerical implementation and the control parameters. Results of the simulations in the absence of emotional Bots are given in section 3.1, where the quantitative measures of self-organized dynamics are computed. In section 3.2 the system is simulated in the presence of a Bot with a predefined positive/negative emotion valence as well as Bots that alternate between two emotional states. In section 3.3 we examine the robustness of the model when several key parameters are altered. Section 4 contains a brief summary of the results and conclusions.
2. Model and methods

We introduce an agent-based model in which agents stand for users with their attributes, which are important for the dynamics. One of the agents is identified as a Bot, which may have different properties, depending on its actual task. We perform numerical simulations of the model maintaining each particular message with its emotional contents, source and recipient agent, and time of creation. Then we analyze the simulated sequence of messages to extract the quantitative measures of collective agent behavior—temporal correlations and fractal properties of the time series and clustering of events (avalanches) with emotional messages. In this section, we describe the mathematical structure of the model and its numerical implementation. We also identify the control parameters of the dynamics and determine several parameters from the empirical dataset of the Ubuntu IRC channel.

In analogy to a real chat channel, Ubuntu (data studied in [4, 5]), the agents in our model interact by posting messages on the channel. Occasionally, with a probability $g$, the posted message is directed to another agent known by its unique ID. Thus, agent-to-agent interactions lead to an evolving network of agents, which are interlinked by the exchanged messages. In contrast to the bipartite network in the dynamics on blogs [18], in the IRC chats the agent-to-agent communications result in a directed monopartite network with weighted links. On this network, each agent has a specific neighborhood on which current connections reflect its activity as well as the activity of the connected neighbor agents in the preceding period. The network evolves by the addition of new agents and/or new links among existing agents. Network evolution as well as the activity of neighboring agents may affect the agent’s emotional state, i.e., its emotional arousal (degree of reactivity), $a_i(t)$, and valence (attractiveness or averseness of stimuli), $v_i(t)$. Elevated arousal may trigger an agent’s action—posting a new message that carries its current emotion. The precise dynamical rules are motivated by real chat channels and result in an appropriate mathematical structure of the model, to be described below.

Messages received within a given time window $T_0$ by agent $i$ from its neighbors on the (evolving) network give rise to the influence fields $h_a^i(t)$ and $h_v^i(t)$, which can modify an agent’s arousal and valence, respectively (see equations below). Thus, these fields are individual properties of each agent and depend on the time and actual events in the agent’s neighborhood on the network. In addition, all recent messages posted on the channel contribute to the common fields $h_a^{mf}(t)$ and $h_v^{mf}(t)$, which may affect all agents.

For the agent-based modeling of web users, several attributes of the agents, which affect their dynamics, have to be taken into account. Specifically, the minimum set of attributes [17] consists of: (i) the occurrence of circadian cycles; (ii) a characteristic delay of action to an event; (iii) agent heterogeneity in the activity profiles; (iv) an agent’s individual list of social connections. Following these lines, for modeling online chats in the presence of web Bots, we consider the following attributes of the agent:

$$A[id, type, N^i_c, g; a_i(t), v_i(t), m(t), \mathcal{L}_{in}(t), \mathcal{L}_{out}(t); \Delta t, status].$$  \hspace{1cm} (2.1)

By adding an agent to the process, we specify its individual $id$ and $type$ (Agent or Bot). In addition, to imitate actual heterogeneity of users, i.e., due to their psychology profiles which impact their activity on the channel, we provide the agent’s capacity to create a number of messages $N^i_c$ during the simulation time as a random number taken
from the empirical distribution \( P(N_c) \). We also specify the probability \( g_i \in P(g) \) for
the agent’s preference towards an identified recipient of its message, compared to writing
the message on the channel, where it can be seen by all active agents. By choosing these
two distributions from the same empirical dataset, we implicitly fix the profile of each
agent. Other approaches are considered in the literature, e.g., introducing fuzzy agents
with dynamic personalities [19].

The remaining attributes of the agent in (2.1) dynamically change with simulation
time. In our model, the dynamic variables of an agent’s emotional state, arousal \( a_i(t) \)
and valence \( v_i(t) \), fluctuate under the influence of other agents and the Bot. During the chat
process, each agent develops personal connections on the network over time. These are
represented by the lists of incoming and outgoing links \( \mathcal{L}_{in}, \mathcal{L}_{out} \), along which the agent
has sent and received messages up to time \( t \). The updated number of messages posted by
the agent \( m(t) \leq N^i_c \), as well as its lists of links and the activity status dynamically change
in the process of chatting. The delay time \( \Delta t \) is derived from the appropriate distribution
whenever it is required by the dynamic rules (see algorithm 1). As it will be evident in
the implementation of the model, the distinction between a regular agent and a Bot is
manifested in the dynamics of their emotional states, the rules of their actions, and the
parameters that control their actions.

2.1. Mathematical structure of the model

Values of the dynamically varying fields \( h^i_s(t) \), \( h^i_y(t) \), and \( h^a_{mf}(t) \) are determined
considering the emotional arousal and valence in recently posted messages, specifically the
messages posted in the time window \( (t, t - T_0) \). The parameter \( T_0 \) is decided according
to the pace of events on the channel; for instance, in the Ubuntu channel the window is
set such that approximately 10 messages are always visible, which roughly corresponds to
\( T_0 = 2 \). Denoting the message \( m \) creation time by \( t_m \), the arousal and the valence affecting
fields \( h^a_s(t) \) and \( h^a_y(t) \) of agent \( i \) are determined from all recent messages directed to \( i \), as follows:

\[
h^a_s(t) = \frac{\sum_{j \in \mathcal{L}_{in,i}} a_j^m (\theta(t_m - (t - 1)) - \theta(t_m - (t - T_0)))}{\sum_{j \in \mathcal{L}_{in,i}} (\theta(t_m - (t - 1)) - \theta(t_m - (t - T_0)))},
\]

(2.2)

where \( \theta(t) \) is Heaviside theta function, \( a_j^m \) is the arousal of the message arriving along
the link \( j \), and the summation is over the messages from the list \( \mathcal{L}_{in,i} \) of agent \( i \)'s incoming
links;

\[
h^a_y(t) = \frac{1 - 0.4r_i(t)}{1.4} \frac{N^p_i(t)}{N^p_i(t)} - \frac{1 + 0.4r_i(t)}{1.4} \frac{N^n_i(t)}{N^n_i(t)}.
\]

(2.3)

Here, \( N^p_i \) and \( N^n_i \) are the number of messages within the considered time window
which are directed to \( i \) and convey positive and negative emotion valences, respectively.
\( N_{i}^{\text{emo}}(t) = N^p_i(t) + N^n_i(t) \) and \( r_i(t) = \text{sgn}(v_i(t)) \) is the sign of the emotional valence
of agent \( i \) at time \( t \). The corresponding components of the common fields \( h^a_{mf} \) and \( h^y_{mf} \) are
computed in a similar way, but considering the list of all recent messages on the channel,
\( \mathcal{S} \), including those that are not addressed to any particular agent:

\[
h^a_{mf}(t) = \frac{\sum_{j \in \mathcal{S}} a_j^m (\theta(t_m - (t - 1)) - \theta(t_m - (t - T_0)))}{\sum_{j \in \mathcal{S}} (\theta(t_m - (t - 1)) - \theta(t_m - (t - T_0)))},
\]

(2.4)
and
\[ h_{mf}(t) = \frac{1 - 0.4r_i(t)}{1.4} \frac{N^p(t)}{N^{emo}(t)} - \frac{1 + 0.4r_i(t)}{1.4} \frac{N^n(t)}{N^{emo}(t)}. \] (2.5)

Here, \( N^p(t) \) and \( N^n(t) \) are the number of positive and negative messages appearing on the channel within the current time window while \( N^{emo}(t) = N^p(t) + N^n(t) \). The sign-dependent dynamics of the valence fields in equations (2.3) and (2.5) is motivated [2] by the nature of the valence map in equation (2.7) with positive and negative fixed points and a plausible assumption that negative fields in the environment would influence more severely an agent with positive emotion than an agent with negative emotion, and vice versa. The factor 0.4 in equations (2.3) and (2.5) is chosen to avoid an unphysical fast switching (factor 1 or 0) and contraction of phase space in the symmetrical case (0.5).

Similar to in the model of blogging dynamics [2, 13] and dialogs in online social networks [14], we assume that the individual emotional state of each agent on the chat network can be described by two nonlinear maps for the variables \( a_i(t) \) and \( v_i(t) \in [-1, 1] \), which are appropriately coupled with the environmental fields introduced above. The rationale is that the arousal is an intensive variable, which can cause an agent’s action, whereas the positive and the negative valence have different dynamics. Consequently, an attractive fixed point in the negative as well as in the positive valence region is expected. In the absence of a psychology-based mathematical model of emotion dynamics (see also [17, 20]), the maps that fulfill these formal requirements include higher-order polynomial nonlinearities, specifically:

\[ a_i(t + 1) = (1 - \gamma_a) a_i(t) + \delta(\Delta_t) \frac{h^a_i(t) + q h^a_{mf}(t)}{1 + q} (1 + d_2(a_i(t) - a_i(t)^2))(1 - a_i(t)), \] (2.6)

\[ v_i(t + 1) = (1 - \gamma_v) v_i(t) + \delta(\Delta_t) \frac{h^v_i(t) + q h^v_{mf}(t)}{1 + q} (1 + c_2(v_i(t) - v_i(t)^3))(1 - |v_i(t)|). \] (2.7)

Here, the index \( i = 1, 2, \ldots, N_a(t) \), where \( N_a(t) \) is the number of agents at time \( t \), indicates agent identity and \( t \) is the time bin, which in the simulations corresponds to one minute of real time, as explained in 2.2. The relaxation with rate \( \gamma_a = \gamma_v \) is executed systematically, whereas the nonlinear terms are added according to the rules when the agent’s interactivity time \( \Delta t \) expires. Note that the variables in equations (2.6) and (2.7) referring to the same agent are coupled indirectly through the feedback fields and the fact that high arousal implies potential activity, then updated valence and arousal are transmitted in the same message. The fields in equations (2.2)–(2.5) are properly normalized at each time step and the dynamical variables are kept in the range \( a_i \in [0, 1] \) and \( v_i \in [-1, +1] \) by the maps (2.6) and (2.7).

2.2. Numerical implementation of the agent-based model of chats

Apart from the Agent and Bot objects defined by (2.1), in the simulations we keep track of each Message as an object \( M[t_m, i, j, a_m, v_m] \) with the following attributes: creation time \( t_m \), identity of the source agent \( i \) and the target agent \( j \), and the emotional contents of the message \( a_m \) and \( v_m \).

Starting with an empty system, we first add a Bot. Then at each time step \( t \) a number \( p(t) \) of new agents are added and animated. The time series \( \{p(t)\} \) is inferred from the...
Figure 1. Parameters used in the simulations are inferred from Ubuntu channel data: (top) cumulative distributions of the number of messages per user, $P(N_c)$, and user delay times, $P(\Delta t)$, and the distribution of Bot delay times, $P_B(\Delta t)$. (Bottom) Distribution of the probability $g$ of a user-to-user message. Inset: initial part of the new arrivals time series $p(t)$ with time resolution in minutes. The total length of the time series is one year.

empirical data of Ubuntu chats as the number of new arrived users (with respect to the beginning of the dataset). Driving the agent’s dynamics by the empirical time series has two advantages [17]. First, the time resolution, which is 1 min in this case, sets the time scale of the simulation step, thus providing a possibility to compare the simulated data with the empirical data. Moreover, the empirical time series of new arrivals $\{p(t)\}$ contains circadian cycles, characteristic of human dynamics. As mentioned above, the existence of circadian cycles is one of key elements of human dynamics [21] that needs to be taken into account in modeling web users [17].

By the first appearance on the channel, each agent gets its fixed profile: its attitude to direct communications $g_i \in P(g)$ and the total number of messages $N^i_c \in P(N_c)$ that the agent can create during the simulation time $n_t$. The distribution $P(N_c)$, $P(g)$ as well as the delay time distributions are inferred from the same empirical dataset. (In this way, we capture potential hidden correlations between different parameters.) On the other hand, the agent’s delay time to an action, $\Delta t$, is dynamically driven from the distribution $P(\Delta t)$ after each completed action and is systematically updated (decreased) until the condition for action $\Delta t = 0$ is reached.

Designing Bots with ‘human-like’ characteristics, we assume that the Bot’s interactivity time is finite. It is given by a specified distribution $P_B(\Delta t)$ with a short average delay (see figure 1). In this case, we also infer the Bot’s interactivity time from the empirical data of the Ubuntu channel, where a Bot is present, but serves different purposes than in our model. Specifically, in the empirical system the Bot is not emotional, it serves predefined messages upon requests from users. We also specify the $g$ value to the Bot. In this work, we are interested in quantifying the Bot’s impact. For this reason, we set $g_B = 0$, i.e. the Bot is posting all messages to the channel. Consequently, the parameter $q$,
Table 1. Three groups of control parameters characterize the nonlinear maps, the attributes of the agents and Bots, and driving the system. The specified distributions and numerical values are used in the simulations.

| Maps          | Agents and Bot | Driving |
|---------------|----------------|---------|
| Rate $\gamma_a = \gamma_v = 0.1$ | Delay time $P(\Delta t), P_B(\Delta t)$ | Agents arrival $p(t)$ |
| Polynomial $c_2 = 0.5$ | Capacity $P(N_c)$ | Mean-field $q = 0.4$ |
| Nonlinearity $d_2 = 0.5$ | Networking $P(g)$ | -fraction $q = 0.1$ |

the fraction of common-field contribution to the arousal and valence of the agents, directly moderates the importance of the Bot’s messages. Other interesting possibilities are, for example, $g_B = 1$ (the Bot always writes directly to an agent), or $g_B \in P_B(g)$, where $P_B(g)$ can be a specified mathematical or empirical distribution.

In the simulations, we distinguish an agent’s status (as active or passive) according to its current participation in the dynamics. The agents arrive with randomly chosen emotional states and their arousal and valence between the actions constantly decay with the rates $\gamma_a, \gamma_v$. The list of active agents contains the agents who were acting or are addressed in the current time window; thus, they are likely recipients of messages from other currently active agents. The Bot and newly arrived agents are automatically placed on the active list. The interactivity time of each agent in the system is updated (decreased by one) in each time step. The state of the agent $i$ is updated when its interactivity time since previous action expires, $\Delta t_i = 0$. By computing the agent’s individual fields $h_a^i(t), h_v^i(t)$ and the corresponding common fields $h_{mf}^a(t), h_{mf}^v(t)$ at the current time $t$, the emotional state (valence and arousal) for each agent is updated and the agent is then placed on the active agents list with a probability proportional to its current arousal $a_i(t)$. Each active agent creates a new message which, with probability $g_i$, is directed to another agent from the active agents list; otherwise it is posted on the channel. (Note that picking an active agent at random is motivated by the fact that, in the online chats, no prior association among users exists. Technically, our algorithm allows other rules such as, for example, motivated by social dynamics [1, 22], which are not being considered in this work.) The agents from the active list obtain a new delay time $\Delta t_i \in P(\Delta t)$. The time step is completed with a decrease of their current delay times by one for all agents, and creating a new active agents list. The program flow, implemented in C++ code, is given in algorithm 1.

As mentioned above, the model rules are motivated by analysis of a real chat system [4, 5]. Consequently, several control parameters which are used in the simulations are identified and computed from the empirical data (see table 1 and figure 1). In addition to these empirically determined quantities, a few other parameters of the model cannot be estimated from the available empirical data; in particular, the parameters of the nonlinear maps (2.6) and (2.7), relaxation rates and the fraction $q$ of the common-field contribution. In principle, the parameters of arousal and valence dynamics can be measured in targeted psychology experiments; however, they are not currently available in the literature. In the simulations, we fixed these parameters in the nonlinear maps such that the entire phase space can be covered when the influence fields vary within their limits. We perform simulations for different values of the parameter $q$. A list of all the parameters and their

doi:10.1088/1742-5468/2013/10/P10014
Algorithm 1 Program flow: chats of emotional agents and Bot.

1: INPUT: Parameter $n_t$, $T_0$, $q$, $a^{\text{bot}}$, $v^{\text{bot}}$; Distributions $P_B(\Delta t)$, $P(\Delta t)$, $P(N_c)$, $P(g)$; Time series $\{p(t)\}$; Start list of active agents;
2: Add Bot, chose $g_B$ and set $\Delta t_B = 0$; change status active = true;
3: for all $1 \leq t \leq n_t$ do
4: for all $1 \leq i \leq p(t)$ do
5: Add agent $i$; chose $a_i \in [0,1]$ and $v_i \in [-1,1]$; chose $g_i \in P(g)$ and $N^i_c \in P(N_c)$; set $\Delta t = 0$; $N_a +=$; add $i$ to a list of active agents;
6: end for
7: for all $i \leq N_a$ do
8: Calculate fields $h_i^v(t)$, $h_i^a(t)$ and $h_i^{a_{mf}}(t)$, $h_i^{v_{mf}}(t)$;
9: if agents delay time $\Delta t = 0$ then
10: Update agent states $v_i(t)$ and $a_i(t)$;
11: with probability $\propto a_i(t)$ change status active = true;
12: end if
13: end for
14: for all active agent $i$ do
15: if $i$ is Bot then
16: create a message $k$; transfer $v^{\text{bot}} - > v^m_k$ and $a^{\text{bot}}(t) - > a^m_k$;
17: else
18: create a message $k$; transfer $v_i(t) - > v^m_k$ and $a_i(t) - > a^m_k$; update $m_i(t) + +$;
19: end if
20: if $\text{rnd.next}() < g$ then
21: pick an agent $j \in \text{active agents list}$; message $k$ is referring to agent $j$;
22: else
23: write message to the channel;
24: end if
25: end for
26: clear and update active agents list (referring preceding $T_0$ steps);
27: for all $1 \leq i \leq N_a$ do
28: change status active = false;
29: $\Delta t -=$
30: if $\Delta t < 0$ OR $i \in \text{active agents list}$ then
31: chose new $\Delta t$ from $P(\Delta t)$ for agent and from $P_B(\Delta t)$ for a Bot
32: end if
33: end for
34: end for
35: END

values used in the simulations is given in table 1. As described above, the dynamic rules and parameters of the model differentiate between ‘human-like’ Bots and ordinary agents in several details. Specifically, a Bot’s delay times are given by a different distribution in which, generally, shorter delays are more probable than in the case of agents, cf figure 1; its emotional state variables are not subject to the dynamic equations (2.6) and (2.7), but are either fixed values or given by another rule, depending on the task that the Bot
Figure 2. Simulated time series of messages in the absence of a Bot: (a) all messages $N_{\text{all}}(t)$ and trend signal with daily cycles and (b) charge of emotional messages $Q(t) = N^+(t) - N^-(t)$ are plotted against time $t$. The length of the simulated time series is limited to 525,600 steps. Here, only a small part is shown for clarity.

performs. Furthermore, like in the real system, the Bot is constantly presented on the channel and its capacity (number of posted messages) is not limited.

3. Results and discussion

Our simulated data are stored as a sequence of events, which describe in detail each message created by the agents and the Bot: creation time, sender agent, recipient agent or channel, and arousal and valence that the message carries. To analyze these data, we first construct several time series and agent’s associations as a network. In particular, by respecting specific attributes of these messages, we consider:

- $N^\pm(t)$: time series of the number of messages at time step $t$ carrying a positive/negative emotion valence;
- $N_{\text{all}}$: time series of the number of all messages at time $t$, irrespective their emotion;
- $Q(t)$: time series of the charge of emotional messages, $Q(t) = N^+(t) - N^-(t)$;
- $C_{ij}(T_W)^\pm$: network connections among agents that emerge within a specified time window $T_W$; links carrying positive emotion messages can be differentiated from the negative message links;

For illustration, in figure 2(a) we show a part of the time series $N_{\text{all}}(t)$ for the first 5000 steps, corresponding roughly to three and half days. Notably, the time series exhibits daily cycles of agent activity, which is induced by the corresponding cycles in the driving signal $p(t)$ (see inset to figure 1). The corresponding time series of the number of positive/negative messages $N^\pm(t)$ are the respective subsets of $N_{\text{all}}(t)$. Consequently, $N^\pm(t)$ also exhibit daily cycles; however, their difference does not have such a periodicity. The excess of the messages of one or the other polarity is defined as the ‘charge’ of emotional messages [2, 23]. Simulated in the absence of Bots, the charges of agent messages appear to fluctuate around zero, as shown in figure 2(b). In contrast to the original time series, $N^+(t)$ and $N^-(t)$, the time series of charge does not exhibit any prominent cycle. These conclusions are supported by the detrended time series analysis in sections 3.1 and 3.2.
Figure 3. Network that emerges after 2000 steps with the direct exchange of emotional messages between agents in the presence of joyBot. Links with mostly positive (red) and negative (black) emotion messages are indicated.

We build the emergent network of chats from the simulated list of messages, by considering directed agent-to-agent, agent-to-Bot and Bot-to-agent communications and disregarding messages that are posted on the channel without a specified recipient. The network that emerges after the first 2000 steps in the presence of a positive emotion Bot contains approximately 1000 agents who were involved in personal communications. By way of illustration, a part of that network is shown in figure 3. The red color of links indicates that predominantly positive messages are exchanged along them while the black color stands for excess negative emotion messages. As one can see, a majority of links among the agents even away from the Bot is positive. Compared with the emotionally balanced messages in the absence of Bots (see, for instance, charge in figure 2(b)), suggests that a predominantly positive emotion spreads over the network when the Bot is active. The chat network belongs to the class of hierarchically organized structures, similar to the ones inferred from the empirical chat data [4, 5]. A detailed analysis of such networks, their multi-relational structure, dependence on the parameters of the model and Bot’s activity, as well as comparisons with real chat systems are studied in a separate paper [24].

3.1. Self-organized behavior of emotional agents

In analogy with the empirical data of Ubuntu chats [4, 5], the time series of chats simulated by our agent-based model exhibit characteristics of fractal stochastic point processes. This implies that different quantitative measures follow scaling behavior within extended time windows [25]. In particular, the power spectral densities, shown in figure 4(a) for different simulated time series, obey a power-law decay $S(\nu) \sim \nu^{-\phi}$ with the scaling exponents close to the flicker noise. We find $\phi^+ = 1.06 \pm 0.06$ for positive and $\phi^- = 1.19 \pm 0.06$ for negative emotion message time series. While, for the signal containing all messages, irrespective of
their emotional polarity, we obtain $\phi = 0.84 \pm 0.06$, which is compatible with the fractal Gaussian-noise driven Poisson process [25].

Furthermore, we analyze persistence of the fluctuations in the integrated time series at varying time intervals $n$, measured by the Hurst exponent. Note that these time series are stationary but obey daily cycles (and potentially higher cycles) which are induced by the fluctuations in the empirical driving signal $\{p(t)\}$. The occurrence of cycles in the time series tends to increase the Hurst exponent [3, 26]. To remove the cycles, we adapted detrended fractal analysis with polynomial interpolation and overlapping subintervals, which is described in detail in [3]. An example of a local trend signal with daily cycles of the time series of all messages is shown in figure 2(a). Then we compute Hurst exponent of the detrended time series. The procedure is as follows: for a time series $h(k)$, $k = 1, 2, \ldots, K$, $K = 16384$, the profile $Y(i) = \sum_{k=1}^{\mu} (h(k) - \bar{h})$ is computed and divided into $N_n$ segments of length $n$; then the scaling of the fluctuations against segment length is determined, i.e.,

$$F_2(n) = \left[ \frac{1}{N_n} \sum_{\mu=1}^{N_n} F^2(\mu, n) \right]^{1/2} \sim n^H.$$  

(3.1)

Here, the fluctuation at the $\mu$th segment $F^2(\mu, n) = (1/n)\sum_{i=1}^{n} [Y((\mu - 1)n + 1) - y_\mu(i)]^2$ is the standard deviation from the local trend $y_\mu(i)$. The results for several time series (indicated in the legend) are shown in figure 4(b). Note that the obtained Hurst exponents for all these time series are in the range $H \in (0.78, 1.04)$, within numerical error bars. This indicates the occurrence of strongly persistent fluctuations in the scaling region, which is indicated by the straight line at each curve.

The observed fractality in the time series of chats suggests that clustering of events over larger time scales occurs in the process. The self-organized nature of the dynamics is further tested by analysis of the avalanches of temporally connected events [27]–[31]. For the purpose of this work, we consider avalanches of emotional messages. To determine avalanches from the time series of events, we apply the methodology which is used in the analysis of Barkhausen noise signals [32, 33] and avalanches of comments in the datasets from Diggs [2]. In a time signal, the avalanche comprises the number of events between
Figure 5. Distributions of the size of avalanches with negative and positive emotion messages of agents in the absence of Bots (a), and when joyBot, favoring positive emotions, is present (b).

two consecutive points where the signal meets the base line (here zero level). Then the distance between these two points determines the duration of the avalanche, $T$, while the amount of messages between these two points is the avalanche size, $s$.

The distributions of avalanche sizes determined from the signals of messages carrying positive and negative emotional valance are shown in figure 5(a). Noticeably, the distributions of sizes of the emotional avalanches (and likewise the distributions of durations, not shown) obey a power-law dependence before a cut-off $s_0$, as expected for self-organized systems of finite size [30, 32]. We find different exponents $\tau_s^-$ = 1.83 ± 0.04 and $\tau_s^+$ = 1.34 ± 0.03 for the avalanches carrying negative and positive emotions, respectively. The duration exponents $\tau_T^\pm$ are in a similar range; the avalanche shape exponents $\gamma_{ST}^\pm = ((\tau_T^\pm - 1)/(\tau_s^\pm - 1))$ are found as follows: $\gamma_{ST}^+$ = 1.47 and $\gamma_{ST}^-$ = 1.23. The larger exponent (broader shape) of positive avalanches suggests that, in propagating, positive emotion branching more often occurs than when negative emotion is transmitted between agents. The observed asymmetry between the cut-off sizes of positive and negative avalanches, emerging through the self-organized dynamics, may have an origin at the microscopic level. Namely, the positive and negative fixed points of the nonlinear maps equation (2.7) are not equally accessible. This feature of the model captures the fact that, in empirical systems, a majority of known positive emotions have larger arousal and thus better chances to trigger an action than typical negative emotions. In section 3.2, we examine how these self-organized mechanisms of chats are altered when mood-modifying Bots are available.

3.2. Collective effects of mood-modifying Bots

To activate a Bot in the system, we first define the Bot’s role as a possible mood modifier. In this work, we are interested in understanding the potential of emotional Bots to promote a collective reaction among interacting agents with dominant positive or negative emotion, and in quantifying the effectiveness of Bots. Therefore, we first consider two Bots with fixed

\begin{align}
P(s) = B s^{-\tau_s} \exp(-(s/s_0)),
\end{align}

as expected for self-organized systems of finite size [30, 32]. We find different exponents $\tau_s^-$ = 1.83 ± 0.04 and $\tau_s^+$ = 1.34 ± 0.03 for the avalanches carrying negative and positive emotions, respectively. The duration exponents $\tau_T^\pm$ are in a similar range; the avalanche shape exponents $\gamma_{ST}^\pm = ((\tau_T^\pm - 1)/(\tau_s^\pm - 1))$ are found as follows: $\gamma_{ST}^+$ = 1.47 and $\gamma_{ST}^-$ = 1.23. The larger exponent (broader shape) of positive avalanches suggests that, in propagating, positive emotion branching more often occurs than when negative emotion is transmitted between agents. The observed asymmetry between the cut-off sizes of positive and negative avalanches, emerging through the self-organized dynamics, may have an origin at the microscopic level. Namely, the positive and negative fixed points of the nonlinear maps equation (2.7) are not equally accessible. This feature of the model captures the fact that, in empirical systems, a majority of known positive emotions have larger arousal and thus better chances to trigger an action than typical negative emotions. In section 3.2, we examine how these self-organized mechanisms of chats are altered when mood-modifying Bots are available.

3.2. Collective effects of mood-modifying Bots

To activate a Bot in the system, we first define the Bot’s role as a possible mood modifier. In this work, we are interested in understanding the potential of emotional Bots to promote a collective reaction among interacting agents with dominant positive or negative emotion, and in quantifying the effectiveness of Bots. Therefore, we first consider two Bots with fixed
emotion, corresponding to the common emotions known as ‘joy’ and ‘misery’, respectively. According to Russell’s two-dimensional circumplex model [8], these are two emotions with opposite valence and similar arousal. In addition, we define a Bot that can dynamically alternate between these two emotions. Specifically, we simulate the system of agents in the presence of the following Bots:

- $\text{joyBot-q04}$ is constantly active with the emotion ‘joy’ ($a^* = 0.5, v^* = +1$);
- $\text{misBot-q04}$ is constantly active with the opposite emotion ‘misery’ ($a^* = 0.5, v^* = -1$);
- $\text{altBot-q04}$ and $\text{altBot-q01}$ alternate between ($a^* = 0.5, v^* = -1$) and ($a^* = 0.5, v^* = +1$) every three days (4320 simulations steps); the parameter values $q = 0.4$ and $0.1$ indicate that the effectiveness of the Bot’s messages on the channel is modified.

Performing simulations of agent activity in the presence of emotional Bots, we determine the time series of positive and negative emotional messages at the level of the entire system. The starts of these time series are displayed in figure 6; they indicate the prevalence of positive emotion messages when $\text{joyBot}$ is active, and similarly, an excess of negative valence emotions in the case of $\text{misBot}$. For illustration, in the bottom panel we display the time series in the case without Bots. These findings are in agreement with the structure of links in the emergent network in figure 3, where one can see that a majority of links carry positive emotion (indicated by red color) between the agents, including those that are not in direct contact with $\text{joyBot-q04}$.

The fractal structure of these time series is also changed, compared to the emotional series in the absence of any Bots. Selecting out all messages posted by Bots, we evaluate emotional time series from the remaining data of agent messages. The results for the power spectral densities $S(\nu)$ versus $\nu$ and fluctuations $F_2(n)$ versus $n$ of agent messages with positive and negative valence in the presence of the two emotional Bots are

![Figure 6](image-url)
shown in figure 7. Specifically, when the negative Bot misBot-q04 is active, the scaling exponents for negative and positive emotion messages of agents are found as $\phi^{--} = 0.66(7)$, $H^{--} = 0.721(3)$ and $\phi^{++} = 0.89(6)$, $H^{++} = 0.952(5)$, respectively. (Here, the first index denotes the Bot’s emotional polarity while the second index stands for the polarity of agent messages.) Similarly, when the positive Bot joyBot-q04 is present the fluctuations of the positive and negative emotion messages differ, leading to the exponents $\phi^{++} = 0.68(8)$, $H^{++} = 0.799(3)$, and $\phi^{+-} = 0.71(5)$, $H^{+-} = 0.741(3)$. The corresponding ranges where the scaling holds are indicated by the straight line along each curve in figure 7. Note that a typical cycle $n = 100$, which is observed in the detrended analysis of these time series, was removed, resulting in the plateau for $n > 100$. The slopes of the fluctuation curves increase in the range $n \in [10, 100]$, which can be related to the impact of Bots. Apart from the persistence that applies to all cases, these results, subject to the finite size $K = 16384$ of the time series, suggest that differences due to the activity of the emotional Bots can be expressed quantitatively. It should be noted that, in contrast with well studied stock market time series, where intrinsic finite size effects are combined with a trend, see, for example, [34], our time series are stationary and exhibit a cyclic trend. The Hurst exponents are computed from the stationary detrended time series within a rather short scaling region, which remains after removal of the $n = 100$ cycle.

Further effects of emotional Bots are found in the distribution of avalanche sizes and durations. As can be expected, the cut-off sizes increase for avalanches of emotional messages matching a Bot’s polarity. In figure 5(b), we show the results for the size distribution of positive and negative emotion avalanches in the presence of joyBot-q04. The cut-off size of positive avalanches increases, while the size of negative avalanches decreases, compared with the situation when the Bot is absent, cf figure 5(a). More importantly, the distribution of the enhanced positive avalanches manifests a different mathematical curve. To be precise, the distribution can be properly approximated by the $q^*$-exponential expression

$$P(s) = C(1 - (1 - q^*)s/s_0)^{1/q^*},$$

(3.3)

when the Bot is active, compared with the Levy-type distribution with cut-off in equation (3.2), which is characteristic for the avalanches in the absence of Bots. In contrast, the frequency of avalanches of negative messages is drastically reduced and...
Figure 8. Effects of the alternating-mood Bots for two values of the parameter $q = 0.1$ and 0.4: charge of the emotional messages of agents (top) and integrated charge (bottom panel) plotted against time. Insets: power spectral density (top) and fluctuations (bottom). In the top inset, data smoothed by logarithmic binning are shown by empty symbols.

obey exponential decay. Qualitatively similar effects are observed, with the interchanged signs of emotions, in the presence of misBot-q04.

Theoretically, a $q^\star$-exponential distribution [35] of the type (3.3) is anticipated in dynamical systems with reduced phase space [36], e.g., accelerating random walk [36], superdiffusion on networks [37, 38] and others. A similar type of distribution has been derived for avalanches in non-interacting dynamical systems exposed to coherent noise [39]. Although the presence of Bots with a constant emotion can be considered as a coherent input directed to a large number of agents (but not all of them), it should be stressed that the agents in our model are interacting. The interactions among agents have profound effects, as demonstrated above. Specifically, the system developed temporal correlations and fractal time series, which is not the case with non-interacting agents in [39]. In the following, we will consider Bots with time-dependent inputs, altBot-q04 and altBot-q01. We will also show that they produce a distinctive impact on the avalanches, in contradiction to the constant emotion Bots.

Bots with time-dependent inputs are suitable to examine how reliable and effective is the impact of Bots on the overall emotional state of agents. Here, we analyze the simulation data for the case of periodically alternating Bots, altRobot-q04 and altRobot-q01. As above, by selecting out the messages posted by the Bot, we consider the remaining data which comprise the agent activity when the Bot was present. In figure 8 (top), we show the charge of the emotional messages by agents in the presence of an alternating Bot when the parameter $q$ is varied as

doi:10.1088/1742-5468/2013/10/P10014 16
$q = 0.4$, corresponding to a strong Bot influence (pink line) and $q = 0.1$, corresponding to decreased influence of Bot messages (cyan). Note that the time series of charge induced by the alternating Bot also shows long-range correlations. For instance, by computing the power spectrum and fluctuations of the charge time series in the case of $\text{altRobot-q01}$, we find the following scaling exponents: $\phi^Q = 0.66(8)$ and $H^Q = 0.791(2)$. The results are shown in the insets to figure 8.

In order to demonstrate how quickly the excess positive/negative charge is built in the agents’ emotional messages, we introduce the normalized charge defined as

$$Q_n(t) = \frac{N_+(t) - N_-(t)}{N_+(t) + N_-(t)}.$$  \hspace{1cm} (3.4)

Then, the integrated normalized charge signal $iQ_n(t) = \sum_{t'=1}^{t} Q_n(t')$ increases/decreases with time, with a rate which is given by the slope of the curve $iQ_n(t)$. In the bottom panel of figure 8, $iQ_n(t)$ is plotted against time $t$ for the four Bots studied in this work. As the figure 8 shows, when $\text{joyBot-q04}$ is present, the excess positive charge is building quite efficiently. Likewise, the excess negative charge builds when $\text{misBot-q04}$ is active. Comparison of the slopes of these two curves, $+0.808$ and $-0.714$, indicates that the positive Bot is slightly more effective than the negative Bot. Note that all other parameters of the system as well as the sequence of random numbers are the same. When the Bot is alternating, starting from the negative episode, the induced total charge of agents’ emotional messages also oscillates with the same period. The respective sections of the $iQ_n(t)$ curve have the same slopes as in the case with negative/positive Bots, although the corresponding slopes are smaller, resulting in a shallow curve in the case $q = 0.1$. This indicates that the alternating Bot for $q = 0.1$ is less effective, compared with the Bot for $q = 0.4$. Owing to slight asymmetry of the charge signal, the overall curve shifts slowly towards positive charge.

Further quantitative measures of the effectiveness of alternating Bots can be inferred from the analysis of persistence of the charge fluctuations and avalanches of emotional messages. In the inset to figure 8 (bottom panel), a larger Hurst exponent $H$ is found for the fluctuations of charge time series when the Bot’s effects are stronger ($q = 0.4$) as compared with the case when the Bot’s messages are not as strongly recognized by the agents ($q = 0.1$). In the latter case, we find the Hurst exponent $H = 0.791 \pm 0.002$ in the time window $n \in [4:1000]$, while in the first $H = 0.992 \pm 0.004$ is found and applies in the area $n \in [20:1000]$ below the Bot-induced periodicity ($n = 4320$). The activity of the alternating-mood Bots tends to enhance long-range correlations in the system. Apart from the persistence of the charge fluctuations this tendency can be also seen in the altered nature of avalanches. In figure 9(a), the distributions of avalanche sizes are induced by the Bot of the same polarity: positive emotion avalanches induced by the behavior of $\text{joyBot-q04}$ and negative emotion avalanches in the presence of $\text{misBot-q04}$ with the same $q$ parameter. Generally, slightly larger positive avalanches can be observed in the presence of the positive Bot than negative emotion avalanches when the negative Bot is available.

The presence of alternating Bots enhances fluctuations in the agent’s emotions, as already mentioned. In figure 9(b) we show that the structure of emotional avalanches is also altered, compared with the fixed-emotion Bots. Power-law distributions with the scaling exponent $\tau_s = 1.5$ are found both for positive and negative emotion avalanches in
Figure 9. Comparison of the distributions of sizes of the emotional avalanche of agent messages in the presence of different emotional Bots: (a) fixed positive and negative emotion Bots with the same parameter $q = 0.4$, and (b) alternating Bots with varied parameter $q = 0.4$ and 0.1.

Apart from the parameter $q$, which measures how a Bot’s messages are taken into account in the common influence fields, a Bot’s activity can be tuned by varying its delay time $\Delta t_B^\text{B}$. In the present work, the characteristic delay of Bots $\langle \Delta t_B^\text{B} \rangle \sim 10$, cf distribution $P_B^\text{B}(\Delta t)$ in figure 1. According to the dynamic rules, the impact of a Bot generally depends on the activity of the agents. Having the simulated data, we can estimate a Bot’s impact $B_I$ from the number of a Bot’s messages $B_a(t)$ until time $t$ as follows:

$$B_a(t) = \frac{1}{\langle N_{\text{active}} \rangle + 1} \frac{t}{\langle \Delta t_B^\text{B} \rangle}; \quad B_I = \left[ \frac{B_a(t)}{t} \right] q$$  \hspace{1cm} (3.5)

where the average number of active agents $\langle N_{\text{active}} \rangle$ affects the likelihood that the Bot is picked up for discussion. Conversely, increased activity of a Bot may induce a larger number of active agents. In the simulated data with two alternating Bots, we have $\langle N_{\text{active}} \rangle = 2.478$ and 1.441, corresponding to $q = 0.4$ and 0.1. Thus, the respective Bot’s impacts per time step are estimated as $B_I = 0.012$ and 0.004.

3.3. Robustness of the model: simulations with altered parameters

In view of the nonlinear dynamics, apart from the parameter $q$, variations in the values of other parameters in the model may influence the process and consequently the impact of Bots on the collective behaviors of agents. As mentioned above, the set of parameters (and distributions) inferred from the same empirical data takes into account potential hidden dependences between these values of the parameters and the profiles of the users of a particular chat channel, which is important for characterizing and predicting collective emotional events on that channel.

Technically, however, the parameters of the model can be varied within a wide range away from their values related to a given empirical system. Here, we demonstrate the robustness of the self-organized chat dynamics in our model when three independently varied parameters—$T_0$, $N_c$ and $\Delta t$—are selected far away from their empirical values ($T_0 = 2$, $N_c \in P(N_c)$, $\Delta t \in P(\Delta t)$). Specifically, fixing the joyBot and keeping other
parameters unchanged, as above, we simulate three situations (the respective abbreviation appears in the related figures) where:

- **no N** : *all agents are equal* and can post an unlimited number of messages $N_e = \infty$; this is in contrast to the empirical heterogeneity given by the power-law distribution $P(N_e)$ in figure 1;
- **$T_0 = 1000$**: *very wide exposure window*, in contrast to the empirical $T_0 = 2$, refers to a large number of messages on the channel and agents who posted them, thus enlarging the ‘active agents list’ from which the agents and the Bot are picked up for communication;
- **$d\Delta t$**: *much shorter delay times* $\Delta t \in P(\Delta t) \sim (\Delta t)^{-2.4}$, which increases the number of actions of each agent, in contrast to the empirical distribution, which decays with power 1.4 at large times;

For the purpose of this work, we compute the fractal properties of the time series of all messages and positive emotion avalanches, which are most interesting in view of the presence of a positive Bot. The results are summarized in figures 10, 11(a) and (b). For comparison, the corresponding curve in each panel (shown in black) refers to the set of empirical parameters.

The activity of agents increases (cf figure 10) in all three cases; the number of messages fluctuates around an average value (all three cases are in the range $\langle N^{\text{all}} \rangle = 10.5 \pm 0.3$) which is much larger compared with the case with empirical parameters $\langle N^{\text{all}} \rangle = 3.49$. However, apart from the increased activity, each of the three mechanisms—reducing delay times, expanding the active agents list, and removing heterogeneity of agents—has different effects on the self-organized process. These effects are quantified by the fractal analysis of time series and avalanches of positive emotion messages shown in figure 11. By performing *detrended fractal time series analysis*, as above, we compute the fluctuations around the local trend of each respective time series. The local trend with cycles, determined from the blue line (time series obtained in the case of reduced delays), is illustrated by the thick line in the lower panel of figure 10.
Our analysis suggests that in the case when the heterogeneity among agents is removed (‘no \( N_c \)’ case), the system enhances self-organization. The computed values of the Hurst exponent from the detrended time series are slightly increased (within numerical error bars): \( H = 0.979 \) for all messages and \( H^+ = 0.969 \) and \( H^- = 0.804 \) for positive and negative valence messages, respectively. The respective scaling regions are indicated by the straight lines in figure 11(a). Similarly, the power spectrum exponent (not shown) is increased \( \phi = 0.96 \), compared with \( \phi = 0.84 \) in the case with empirical parameters. Also, compatible with the large activity of agents, the distribution of avalanche sizes exhibits a smaller slope, fitted by the expression in equation (3.3) with \( q^* = 1.83 \).

In the other two mechanisms, where the enhanced agent activity is due to either reduced delay times or an enlarged active agents list, we observe greater randomness than in the reference system with the empirical parameters. Specifically, a strong local trend with the \( n = 100 \) cycle is observed in both cases (the curves are shown in the middle part of figure 11(a)). The detrended time series, which is obtained after removing the cycle, has a reduced scaling region and a small Hurst exponent \( H = 0.579 \). The Hurst exponent of the trend is also computed \( H^{\text{tr}} = 1.57 \). Despite their similarity in the values of the Hurst exponent and a short scaling region, the two mechanisms have diverse effects on avalanches and different patterns of communications with the Bot. In particular, the reduced delay times lead to a distribution of avalanches which is similar to the one in the original system (\( q^* = 1.47 \)), but with a larger cut-off \( s_0 = 18 \) (top line in figure 11(b)). However, when \( T_0 = 1000 \), the enlarged active agents list increases communications among agents on the list, which often leads to large avalanches and thus a smaller slope, yielding \( q^* = 1.90 \). In this case, due to a large number of agents on the list, the Bot is picked rarely for communication. (Nevertheless, the Bot is active, posting messages to the channel whenever its delay time \( \Delta t_B = 0 \).) In figure 10, in the top panel we show the time series of valence of the messages directed to the Bot that are selected from the simulated list of messages. It is interesting to note the different pattern of the valence fluctuations in the no \( N_c \) case, compared with the \( d\Delta t \) case, and that the fluctuations occur about different positive values (cf red and blue line in figure 10 top).
4. Conclusion

We have introduced an agent-based model of online chats in the presence of emotional Bots. The properties of the agents and the model rules are motivated by user dynamics observed [4, 5] in the analysis of empirical data in the Ubuntu IRC channel. Several control parameters of the model are inferred by analysis of the same empirical data, and the system is driven by the empirical time series—arrival of new users (agents).

First, by shutting down the Bots, we have analyzed the underlying stochastic process of emotional interactions among the agents. Systematic analysis of the simulated time series of agent activity in the absence of Bots reveals the self-organized nature of the dynamics. Several quantitative measures that we determine imply fractal Gaussian-noise driven processes. The persistent fluctuations, correlations in the time series and power-law avalanches carrying positive and negative emotion messages are determined as quantitative characteristics of the collective behaviors of agents. The observed temporal correlations, as well as the emergence of a network of agents, share striking similarity to the empirical system [4, 5]. Moreover, the persistence and clustering (emotional avalanches) can be seen as a manifestation of a more general principle at work in online social processes, demonstrated in [1] within a concept of positive (good) and negative (bad) conduct studied in online games.

By animating emotional Bots with ‘human-like’ characteristics, we have shown that the character of the underlying fractal process is altered, enabling a Bot’s impact on the collective emotional behaviors of agents. In particular, we have demonstrated that Bots with a fixed emotional state (the opposite emotions ‘joy’ and ‘misery’ are analyzed), interacting with a certain number of agents, induce a dominant emotional valence among the agents in the whole system. A detailed study of the persistence, correlations and clustering (avalanche) of emotional messages of agents, suggests that a Bot’s activity induces changes in the quantitative measures of the process and a reduction of the phase space. Based on the self-organized nature of the process, these mechanisms guarantee reliable effects of a Bot’s activity. Quantitative measures of a Bot’s impact depend on several parameters of the Bot and the interacting agents. For the set of empirical parameters used in our simulations, we find that, in general, processes building positive emotional states are more effective than those with a negative collective response.

Moreover, our simulations revealed that the presence of Bots which alternate between positive and negative moods enhances fluctuations and further changes temporal correlations in the emotional messages at the level of the whole system. When the mood-alternating Bot is extremely effective, as in the case of altBot-q04, the fractal characteristics of the process approach those of flicker noise and avalanches resembling self-organized critical behavior. These theoretical aspects, as well as the design of Bots with different functions, are left for future work.

Our primary intention in this work was to demonstrate how emotional Bots can affect the global emotional state of agents when the parameters are kept at their ‘native’ values inferred from the empirical system. In the model, the parameters could be modified or deduced from other empirical data. We have confirmed the robustness of these processes by simulations in which three key parameters are independently changed far away from their empirical values. The qualitative features of the self-organized dynamics, i.e., persistent
fluctuations and avalanching of emotional messages, as well as the impact of the emotional Bot, continue to exist, although with modified quantitative measures.

Acknowledgments

We are grateful for support from program P1-0044 of the Research Agency of the Republic of Slovenia and from the European Community’s program FP7-ICT-2008-3 under grant no. 231323. We would also like to thank V Gligorijević for useful comments.

References

[1] Thurner S, Szell M and Sinatra R, Emergence of good conduct, scaling and Zipf laws in human behavioral sequences in online world, 2012 PLoS One 7 e29796
[2] Mitrović M, Paltoglou G and Tadić B, Quantitative analysis of bloggers’ collective behavior powered by emotions, 2011 J. Stat. Mech. P02005
[3] Šuvakov M, Mitrović M, Gligorijević V and Tadić B, How the online social networks are used: dialogues-based structure of MySpace, 2012 J. R. Soc. Interface 10 20120819
[4] Gligorijević V, Skowron M and Tadić B, Structure and stability of online chat networks built on emotion-carrying links, 2013 Physica A 392 538
[5] Gligorijević V, Skowron M and Tadić B, Directed networks of online chats: content-based linking and social structure, 2012 STTIS: 8th Int. Conf. on Signal Image Technology and Internet Based Systems, 2012 pp 725–30
[6] Skowron M and Paltoglou G, Affect bartender-affective cues and their application in a conversational agent, 2011 Proc. IEEE Symp. Series on Computational Intelligence pp 1–5
[7] Skowron M, Theunis M, Rank S and Bowowiec A, Effect of affective profile on communication patterns and affective expressions in interactions with a dialog system, 2011 ACII’11: Proc. 4th Int. Conf. on Affective Computing and Intelligent Interaction—Volume Part I (Berlin: Springer) pp 347–56
[8] Russell J A, A circumplex model of affect, 1980 J. Pers. Soc. Psychol. 39 1161
[9] Calvo R A and D’Mello S, Affect detection: an interdisciplinary review of models, methods, and their applications, 2010 IEEE Trans. Affect. Comput. 1 18
[10] Thelwall M, Buckley K, Paltoglou G, Cai D and Kappas A, Sentiment strength detection in short informal text, 2010 J. Am. Soc. Inf. Sci. Technol. 61 2544
[11] Paltoglou G, Thelwall M and Buckely K, Online textual communication annotated with grades of emotion strength, 2010 Proc. 3rd Int. Workshop on EMOTION (Satellite of LREC): Corpora for Research on Emotion and Affect pp 25–30
[12] Skowron M, Rank S, Theunis M and Sienkiewicz J, The good, the bad and the neutral: affective profile in dialog system-user communication, 2011 ACII’11: Proc. 4th Int. Conf. on Affective Computing and Intelligent Interaction—Volume Part I (Berlin: Springer) pp 337–46
[13] Mitrović M and Tadić B, Dynamics of bloggers’ communities: bipartite simulations from empirical data and agent-based modeling, 2012 Physica A 391 5264
[14] Šuvakov M, Garcia D, Schweitzer F and Tadić B, Agent-based simulations of emotion spreading in online social networks, 2012 arXiv:1205.6278
[15] Vázquez A, Oliveira J G, Dezső Z, Goh K-I, Kondor I and Barabási A-L, Modeling bursts and heavy tails in human dynamics, 2006 Phys. Rev. E 73 036127
[16] Mitrović M and Tadić B, Bloggers behavior and emergent communities in blog space, 2010 Eur. Phys. J. B 73 293
[17] Tadić B, Modeling behavior of web users as agents with reason and sentiment, 2013 Advances in Computational Modeling Research: Theory, Developments and Applications ed A B Kora (New York: Nova Publishing) ISBN 978-1-62618-065-9
[18] Mitrović M, Paltoglou G and Tadić B, Networks and emotion-driven user communities at popular blogs, 2010 Eur. Phys. J. B 77 597
[19] Pour Mohamad Bagher L, Kaedi M and Ghasem-Aghae N, Anger evaluation for fuzzy agents with dynamic personality, 2009 Math. Comput. Modelling Dyn. Syst. 15 535
[20] Schweitzer F and Garcia D, An agent-based model of collective emotions in online communities, 2010 Eur. Phys. J. B 77 533
doi:10.1088/1742-5468/2013/10/P10014
Agent-based model of chats with Bots

[21] Malmgren R D, Stouffer D B, Campanharo A S L O and Amaral L A, *On universality in human correspondence activity*, 2009 Science 325 1696

[22] Shalizi C R and Thomas A C, *Homophili and contagion are generally confounded in observational social networks*, 2011 Sociological Methods Res. 40 211

[23] Chmiel A, Sobkowicz P, Sienkiewicz J, Paltoglou G, Buckley K, Thelwall M and Holyst J, *Negative emotions boost user activity at BBC forum*, 2011 Physica A 390 2936

[24] Gligorijevic V, Šuvakov M and Tadić B, *Building social networks of online chats with users, agents and Bots*, 2013 Complex Networks and their Applications ed H Cherifi (Cambridge: Cambridge Scholar Publishing) at press

[25] Lowen S B and Teich M C, *Estimation and simulation of fractal stochastic point processes*, 1995 Fractals 3 183

[26] Hu J, Gao J and Wang X, *Multifractal analysis of sunspot time series: the effect of the 11-year cycle and Fourier truncation*, 2009 J. Stat. Mech. P02066

[27] Dhar D, *Self-organized critical state of sandpile automaton models*, 1990 Phys. Rev. Lett. 64 1613

[28] Jensen H J, 1998 *Self-Organized Criticality: Emergent Complex Behavior in Physical and Biological Systems* (Cambridge Lecture Notes in Physics) (Cambridge: Cambridge University Press)

[29] Corral A, *Long-term clustering, scaling, and universality in the temporal occurrence of earthquakes*, 2004 Phys. Rev. Lett. 92 108501

[30] Tadić B and Dhar D, *Emergent spatial structures in critical sandpiles*, 1997 Phys. Rev. Lett. 79 1519

[31] Tadić B, *Dynamic criticality in driven disordered systems: role of depinning and driving rate in Barkhausen noise*, 1999 Physica A 270 125

[32] Spasojević D, Bukvić S, Milošević S and Stanley G, *Barkhausen noise: elementary signals, power laws, and scaling relations*, 1996 Phys. Rev. E 54 2531

[33] Spasojević D, Janićević S and Knežević M, *Avalanche distributions in the two-dimensional nonequilibrium zero-temperature random field Ising model*, 2011 Phys. Rev. E 84 051119

[34] Allī V, Coccetti F, Petri A and Pietronero L, *Roughness and finite size effects in NYSE stock-price fluctuations*, 2007 Eur. Phys. J. B 55 135

[35] Tsallis C and Bukman D J, *Anomalous diffusion in the presence of external forces: exact time-dependent solutions and their thermostatistical basis*, 1996 Phys. Rev. E 54 R2197

[36] Hanel R and Thurner S, *When do generalized entropies apply? How phase space volume determines entropy*, 2011 Europhys. Lett. 96 50003

[37] Tadić B, Thurner S and Rodgers G J, *Traffic on complex networks: towards understanding global statistical properties from microscopic density fluctuations*, 2004 Phys. Rev. E 69 036102

[38] Tadić B and Thurner S, *Information super-diffusion on structured networks*, 2004 Physica A 332 566

[39] Sneppen K and Newman M E J, *Coherent noise, scale invariance and intermittency in large systems*, 1997 Physica D 110 209