LETTER

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# Internet comments as a barometer of public opinion

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**Abstract** – A new method is developed to estimate social influence in Internet communities that follow a specific developing news story. The technique stems from mean-field treatment of magnetic systems and provides a measure for community stability, such as the potential of a small perturbation to culminate in a phase-transition–like phenomenon. Three real cases of developing news stories from CNN news website are analyzed. Continuous dynamics of social influence together with time is observed together with a significant increase of social influence after the announcement of important information, such as the jury decision in a legal case. This work makes it possible to estimate the size of a group that can change the opinion of the entire population. We argue that Internet comments may predict the level of social response similar to a barometer that predicts the intensity of a coming storm in still calm environment.



In recent years, governments throughout the Arab world have been overthrown by uprisings that followed the self-immolation of a single person, Mohamed Bouazizi. Similarly, the Occupy Wall Street protest movement was triggered by a single call to action via a social network. Such cases raise an important question: How can an individual possessing no special reputation or authority mobilize an entire community by a single call to stand and fight, while large and professionally organized companies may remain unnoticed? Answering this question will help to estimate the appropriate timing and the required size for an initial group to evoke a large-scale social response.

A clear and strong display of personal opinions affects the decision-making processes of others. This phenomenon of social influence may be either positive or negative. Positive social influence facilitates the correlated behavior called herding [1]. Herding contributes significantly to the formation of market prices [2,3], the results of artificial market experiments [4–6], traffic flows [7], voting outcomes [8,9], and dynamics of social networks [10–12].

Acute herding phenomena, such as social revolutions or financial crises, are extremely difficult to predict, though they are evident when they occur [13]. A parameter, such as temperature in phase transitions, is required to estimate the stability of a community's opinion, *i.e.* the potential of a small perturbation to culminate in abrupt changes in opinion dynamics. Therefore, to understand the population dynamics prior to a possible transition, it is important to develop a measure of the herding at different points in time.

Internet communities are of special interest for the analysis of the herding phenomenon. Individual opinions are widely exposed in binary form of "like" and "dislike" votes ("likes" and "dislikes") over Internet news websites and via social networks. The data span any important event and expose millions of opinions [14]. Simultaneous analysis of a developing news story and the corresponding herding in relevant Internet communities may provide a unique opportunity to study the opinion dynamics in a population as it approaches a critical point and becomes unstable. To the best of our knowledge, the definition and evaluation of the temporal dynamics of the herding phenomenon in Internet communities remains a challenge.

In this paper, we measure the social influence at different points in time in Internet communities that followed any of the following three news stories reported on the CNN website: the Zimmerman trial, Iran Nuclear Negotiations, and the US Government shutdown of 2013. We show continuous herding dynamics in all three cases and significant amplification of social influence near the verdict

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announcement in the Zimmerman case. The method we propose allows for the quantitative estimation of a community response to the injection of a group of non-responsive individuals with predefined opinion. This quantitative analysis is possible due to our novel approach to herding as the conditional probabilities to agree or disagree with other people's opinions.

To estimate social susceptibility, we use a specific type of Internet news discussion. Some Internet news websites provide a commentary section where readers can comment and vote (*i.e.*, like or dislike) other readers' comments (see fig. 1). A reader can usually vote for any number of comments, with the restriction of one vote per comment. These data constitute a natural large-scale social experiment where the population responds to some external signal (*i.e.*, a comment). A comment, however, is not completely external, but rather created by a community member who responds to the comments of other community members. Consequently, statistics of Internet comments and responses can be used as a measure for mean-field opinion dynamics of the corresponding community.

Consider a large population of $N$ individuals who are debating on a subject $S$ and continuously voting in favor of $S$ (up $\uparrow$) or against it (down $\downarrow$). The debate process implies that individuals may change their vote in time. In our model, the interaction between individual $i$ and any other randomly selected individual $j$ is expressed by the fact that the probability per contact of individual $i$ to vote down ($P_\downarrow^{ij}$) depends on the vote of individual $j$. This conditional probability is given by

$$P_\downarrow^{ij} = \begin{cases} \alpha_{ij}, & \text{if } s_j = 1 \\ \beta_{ij}, & \text{if } s_j = 0 \end{cases} = \alpha_{ij} s_j + \beta_{ij}(1 - s_j), \qquad (1)$$

where $s_j$ is the vote of individual $j$ ($s_j = 1$ for up vote and $s_j = 0$ for down vote) and parameter $\alpha_{ij}$ ($\beta_{ij}$) is the probability per contact of individual $i$ voting down given individual $j$ is voting up (down), respectively, regardless of the vote of individual $i$ prior to the interaction with individual $j$.

Probabilities $\alpha$ and $\beta$ (1) of an individual to vote down $\downarrow$ are conditional with respect to the votes of others (see (1)). For the rest of this work we assume the mean-field approximation. This approximation makes the average vote of a single individual (such as an internet comment) and the average vote of a near or global environment (such as responses of others to a comment) indistinguishable.

Consider a population composed of identical individuals $(\alpha_{ij}, \beta_{ij}) = (\alpha, \beta)$ at steady state. If the number of contacts per individual is $N-1$, then following (1) the probability of an individual to vote down is

$$P_\downarrow \equiv P_\downarrow^i = \frac{1}{N-1} \sum_{j=1}^{N-1} P_\downarrow^{ij} = \frac{1}{N-1} \sum_{j=1}^{N-1} [\alpha s_j + \beta(1 - s_j)]. \qquad (2)$$

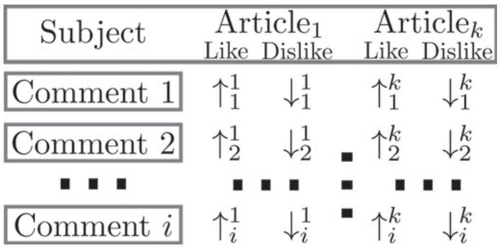


Fig. 1: Internet news and social influence. Consider articles that follow some developing news story. Contrary to printed newspapers, Internet news websites open some articles for commentary by the public and for expressing like or dislike votes for each comment. Comments, together with their likes and dislikes, are written and voted for from both supporters and opponents of the articles statements. Quantitative data of likes ($\uparrow$) and dislikes ($\downarrow$) reveal the conditional probabilities of individual community members to respond positively or negatively to others opinions. These conditional probabilities reflect the level of social influence in the community and allow monitoring the temporal dependence of the level of social influence by following articles on the same subject from different dates.

Defining $\gamma_{\text{mean}} \equiv \frac{1}{N}\sum_{i=1}^{N} s_i$ as the mean fraction of individuals who vote up, and noting that mean-field assumptions imply $\gamma_{\text{mean}} = P_\uparrow = 1 - P_\downarrow$ and $\gamma_{\text{mean}} = s_i$ for any $i$, eq. (2) may be written as

$$P_\downarrow = 1 - \gamma_{\text{mean}} = \gamma_{\text{mean}}\alpha + (1 - \gamma_{\text{mean}})\beta. \qquad (3)$$

Consequently, the individual probability to vote down $1 - \gamma_{\text{mean}}$ is a sum of two probabilities: to vote down with probability $\alpha$ in environment that vote up and to vote down with probability $\beta$ in environment that vote down.

Solution of (3) results in an expression for steady state mean vote $\gamma_{\text{mean}}$ [15]:

$$\gamma_{\text{mean}} = \frac{1-\beta}{1+\alpha-\beta}, \qquad (4)$$

as a function of conditional probabilities $(\alpha, \beta)$. It is valid for a population where individuals define their votes in response to the votes of others.

To study social influence, one may ask how an individual or an entire population responds to the introduction of individuals that vote independently of the environment. These inflexible voters [16] provide an analogy of external force in magnetic systems.

In order to measure social influence, consider a population composed of two groups. The first group is composed of individuals that vote up or down in response to their environment with conditional probabilities $(\alpha, \beta)$. The individuals of the second group do not respond to the environment and vote up or down with constant probabilities $\gamma_{\text{const}}$ and $1 - \gamma_{\text{const}}$, respectively. In this case, the mean vote of the first group $\gamma'_{\text{mean}}$ is given by

$$\begin{aligned} 1 - \gamma'_{\text{mean}} = {} & (1 - \rho_{\text{const}})(\gamma'_{\text{mean}}\alpha + (1 - \gamma'_{\text{mean}})\beta) \\ & + \rho_{\text{const}}(\gamma_{\text{const}}\alpha + (1 - \gamma_{\text{const}})\beta), \end{aligned} \qquad (5)$$

where $\rho_{\text{const}}$ is a fraction of non-responsive individuals in the population. Expression (5) follows from (3), taking into account the possibilities to interact with non-responsive and responsive individuals with probabilities $\rho_{\text{const}}$ and $1-\rho_{\text{const}}$, respectively.

Solution of (5) results in mean vote $\gamma'_{\text{mean}}$ in a population of $N$ individuals characterized by $(\alpha, \beta)$, which is perturbed by applying the specific value of mean vote $\gamma_{\text{const}}$ to a fraction $\rho_{\text{const}} \in [0,1]$ of the population:

$$\gamma'_{\text{mean}} = \frac{1-\beta-\gamma_{\text{const}}\rho_{\text{const}}(\alpha-\beta)}{1+\alpha-\beta-\rho_{\text{const}}(\alpha-\beta)}, \tag{6}$$

Mean vote in a perturbed population (6) converges to mean vote in a homogeneous population (4) $\gamma'_{\text{mean}} \to \gamma_{\text{mean}}$ if $\rho_{\text{const}} = 0$ or if $\gamma_{\text{const}} = \gamma_{\text{mean}}$.

We define social susceptibility $\chi_s$ as

$$\begin{aligned}\gamma'_{\text{mean}} &= \gamma_{\text{mean}} + \chi_s \rho_{\text{const}}(\gamma_{\text{const}} - \gamma_{\text{mean}}) \\ &\quad + O(\rho^2_{\text{const}}(\gamma_{\text{const}} - \gamma_{\text{mean}})^2).\end{aligned} \tag{7}$$

Following (6) and (7) $\chi_s$ is

$$\chi_s = \frac{\beta-\alpha}{1-(\beta-\alpha)}, \tag{8}$$

and therefore depends on a single parameter $I = \beta - \alpha$.

The herding parameter $I = \beta - \alpha$ ($I \in [-1,1]$) is a measure of the social influence of one individual on others, because $I = \beta - \alpha$ is the difference of conditional probabilities for correlated and anti-correlated behaviors, see (1). It is similar to herding or percolation parameter $0 \le c \le 1$ from [2]. However, since our definition of the herding parameter $I$ accounts for both positive and negative social influence, it is better suited for analyzing opinion dynamics in binary vote communities.

Social susceptibility $\chi_s$ as a function of herding parameter $I$ (see fig. 2) is a measure for the fraction of players who flip votes ($\propto \gamma'_{\text{mean}} - \gamma_{\text{mean}}$) in response to the perturbation $\rho_{\text{const}}(\gamma_{\text{const}} - \gamma_{\text{mean}})$, see (7). The number of players that flip their votes may be either positive or negative in the case of populations with correlated ($I > 0$) and anti-correlated ($I < 0$) behaviors, respectively. Significant social transitions by small perturbations are possible for $I \approx 1$ because susceptibility $\chi_s$ diverges in the limit $I \to 1$.

To analyze significant social transitions, one should estimate required herding parameter $I$ (or social susceptibility $\chi_s$) that makes it possible to convert a community to an almost polarized state ($\gamma'_{\text{mean}} \approx 0, 1$) with minimal perturbation group size ($\rho_{\text{const}} \ll 1$). Equation (5), however, has no solution for $\gamma'_{\text{mean}} = 1$ or $\gamma'_{\text{mean}} = 0$ with parameters $0 \le \alpha, \beta, \rho_{\text{const}}, \gamma_{\text{const}} \le 1$ in their physical limits. Consequently it is impossible to get to a completely polarized state by applying perturbation of inflexible individuals.

Consider transition of a community to an opposite view $\gamma'_{\text{mean}} = 1 - \gamma_{\text{mean}}$, where $\gamma_{\text{mean}}$ and $\gamma'_{\text{mean}}$ are the initial and final average votes of the community. The density

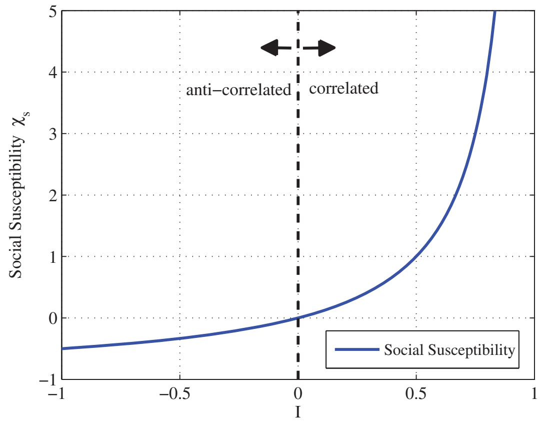


Fig. 2: (Colour on-line) The social susceptibility $\chi_s$ as a function of herding parameter $I$. Social susceptibility is a measure of how many individuals follow a single one who changes his or her opinion. Thus, $\chi_s \gg 1$ ($I \approx 1$) makes possible significant social transitions that are initiated by a small group. Social influence vanishes if $\chi_s = 0$. The case of $\chi_s < 0$ corresponds to the populations with negative (antagonistic) social influence.

$\rho^{0\to 1}_{\text{const}}$ for the transition ($\gamma_{\text{mean}} \ll 1$ to $\gamma'_{\text{mean}} \approx 1$) follows from (6) to be

$$\rho^{0\to 1}_{\text{const}} = \frac{(1-I)(1-\gamma_{\text{mean}})}{\gamma_{\text{mean}}(1-(1-I)(1-\gamma_{\text{mean}}))} \approx \frac{1-I}{\gamma_{\text{mean}}}. \tag{9}$$

Thus $\rho^{0\to 1}_{\text{const}} \ll 1$ can be obtained if $1 - I \ll \gamma_{\text{mean}}$. The opposite transition requires $\rho^{1\to 0}_{\text{const}} \approx (1-I)/(1-\gamma_{\text{mean}})$.

Conditional probabilities $(\alpha, \beta)$ define herding $I$, which in turn defines the social susceptibility of the community $\chi_s$. To calculate conditional probabilities $\alpha$ and $\beta$ as a function of likes $\uparrow_i$ and dislikes $\downarrow_i$ votes for comment $i$ of article $k$ (see fig. 1), we assume that voters and commentators populations are equivalent and that the number of comments and votes is large enough to apply the mean-field assumption. In addition we assume that votes for a single article represent the steady state of the community, meaning that the time span of a single article is smaller than the persistent time of opinion dynamics. The state of the community, however, changes for articles from different dates. Consequently, to observe the dynamics of the community in time one should calculate conditional probabilities $(\alpha_k, \beta_k)$ for articles $k$ from different dates.

Following the mean-field assumption, the probabilities for a commentator and a voter to be in favor of the article $k$ are both equal to $\gamma$. Therefore, the comments should consist of two groups: positive and negative with relative sizes $\gamma$ and $1-\gamma$, respectively. Positive and negative comments should be different by the ratio between likes $\uparrow_i$ and all responses (likes $\uparrow_i$ and dislikes $\downarrow_i$). According to the definition of the conditional probabilities (1), the ratios of likes for a positive comment $+$ and for a negative comment $-$ are

$$\frac{\uparrow_+}{\uparrow_+ + \downarrow_+} = 1-\alpha, \qquad \frac{\uparrow_-}{\uparrow_- + \downarrow_-} = \beta, \tag{10}$$

respectively. It is important to note that (10) for the negative comment differs from (1) (probability is $\beta$ instead of $1-\beta$) since expressing a like vote for a negative comment is equivalent to expressing a dislike vote for the article commented upon. It has two interesting consequences: First, probability of a dislike vote $P_{\text{dislike}}$ averaged over all the comments is invariant under the transformation $\gamma \to 1-\gamma$, reflecting the uncertainty regarding the opinion of the Internet article itself:

$$P_{\text{dislike}} = \alpha\gamma + (1-\beta)(1-\gamma) = 2(1-\gamma)\gamma. \tag{11}$$

Second, $P_{\text{dislike}} < 0.5$, *i.e.* comments cannot include only dislikes because the community cannot dislike its own opinion.

Following (10) in an "ideal" mean-field binary opinion world comment may be separated into positive and negative according to their likes fraction, see fig. 3. Moreover, the fraction of positive comments should be $\gamma$, which should be consistent with $\alpha$, $\beta$ values following (4). The real situation is different: an iterative method is required to separate comments into positive and negative ones for the sake of social susceptibility $\chi_s$ estimation, see fig. 3.

Calculating $\alpha$, $\beta$ and $\gamma$ of the community from data of specific article $k$ proceeds through iterations. First, all comments are sorted by their like vote fraction. Then, at each step $n$, the comments are divided into two groups with ratio of $\gamma^n$ and $1-\gamma^n$ according to their like vote fraction, where group $L$ receives the $\gamma^n$ comments with the highest like vote fraction and group $D$ receives all other comments. The population characteristic parameters $\alpha^n$ and $\beta^n$ are then calculated according to mean ratios of likes:

$$1-\alpha^n = \left\langle \frac{\uparrow_i}{\uparrow_i + \downarrow_i} \right\rangle_{i\in L}, \quad \beta^n = \left\langle \frac{\uparrow_i}{\uparrow_i + \downarrow_i} \right\rangle_{i\in D}, \tag{12}$$

for the comments in the groups $L$ and $D$, respectively. A new population mean vote $\gamma^{n+1}$ is calculated using the values of $\alpha^n$ and $\beta^n$:

$$\gamma^{n+1} = \frac{1-\beta^n}{1+\alpha^n-\beta^n}. \tag{13}$$

The process is repeated until the convergence of $\alpha^n$, $\beta^n$ and $\gamma^n$. Figure 3 presents the iteration process at its converged state and at a state far from convergence, for a real case of likes/dislikes statistics.

This method is ambiguous for the $\gamma \to 1-\gamma$ transformation. It is a consequence of the fact that the division of the comments into two groups with contrasting opinions does not reveal the opinions themselves. Since $\chi_s$ is invariant under the transformation $\gamma \to 1-\gamma$, we arbitrarily chose $\gamma > 0.5$.

The formalism of the analysis of the social influence presented above is applied to news articles published on the CNN website that discuss three different topics. The first story includes six articles, published between June 24th and July 25th, 2013, covering the George Zimmerman

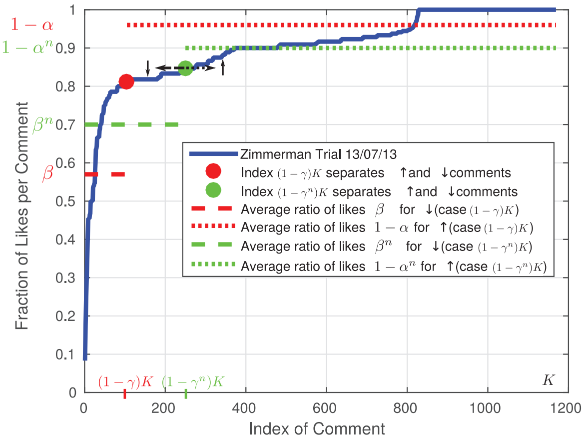


Fig. 3: (Colour on-line) Values $(\alpha, \beta, \gamma)$ as a function of likes/dislikes statistics in the case of a single Internet article (Zimmerman trial 13/07/13, see table 1). The total amount of $K$ comments for this article are ordered by increasing value of the ratio of likes per comment. The ratio of likes per comment is plotted *vs.* the index of the comment (solid line). According to our model, if every comment is unambiguously in favor or against the main article, then the ratio of likes is $1-\alpha$ for each positive comment (dotted line) and $\beta$ for each negative comment (dashed line), respectively. Real comments possess different values of likes ratios, in our opinion, due to fuzzy, rather than clear positive or negative, content of the comments. For real comments, there exists an iteration process to derive $(\alpha, \beta, \gamma)$ that fit mean-field condition (4). In addition, if index $(1-\gamma)K$ separates comments into positive $\uparrow$ and negative $\downarrow$ ones then the average ratios of likes are $1-\alpha$ and $\beta$ for positive and negative comments, respectively. Separation of the comments into positive and negative ones at any other index $(1-\gamma^n)K$ and calculation of average ratio's of likes $1-\alpha^n$ and $\beta^n$ for positive and negative comments, respectively, see eq. (12), results in $(\alpha^n, \beta^n, \gamma^n)$ that deviate from the mean-field condition (4). In this case a new value of $\gamma^{n+1}$ is calculated, see (13), and the process proceeds until convergence.

trial [17–22]. These articles cover the legal proceeding, the verdict, and the post-verdict jurors opinions about the trial. The second story includes three articles, published between October 25th and November 25th, 2013, covering the negotiations and signing of the Geneva interim agreement on the Iranian Nuclear Program [23–25]. The third story includes three articles, published on October 1st and 2nd, 2013, covering the US federal Government shutdown of that year [26–28]. These articles cover the first day of the shutdown and the White House failing efforts to end it. The results of these analyses are presented in table 1 and in fig. 4.

In the Iran Nuclear Program and US Government shutdown cases, the population's characteristic parameters $(\alpha, \beta)$ are constant, although they correspond to different CNN articles and, in the case of the Iran Nuclear Program, span one month. This result may also indicate the absence of special events during the observation period.

Table 1: The results of social susceptibility calculation for 12 CNN articles from different dates that cover three different events. For each article, the values of conditional probabilities $(\alpha, \beta)$ and social susceptibility $\chi_s$ were calculated.

| Article's topic | Date | $\alpha$ | $\beta$ | $\gamma$ | $\chi_s$ |
|---|---|---|---|---|---|
| Zimm. trial | 24/06/13 | 0.14 | 0.53 | 0.77 | 0.63 |
| Zimm. trial | 05/07/13 | 0.12 | 0.38 | 0.84 | 0.34 |
| Zimm. trial | 12/07/13 | 0.08 | 0.47 | 0.87 | 0.64 |
| Zimm. trial | 13/07/13 | 0.04 | 0.57 | 0.91 | 1.10 |
| Zimm. trial | 17/07/13 | 0.04 | 0.67 | 0.89 | 1.70 |
| Zimm. trial | 25/07/13 | 0.06 | 0.77 | 0.79 | 2.39 |
| Iran Nuc. Prog. | 25/10/13 | 0.16 | 0.58 | 0.72 | 0.74 |
| Iran Nuc. Prog. | 23/11/13 | 0.15 | 0.56 | 0.75 | 0.70 |
| Iran Nuc. Prog. | 24/11/13 | 0.15 | 0.59 | 0.73 | 0.78 |
| US G. shutdown | 01/10/13 | 0.16 | 0.51 | 0.75 | 0.53 |
| US G. shutdown | 02/10/13 | 0.13 | 0.51 | 0.79 | 0.63 |
| US G. shutdown | 02/10/13 | 0.09 | 0.48 | 0.85 | 0.62 |

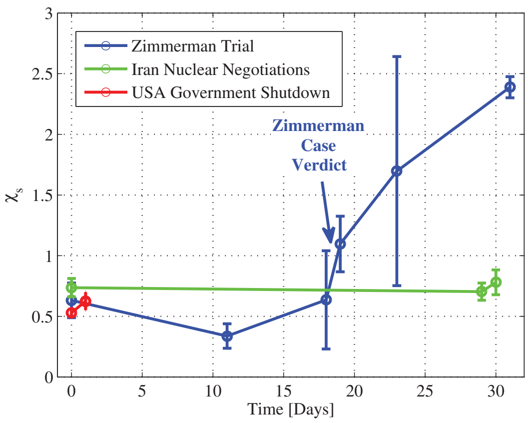


Fig. 4: (Colour on-line) The social susceptibility $\chi_s$ as a function of time. Social susceptibility remains almost constant in the cases of US Government shutdown and Iran Nuclear Program negotiations. This preservation of community state is surprising because there is no reason why the opinion of a population should remain the same for short or for long periods. Even more interesting, however, is that social susceptibility in the case of the Zimmerman trial changes after the verdict is announced on July 13, 2013. Significant social transition becomes possible after the announcement of the verdict.

The social susceptibility level in the Zimmerman trial case changes near the verdict announcement. In the period prior to the verdict day, see fig. 4, the level of social susceptibility in the population remains almost constant and similar to the social susceptibility in the other cases (*i.e.*, $\chi_s \sim 0.5$), despite the changes in $\alpha$ and $\beta$. From the verdict day on, the social susceptibility in the community grows rapidly and the population approaches the singular point $(\alpha, \beta) \to (0, 1), \chi_s \to 1$. It is out of the scope of this work to interpret social phenomena, though the results demonstrate that our method allows to observe the otherwise hidden herding level in a community together with its response to social triggers.

The results of community state as a function of time presented in table 1 and fig. 4 support our assumption that community is at quasi-steady state during the time span of a single article (about 1 day). The results also indicate the possibility of continuous dynamics of population in $(\alpha, \beta)$ space or dynamics of social susceptibility $\chi_s$ with time. More data, however, is required to support or refute the hypothesis of continuous dynamics. The hypothesis of continuous dynamics is interesting considering that the analysis is applied to the articles separated in time by days or even months. One could expect completely uncorrelated (white-noise–like) results from different dates.

The assumption of opinion dynamics as transitions from one quasi-stable state to another follows the models of herding of the type assumed in refs. [1–3]. This approach differs from the models that present opinion dynamics using an update function: an individual (agent) changes its opinion as a function of opinions of the other agents in the near environment (connectivity of agents may depend on a complex topology metrics). This work utilizes the separation of individuals into flexible, inflexible and contrarian types following different types of update function discussed in [16,29,30]. Our model is independent of specific update function and provides a possibility to estimate social susceptibility $\chi_s$ from Internet discussions. Comparison with specific local opinion dynamics and deviations from mean-field approximation are interesting tasks for the future.

The model assumes an asymmetry between the reaction of an individual to a positive and negative vote ($\alpha \neq \beta$). It is supported by accepting in game theory different strategies against cooperator or defector [31], as well as by recent studies of positive and negative comments [6].

The limitations of our work include the absence of external forces, *i.e.* government control, and lack of interaction topology constrains, such as the prevalence of near-neighbors interactions. Omitting topological constraints seems to be justified in Internet communities. The same is true regarding forces that shape opinion or add weight to some opinion, such as government control or mass media. We assume that the Internet is still a free zone. The model can be extended to include such a force, though there is no clear way to quantify it.

Shortly after the data collection phase for this work was completed, the CNN website changed its comments policy and the dislike count per comment is no longer displayed. This change made the CNN website articles and comments unsuitable for the above comment analysis procedure, since the main assumption underlying our model, (that both like and dislike vote counts are available to all individuals in the population) is no longer valid. This study demonstrates the potential of *both* like/dislike votes in estimating the social state of a community and may contribute to the evolving formation of the Internet news format.

To conclude, the developed tools for social influence in Internet communities reveal the previously hidden level of herding and social influence as a function of time in populations. In addition, this work provides a measure for the stability of public opinion in a community and for the size of a group capable to cause critical change in the average opinion. The presented method can be compared with other methods and can be extended to other fields such as financial markets [32]. Therefore, this work enables an intriguing comparison of the herding in the same community calculated from different sources, such as Internet news and financial markets [33].

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