Unfolding large-scale online collaborative human dynamics

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Edited by Didier Sornette, ETH Zurich, Zurich, Switzerland, and accepted by Editorial Board Member David L. Donoho October 27, 2016 (received for review January 31, 2016)

Large-scale interacting human activities underlie all social and economic phenomena, but quantitative understanding of regular patterns and mechanism is very challenging and still rare. Self-organized online collaborative activities with a precise record of event timing provide unprecedented opportunity. Our empirical analysis of the history of millions of updates in Wikipedia shows a universal double–power-law distribution of time intervals between consecutive updates of an article. We then propose a generic model to unfold collaborative human activities into three modules: (*i*) individual behavior characterized by Poissonian initiation of an action, (*ii*) human interaction captured by a cascading response to previous actions with a power-law waiting time, and (*iii*) population growth due to the increasing number of interacting individuals. This unfolding allows us to obtain an analytical formula that is fully supported by the universal patterns in empirical data. Our modeling approaches reveal "simplicity" beyond complex interacting human activities.

human dynamics | online collaboration | double power law | multibranching

Quantitative understanding of regular patterns in human dynamics is of great importance but fairly challenging because they are driven by complex decision-making processes, involving competing choices under limited time and cost, interactions with social peers, influences from the external environment, and so on. Previously, when detailed and precise records of human activities were rare, individual activities were assumed to follow random Poissonian processes with exponential distributions of interevent times (1). In contrast, recent analysis and experiments on deliberate human behaviors, such as communication through emails (2), surface mails (3), cell phones (4), instant messages (5), text messages (6), social contacts (7), and online activities including web browsing (8), movie watching (9), searching (10), and shopping (11), showed that individual activities usually embody the bursty nature featured by fat-tailed, power-law–like distributions of interevent times. Several models have been proposed to explain the possible underlying mechanisms, including a task competition model driven by individual decision (2, 12, 13), a nonstationary Poisson process driven by daily and weekly circadian circles (14–16), and adaptive interest (17). Besides the complexity in individual decision making, these works do not take the interaction between individuals into explicit consideration. The interaction was theoretically explored by placing a task competition model into a network of two (18) or more agents (19–22). Only recently, it was explicitly demonstrated that interaction can lead to a bimodal distribution of the interevent times in short message communication, which is mainly a two-person interaction system (23). Thus far, how interactions happen in a real system organized by a large number of individuals is still unknown.

Modern information technology has allowed many new types of human interacting activities. In particular, a lot of online communities emerge in the Internet world to perform collaborative activities, such as distributed collaborative writing based on wikis (24) and globalized development of software (25), where interactions between hundreds or even thousands of participants are widely found and the event times are precisely recorded, providing unprecedented opportunity to uncover statistical regularities and to reveal underlying mechanisms in a quantitative way. Thus far, previous works on human collaborative systems have mainly focused on the network structural analysis and vandalism detection (26–29), whereas the temporal patterns are less considered.

Wikipedia (https://wikipedia.org) is the world's largest wiki system and it precisely records all online collaborative activities. Different from the collaborative development of software and other actions under regulation and control, Wikipedia is a typical self-organized system without centralized management. We analyzed millions of updating records of hundreds of articles in Wikipedia and found that the interupdate time distribution follows a double–power-law form for most articles. Namely, the "head" and "tail" of such distribution are both power-law like, but with different exponents. Strikingly, we show that this universal yet complicated distribution can be quantitatively predicted by an analytical formula via unfolding the seemingly complex collaborative patterns into three generic modules related to

Significance

This paper uncovered a universal double–power-law distribution of interupdate times for articles in Wikipedia and unfolded the seemingly complex collaborative patterns into three generic modules related to individual behavior, interaction among individuals, and population growth. The model is analytically solved and fully supported by the real data. As this model does not depend on any specific rules of Wikipedia, it is highly applicable for other online collaborative systems like software development and email communication. Similar scaling properties and models were reported for earthquake recurrence times, suggesting that interacting natural and social systems share universal collective mechanisms.

Author contributions: Y.Z., T.Z., and C.Z. designed research, performed research, analyzed data, and wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission. D.S. is a Guest Editor invited by the Editorial Board.

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This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1601670113/-/DCSupplemental.

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individual behavior, interaction among individuals, and growth of the interacting population, respectively.

Model

The updating records in Wikipedia (*Materials and Methods*, *Data Description*) show universal temporal patterns in articles' evolutionary process. In a large percentage of articles, the number of updates of an article, N, grows in an exponential form in its early stage and then saturates (Fig. 1*A*). A profound double–power-law distribution $P(\tau)$ is observed, where τ is the time interval between two consecutive updates of an article. Notice that we concentrate on the statistics of an article rather than a user, with a different viewpoint to most previous studies. This distribution has a power-law head and a power-law tail, with different exponents (see the eyes-guiding lines with different slopes in Fig. 1*B*). Such regular distribution pattern is insensitive to articles' contents, updating rates, total number of updates, and lasting time (see *SI Appendix*, section S1, and Fig. S1 for the statistics of all 625 articles with >5,000 updates). As we will show later, our model can quantitatively explain both the rather common exponential growing patterns and a few exceptions with irregular growing patterns.

Collaborative activities typically happen in an evolving dynamical system consisting of many interacting individuals. To understand the major factors responsible for the above-observed regular patterns, we need to identify the dynamical features of individuals, the characteristics of interactions, and the evolution of the whole system. In the collaborative editing of an article in Wikipedia, there are generally two types of updates: to initiate an update or to respond to others. Responsive updates are closely related to the earlier ones (e.g., reverting the last update), typically with short waiting time from the last updates. Some updates are rather independent (e.g., adding a new section), typically with a relatively longer time interval from the last updates, and may further lead to a series of responsive updates. These two types of updates are respectively named as "Initiations" and "Responses," respectively. Such properties are not particular to the Wikipedia but appear to be generic in other human communication systems, such as email and short-message communications, where responses to previous messages and initiations of new, likely more independent messages, are related to different time intervals. Here, we propose to unfold a typical collaborative system into the following three generic modules.

i) Individual behavior. Initiations by individuals are assumed to be largely independent of other events, characterized by a random Poissonian process with an initiation rate λ. That is to say, at each time step, with probability λ, an Initiation happens. Notice that, in Wikipedia, λ reflects the overall activity in editing the article and will increase with the number of participants.

ii) Interaction. Responses can be induced by either type of earlier events. They are characterized by a cascading process with branching rate $a < 1$, namely, each event has a chance a to induce a responsive event. Inspired by the known empirical observations (2, 3, 6, 13, 30–33), the interval time between an event and its possibly induced event (i.e., waiting time) follows a power-law distribution as follows:

$$q(\tau) = \tau^{-\beta}/\zeta(\beta), \quad [1]$$

where $\tau = 1, 2, 3...$ denote discrete time intervals, and the normalizing factor $\zeta(\beta) = \sum_{i=1}^{\infty} i^{-\beta}$ is the Riemann ζ function.

iii) Population growth. Growth of population of participants leads to the growth of events through modules *i* and *ii*; therefore, the initiation rate λ changes with time. We found that, in Wikipedia, the number of events N (i.e., updates or submits) is linearly proportional to the number of users (i.e., editors; *SI Appendix*, Fig. S2); thus, we only consider the growing patterns of $N(t)$. Typically, the growing rate $r(t) = dN(t)/dt$ is proportional to the size N, resulting in an exponential form $N(t) = e^{\alpha t}$ [we set $N(0) = 1$], until some saturation sets in.

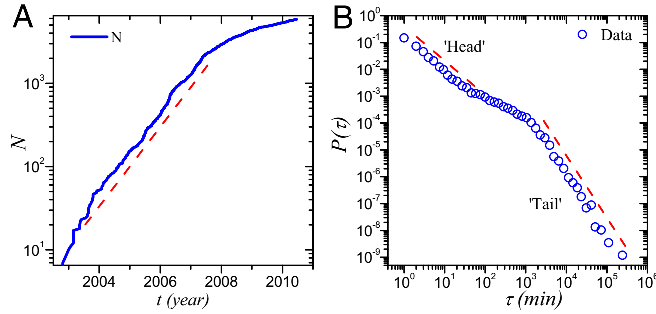

Fig. 1. Regular patterns in the updating process of a typical Wikipedia article. An example article "Wikipedia" (https://en.wikipedia.org/wiki/Wikipedia) is used to illustrate the growing and distribution patterns. (*A*) Growth of the number of updates *N*. The eyes-guiding dashed line shows that the growth in early stage can be reasonably described by an exponential function. (*B*) Double–power-law distribution of the interupdate time τ, with the eyes-guiding dashed lines showing different slopes of the head and tail. More sophisticated fitting of the distribution by analytical formula will be developed later.

Analysis

The analytical solution (*SI Appendix*, section S2) shows that the combination of modules *i* and *ii* with a constant initiation rate λ will lead to a bimodal distribution of a power-law head and an exponential tail:

$$P_\lambda(\tau) = e^{-\frac{\lambda}{1-a}\sum_{t=0}^{\tau-2}K(t)}K(\tau-1) - e^{-\frac{\lambda}{1-a}\sum_{t=0}^{\tau-1}K(t)}K(\tau), \quad [2]$$

where $K(\tau) = 1 - a\zeta_\tau(\beta)/\zeta(\beta)$ and $\zeta_\tau(\beta) = \sum_{t=0}^{\tau} t^{-\beta}$. The head at small τ has the same form $a\tau^{-\beta}/\zeta(\beta)$ as the waiting time in Eq. **1**, and the asymptotic tail $(1 - a) \cdot \lambda(1-\lambda)^{\tau-1}$ is an exponential curve resulted from the Poissonian process, mainly contributed by the Initiations. Fig. 2*A* shows three typical examples according to Eq. **2**, where one can observe that the exponential tail shifts rightward when λ gets smaller. In addition, the theoretical prediction in Eq. **2** is perfectly in accordance with direct simulations of the growing process with constant initiation rates.

Because each Initiation will induce a sequence of branching process with probability a, the expected number of updates induced by each Initiation is $S = 1/(1-a)$. The growth rate of the events is then $r = \lambda S$, leading to a theoretical relation between initiation rate and growth rate as follows:

$$\lambda = (1-a)r. \quad [3]$$

Considering the population growth in module *iii*, λ becomes inhomogeneous and follows a distribution $\rho(\lambda)$, and the distribution of τ is as follows:

$$P(\tau) = \int \rho(\lambda)P_\lambda(\tau)d\lambda. \quad [4]$$

For the exponential growth $N(t) = e^{\alpha t}$, it is obvious that $\rho(\lambda) = 1/(\lambda_2 - \lambda_1)$ is a uniform distribution between $\lambda_1 = (1-a)\alpha N_1$ and $\lambda_2 = (1-a)\alpha N_2$, which are determined (following Eq. **3** and using $r = \alpha N$) by the population size of the starting N_1 and ending N_2 of the exponential growth. Applying

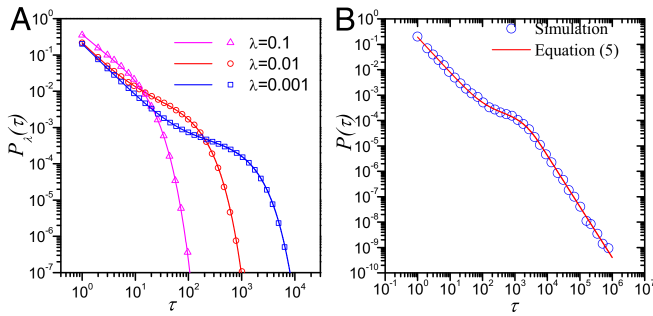

Fig. 2. Bimodal and double–power-law distributions from the model. (*A*) The bimodal distribution at constant λ predicted by the theory (Eq. **2**, represented by solid curves), compared with the results from direct simulations (represented by symbols). (*B*) The double–power-law distribution Eq. **5** with $\lambda_1 = 10^{-7}$ and $\lambda_2 = 10^{-3}$, compared with the result from a simulated growing process from λ_1 to λ_2. Other parameters are $\beta = 1.3$ and $a = 0.6$.

this uniform distribution $\rho(\lambda)$ to the general form in Eq. **4**, it arrives at a very complicated analytical solution:

$$P(\tau)=\begin{cases}\dfrac{K(\tau)\left(e^{-\frac{\lambda_2}{1-a}\sum_{t=0}^{\tau-1}K(t)}-e^{-\frac{\lambda_1}{1-a}\sum_{t=0}^{\tau-1}K(t)}\right)}{\frac{\lambda_2-\lambda_1}{1-a}\sum_{t=0}^{\tau-1}K(t)} \\ \quad -\dfrac{K(\tau-1)\left(e^{-\frac{\lambda_2}{1-a}\sum_{t=0}^{\tau-2}K(t)}-e^{-\frac{\lambda_1}{1-a}\sum_{t=0}^{\tau-2}K(t)}\right)}{\frac{\lambda_2-\lambda_1}{1-a}\sum_{t=0}^{\tau-2}K(t)}, & \text{if } \tau>1 \\ 1+\dfrac{K(\tau)\left(e^{-\frac{\lambda_2}{1-a}\sum_{t=0}^{\tau-1}K(t)}-e^{-\frac{\lambda_1}{1-a}\sum_{t=0}^{\tau-1}K(t)}\right)}{\frac{\lambda_2-\lambda_1}{1-a}\sum_{t=0}^{\tau-1}K(t)}, & \text{if } \tau=1.\end{cases} \qquad [5]$$

Despite its complicated form, Eq. **5** describes a double–power-law distribution, as it has a power-law head $a\tau^{-\beta}/\zeta(\beta)$ and a power-law tail $(1-a)/(\lambda_2-\lambda_1)\tau^{-2}$ in the range $1/\lambda_2 < \tau < 1/\lambda_1$ (*SI Appendix*, section S2*B*). The universal power-law exponent -2 for the tail is independent of the growing exponent α. This analytical solution is based on a mechanistic model for the observed double power laws in human-activated systems (see also some other complex systems exhibiting double power laws (34–37)). Fig. 2*B* compared the analytical solution with the simulation of an exponential growing process (see *Materials and Methods* for simulation details), showing prefect consistence.

In addition to the consistence between analytical solution and simulation, our model assumptions and analytical solutions are also fully supported by the empirical data from Wikipedia. We next show the fitting to data in three aspects.

Universal Power-Law Distribution of Waiting Time. We have identified a large portion of Responses from the history record of the 625 articles (see *Materials and Methods* for how to distinguish Initiations and Responses). The waiting time for each article, as the model assumed, universally follows a power-law distribution (see a typical example in Fig. 3*A*), with the exponent β narrowly distributed around $\bar{\beta} = 1.55$ (*SI Appendix*, Fig. S5*A*). The waiting-time distributions of all of the 625 articles under consideration can be found in *SI Appendix*, Figs. S3*A* and S4*A*.

Bimodal Distribution in the Data Segments with Constant Growth Rates. According to Eqs. **2** and **3**, a data segment with constant growth rate r is supposed to follow the bimodal distribution with power-law head and exponential tail. We have designed an algorithm to find segments with nearly constant initiation rates (*SI Appendix*, section S4). Altogether, 334 segments, each of which contains more than 1,000 updates, were selected from 1,948 articles, and the growth rates r are measured accordingly. The interupdate time distribution for each segment appears to be bimodal (Fig. 3*B*). We fit Eq. **2** to each segment by the maximum-likelihood estimation, and 95.81% of the fittings can pass the Kolmogorov–Smirnov (KS) test with a significance level of 5% (see *SI Appendix*, section S4, for the fitting procedure and the statistics of the 334 segments). The parameters β and a, estimated from the fitting, distribute narrowly around their mean values $\bar{a} = 0.605$ (*SI Appendix*, Fig. S7*A*) and $\bar{\beta} = 1.306$ (*SI Appendix*, Fig. S7*B*) and could be largely regarded as independent of the measured r (*SI Appendix*, Fig. S6). A possible explanation to the small discrepancy of β in the above two very different experiments can be found in *SI Appendix*, section S4. Fig. 3*C* shows excellent consistence of the theoretically predicted relationship Eq. **3** between the initiation rate λ (λ is estimated from the fitting) and growth rate r with empirical data. In a word, empirical analysis validates our model and demonstrates that the bimodal interevent time distribution is a signature of a stable collaborative multiindividual system without variation of activity level (23).

Double–Power-Law Distribution. To compare the analytical solution of double power law in Eq. **5** with empirical data, we first identify the region $N < N_E$ with exponential growth (e.g., Fig. 3*D*) and the exponent α (see *SI Appendix*, section S5*A*, for the method). As shown in Fig. 3*E*, the distribution $P(\tau)$ of the above exponentially growing part is fitted by the analytical solution Eq. **5** with parameters a, β, and λ_2 estimated by the maximum-likelihood method (we take $\lambda_1 = 1/\tau_{max}$; please see *SI Appendix*, section S5B, for detailed explanation), and 80.77% of the samples have passed the KS test of the double–power-law hypothesis (*SI Appendix*, section S5*B*, and Figs. S7 *C* and *D*, and S8). For the remaining part of the article ($N > N_E$), Eq. **4** is fitted to the empirical distribution by using the average parameters from the fitting of the bimodal distribution to the linear segments (i.e., $a = \bar{a} = 0.605$ and $\beta = \bar{\beta} = 1.306$; Fig. 3*F*), in which the distribution of initiation rate $\rho(\lambda)$ is obtained by numerical estimation of the growth rate r from the data via Eq. **3** (see *SI Appendix*, section S5*C*, for details). In fact, Eq. **4**, as the most general form, also fits to the complete data containing both the exponential ($N < N_E$) and nonexponential ($N > N_E$) growing parts, with $\rho(\lambda)$ being numerically estimated from the complete data (*SI Appendix*, section S5*C* and Fig. S9). The theory is very robust: the fittings to most articles are as good as Fig. 3 *E* and *F*, even including articles whose growing processes do not contain considerable exponential part (see *SI Appendix*, Figs. S3 and S4, for the fittings to all of the 625 articles).

Discussion

Wikipedia sets up simple rules but displays complex phenomena that are largely originated from extensive human interactions. Despite its high complexity, we show that such a system could still be unfolded into several simple and analytically accessible components. Indeed, the temporal patterns of editing for disparate articles can be analytically reproduced with surprisingly high precision by the integration of three generic modules that respectively characterize the individual behavior, the interaction among individuals, and the population growth. The formula in Eq. **4** is general for arbitrary growing patterns. In particular, for most of the articles containing an exponential growth pattern, the distribution of the interupdate interval τ follows a double–power-law distribution (Eq. **5**) and the power-law exponent of the tail is predicted to be -2.

In addition to the optimized fitting using maximum-likelihood method for each article, our model is surprisingly robust, with universal explanatory ability insensitive to specific details of different articles. Considering the fitting to the double–power-law interupdate time distribution for the exponential growing part in

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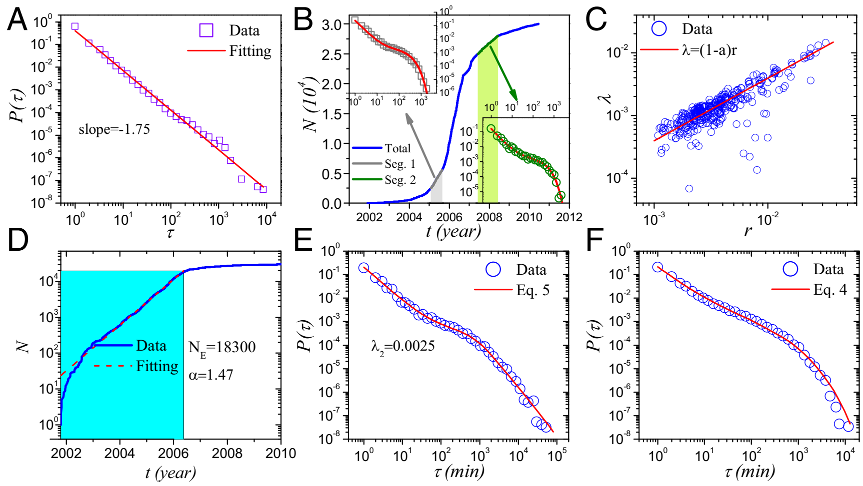

Fig. 3. Verifying the model with data. (*A*) Power-law distribution of waiting time extracted from responsive updates of the article "Wikipedia" (https://en.wikipedia.org/wiki/Wikipedia). (*B*) The growth of the number of updates $N(t)$ of the article "Wikipedia." Two linear segments (Seg. 1 and Seg. 2) were selected, each of which contains 3,000 updates. Two *Insets* show the bimodal distributions $P(\tau)$ for the two segments (symbols) and the corresponding theoretical predictions by Eq. **2** (red lines). (*C*) The estimated parameter λ as a function of the growth rate r from the 334 linear segments, compared with the theoretical prediction (red line) by Eq. **3** with $a = \bar{a} = 0.605$. (*D*) $N(t)$ of "Wikipedia" (blue line) along with the fitting of an exponential function $\sim e^{\alpha t}$ (red dashed line) to the range $N < N_E$ (cyan area). (*E*) Theoretical double–power-law distribution (Eq. **5**, red line) vs. real data (blue circles) corresponding to the cyan area in *D*. The parameters for theoretical formula are estimated using the maximum-likelihood estimation. (*F*) The fitting of distribution of data from nonexponential part ($N > N_E$) by Eq. **4**, where $\rho(\lambda)$ was estimated from the data.

364 articles. As shown in the above discussion and Fig. 3*E*, for each article, we need to estimate four parameters β, a, λ_1, and λ_2 from the real data. However, given an article, even if we simply set $\lambda_1 = 0$, $\beta = \bar{\beta} = 1.306$, and $a = \bar{a} = 0.605$ (the average parameters from the fitting of bimodal distribution to the linear segments), and only estimate one parameter $\lambda_2 = (1 - \bar{a})\alpha N_E$ from the data, such a universal model can get a very good fitting approximated to the optimized one (see *SI Appendix*, Fig. S2*C*, for such universal fitting results for all of the 364 articles). Such a simple, universal, yet well-performed fitting suggests that the power-law distributed waiting time and cascading branching process (the second module of the model) can be regarded as the fundamental underlying mechanisms for different articles during different growing stages. The universality is further confirmed by empirically fitting the tail (i.e., $\tau > 1/\lambda_2$) in the interupdate time distribution of the complete data for these 364 articles. Although these articles generally contain both the exponential and nonexponential growing parts, their tails can be well fitted by power laws (*SI Appendix*, section S5*D* and Fig. S9), and the fitting exponents narrowly distribute around the predicted value -2 (*SI Appendix*, Fig. S10).

The above universal way to fit the double–power-law distribution shows the robustness of our model for Wikipedia articles. In fact, this model is of potential to explain collaborative human-activated systems other than Wikipedia, because all its mechanisms do not depend on the detailed rules or particular structures of Wikipedia. For example, email communication is another interacting system typically with higher updating frequencies than Wikipedia, so the initiation rates can reach large values, corresponding to large values of λ_2. According to the present theory, increasing the initiation rate λ_2 will result in a transition from double power law to effectively a single power law in interevent time distribution (Fig. 4), which is also in accordance with the previous observations (2, 13, 38, 39). More detailed discussion can be found in *SI Appendix*, section S6.

Furthermore, our theory could find applications in detecting abnormal activities in online collaborative systems. Wikipedia articles being manipulated for commercial or political reasons may behave much differently from self-organized articles; for example, in the former articles, some watchdogs will immediately revert the guarded article version if there is any unfavorable update (40). Such abnormal articles may be detected out by our theory. In principle, the senders of junk emails and spammers in a social network can also be found by comparing their behavioral data with the theoretical prediction. Because those hecklers will largely harm the quality (in particular, the neutrality) of Wikipedia articles and reduce user experience in email communication and social networking, our theory should be very useful, for example, as a watchdog for watchdogs in Wikipedia.

Besides the interacting human communication and collaboration systems discussed in this paper, power-law, bimodal, and double–power-law distributions have also been observed

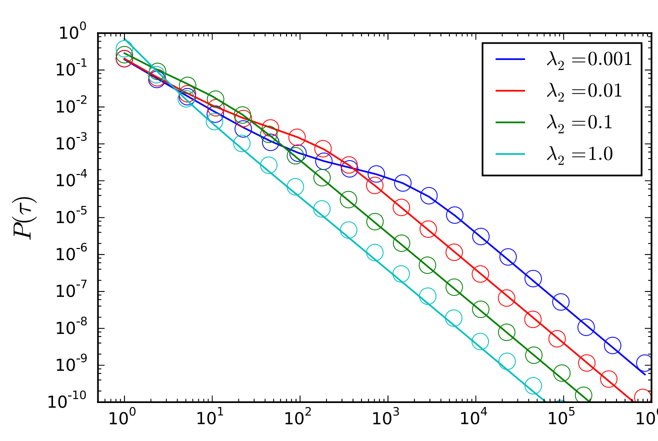

Fig. 4. Transition from double power law to single power law: direction simulation (symbols) vs. analytical result of the model (solid lines). The interevent time distributions from direct simulations of exponential growth process (as Fig. 2*B*) are compared with Eq. **5**, given four different λ_2 values. The results show that the theoretical formula (Eq. **5**) is still good for very large λ_2. Actually, the effective single power law only requires inhomogeneous initiation rates λ, which can approach large values.

in earthquake recurrence times. The time interval between a main shock and its triggered first-generation aftershock follows the Omori power-law function (41) $\sim 1/t^{1+\theta}$ with the power-law exponent $1+\theta \sim 1.3-1.4$, very similar to the universal power-law waiting-time distribution of the Wikipedia articles with exponent $\beta \sim 1.3$. The recurrence times of earthquakes in a given region display power-law distribution with crossover to an exponential tail (42), very similar to the bimodal distribution in human communications (23), and for multiple regions, the rates of earthquakes are heterogeneous (35), resulting in a double–power-law distribution of recurrence times (43). The so-called epidemic-type aftershock sequence (ETAS) model (44, 45) was proposed to treat an earthquake as an event that can trigger more events like a branching process with a decaying probability following the Omori power-law function. Combining both the exogenous and endogenous shocks (46–50), similar to our model with random initiation (exogenous factor) and response with power-law waiting time (endogenous factor), the extended ETAS model can explain the locally bimodal distribution (46) as well as the globally double–power-law distribution with heterogeneous earthquake rates (47, 48). The transition from subcritical to supercritical regime (45) due to the change of the branching parameter across criticality at 1.0 could also be similar to other online human communication systems. The striking similarity of the scalings features indicates the existence of universal collective mechanisms underlying many complex social and natural systems (23, 49–52).

Materials and Methods

Data Description. Wikipedia is a collaboratively edited, multilingual, free online encyclopedia, which has 37 million articles in 250 languages, over 5 million in the English Wikipedia alone, written by volunteers around the world. Almost all of its articles can be edited by anyone with access to the site. Every time someone modifies an article, a new version will be created. To maintain and improve the articles, all versions are recorded by the website, and information of the versions is displayed in a history page, including the editor's ID, updating time, article size, and editor's comments of each version.

The data were obtained by parsing the html code of "view history" web pages of articles in Wikipedia in English language. Our data contain 1,984 articles, each article having more than 1,000 update records, and 625 articles with more than 5,000 update records. Altogether, there are 8,790,110 updating records in the dataset.

Simulating the Exponential Growing Process. In Fig. 2*B*, we compared the theoretical formula Eq. **5** of the double power law with direct simulation of the full model including an exponential growing process. The simulation was made in this way: (*i*) A random Poisson process (starting with a rate $\lambda_1 = 10^{-7}$) is applied to simulate the Initiation. The current total number of Initiations N_I and the initiating rate λ are updated as $N_I = N_I + 1$ and $\lambda = \lambda_1 N_I$ every time when there is a new Response. The simulation lasts until $N_I = 10^4$ ($\lambda = \lambda_2 = 10^{-3}$). (*ii*) Every time when there is an event (Initiation or Response), there is a probability $a = 0.6$ to generate a new Response, which will happen with a waiting time following the power-law distribution in Eq. **1** with an exponent $\beta = 1.3$. In Fig. 2*B*, the distribution of the resulting interevent time from the simulations is compared with the analytical result in Eq. **5** with the same parameters ($\lambda_1 = 10^{-7}$, $\lambda_2 = 10^{-3}$, $\beta = 1.3$, and $a = 0.6$). This simulating process is also applied in showing a transition to the single–power-law distribution under larger λ_2 as in Fig. 4.

Detecting Responsive Events in Wikipedia. In the context of collaborative editing in Wikipedia, an update could be divided into an Initiation or a Response. The difference might be implicit, but intuitively, we can refer to Initiations as the updates with independent contents, whereas Responses are the updates that are motivated by or closely related to earlier updates. First of all, we can observe some difference in the data for the two types of updates. In Wikipedia, we can trace the change of content between article versions, and examine whether there are direct causal relationships between two updates, such as "vandalism reverting," "neutrality maintenance," and "grammar modification." The time interval between such two causal events is the waiting time, which is likely to be quite short. If there is a long time silence, the next update is very likely to be an Initiation, whose content is more independent of the earlier updates, such as adding new topics to the article or replacing invalid links.

We obtained the statistical properties of the waiting time based on this intuitive understanding. We applied the following simple rules to systematically select at least a significant part of Responses in each article that can be identified based on user ID and comments: an update is selected as Response and the interval from the last update of this article is recorded as the waiting time, if the update meets one of the following requirements: (i) the update has the same author (user ID) as the last update; (ii) the author's comment of this update includes the user ID of the last update; or (iii) there are key words "revert," "undo" (including different forms of this two words) in the author's comments.

As shown in *SI Appendix*, Figs. S3*A* and S4*A*, the waiting times between Responses detected in the above manner follow power-law distributions for the 625 articles with more than 5,000 total update records. The exponents of these power-law distributions fall in a narrow range with mean −1.553 as shown in *SI Appendix*, Fig. S5*A*. These results serve as good evidence for the assumption that the power-law head of the bimodal distribution resulted from the responsive behavior.

ACKNOWLEDGMENTS. This work was partially supported by Hong Kong Baptist University (HKBU) Strategic Development Fund and the Hong Kong Research Grant Council (HKBU12302914), and National Natural Science Foundation of China under Grants 11222543, 11275027, and 61433014.

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