Rise and Fall Patterns of Information Diffusion: Model and Implications

Yasuko Matsubara
Kyoto University
y.matsubara@
db.soc.i.kyoto-u.ac.jp

Yasushi Sakurai
NTT Communication
Science Labs
yasushi.sakurai@acm.org

B. Aditya Prakash
Carnegie Mellon University
badityap@cs.cmu.edu

Lei Li
University of California, Berkeley
leili@cs.berkeley.edu

Christos Faloutsos
Carnegie Mellon University
christos@cs.cmu.edu

ABSTRACT

The recent explosion in the adoption of search engines and new media such as blogs and Twitter have facilitated faster propagation of news and rumors. How quickly does a piece of news spread over these media? How does its popularity diminish over time? Does the rising and falling pattern follow a simple universal law?

In this paper, we propose SpikeM, a concise yet flexible analytical model for the rise and fall patterns of influence propagation. Our model has the following advantages: (a) unification power: it generalizes and explains earlier theoretical models and empirical observations; (b) practicality: it matches the observed behavior of diverse sets of real data; (c) parsimony: it requires only a handful of parameters; and (d) usefulness: it enables further analytics tasks such as forecasting, spotting anomalies, and interpretation by reverse-engineering the system parameters of interest (e.g. quality of news, count of interested bloggers, etc.).

Using SpikeM, we analyzed 7.2GB of real data, most of which were collected from the public domain. We have shown that our SpikeM model accurately and succinctly describes all the patterns of the rise-and-fall spikes in these real datasets.

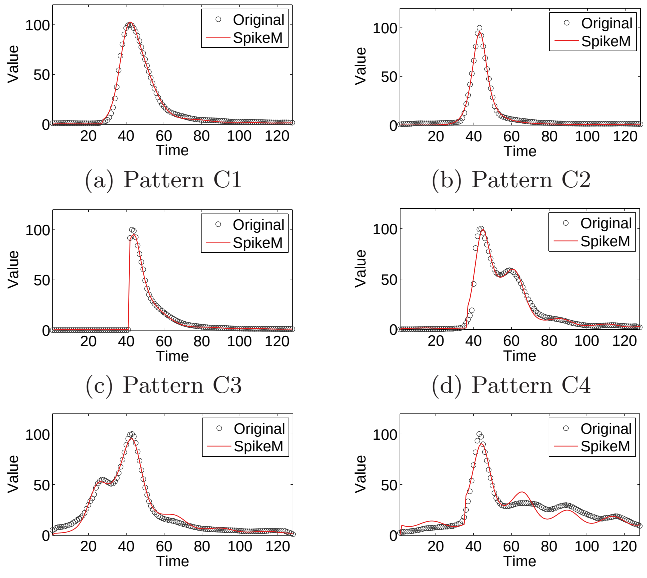
Categories and Subject Descriptors: H.2.8 [**Database management**]: Database applications–*Data mining*

General Terms: Algorithms, Experimentation, Theory

Keywords: Information diffusion, Social networks

1. INTRODUCTION

How do spikes behave in social media? Online social media is spreading news and rumors in new ways and search engines have facilitated such spreading magnificently, creating bursts and spikes. Some rumors (or memes, hashtags) start slowly and linger; others spike early and then decay; others show more complicated behavior, as we show in Figure 1.



(a) Pattern C1

(b) Pattern C2

(c) Pattern C3

(d) Pattern C4

(e) Pattern C5

(f) Pattern C6

Figure 1: Modeling power of SpikeM: six types of spikes (K-SC from [41]) shown as dots, and our model fit in solid red line. Data sequences span over 120 time-ticks, while SpikeM requires only seven parameters. The fit is so good, that the red line is often invisible, due to occlusion.

Do real rise-and-fall patterns have any qualitative differences? Do they form different classes? If yes, how many? Earlier work on Youtube data claims there are four classes [6]. Empirical work found six classes [41]. How many classes are there after all?

Our answer is: *one*. We provide a unifying model, SpikeM, that requires only a handful of parameters, and we show that it can generate all patterns found in real data simply by changing the parameter values.

Figure 1 shows six representative spikes of online media (memes) from K-SC [41], as gray circles, as well as our fitted model, as a solid red line. Notice that the fitting is very

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	C-S	K-SC	SI	AR	**SpikeM**
System identification			✓		✓
Non-linear			✓		✓
Power law decay	✓				✓
Periodicity				✓	✓
Forecasting				✓	✓

Table 1: Capabilities of approaches. Only our approach meets all specs.

good, despite the fact that our SpikeM model requires only seven parameters, and that the time-sequences span 120 intervals.

Informally, the problem we want to solve is to model/predict an activity (e.g., number of blog postings), as a function of time, given some breaking-news at a given timetick. We will use a blogger example for brevity and clarity, but many other processes could be also modeled (people buying products, computer viruses infecting machines, rumors spreading over Twitter, etc). Thus, we have:

Informal Problem 1 (what-if). **Given** *a network of bloggers (/hosts/buyers), a shock (e.g., event) at time n_b, the interest/quality of the event, the count S_b of bloggers that immediately (= time n_b) blog about the event,* **find** *how the blogging activity will evolve over time.*

A closely related problem is to develop a parsimonious model, that can be made to fit several spikes observed in the past (as we do in Figure 1). That is,

Informal Problem 2 (model design). **Given** *the behavior of several spikes in the past,* **find** *an equation/model that can explain them, with as few parameters as possible.*

It would be good if the parameters had an intuitive explanation (like, 'number of bloggers', 'quality of news', etc, as opposed to, say, a_1, a_2 of an autoregressive model (AR/ARIMA)).

In this paper, we propose SpikeM model to solve both of the aforementioned problems. Our SpikeM has the following advantages:

- **Unification power**: it includes earlier patterns and models as special cases ([41, 21]),
- **Practicality**: it matches the behavior of numerous, diverse, real datasets, including power-law decay
- **Parsimony**: our model requires only a handful of parameters
- **Usefulness**: thanks to the SpikeM model, we can answer 'what-if' questions (see subsection 5.1), spot outliers, reverse-engineer the system parameters (quality of news, count of interested bloggers, time-of-day behavior of bloggers)

Our SpikeM model is enabled by a careful design to incorporate (a) the power-law decay in infectivity, (b) a finite population, and (c) proper periodicities. Earlier models ignored one or more of the above issues.

Thanks to the *practicality* of SpikeM, we can make forecasting, analysis of 'what-if' scenarios, and detection of anomalies, as we show in section 4 and section 5. We should highlight that traditional AR, ARIMA and related linear models are fundamentally unsuitable, because they are *linear* (and can diverge to infinity) and because they lead to exponential decays (as opposed to the power law that reality seems to obey). Table 1 illustrates the relative advantages of our method: the C-S method (Crane and Sornette) [6] assumes an infinite population of bloggers; the clusters in K-SC [41] (repeated in Figure 1) are non-parametric and are incapable of forecasting. The SI model (closely related to the Bass model [3] of the market penetration of new products) leads to exponential decay, as opposed to the power-law decay that we observe in real data.

Outline. The rest of the paper goes as follows: Section 2 presents an overview of the related work and Section 3 the proposed model. Sections 4 and 5 show our experimental results on a variety of datasets. We conclude in section 7.

2. BACKGROUND

In this section, we present the fundamental concepts.

Epidemiology fundamentals. The most basic epidemic model is the so-called 'Susceptible-Infected' (SI) model. Each object/node is in one of two states - Susceptible (S) or Infected (I). Each infected node attempts to infect each of its neighbors independently with probability β, which reflects the strength of the virus. Once infected, each node stays infected forever. If we assume that the underlying network is a clique of N nodes, and use our notation ('B' for blogged = infected) the most basic form of the model is:

$$\frac{dB(t)}{dt} = \beta * (N - B(t))B(t) \tag{1}$$

where the time t is considered continuous, dB/dt is the derivative, and the initial condition reflects the external shock (say, $B(0) = b$ externally infected people). The justification is as follows: β is the strength of the virus, that is, the probability that an encounter between an infected person ('B') and an uninfected one, will end up in an infection - and we have $B * (N - B)$ such encounters. The solution for $B()$ is the sigmoid, and its derivative is symmetric around the peak, with an exponential rise and an exponential fall (we discuss later in Figure 2). There we also show the weakness of the SI model: real data have a power-law 'fall' pattern.

Self-excited Hawkes process. Crane et al. [6] used a self-excited Hawkes conditional Poisson process [12] to model YouTube views per day, showing that spikes in the activity have a power-law rise pattern, and a power-law fall pattern, depending on the model parameters. Roughly, the Hawkes process is a Poisson process where the instantaneous rate is not constant, but depends on the count of previous events, whose effect drops with the age τ of the event. That is, if there were a lot of events (viewings/bloggings) recently, we will have many such events today.

The base model states that the rate of spread of infection depends on (a) the external source $S(t)$ and (b) self-excitation, that is, on earlier-infected nodes ($i = 1, \ldots$); these nodes spread the infection with decaying virus strength $\phi(\tau)$, their age τ grows, times some constant μ_i. The constant μ_i is equivalent to the degree of the infected node i.

$$\frac{dB(t)}{dt} = S(t) + \sum_{i, t_i \leq t} \mu_i \phi(t - t_i) \tag{2}$$

The model typically assumes that the μ_i values are equal, namely that all nodes have the same degree ('homogeneous' graph). It also silently assumes that there are infinite nodes available for infection, and it may actually diverge to infinity.

Next we present our SpikeM model, which avoids the shortcomings of the SI and Hawkes models, and has several more desirable properties.

3. PROPOSED METHOD

In this section we present our proposed method, we analyze it and we provide the reader with several interesting -at least in our opinion- observations.

Our model tries to capture the following behaviors, that we observed with several of our real data

- P1: power-law fall pattern
- P2: periodicities

and at the same time we want to

- P3: avoid the divergence to infinity

that other models may have. To handle P3 (divergence), we force our model to have a finite population, and adjust the equations accordingly. To handle P1 (power-law fall pattern), we assume that the infectivity of a node (= popularity of a blog post) decays with the INFLUENCE EXPONENT, which we set at -1.5. The handling of periodicities is discussed in subsection 3.2.

We describe our model in steps, adding complexity, and we start with the base model.

Preliminaries. We assume there are N bloggers, and none of them is yet blogging about the topic of interest. At time n_b, an event happens (such as the 2004 Indonesian tsunami, or a controversial political speech such as 'lipstick on a pig'), and S_b bloggers immediately blog about it. We refer to this external event as a *shock*, and n_b and S_b are the birth-time and the initial magnitude of the shock.

Our model needs a few more parameters: the first is the quality/interestingness of the news, which we refer to as β, since this is the standard symbol for the infectivity of a virus in epidemiology literature. If β is zero, nobody cares about this specific piece of news; the higher the value, the more bloggers will blog about it.

Finally, we have the decay function $f(n)$, which models how infective/influential a blog posting is, at age n. Standard epidemiology models assume that $f()$ is constant (once sick, you have the same probability of infecting others); recent analysis has shown that the influence drops with age, following a power law.

The above are the parameters of the base model. Before we list the equations, we want to briefly mention a derived quantity, $\beta * N$; this quantity roughly corresponds to the R_0 ('R-naught') found in the epidemiology literature. This tells us the size of the "first burst": if only one person was infected, how many would be infected in the next time-tick?[1]

In summary, the scenario we model is as follows:

- nothing happens, until a news-event appears, at birth-time n_b.
- S_b bloggers immediately blog about it.
- other bloggers visit the initial S_b (or follow-up) bloggers, and occasionally get 'infected' and blog about the event, too.

We also assume that

- each blogger blogs at most once about the event
- no other related event occurs - that is, the shock function $S()$ has only one spike.

Without loss of generality, we also assume that once an uninformed blogger sees an infected/informed blog, he/she always blogs about the event (if he/she blogs with probability $\rho < 1$, we could absorb ρ in the infectivity factor β)

Our goal is to find an equation to describe the number $\Delta B(n)$ of people blogging at time-tick n, as a function of n and of course the system parameters (total number of bloggers N, strength of infection β etc).

3.1 Base model - SpikeM-Base

The model we propose has nodes (=bloggers) of two states:

- U: **U**n-informed of the rumor
- B: informed, and **B**logged about it

For those who just got informed at time-tick n, we'll use the symbol $\Delta B(n)$, and we assume that, once informed, a person will blog about the rumor immediately.

Let $U(n)$ be the number of un-informed people at time n, and let $\Delta B(n)$ the number of people that just found out about the rumor at time n, and blogged immediately about it.

MODEL 1 (SPIKEM-BASE). *Our base model is governed by the equations*

$$\Delta B(n+1) = U(n) \cdot \sum_{t=n_b}^{n} \big(\Delta B(t) + S(t)\big) \cdot f(n+1-t) + \epsilon \tag{3}$$

$$U(n+1) = U(n) - \Delta B(n+1) \tag{4}$$

where,

$$f(\tau) = \beta * \tau^{-1.5} \tag{5}$$

and initial conditions:

$$\Delta B(0) = 0, \quad U(0) = N$$

In addition, we add an external shock $S(n)$, a spike generated at birth-time n_b. Mathematically, it is defined as follows:

$$S(n) = \begin{cases} 0 & (n \neq n_b) \\ S_b & (n = n_b) \end{cases} \tag{6}$$

Justification of the model. We do it in steps:

- The term $\Delta B(t) + S(t)$ captures the count of bloggers plus external sources, that got activated at time-tick t; their infectivity is modulated by the $f()$ infectivity function, since we assume that the infectivity of a source/blogger decays with time. The summation is over all past time-ticks since the birth-time n_b the shock.
- The infectivity function $f()$ exactly follows a power law with exponent -1.5 as discovered by earlier work on read data: real bloggers [22], and response to mails by Einstein and Darwin [2].
- The meaning of the summation is the available stimuli at time-tick n; the available targets are the uninformed bloggers $U(n)$, and the product gives the number of new infections.
- We add a noise term ϵ to handle cases such as hashtag 'egypt' on Twitter: some people tweet about Egypt anyway, but a large shock occurred during the events in Tahrir square. Very often, $\epsilon \simeq 0$.

[1] yes, it should be $N - 1$, but we sacrifice accuracy, for intuition.

Symbol	Definition
N	total population of available bloggers
n_d	duration of sequence
n	time-tick ($n = 0, \ldots, n_d$)
$U(n)$	count of **u**n-informed bloggers
$B(n)$	count of informed **b**loggers
$\Delta B(n)$	delta: count of informed **b**loggers at exactly time n
$f(n)$	infectiveness of a blog-post, at age n
β	strength of infection
$\beta * N$	"first-burst" size of infection
$S(n)$	volume of external **s**hock at time n
n_b	starting time of **b**reaking news
S_b	strength of external shock at birth (time n_b)
ϵ	background noise
P_a	strength of periodicity
P_p	period
P_s	phase shift of periodicity

Table 2: Symbols and definitions

This completes the justification of our base model.

We also mention some facts that our model obeys: by definition

$$B(n) = \sum_{t=0}^{n} \Delta B(t)$$

and of course we have the invariant

$$B(n) + U(n) = N$$

where N is the total number of people/bloggers.

3.2 With periodicity - SpikeM

Bloggers may modulate their activity following a daily cycle (or weekly, or yearly). For example, among the $U(n)$ uninformed bloggers at time n, a fraction of them are not paying attention (say, because they are tired or asleep). How can we reflect this in our equations? We propose an answer below, and then we provide the justification.

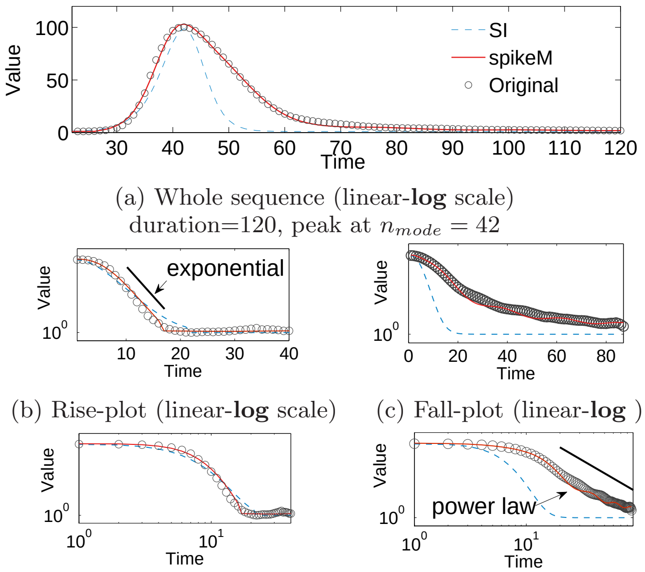
Model 2 (SpikeM). *We can capture the periodic behavior of bloggers with the following equations:*

$$\boxed{\begin{aligned}\Delta B(n+1) = p(n+1)\cdot \\ \Big(U(n)\cdot \sum_{t=n_b}^{n} \big(\Delta B(t)+S(t)\big)\cdot f(n+1-t)+\epsilon\Big) \quad (7)\end{aligned}}$$

$$p(n) \quad = 1 - \tfrac{1}{2} P_a \Big(sin\big(\tfrac{2\pi}{P_p}(n + P_s)\big) + 1\Big) \qquad (8)$$

where, $U(n)$, $S(t)$ and $f(n)$ are defined in Model1.

Justification. The model is identical to SpikeM-base (1), with the addition of the periodicity factor $p(\cdot)$. This captures the fact that bloggers tone down their activity, say, during the night, or even stop it altogether. The idea is that $U(\cdot)$ is the count of victims available for infection, and the summation is the number of attacks. Under normal circumstances, each victim-attack pair would lead to a new victim; however, since the victims are not paying full attention (tired/asleep), the attacks are not so successful, and thus we prorate them by the $p()$ periodic function.



(a) Whole sequence (linear-**log** scale) duration=120, peak at $n_{mode} = 42$

(b) Rise-plot (linear-**log** scale)

(c) Fall-plot (linear-**log**)

(d) Rise-plot (**log-log** scale) Time n:42, 41, ... 1

(e) Fall-plot (**log-log**) Time n:42, 43, ...120

Figure 2: Fitting results of SpikeM vs. SI for pattern C1 in Figure 1. The original sequence (in gray circles), and our model (red line) have an exponential rise and a power-law drop; the SI model (blue dashed line) is exponential on both and thus unrealistic. top row: full interval; left column: only the rise part; right column: only the 'fall' part.

- P_p stands for the period of the cycle (say, 24 hours).
- P_s stands for the phase shift: if the peak activity is at noon, and the period is P_p=24 hours, then P_s=18.
- P_a depends on the amplitude of the fluctuation, and specifically it gives the relative value of the off-time (say, midnight), versus peak time (say, noon). Thus, if P_a=0, we have no fluctuation.

3.3 Additional details

Model extensions. We could easily extend our model so that it has several shocks as opposed to just one as considered here. We could also extend it to have multiple cycles (daily, weekly, yearly). We do not elaborate on these extensions for two reasons: (a) for clarity and (b) because the current model fits real data very well, anyway.

Learning the parameters. Our model consists of a set of seven parameters: $\boldsymbol{\theta} = \{N, \beta, n_b, S_b, \epsilon, P_a, P_s\}$. Given a real time sequence $X(n)$ of bloggers at time-tick n ($n = 1, \ldots, n_d$), we use *Levenberg-Marquardt (LM)* [23] to minimize the sum of the errors: $D(X, \boldsymbol{\theta}) = \sum_{n=1}^{n_d}(X(n) - \Delta B(n))^2$.

Analysis - exponential rise, power-law fall. It is not obvious from the equations of our model, but its rise pattern is exponential, while the fall pattern obeys a power law. This is desirable, because this behavior seem to be prevailing in real data, as we show in Figure 2. Let n_{mode} denote the time-tick at which the wave $\Delta B()$ reached its maximum volume. By *rise plot* we mean the plot of values from the birth-time n_b until n_{mode} (and reversing time

$abs(n - n_{mode})$) The *fall-plot* is defined similarly: activity $\Delta B()$ versus delay from the peak $n - n_{mode}$. Notice that there is a power law for the fall, and an exponential shape for the rise. We also show the traditional 'SI' model, which, as expected, exhibits exponential behavior for both rise and fall.

4. EXPERIMENTS

To evaluate the effectiveness of SpikeM, we carried out experiments on real datasets. The experiments were designed to answer the following questions:

- Q1: Can we explain the cluster centers of K-SC?
- Q2: How well do we match *MemeTracker* data?
- Q3: How does it compare with other data?
- Q4: How well do we forecast future patterns?

Dataset description. We performed experiments on the following three real datasets.

- *MemeTracker*: This dataset covers three months of blog activity from August 1 to October 31 2008[2], It contains short quoted textual phrases ("memes"), each of which consists of the number of mentions over time. We choose 1,000 phrases in blogs with the highest volume in a 7-day window around their peak volume.
- *Twitter*: We used more than 7 million Twitter[3] posts covering an 8-month period from June 2011 to January 2012. We selected the 10,000 most frequently used hashtags.
- *GoogleTrends*: This dataset consists of the volume of searches for various queries (i.e., words) on Google[4]. Each query represents the search volumes that are related to keywords over time.

4.1 Q1: Explaining K-SC clusters

The results on this dataset were already presented in section 1 (see Figure 1). Our model correctly captures the six patterns of K-SC. Table 3 gives a further description of the SpikeM fitting. Our model consists of seven parameters, each of which describes the behavior of spikes. Note that the total populations N are almost the same for all patterns, (around 2,000 to 3,000). This is because these six patterns are scaled on the y-axis so that they all have a peak volume of 100. We can see that $\beta * N$ is between $0.7 - 1.0$ for these six patterns. We also see that Pattern C3 has an extreme shock $S_b = 114$ at time $n_b = 40$, which means that this spike is strongly affected by the external burst of activity (see Figure 1 (c)). On the other hand, Patterns C4-C6 have several peaks about 24 hours apart with a strength $P_a \simeq 0.4$.

We also evaluated our fitting accuracy by using the root mean square error ($RMSE$) between estimated values and real values: $RMSE = \sqrt{\frac{1}{n_d}\sum_n^{n_d}(X(n) - \Delta B(n))^2}$. Table 4 shows the fitting accuracy result for six patterns of K-SC. We compared SpikeM with SI model. As discussed in section 3 (see Figure 2), SI cannot model the tail parts of the spikes. On the other hand, our solution, SpikeM achieves high accuracy for every pattern of K-SC.

	C1	C2	C3	C4	C5	C6
N	2407	1283	1466	3079	4183	3435
$\beta * N$	0.95	1.00	0.86	0.92	0.79	0.69
n_b	26	17	**40**	35	0	34
S_b	4.73	0.06	**114.13**	23.24	2.58	45.58
ϵ	0.36	0.01	0.43	1.48	0.32	13.97
P_a	0.18	0.06	0.22	**0.38**	**0.28**	**0.39**
P_s	12	5	7	**6**	**2**	**2**

Table 3: The model parameters of our SpikeM best fitting on six patterns of K-SC (see Figure 1).

Pattern	C1	C2	C3	C4	C5	C6
SpikeM	**1.84**	**1.61**	**0.97**	**4.08**	**3.33**	**5.89**
SI	15.64	6.78	19.65	25.29	20.36	21.76

Table 4: Fitting accuracy of SI vs. SpikeM on six patterns of K-SC. SpikeM consistently outperforms SI with respect to accuracy ($RMSE$) between the original values and the models.

4.2 Q2: Matching *MemeTracker* patterns

Figure 3 shows the results of model fitting on the *MemeTracker* dataset. We selected six typical sequences according to the K-SC clusters. That is, each sequence corresponds to each pattern (C1-C6). We show the original sequences (black dots) and SpikeM fitting, $\Delta B(n)$ (red line) in both linear-linear (top) and log-log (bottom) scales. In the log-log scale, we also show the count of un-informed bloggers, $U(n)$. In Figure 3, the bottom table shows the short phrases (memes) of each sequence. All of the phrases are sourced from U.S. politics in 2008. We obtained several observations for each sequence:

- Patterns C1 and C2: almost the same size of population, $N \simeq 500$, except that C2 has a quicker rise and fall (i.e., stronger infection, $\beta * N = 1.4$) than C1 ($\beta * N = 0.94$).
- Pattern C3: this sequence has a sudden rise and a power law decay. There is a slight daily periodicity.
- Patterns C4 and C5: there are clearly daily periodicities. Pattern C6, "lipstick on a pig" has the largest population of all six sequences (i.e., $N = 6259$).
- Pattern C6: the sequence: "yes we can" consists of huge spikes around $n = 40$, and constant periodic noise. This is because the bloggers mention this phrase as Barack Obama's slogan as well as with more general meanings. We can also find that there are several extreme points (i.e., missing values) around $n = 120$ (see blue circle in log-log scale).

4.3 Q3: Matching other data

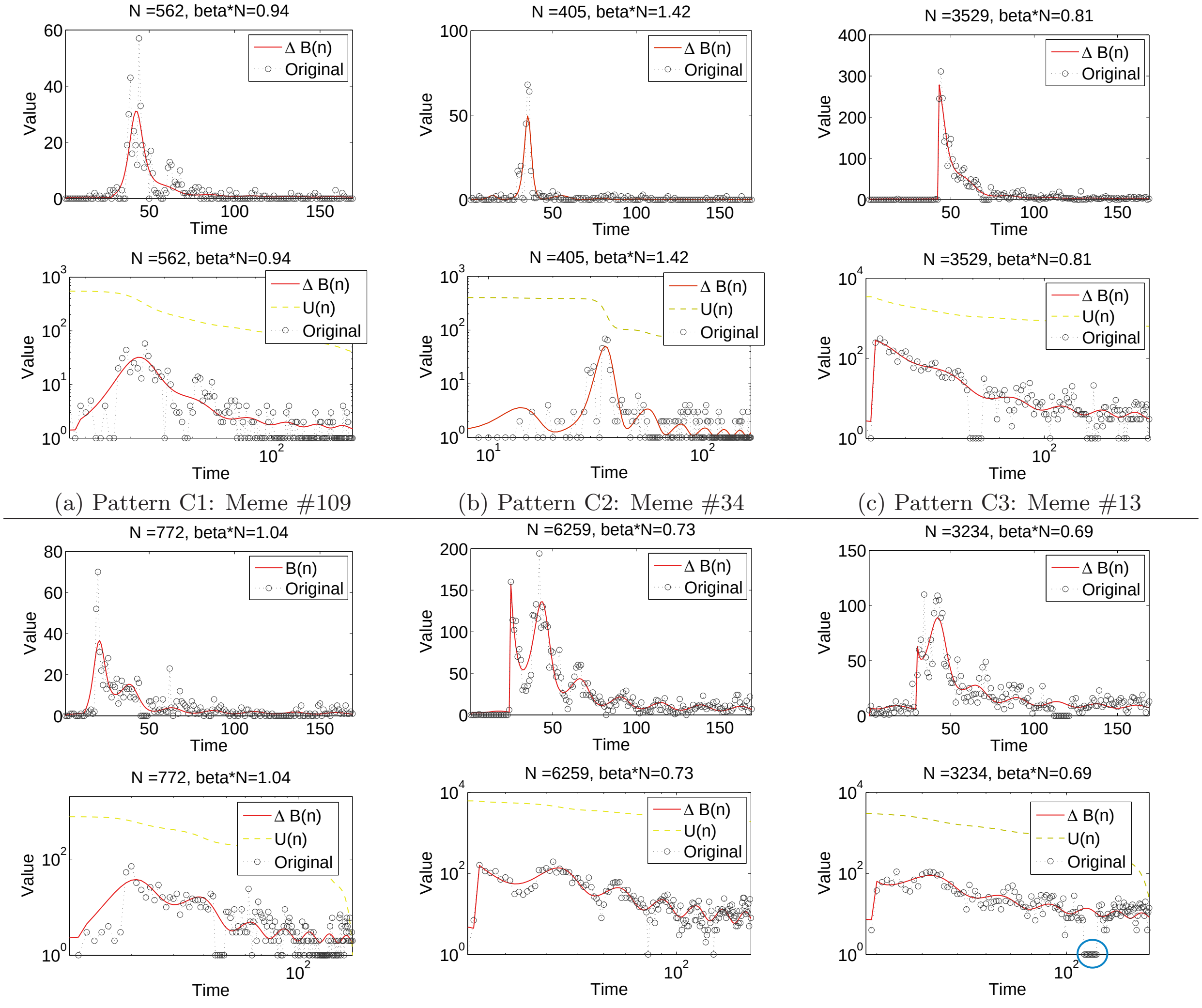
We also demonstrate the effectiveness of our model for other types of spikes.

Fitting on Twitter data. Figure 4 describes our fitting results on the *hashtags* of *Twitter* data. In this figure, we can see that *Twitter* data behave similarly to *MemeTracker* data. Due to space limitations, we show only three major hashtags. Note that the top and bottom rows are in linear-linear and log-log scales, respectively. Our model captures the following characteristics: (a) #assange: this is a topic about Julian Assange, the founder of WikiLeaks. There are several mentions before the peak point (December 5, 2011). (b) #stevejobs: there is a sudden peak on Octo-

[2] http://memetracker.org/

[3] http://twitter.com/

[4] http://www.google.com/insights/search/

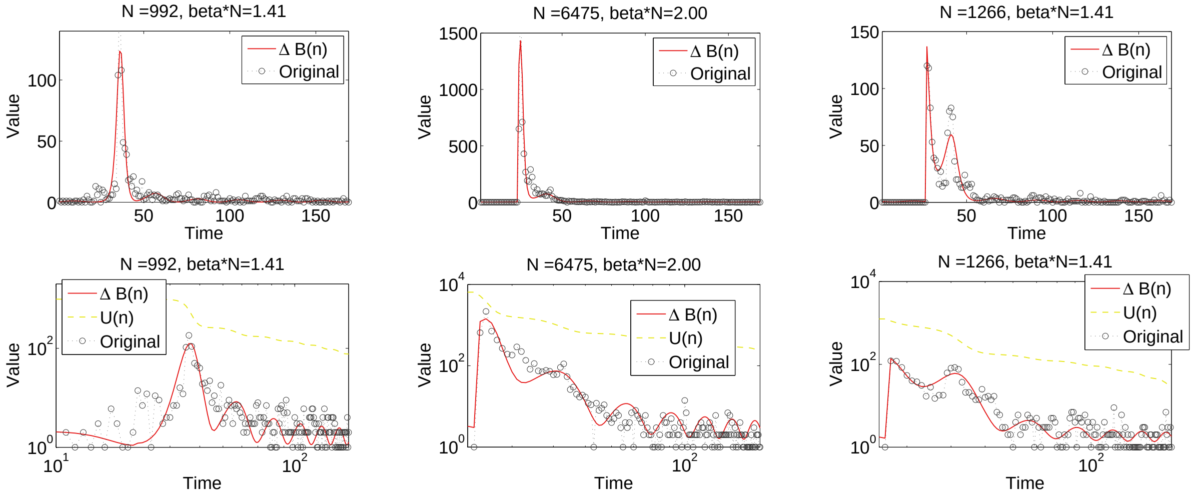


(a) Pattern C1: Meme #109 (b) Pattern C2: Meme #34 (c) Pattern C3: Meme #13

(d) Pattern C4: Meme #87 (e) Pattern C5: Meme #9 (f) Pattern C6: Meme #3

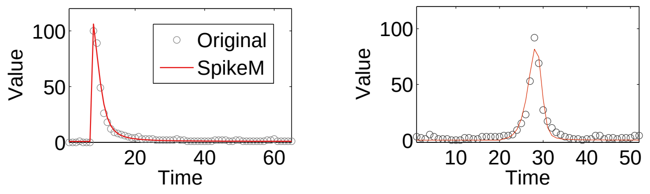
#109	the most serious financial crisis since the great depression	#87	what is required of us now is a new era of responsibility
#34	i love this country too much to let them take over another election	#9	you can put lipstick on a pig
#13	hope over fear, unity of purpose over conflict and discord	#3	yes we can yes we can

Figure 3: Results of SpikeM fitting on six patterns from *MemeTracker* dataset. The figures show in both 'linear-linear'(top) and 'log-log'(bottom) scales. The bottom table lists the phrase ("meme") of each patterns.



(a) #assange (b) #stevejobs (c) #arresteddevelopment

Figure 4: Results of SpikeM fitting on three hashtags from *Twitter* dataset. The top and bottom rows show in linear-linear scale, and log-log scale, respectively.



(a) "tsunami" (2005)

(b) "Harry Potter" (2007)

Figure 5: SpikeM fitting on *GoogleTrends* dataset: the volume of searches for the keyword (in black dots) and fitting results (in red lines). Note that the window size is per week.

ber 5, 2011, with a long heavy tail (see Figure 4(b) in log-log scale). This was caused by the death of Steve Jobs. (c) #arresteddevelopment: this a topic about the movie "Arrested Development". There is a clear daily periodicity with a peak point.

Fitting on GoogleTrend data. We can also observe influence propagation in queries on internet search engines. Figure 5 shows two different types of spikes on *GoogleTrends*. For an external catastrophic event (a) "tsunami", we see that there is a super quick rise immediately after the Indian Ocean earthquake and tsunami in 2005. In contrast, (b) "harry potter" has a slower rise, which is because this spike was generated by "word-of-mouth" activity surrounding the release of a Harry Potter movie in 2007. SpikeM evidently captures both types of spikes successfully.

4.4 Q4: Tail-part forecasts

So far we have seen how SpikeM captures the pattern dynamics for various spikes. Here, we answer a more practical question: given the first part of the spike, how can we forecast the future behavior of the tail part? Figure 6 shows results of our forecasts on *MemeTracker* data. We selected two the highest population phrases (#9 and #13 in Figure 3). We trained our models by using the values obtained over a period of 54 hours (dotted black lines in the figure), and then forecasted the following days (solid red lines, about five days). Note that the vertical axis uses a logarithmic scale. We compared SpikeM with the auto regressive model (AR). For a fair comparison, we used seven regression coefficients, which was the same size as our model parameters.

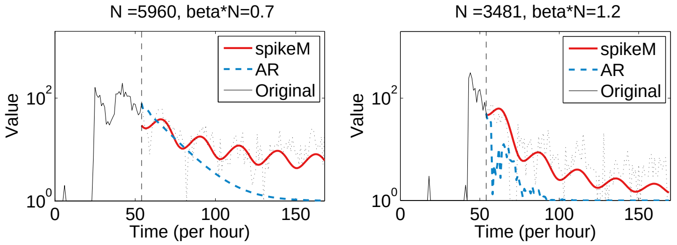
Our method achieves high forecasting accuracy while AR failed to forecast future patterns. More specifically, the reconstruction errors of SpikeM are $RMSE = 9.26$ and 8.93 for #9 and #13, while AR has errors of 13.98 and 14.19. Similar trends are observed in other phrases, however we omit the results due to space limitations. More importantly, our model can forecast the rise part of spikes as well as the tail part (discussed in Section 5).

5. DISCUSSION - SpikeM AT WORK

Our proposed model, SpikeM is capable of various applications. Here, we describe important applications and show some usefulness examples of our approach.

5.1 "What-if" forecasting

We have discussed tail-part forecasting in subsection 4.4. Ideally, we want to forecast not only the tail-part, but also the rise-part of a spike. This is much more difficult, because we usually have very few points in the rise-part of a spike. However, if this is a repeating event, like, say, the spikes induced by 'Harry Potter' movies releases, can we forecast future spikes if we know the release date of the next movie? It turns out that our SpikeM model can help with this (difficult) task, too.



(a) Meme #9

(b) Meme #13

Figure 6: Results of tail-part forecasting on *MemeTracker* data. We train spikes from $n = 0$ to 54, and then, start forecasting at time $n = 54$. Our SpikeM reflects reality better, while AR quickly converges to the zero.

Thus, the problem we address in Figure 7 is as follows: we are given (a) the first spike in 2009, "Harry Potter and the Half-Blood Prince" ($n = 185$); (b) the release dates of the two sequel movies (blue text with as arrows pointed at $n = 255$ and 289), and (c) the access volume before the release dates (and specifically from 8 to 2 weeks before). Can we forecast the rise and fall shapes of upcoming spikes and their peak points?

Solution and results. SpikeM can predict the potential population N of users who are interested in "Harry Potter", and the strength of 'word-of-mouth' infection: β. Our solution is to assume that these values are fixed for all of the sequel spikes. The only difference is the strength of the "external shock", i.e., n_b and S_b. Our solution consists of the following three-step process:

1. Train the parameter set $\boldsymbol{\theta}$ by using the first spike (solid black line in the figure).
2. With the fixed parameters $\boldsymbol{\theta}$, infer the new values of $\tilde{n_b}$ and $\tilde{S_b}$ by using the beginning part of the next spike (blue lines between double arrows at $n = 250$ and 280).
3. Generate the spikes using $\boldsymbol{\theta}$ and $\tilde{n_b}$ and $\tilde{S_b}$ (red lines).

In conclusion, Figure 7 shows that our model successfully captures the two sequel spikes and peak points n_{mode}.

5.2 Outlier detection

Since SpikeM has a very high fitting accuracy on real datasets (described in section 4), another natural application would be anomaly detection. Figure 8 shows the fitting result of Figure 5 (a), in a **log-log** scale. Note that the black circles are the original sequence, and the pink line is our model fitting. We can visually observe that there are several points that do not overlap the model. For example, (a) on March 29, there is one spike, since another earthquake occurred on March 28. (b) There is a huge spike on December 26, 2005, which is exactly one year after the Indian Ocean earthquake.

5.3 Reverse engineering

Most importantly, our model can provide an intuitive explanation such as the potential number of interested blog-

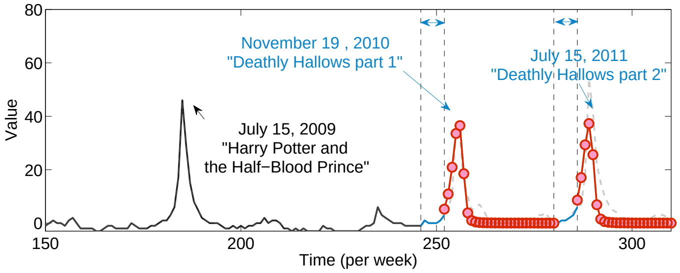


Figure 7: Results of "what-if" forecasting for the Harry Potter series. We trained parameters by using (a) the first spike around July 15, 2009 (black solid line), and (b) access volume two months before the release (blue lines with double arrows around time n = 250, 280) and then, forecasted the following two spikes (red lines).

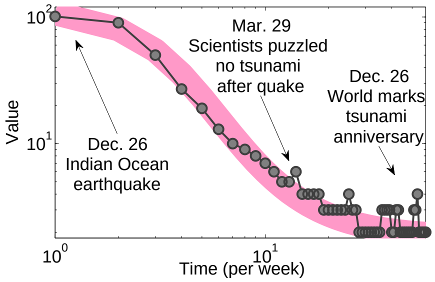


Figure 8: Outlier detection on *GoogleTrends* dataset (in log-log scale). Notice that the biggest spike,"world marks tsunami anniversary" occurred after one year (i.e., 52 weeks later).

gers, and the quality of news. Here we report our discoveries on *MemeTracker* and *Twitter* datasets (see Figure 9).

Observation 1 (Total population of bloggers). *The total populations of potential bloggers/users N are almost same for both datasets (around $N = 1,000 - 2,000$).*

We also note that they are skewed to the right, i.e., there is a long tail of larger values.

Observation 2 (Strength of first infection). *The strength of the "first burst" is $\beta * N \simeq 1.0$ for each dataset.*

The above two observations agree with the intuition: we can see common behavior for *MemeTracker* and *Twitter*, which means that they have similar characteristics in terms of social activities.

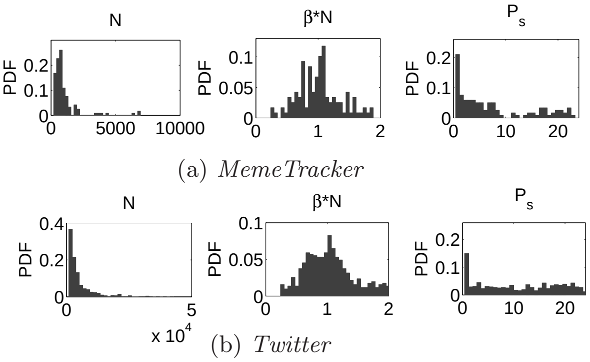
Observation 3 (Common activity and periodicity). *Typical user behavior is to have a daily periodicity with (a) phase shift $P_s = 0$ (small population during early morning, large population at peak point, 6pm) for MemeTracker, while (b) more spread in P_s.*

Note that more than 90% of all spikes have a daily periodicity in both datasets. The only the difference between the two datasets is that *Twitter* has several P_s values. This is because *Twitter* has multiple time zones (e.g., US, UK, Australia, and India).

6. RELATED WORK

We present the related work, in three areas: time series analysis, influence propagation, and burst detection.

Time series Analysis. This is an old topic, that has attracted huge interest, and that is dealt with in well-regarded textbooks [4]. Traditional approaches applied to data mining include Auto-Regression (AR) and variations [24], or Linear dynamical systems (LDS), Kalman filters (KF) and variants [13, 25, 26] but they are all linear methods. Nonlinear methods for forecasting tend to be hard to interpret, because they rely on nearest-neighbor search [5], or artificial neural networks [39]. Similarity search, indexing and pattern discovery in time sequences have also attracted huge interest [7, 14, 8, 16, 27, 38, 30, 34, 35, 28], but none of these methods specifically focused on modeling bursts.



(a) *MemeTracker*

(b) *Twitter*

Figure 9: Reverse engineering: pdf of three parameters: $N, \beta * N, P_s$ over 1,000 memes/hashtags. (a) *MemeTracker*: total potential bloggers $N \simeq 1,000$, and strength of "first burst" $\beta * N \simeq 1.0$. More than 90% of the memes have clear daily periodicity with high activities around 6pm (i.e., $P_s \simeq 0$). (b) *Twitter*: similar trends except more spread in P_s, possibly, due to multiple time zone. Also see the text for more observations.

Influence propagation. The canonical text-book for epidemiological models like SI is Anderson and May [1]. The power-law decay of influence has been reported in blogs [29], with a exponent of -1.5. Barabasi and his colleagues reported exponents of -1 and -1.5, for the response time in correspondence [2]. Analyses of epidemics, blogs, social media, propagation and the cascades they create have attracted much interest [21, 40, 18, 33, 32, 15, 37, 9, 10, 11, 20], and recently the reverse problem ('find who started it') [19, 36].

Burst detection. Remotely related to our work are the efforts to spot bursts. This includes the work of Kleinberg [17], the algorithm of Zhu and Shasha [42], and the algorithm of Parikh et al. [31]. None of the above gives a parsimonious model for describing the activity in a network.

7. CONCLUSIONS

In this paper, we study the rise-and-fall patterns in information diffusion process through online medias. We presented SpikeM, a general, accurate and succinct model that explains the rise-and-fall patterns. Our proposed SpikeM has the following appealing advantages:

- **Unification power**: it includes earlier patterns and models as special cases (K-SC, as well as the SI model);
- **Practicality**: it matches the behavior of numerous, diverse, real datasets, including the power-law decay and much more beyond;
- **Parsimony**: our model requires only a handful of parameters;
- **Usefulness**: we showed how to use our model to do 'short-term' forecasting, to answer what-if scenarios, to spot outliers, and to learn more about the mechanisms of the spikes.

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