



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

Motivation

Social media facilitates faster diffusion of news, rumors



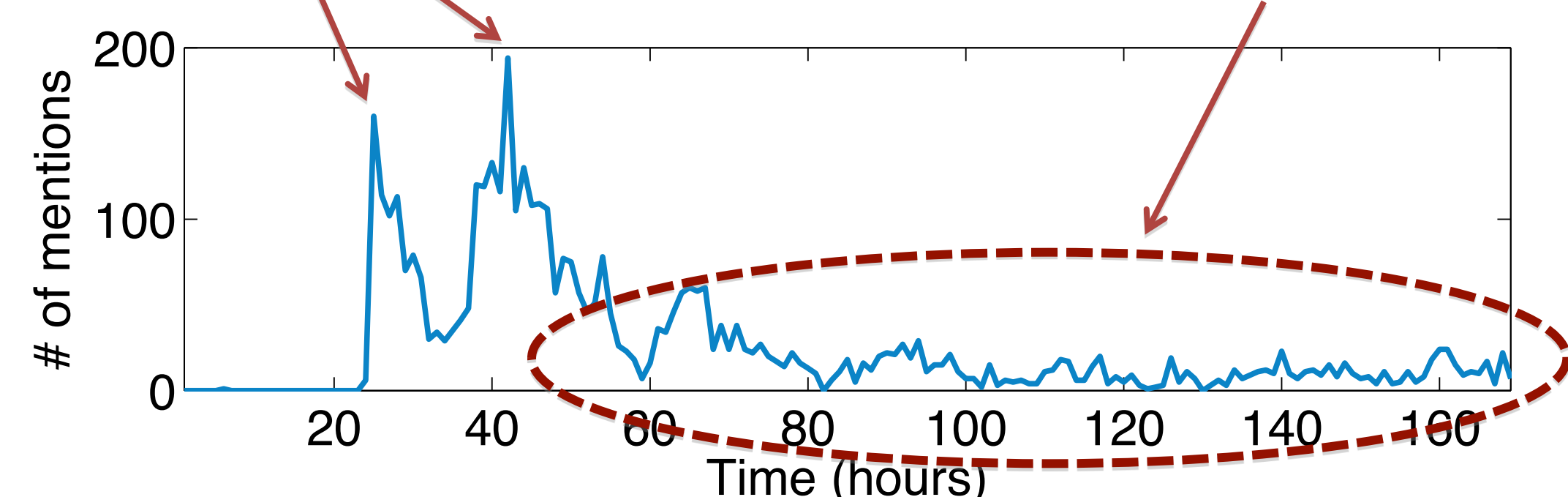
Q. How do news & rumors spread in social media?

Rise-and-fall patterns

in information diffusion through online media

e.g., Meme (# of mentions in blogs) [KDD'09]

daily or weekly periodicities power-law fall pattern



“lipstick on a pig” : Short phrases sourced from U.S. politics in 2008

Q. Do the rise-fall patterns follow a simple law?

Problem definition

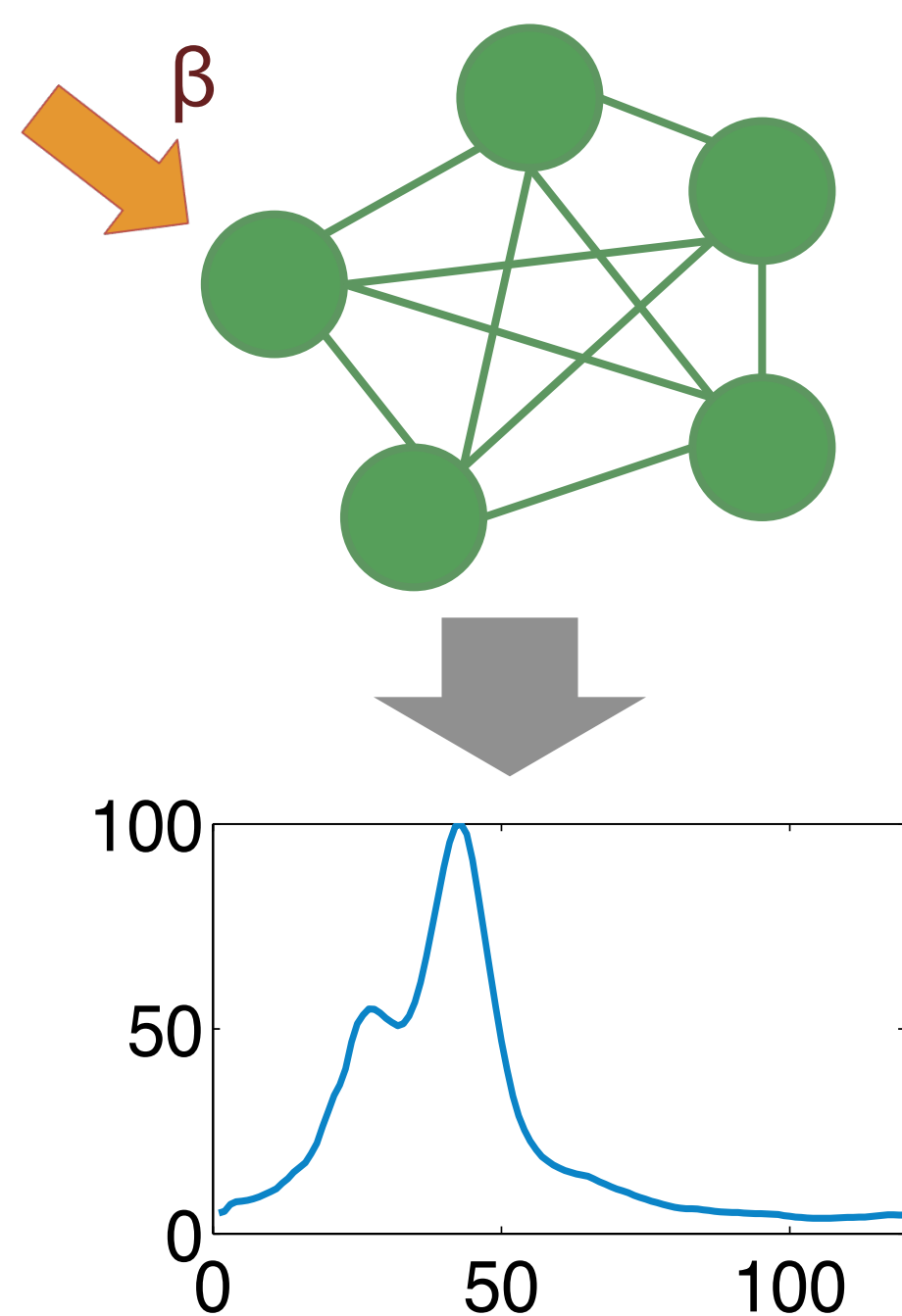
Goal: predict/model social activity

Given:

- Network of bloggers/users
- External shock/event
- Quality of the event β

Find:

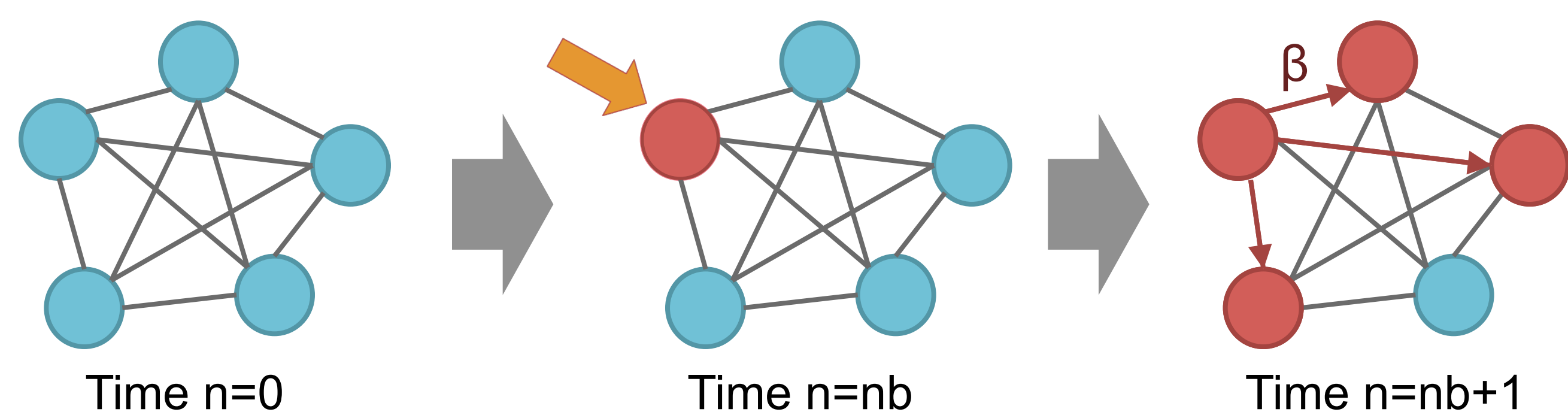
- How blogging activity will evolve over time



Proposed method: SpikeM

Main idea:

1. **Un-informed bloggers** (uninformed about rumor)
2. **External shock** at time n_b (e.g, breaking news)
3. **Infection** (word-of-mouth)



- U - Un-informed node (bloggers)
- B - informed, and Blogged about rumor

External shock

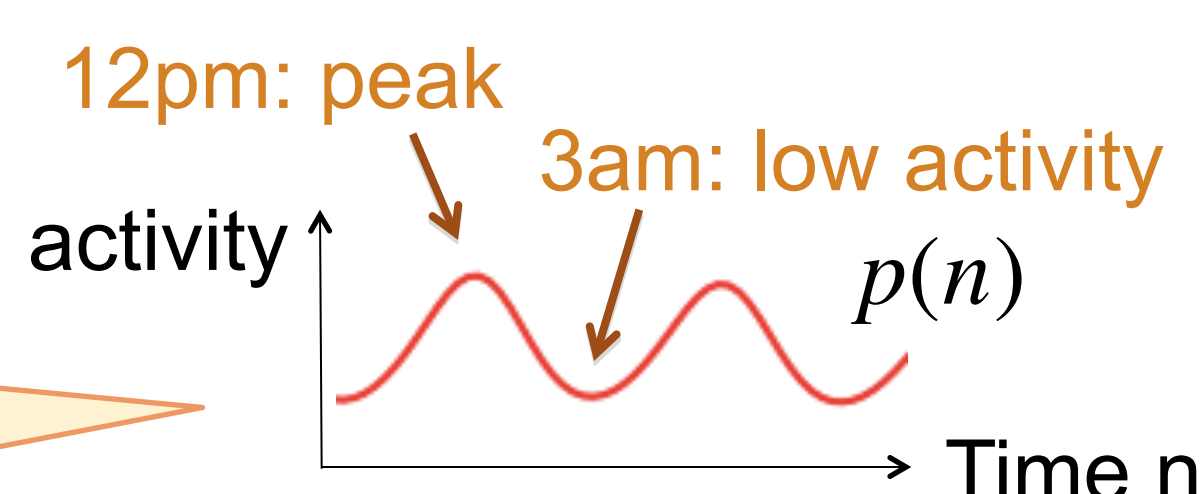
- S_b - Strength of external shock at birth
- n_b - Starting time of breaking news

Infectiveness of a blog-post at age n : $f(n) = \beta * n^{-1.5}$

- β - Strength of infection (quality of news)
- $f(n)$ - Decay function (how infective a blog posting is)

SpikeM – with periodicity

Bloggers change their activity (e.g., daily, weekly, yearly)



Code: <http://www.kecl.ntt.co.jp/csl/sirg/people/yasuko/software.html>

Equations of SpikeM

$$\Delta B(n+1) = p(n+1) \cdot \left[U(n) \cdot \sum_{t=n_b}^n (\Delta B(t) + S(t)) \cdot f(n+1-t) + \varepsilon \right]$$

Blogged ... count of informed bloggers at time n

$$U(n+1) = U(n) - \Delta B(n+1)$$

Un-informed ... count of un-informed bloggers

N - Total population of available bloggers

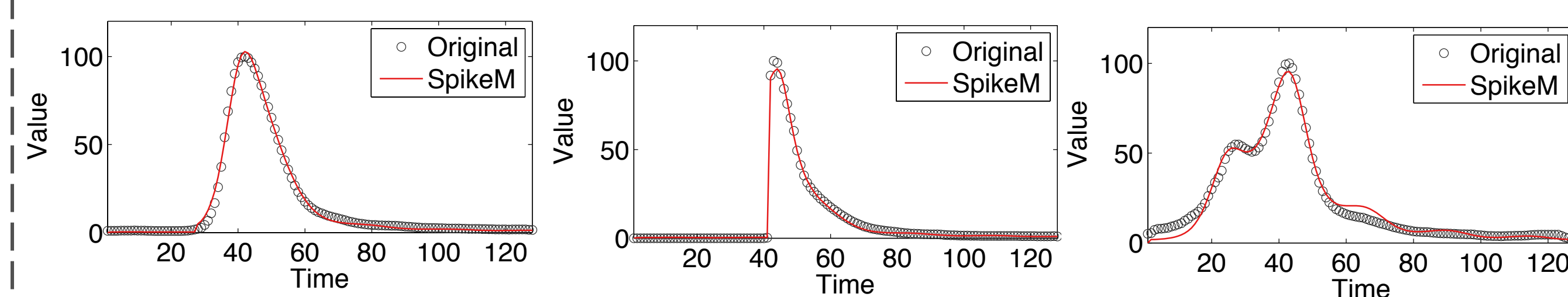
β - Strength of infection/news

n_b, S_b - External shock S_b at birth (time n_b)

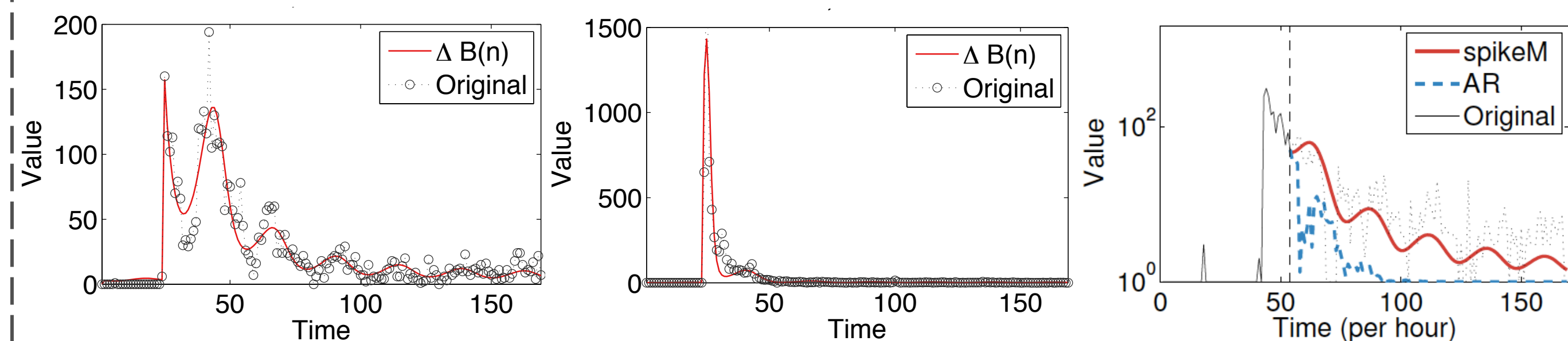
$p(n)$ - Periodicity

Experiments – fitting results

K-SC [WSDM'11] ... spikes of online media (memes)



Other datasets



Memetracker
“lipstick on a pig”

Twitter (hashtag)
“#stevejobs”

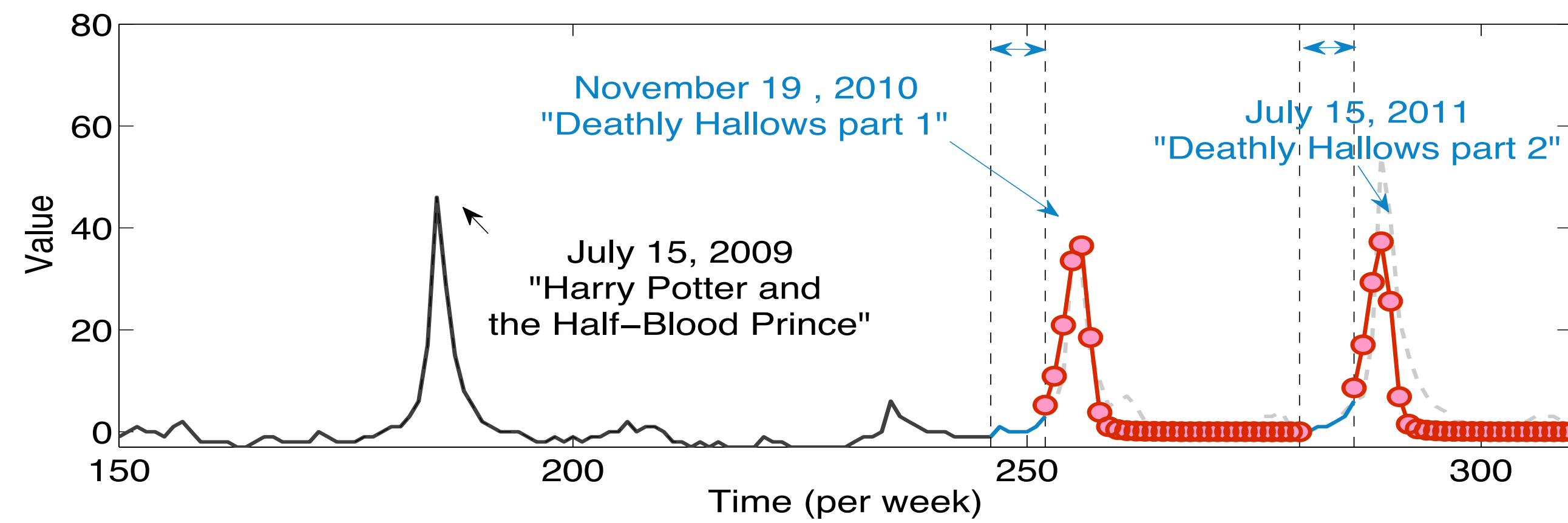
Tail-part forecasts
SpikeM vs. AR

SpikeM – at work

(a) “What-if” forecasting:

Given (1) first spike (2) release date (3) two weeks before release

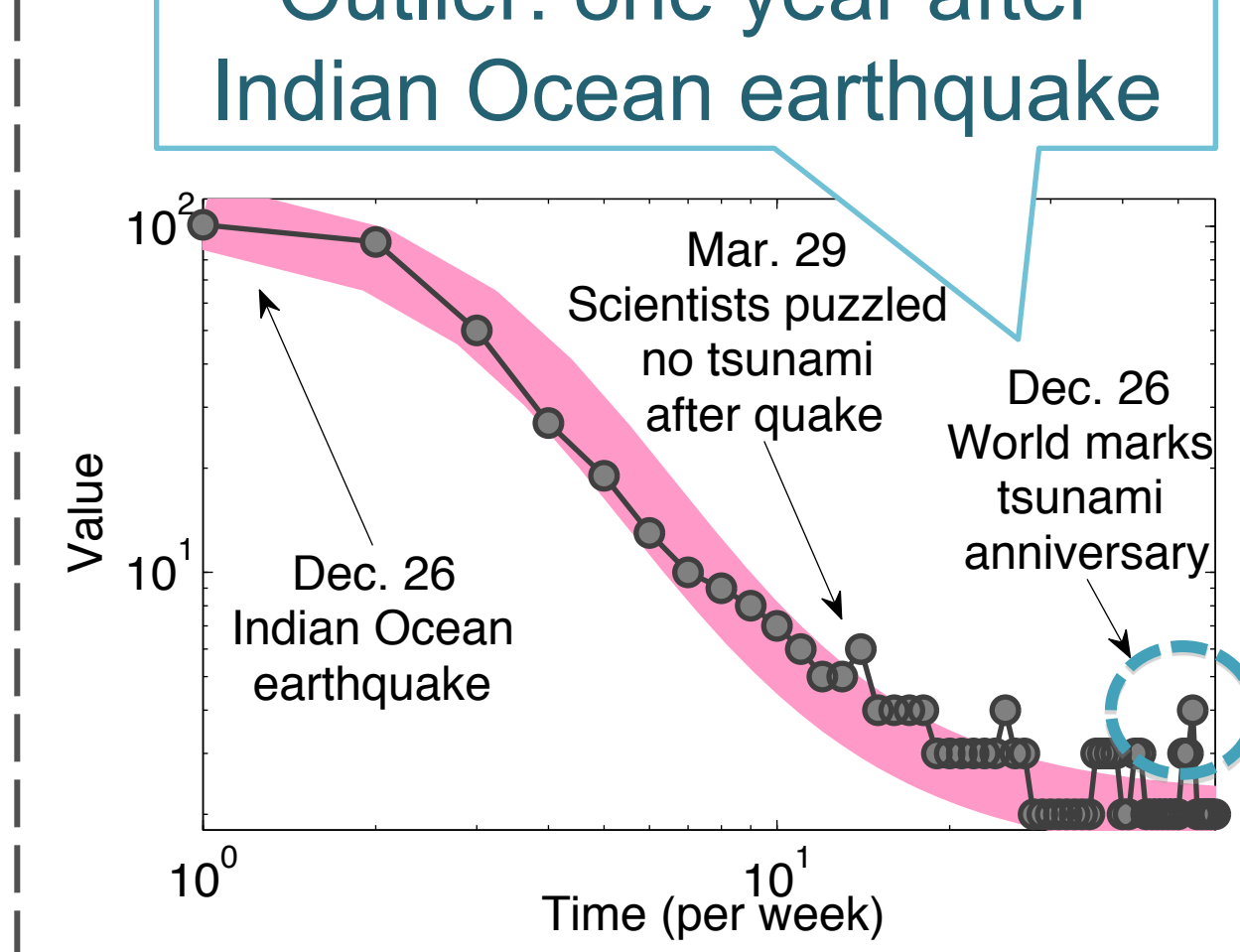
Forecast: upcoming spikes (red)



“Harry potter” (Google trends)

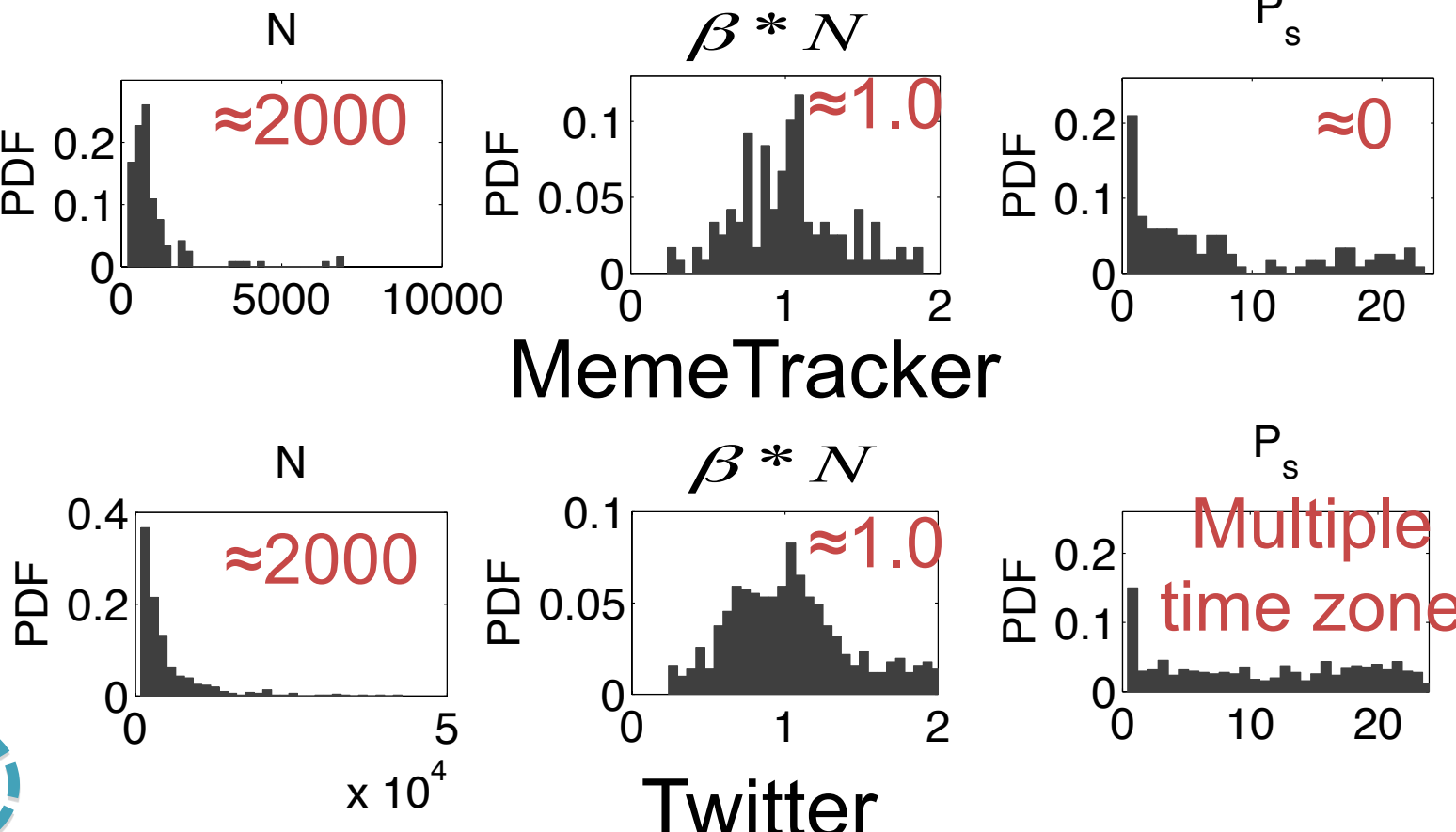
(b) Outlier detection

Outlier: one year after Indian Ocean earthquake



“Tsunami” (Google trends)

(c) Reverse engineering



PDF of SpikeM parameters over 1,000 memes/hash tags

Conclusions

SpikeM has following advantages:

- **Unification power**: includes earlier patterns/models
- **Practicality**: matches behavior of real datasets
- **Parsimony**: requires only 7 parameters
- **Usefulness**: answers what-if scenarios, spot outliers, forecasting, reverse engineering