# SEISMIC: A Self-Exciting Point Process Model for Predicting Tweet Popularity

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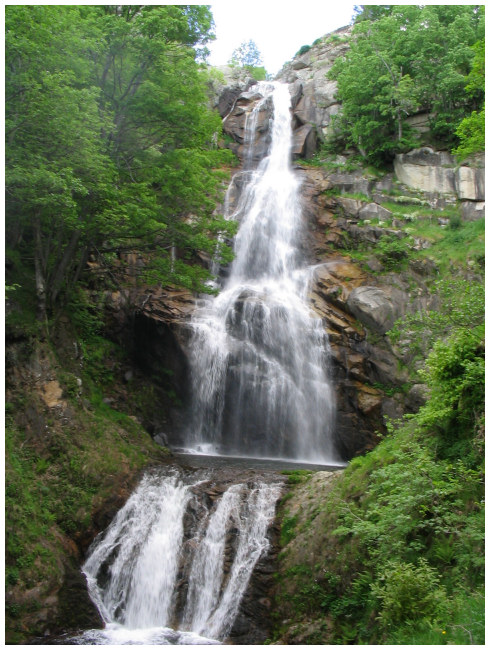
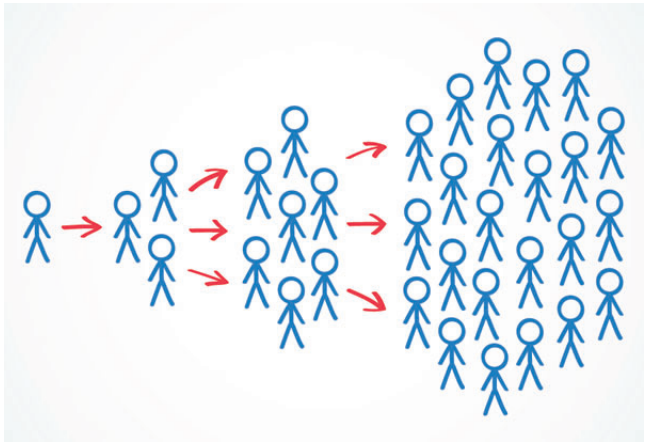
# Information cascade



An information cascade occurs when people engage in the same actions.



Source: *wikimedia.org*



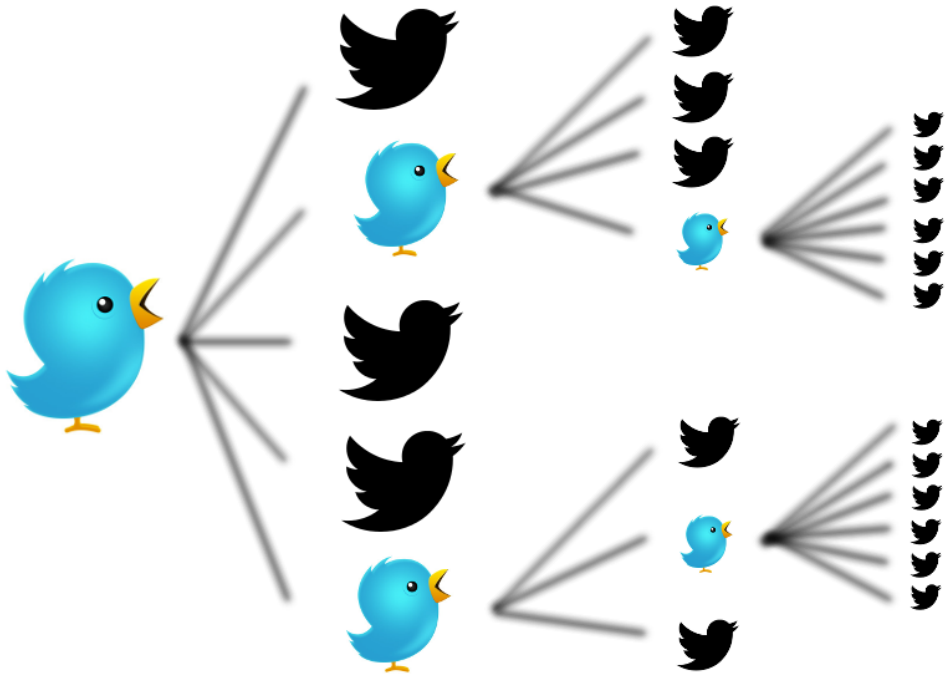
Source: *adweek.com*

# Twitter



Twitter provides the ideal playground to study information cascades.

- Start: a Twitter user posts a 140-character message which can be seen by his/her followers.
- Spread: a tweet is forwarded in Twitter by another user.



# Predicting cascades in real time



**Goal**

Given the tweet and retweets up to time $T$, predict its final popularity.

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## Applications

- Ranking content.
- Detecting viral/breakout tweets.
- Understanding human social behavior.

# Mathematical definitions



## Data

- Relative retweet time $t_0 = 0, t_1, t_2, \ldots$
  - Number of retweets by time $t$: $R_t = \sum_{t_i \leq t} 1.$
- Number of followers of each retweeter $n_0, n_1, n_2, \ldots$
  - Number of exposed users by time $t$: $N_t = \sum_{t_i \leq t} n_i.$

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## Problem statement

Given $(R_t, N_t)$ for $0 \leq t \leq T$, predict $R_\infty$.

# Approaches to cascade prediction



Broadly categorized into two groups:

- **Feature based methods (the majority):**
- **Point process based methods:**

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  - Our model (SEISMIC): self-exciting point process.

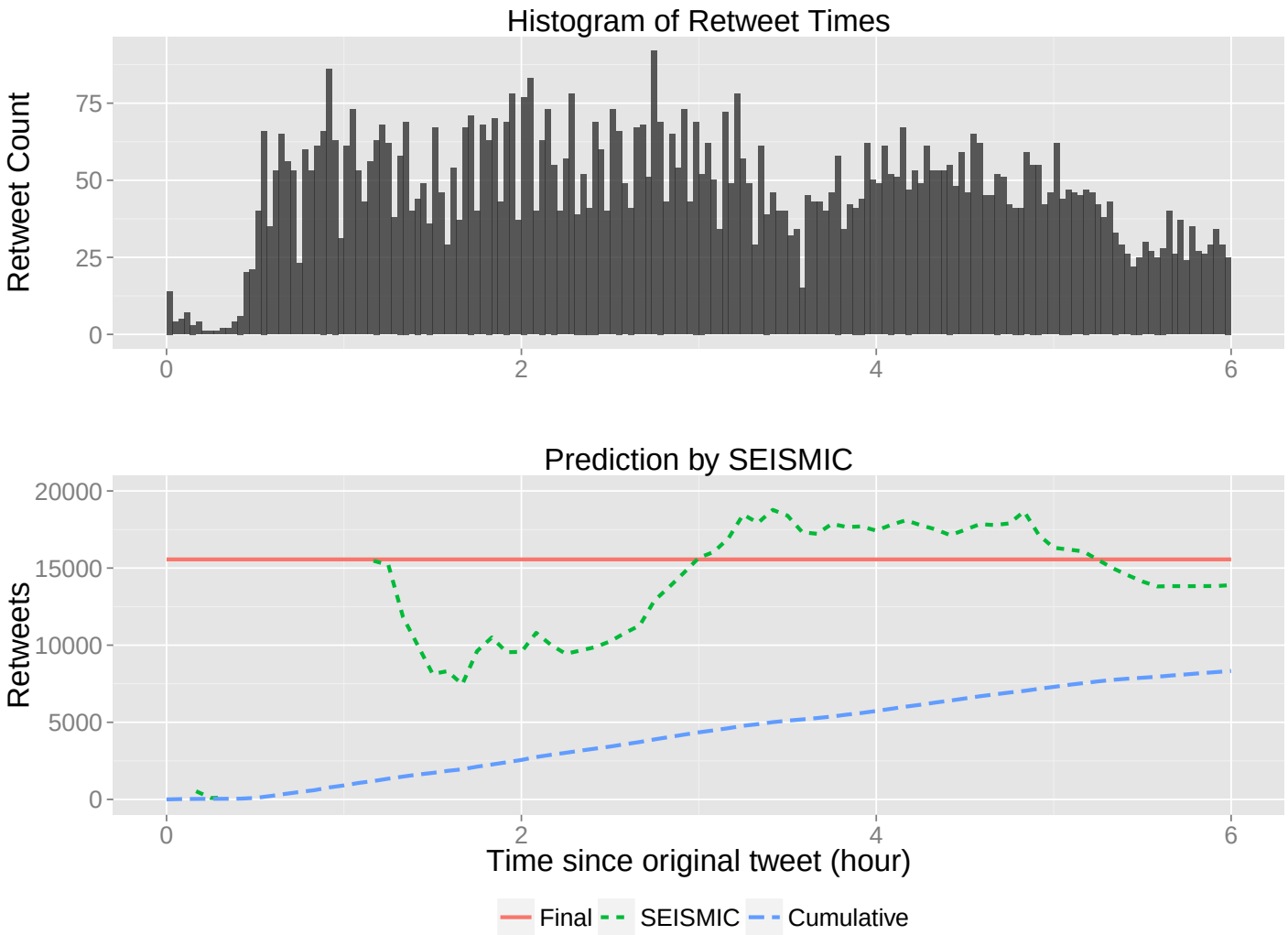
# Example




Matt Bellamy
@mottbollomy
Follow
- Saddam Hussein
- Osama Bin Laden
- Col. Gaddafi
- Justin Bieber
RETWEETS
16,258
FAVORITES
906
5:40 AM - 20 Oct 2011

# Example

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50
25
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Prediction by SEISMIC
Retweets
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15000
10000
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Time since original tweet (hour)
Final
SEISMIC
Cumulative

# SEISMIC



SEISMIC (Self-Exciting Model of Information Cascades) is a flexible model of information cascades.

## Highlights

- Generative model.
- Easy interpretation.
- Scalable: prediction takes $O(\#\ \text{retweets})$.
- State-of-the-art performance.

# Background: point processes



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- Poisson process: $\lambda_t = \lambda$;
- Reinforced Poisson process[1]: $\lambda_t = p \cdot \phi(t) \cdot g(R_t)$.

[1] S. Gao, J. Ma, and Z. Chen. Modeling and predicting retweeting dynamics on microblogging platforms. In WSDM '15, 2015.

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**They are not suitable to model viral tweets.**

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# SEISMIC



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## Self-exciting point process

- Infectiousness: "probability" of retweeting

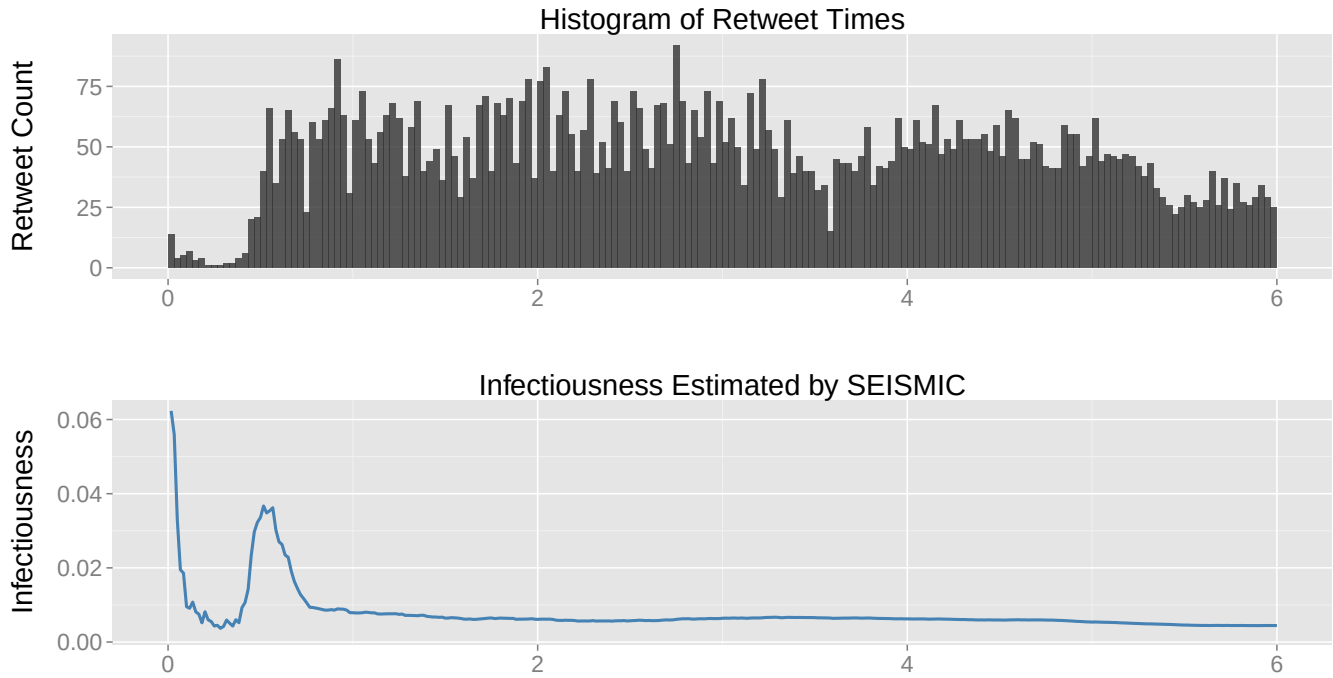
$$\lambda_t = p \cdot \sum_{t_i \le t} n_i \phi(t - t_i), \quad t \ge t_0.$$

- Self-exciting: "rate" of viewing

# Time-varying infectiousness



- Fixed $p$ is not enough to model viral tweets.




- SEISMIC replaces $p$ by a smooth process $p_t$.

# Estimate infectiousness



We estimate $p_t$ by locally smoothing the maximum likelihood estimator (MLE):

- "Number of retweets"

$$\hat{p}_t = \frac{\sum_{i=1}^{R_t} K_t(t - t_i)}{\sum_{i=0}^{R_t} n_i \int_{t_i}^{t} K_t(t - s)\phi(s - t_i)ds}.$$

- "Number of views"

# Predict popularity



## SEISMIC prediction formula

Assume the out-degrees in the network have mean $n_*$ and the infectiousness parameter $p_t \equiv p$ for $t \geq T$. Then

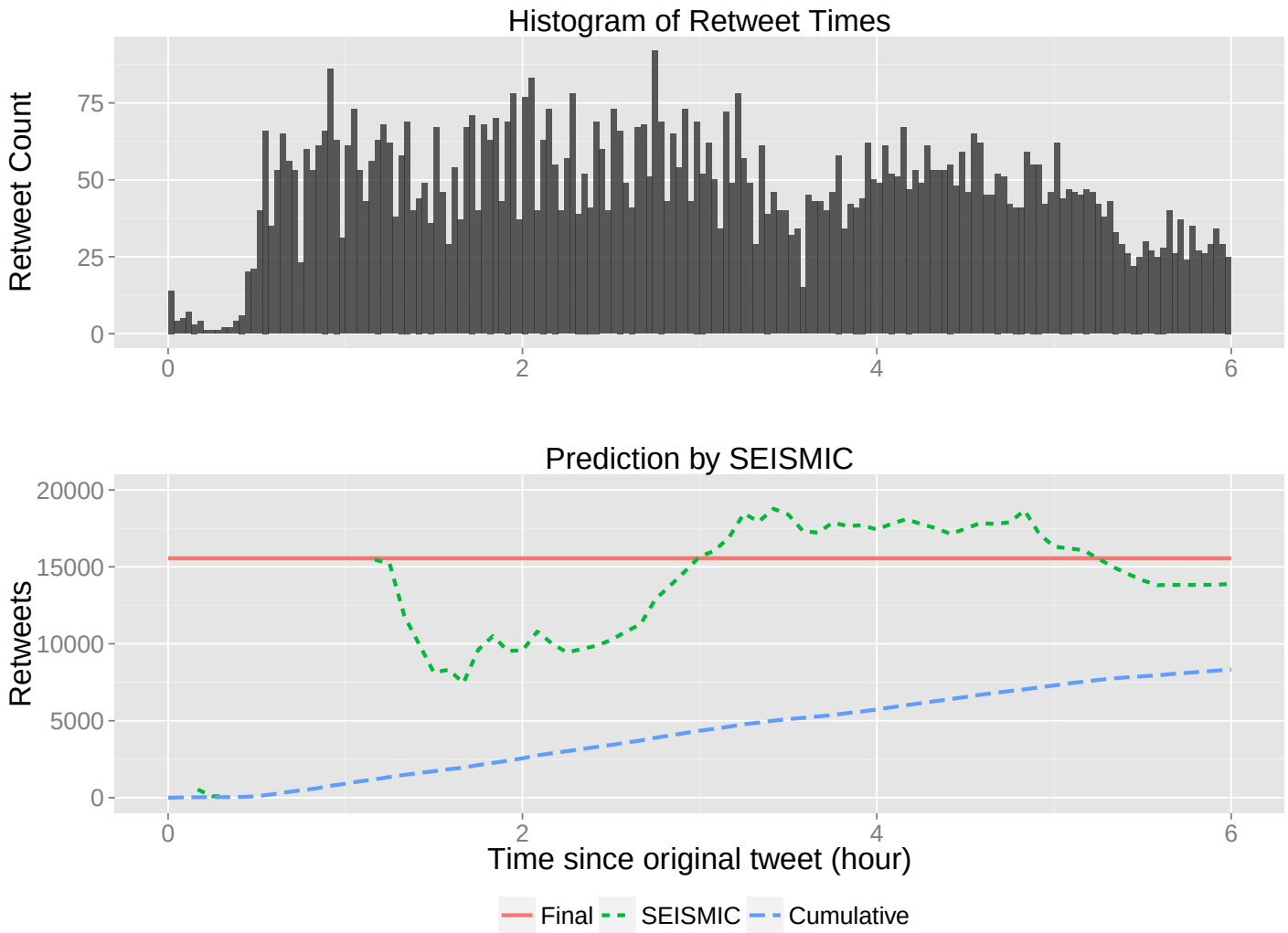
$$\mathbb{E}[R_\infty | \mathcal{F}_T] = \begin{cases} R_T + \dfrac{p(N_T - N_T^e)}{1 - pn_*}, & \text{if } p < \dfrac{1}{n_*}, \\ \infty, & \text{if } p \geq \dfrac{1}{n_*}. \end{cases}$$

where $N_T^e = \sum_{i=0}^{R_T} n_i \int_{t_i}^{T} \phi(t - t_i) dt$.

See our paper for derivation.

# Example

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# Experiments: dataset



- Raw dataset: all tweet and retweet activities from October 7 to November 7, 2011.
- Filter by:
  - Posted in the first 15 days.
  - English tweets;
  - No hashtag;
  - At least 50 retweets;
- End up with 166076 cascades (in total over 34 million tweets/retweets).

# Baselines



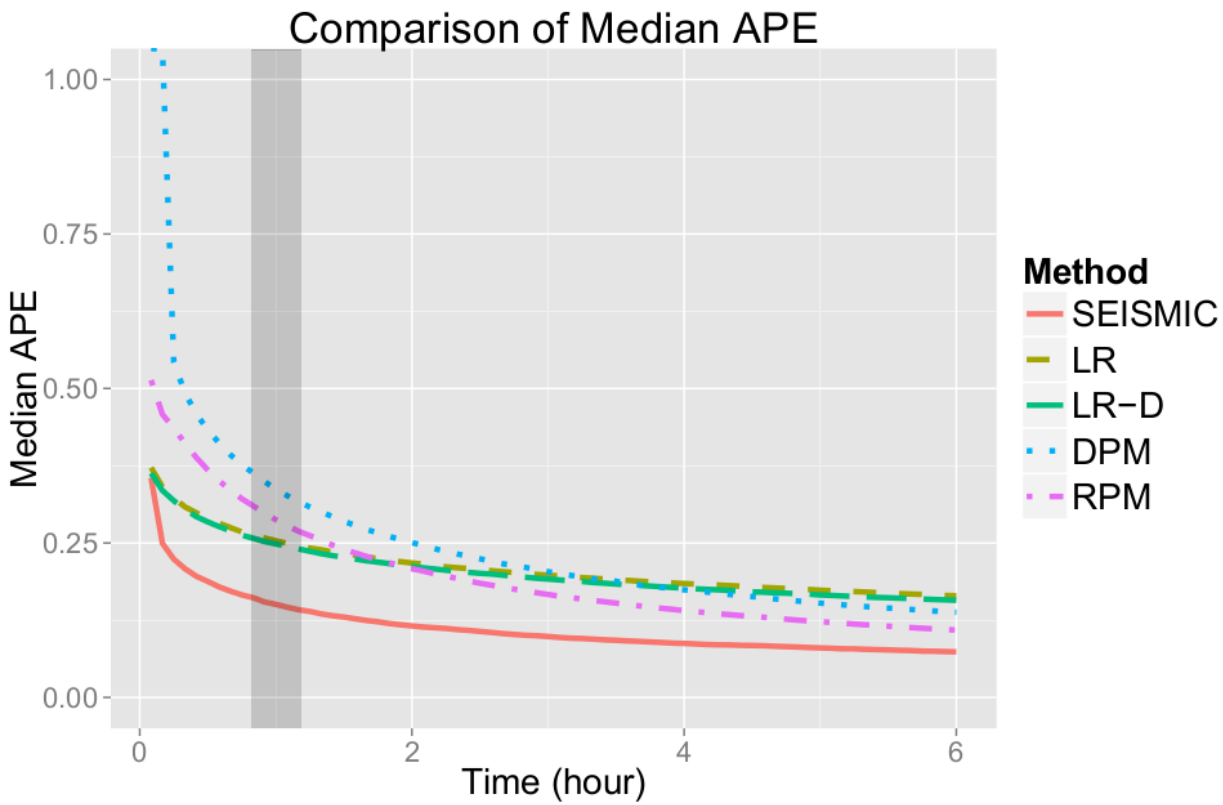
We compare SEISMIC to four different baselines:

1. LR: linear regression
2. LR-D: linear regression with degree
3. DPM: dynamic Poisson model
4. RPS: reinforced Poisson model

# Comparison: Absolute Percentage Error (APE)



$$\text{APE} = |\hat{R}_\infty - R_\infty|/R_\infty.$$

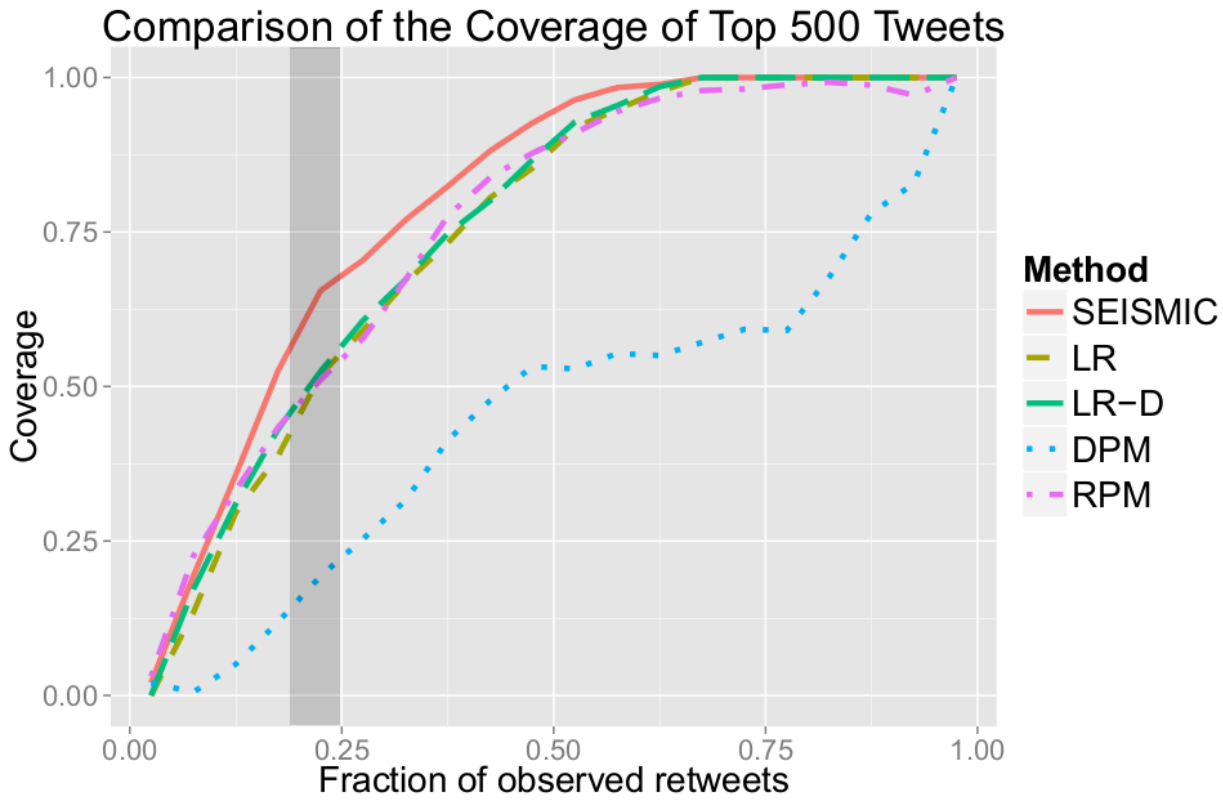



15% vs 25% percentage error when observe 1 hour.

# Comparison: Coverage of breakouts



- A list of true top 500 tweets with most retweets.
- Lists of predicted top 500 tweets at all time points.




70% vs 55% coverage when observe 25% retweets.

# Summary



In conclusion, SEISMIC

- Effectively models information cascades by self-exciting point processes;
- Efficiently updates parameters and makes prediction;
- Outperforms several baselines and state-of-the-art.

Code and data available online at
`http://snap.stanford.edu/seismic`.

# Estimation of memory kernel $\phi(t)$



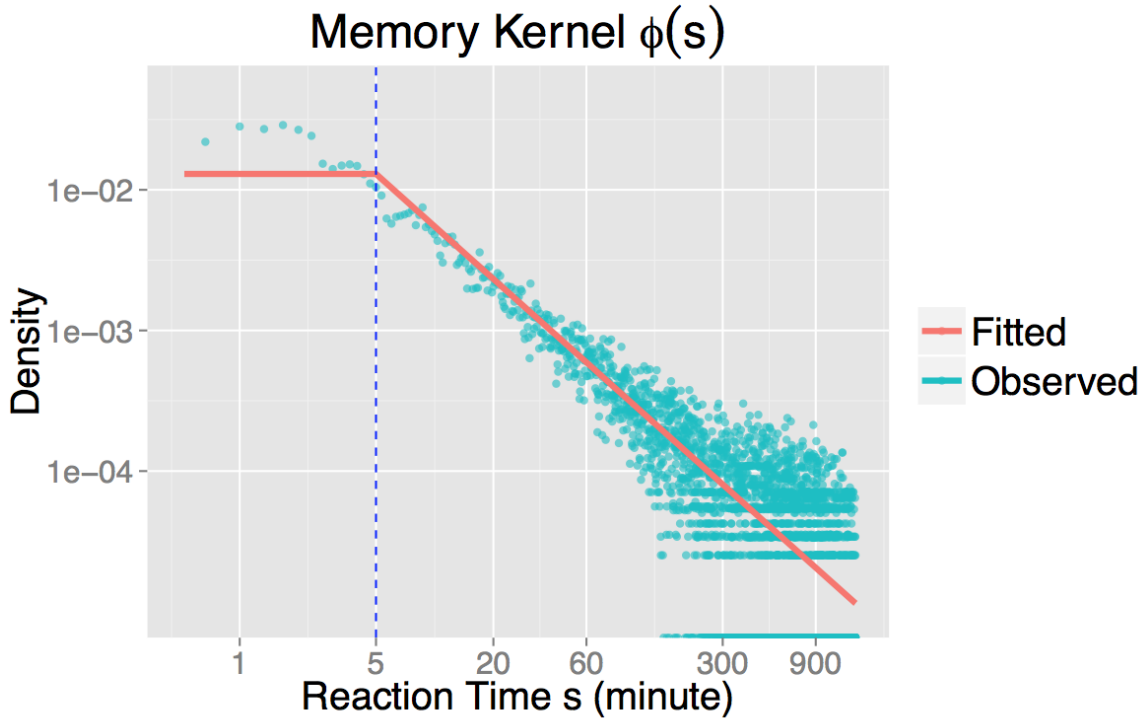



**Figure 4: Plot of observed reaction time distribution and estimated memory kernel $\phi(s)$. The reaction time is plotted on a log scale, hence a linear trend in the plot suggests a power law decay in the distribution.**

# More detail: final tweak



- The prediction is unstable when $\hat{p}_t$ is close to $\frac{1}{n^*}$.
- The real $p_s$ is likely to decrease.

**Stabilized prediction**

$$\hat{R}_\infty(t) = R_t + \alpha_t \frac{\hat{p}_t(N_t - N_t^e)}{1 - \gamma_t \hat{p}_t n_*}$$

where $0 < \alpha_t, \gamma_t \leq 1$ are trained for the network.