From Micro to Macro: Uncovering and Predicting Information Cascading Process with Behavior Dynamics

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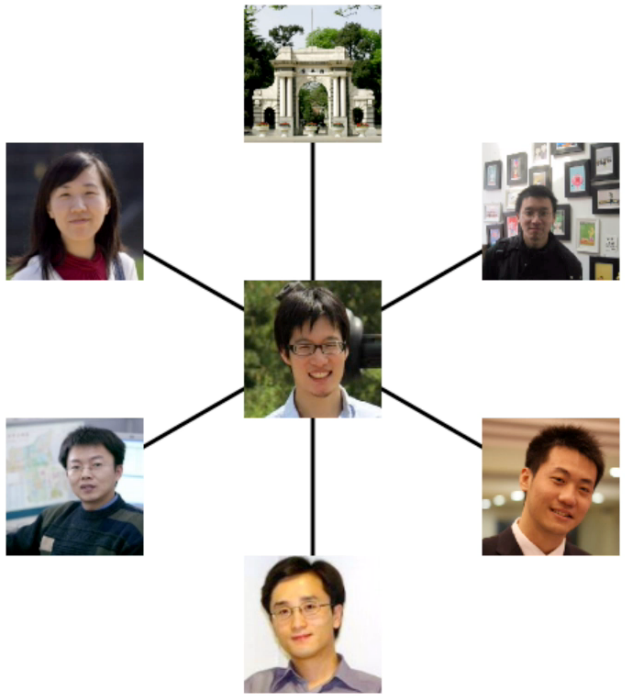
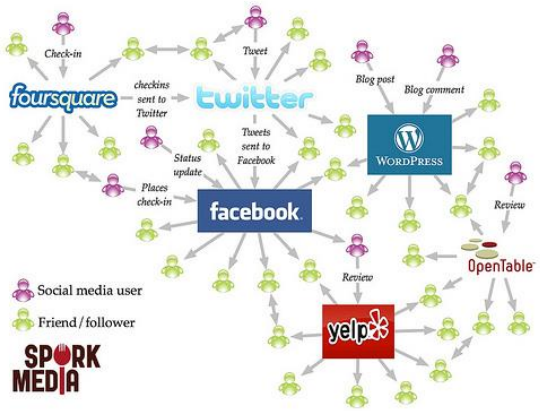
Information Cascade

- In network environment, if decentralized nodes act on the basis of how their neighbors act at earlier time, cascades will be formed.



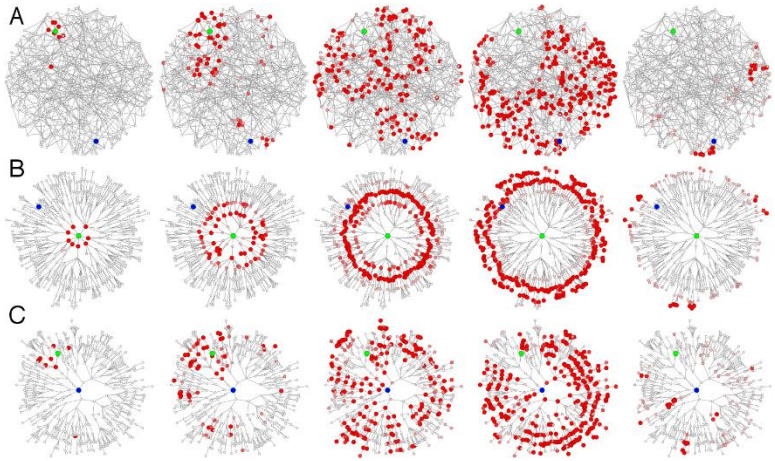
Information spreading is ubiquitous

Social Media

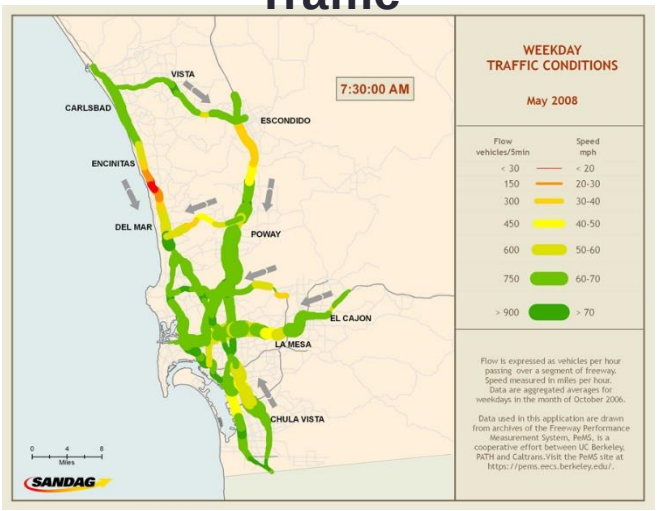


Word-of-Mouth (Marketing)

Epidemics

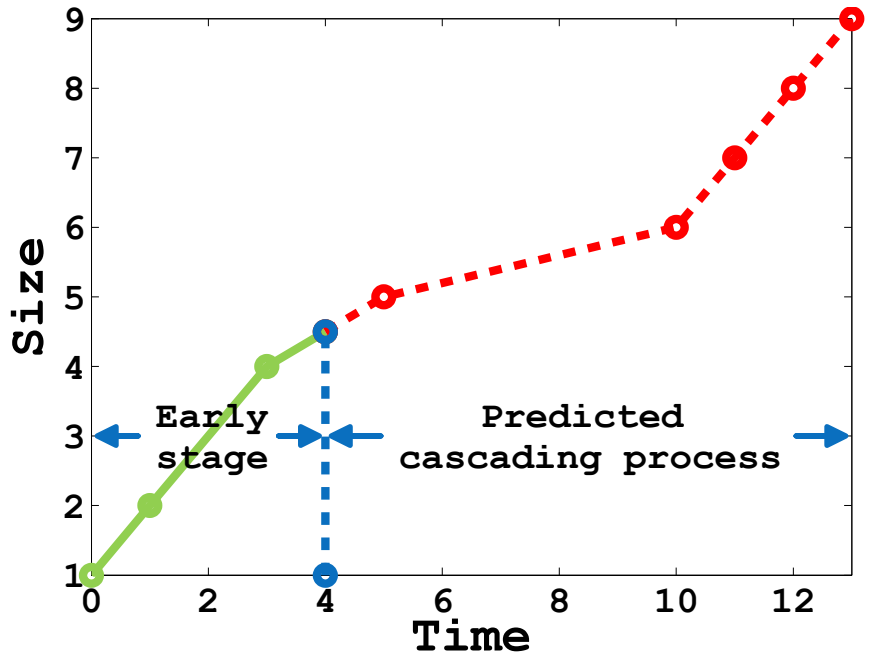


Traffic



Cascading Process Prediction

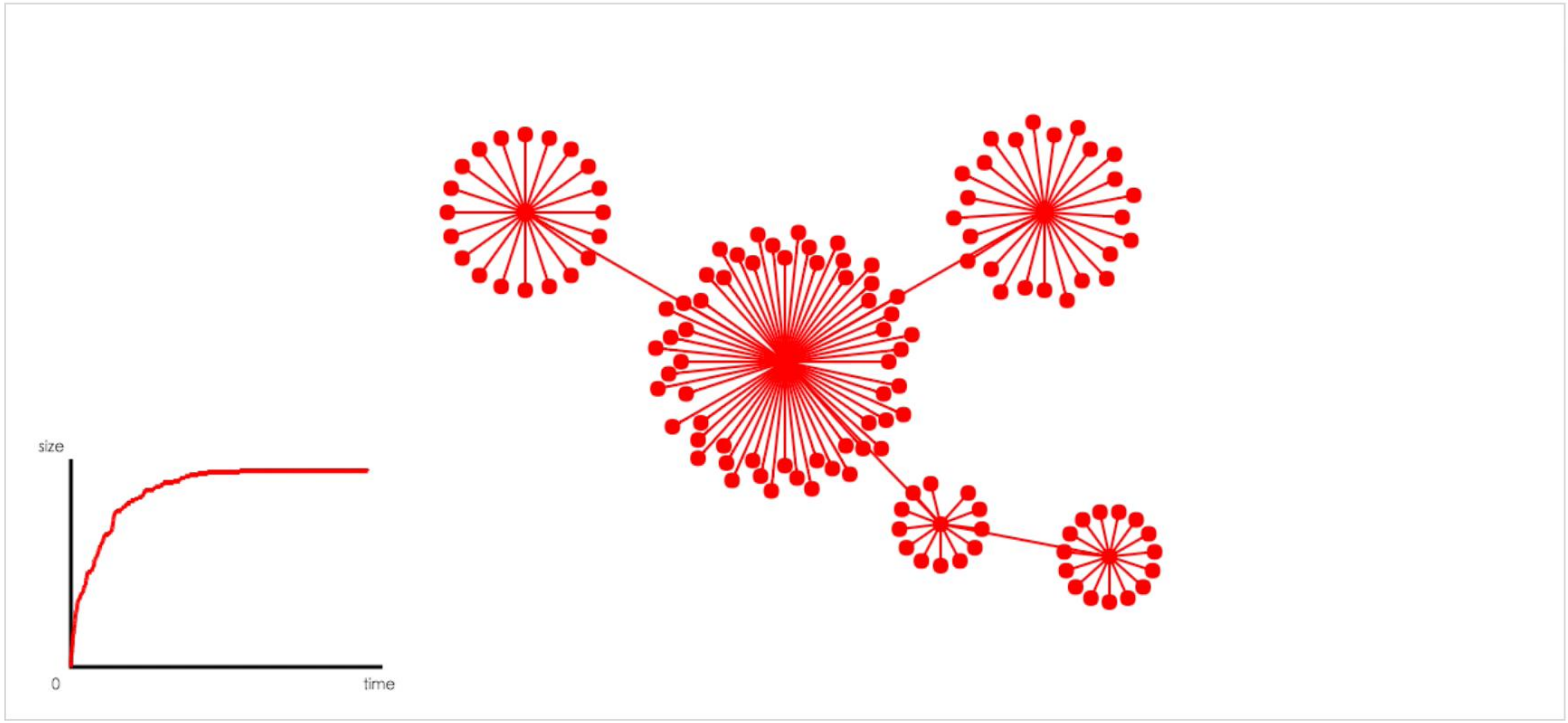
- Problem Definition:
  - Source: the early stage of an information cascade
  - Target: the later stage of the information cascade, or its cumulative cascade size of any later time



Cascading Process

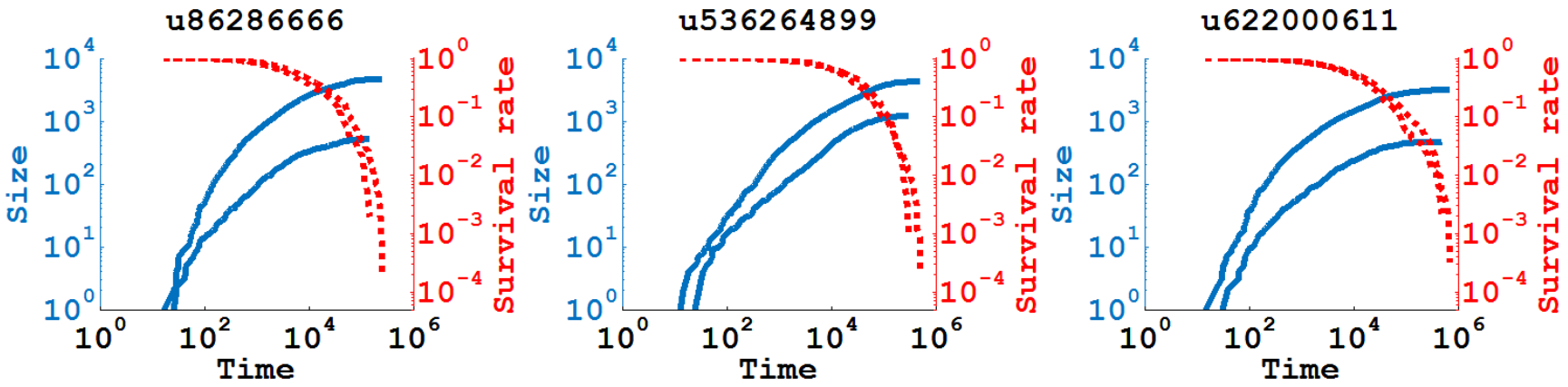
From Macro to Micro: Subcascades

- How to model subcascades?
- How to connect subcascades and the global cascade?
- How to make predictions fast and accurate?



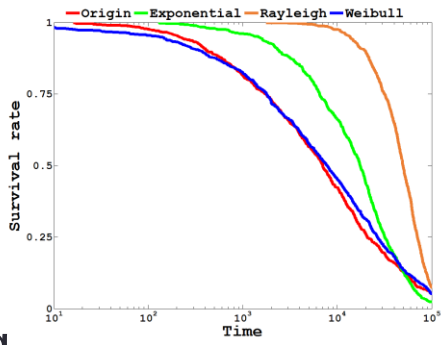
User Behavioral Dynamics

- **Behavioral Dynamics of a user**: The changing process of its offspring nodes that involve in the cascade after the user involved in the post.
- **Representation**
  - Averaging the size growth curve:
    - Different subcascades of the same user might have different size growth curves.
  - Survival rate: the percentage of nodes that has not been but will be infected
    - For different subcascades of the same user, the survival function is quite stable.



Parameterize Behavioral Dynamics

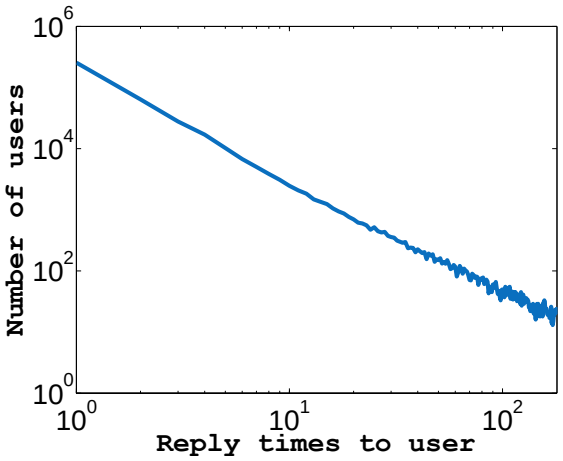
- The behavioral dynamics need to be parametrized for the ease of computation and modeling.
- Exponential and Rayleigh distributions cannot well capture both the scale and shape characteristics of behavioral dynamics.
- The Weibull distribution is adequate for parameterizing behavioral dynamics:
  - λ: control the scale parameter
  - k: control the shape parameter

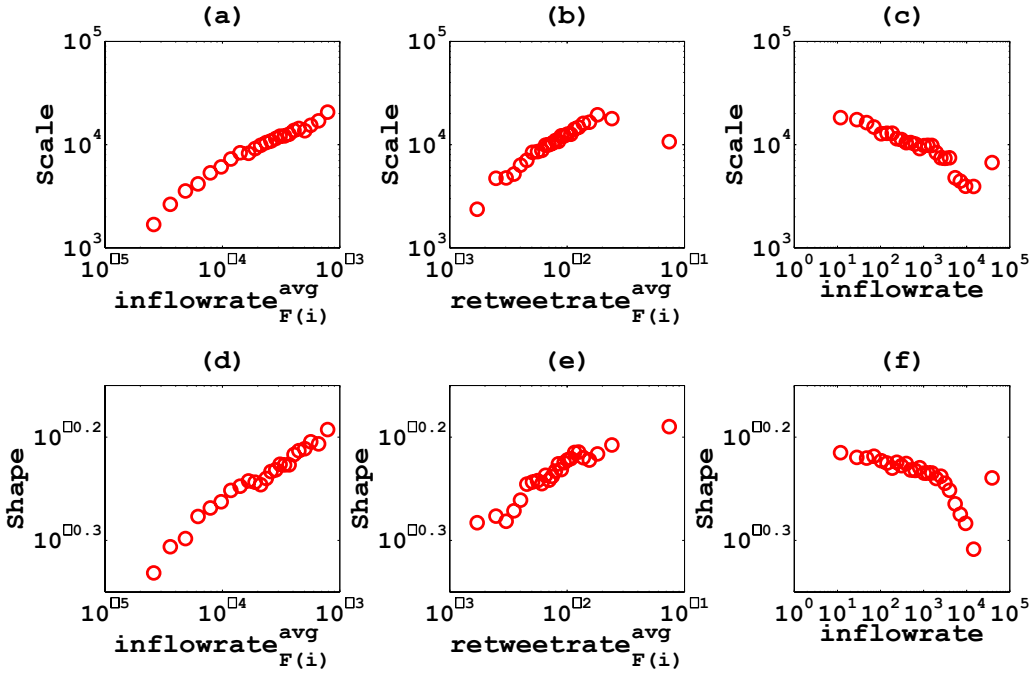


model	density function	survival function	hazard function	ks-static in Weibo
Exponential	$\lambda_i e^{-\lambda_i t}$	$e^{-\lambda_i t}$	λ_i	0.2741
Power Law	$\frac{\alpha_i}{\delta}\left(\frac{t}{\delta}\right)^{-\alpha_i-1}$	$\left(\frac{t}{\delta}\right)^{-\alpha_i}$	$\frac{\alpha_i}{t}$	0.9893
Rayleigh	$\alpha_i t e^{-\alpha_i \frac{t^2}{2}}$	$e^{-\alpha_i \frac{t^2}{2}}$	$\alpha_i t$	0.7842
Weibull	$\frac{k_i}{\lambda_i}\left(\frac{t}{\lambda_i}\right)^{k_i-1} e^{-\left(\frac{t}{\lambda_i}\right)^{k_i}}$	$e^{-\left(\frac{t}{\lambda_i}\right)^{k_i}}$	$\frac{k_i}{\lambda_i}\left(\frac{t}{\lambda_i}\right)^{k_i-1}$	**0.0738**

Covariates of Behavioral Dynamics

- Interaction information between nodes is not always available. It is difficult to measure out-of-sample nodes.





The parameters of the user's behavioral dynamics can be well estimated by the behavioral features of its network neighbors.

NEtworked WEibull Regression (NEWER)

$$F(\lambda, k, \beta, \gamma) = G_1(\lambda, k) + \mu G_2(\beta, \lambda) + \eta G_3(\gamma, k)$$

$$G_1(\lambda, k) = -\log L(\lambda, k)$$ Log likelihood

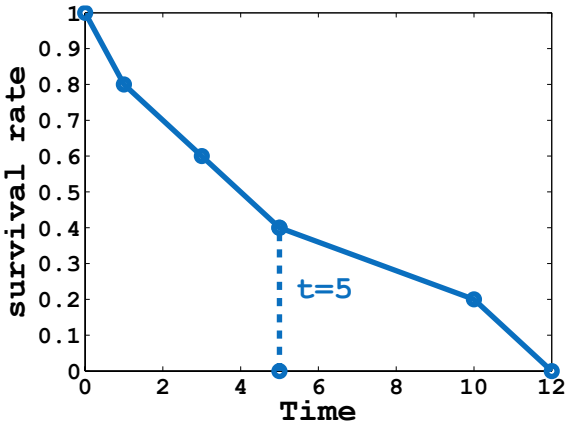
$$G_2(\lambda, \beta) = \frac{1}{2N} \left\| \log \lambda - \log X \cdot \beta \right\|^2 + \alpha_\beta \left\| \beta \right\|_1$$ Parameterize λ

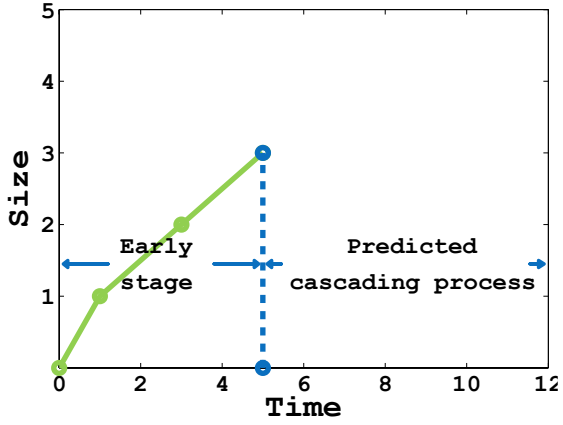
$$G_3(k, \gamma) = \frac{1}{2N} \left\| \log k - \log X \cdot \gamma \right\|^2 + \alpha_\gamma \left\| \gamma \right\|_1$$ Parameterize k

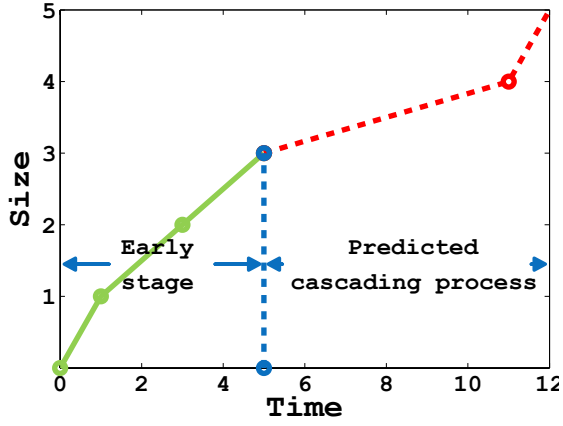
- Theoretically proved to be lower-bounded.
- Coordinate Descent strategy is exploited with guaranteed convergence.

Subcascade Process Prediction

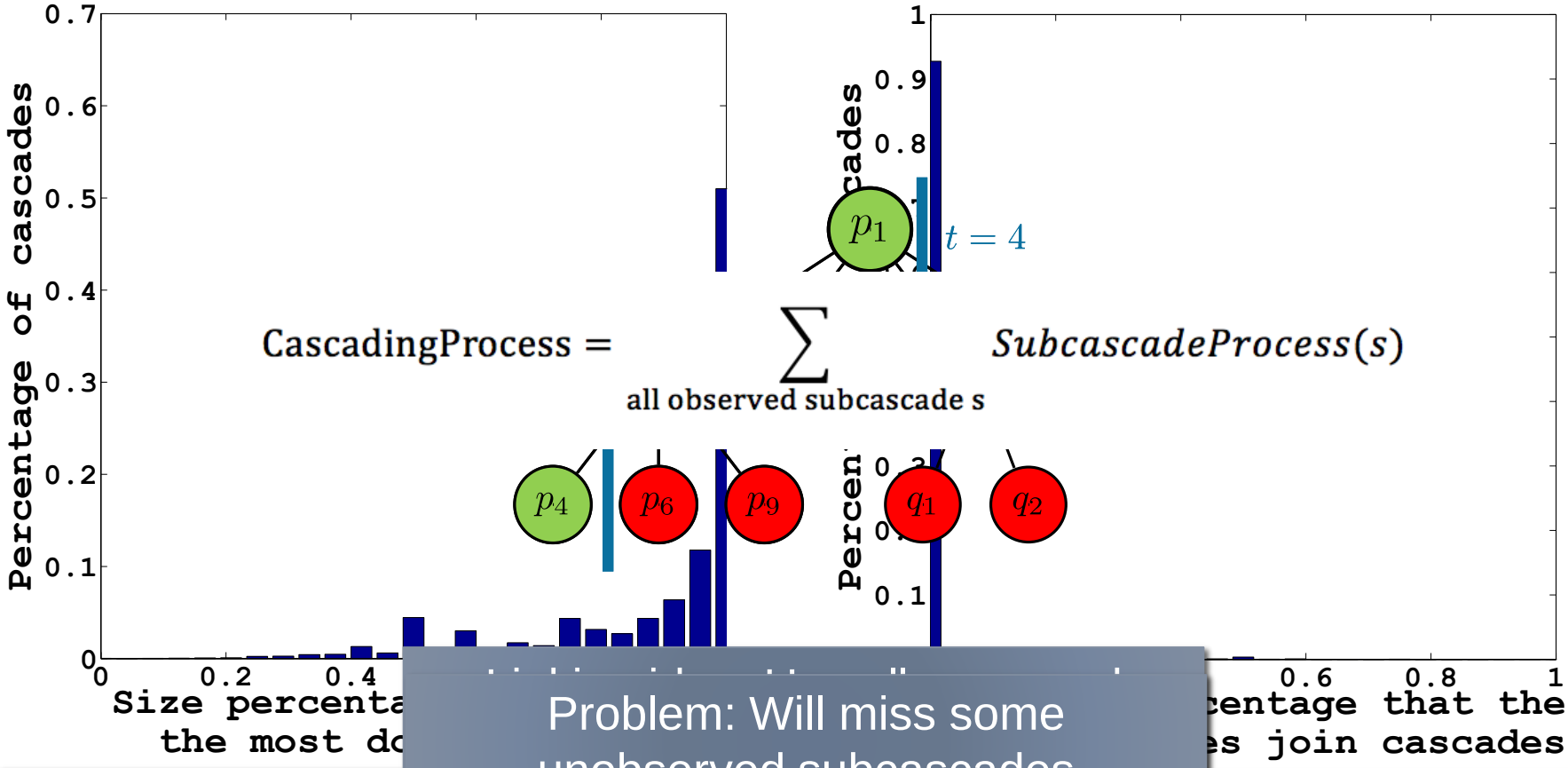
- From rate dimension to size dimension







From Subcascades to Cascade



$$\text{CascadingProcess} = \sum_{\text{all observed subcascade s}} \textit{SubcascadeProcess}(s)$$

Problem: Will miss some unobserved subcascades

Minor dominan… dominate the cascading process.

…inance: Dominant nodes are prone to join early.

Dynamic Prediction

Real Application Demand:

- Accuracy
- Real-time

Sampling strategy:

- Ignore most recalculations for subcascades by using the previous calculation instead.
- Setting the calculation time point based on the last calculation.

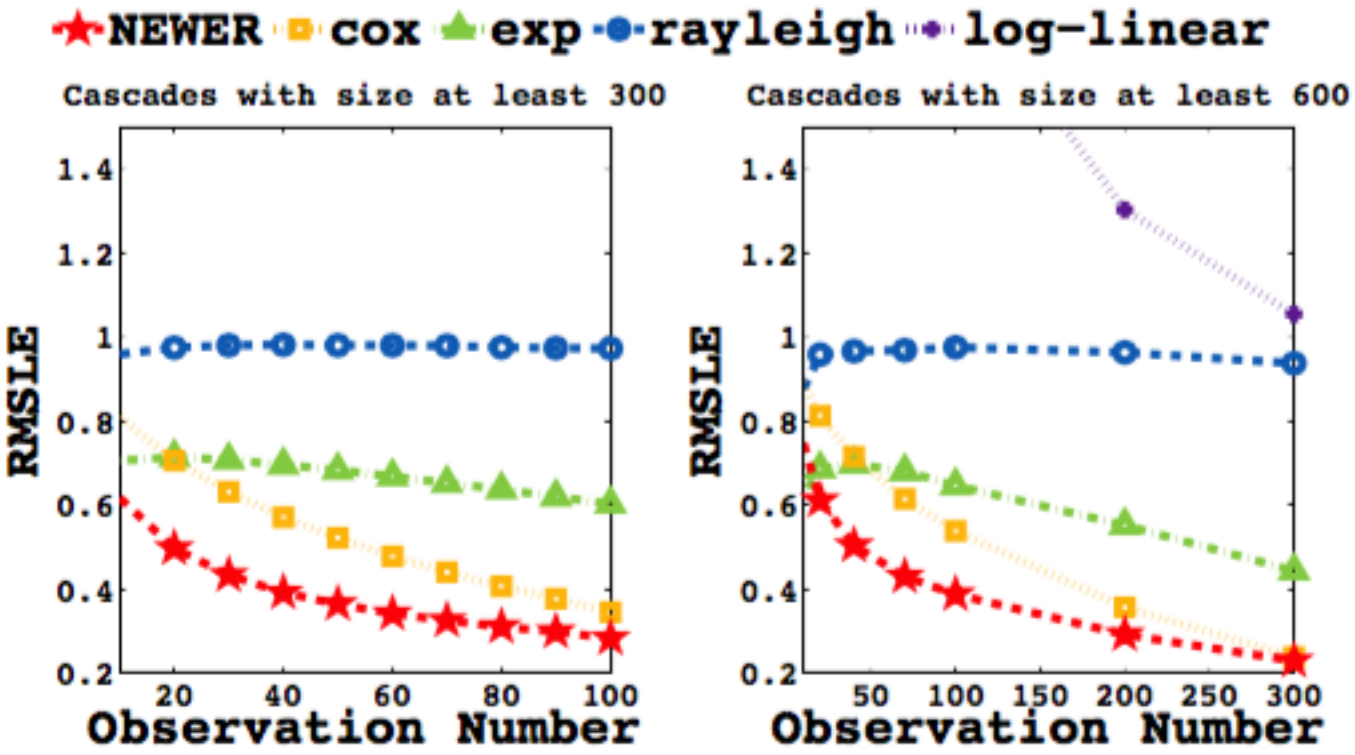
Time complexity: from $O(T^2)$ to $O(T)$ (with an error bound)

Experiments

- Datasets: Tencent Weibo
  - All cascades generated between Nov 15th and Nov 25th in 2011.
  - retain all 0.59 million cascades that the cascades size are at least 5.
- Baseline:
  - Cox Proportional Hazard Regression Model (Cox)
  - Exponential/Rayleigh Proportional Hazard Regression Model (Exponential/Rayleigh)
  - log-Linear regression(Log-linear)
- Evaluation metric:
  - RMSLE: Root Mean Square Log Error
  - $\Delta\sigma$-Precision: Precision value that the predicted value within $(1+\sigma) \pm 1$groundtruth

Cascade Size Prediction

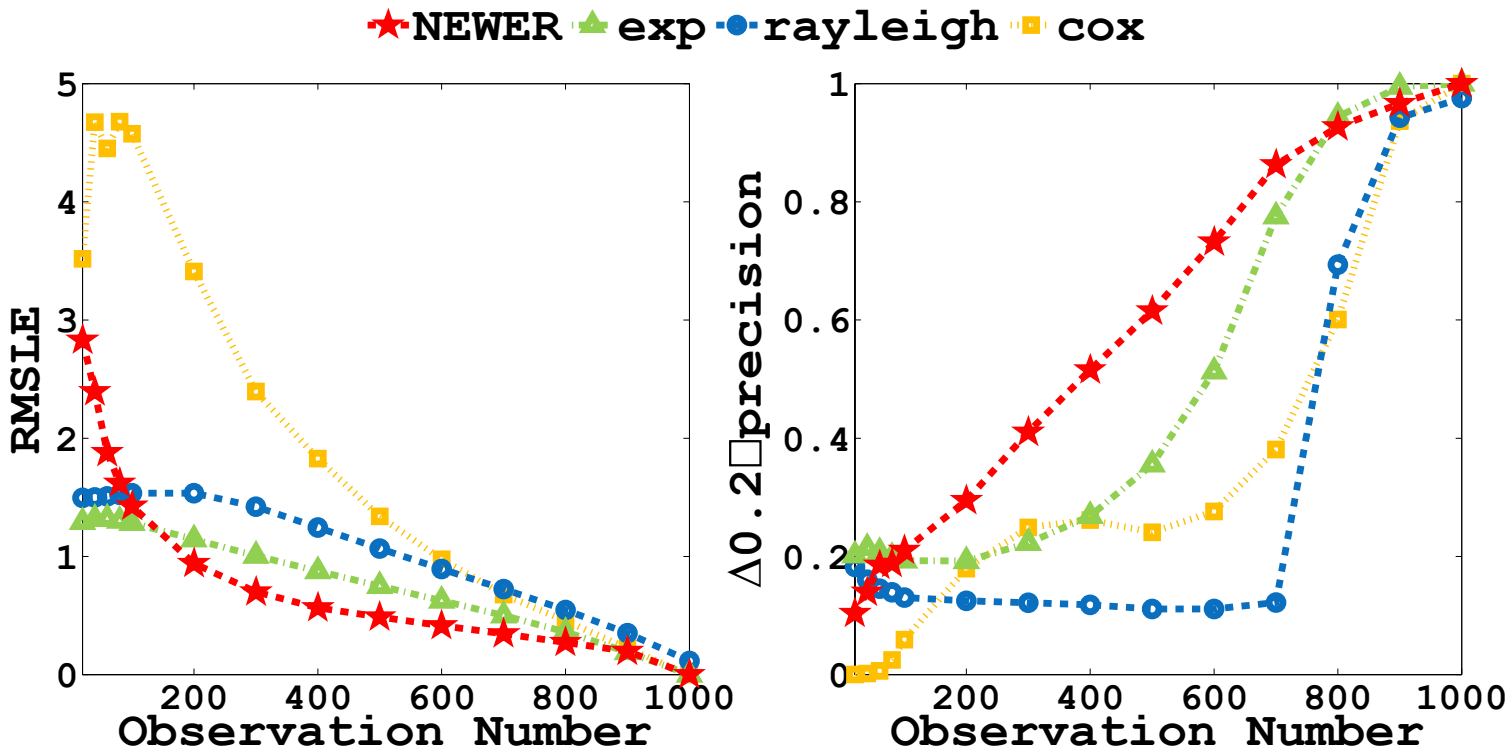
- What is the final size of the cascade?



The improvements are more obvious in early stage.

Outbreak Time Prediction

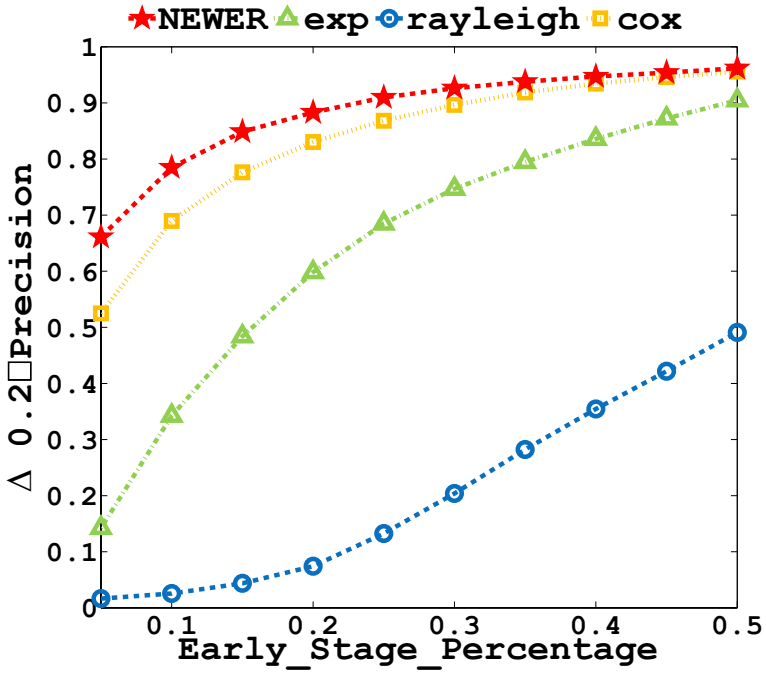
- When will the cascade break out?



Average improvements in early stage:
70%

Cascading Process Prediction

- What is the size of the cascade at any later point?



90% percentage accuracy when we have only 20% early stage informations.

Efficiency of the method

- How fast can our method achieve?

Method	Without Sampling Strategy	With Sampling Strategy ($\delta = 0.1$)
Size ≥ 20	$8.47 * 10^5 s$	$10.73s$
Size ≥ 50	$7.61 * 10^5 s$	$8.62s$
Size ≥ 100	$6.65 * 10^5 s$	$7.09s$
Size ≥ 500	$4.35 * 10^5 s$	$4.33s$
Size ≥ 1000	$3.4 * 10^5 s$	$3.30s$

Running time for cascade size prediction

improvements: 10^5

Size	Without Sampling Strategy	With Sampling Strategy ($\epsilon_1 = 0.1$ and $\epsilon_2 = 0.1$)
20	$1.4 * 10^{12}$	$4.2 * 10^6$
50	$3.5 * 10^{12}$	$7.6 * 10^6$
100	$6.9 * 10^{12}$	$1.4 * 10^7$
500	$3.5 * 10^{13}$	$3.4 * 10^7$
around 1000	$6.9 * 10^{13}$	$4.2 * 10^7$

Calculation number for cascade process prediction

improvements: 10^6

Conclusion

- A new Problem:
  - Given early stage information, predict the future cascading process.
- A new angle:
  - Uncover the cascading process through behavioral dynamics.
- A new model (NEWER):
  - Model the behavioral dynamics and predict the subcascading process
- A scalable solution:
  - Predict the dynamic process of information cascade with linear complexity

The proposed method has been transferred to Tencent for social marketing.

Thanks!