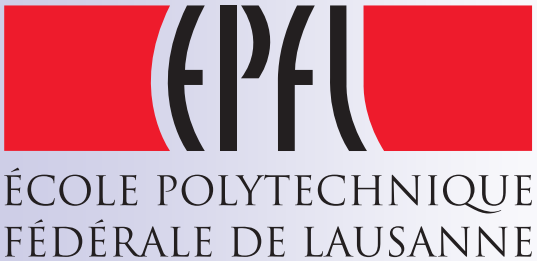
Outtwitting the Twitterers – Predicting Information Cascades in Microblogs



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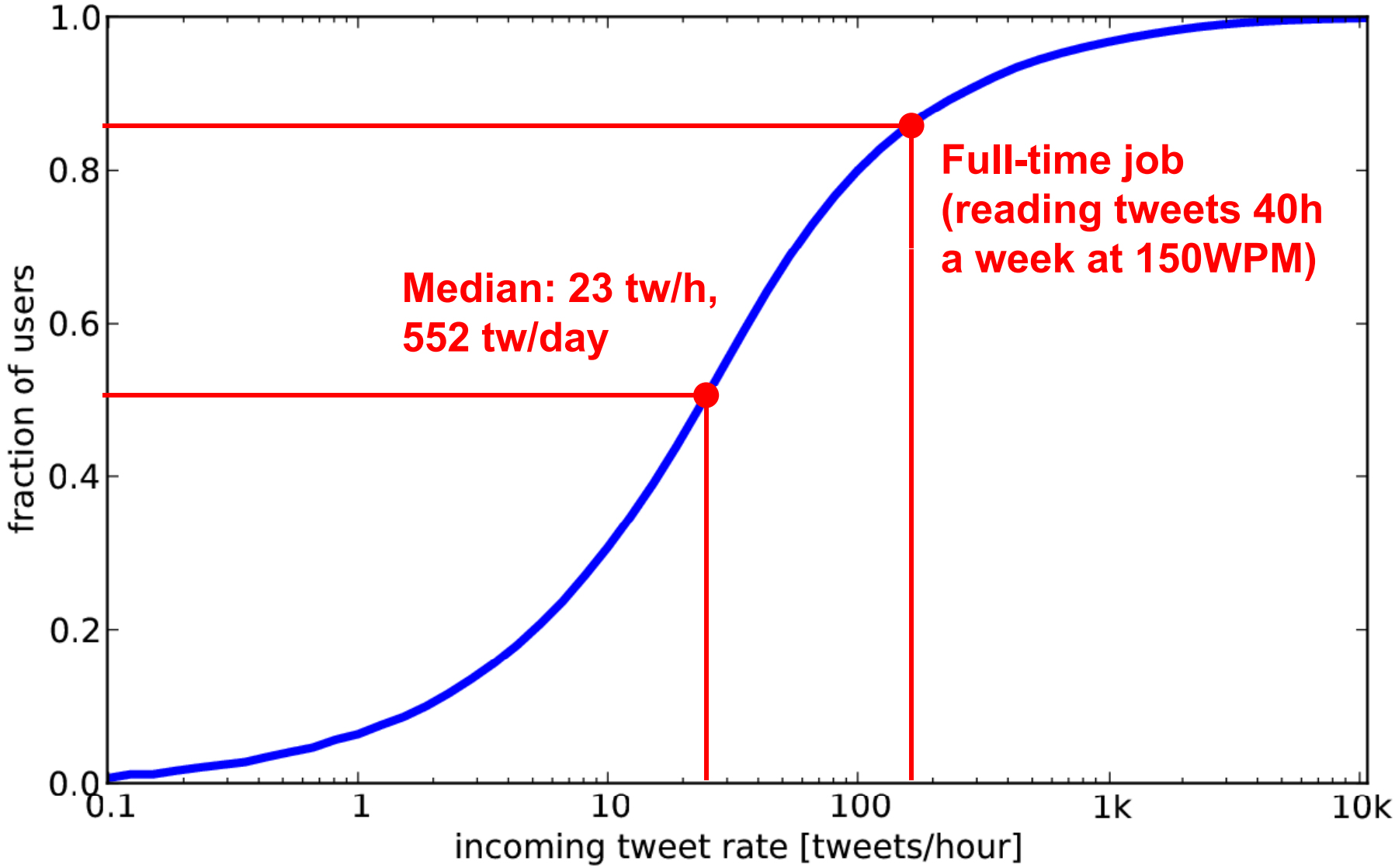
Why study information flows in OSNs?

Modeling

- improve how information flows
- new applications
- insights into underlying sociology

Information overload?



(Sep 2009 data)

OSN information spread modeling

- Related work:
  - generative models
    - reproduce statistical properties of info spread
  - predict coarse-grained aggregates
    - # of nodes reached by spread etc.
- Our approach:
  - Look at URL diffusion on Twitter
  - Can we predict which **user** will mention which **URL** with what **probability?**

Why predict URL tweets?

- Protect from information overload
  - Sort incoming URLs by probability of retweeting
- Viral marketing
  - Select a subset of users that ensure successful URL propagation
- Spam detection
  - Mispredictions are a sign of anomalous activity

Realtime results for http

taksilover RT @taksilover HAHAHAHA OF FENNE STUURT JE FF BABYFOTO VAN TREY SONGZ HAHAHA < **http**://bit.ly/bkoOFY

less than 10 seconds ago from web

its_shauny_yo So beautiful imy !RT @MrsPinkyIvory: **http**://twitpic.com/1o1fnm

less than 10 seconds ago from UberTwitter

dominos_JP やや重たくてすみません。充実の動画でして・・・。RT @mitsuyamarines **http**://tl.gd/1af1mc

less than 10 seconds ago from TwitBird iPhone

soro09 @NMANUELX_x 1235 firmas por la libertad de los presos políticos venezolanos Necesitamos tu apoyo **http**://bit.ly/cxRjjH

less than 10 seconds ago from web

CisaOficial RT @MaiteOficial: Para que se den una idea este fue mi postre ayer... Mmmmmmm buenisimo **http**://twitpic.com/1o1gnp

less than 10 seconds ago from Twitpic

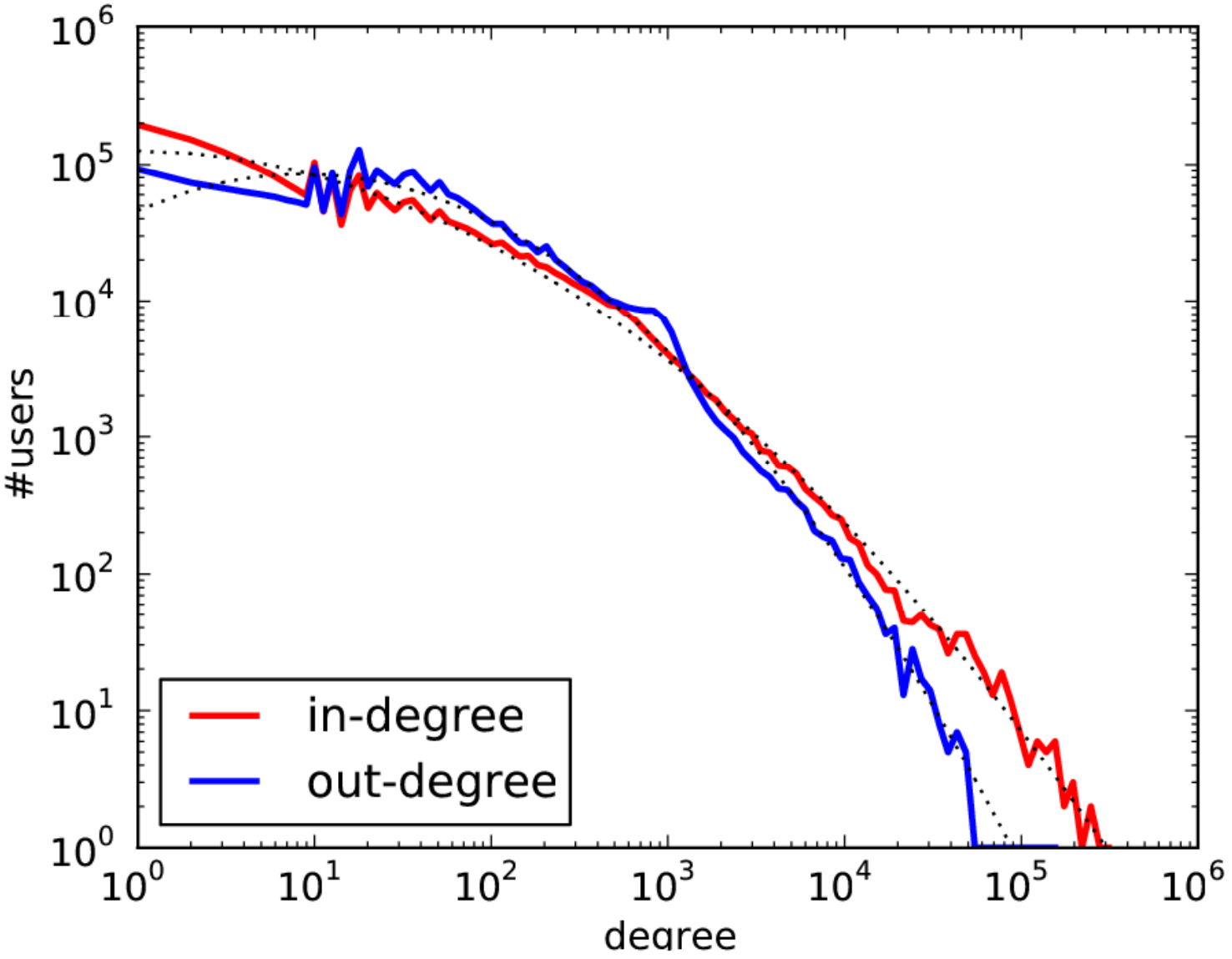
Taigenz Q:Girl or boy? A:Lol **http**://formspring.me/TaigenzB/q/549093468

less than 10 seconds ago from formspring.me

Data

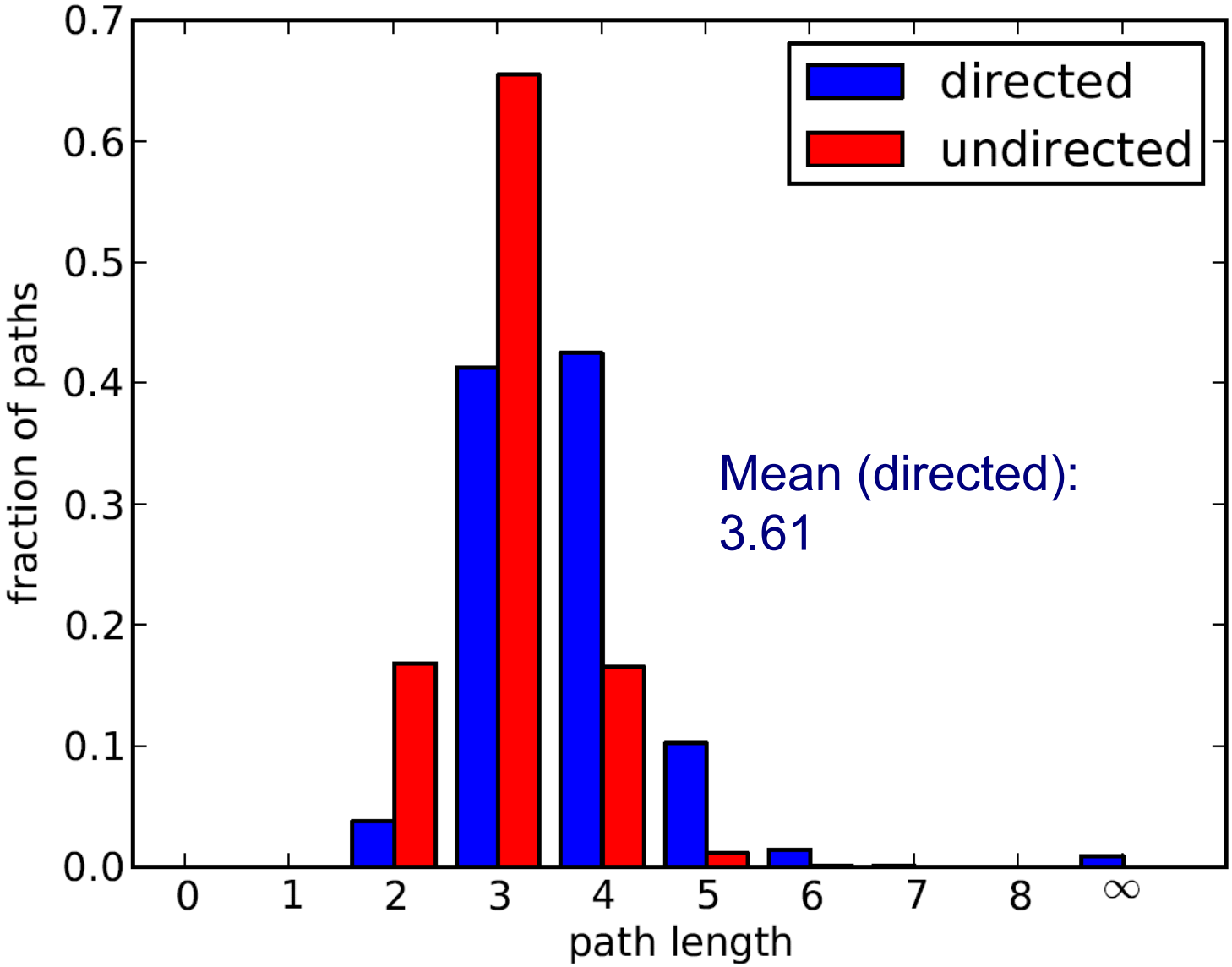
- 300 hour window in Sep'09
- 22M tweets
- 2.7M unique users
- 15M unique URLs
- 700M connections in the follower graph
- Approx. 1/15th of the Twitter traffic

Follower graph*



* active users only: that have sent at least one URL in 300h

Follower graph*



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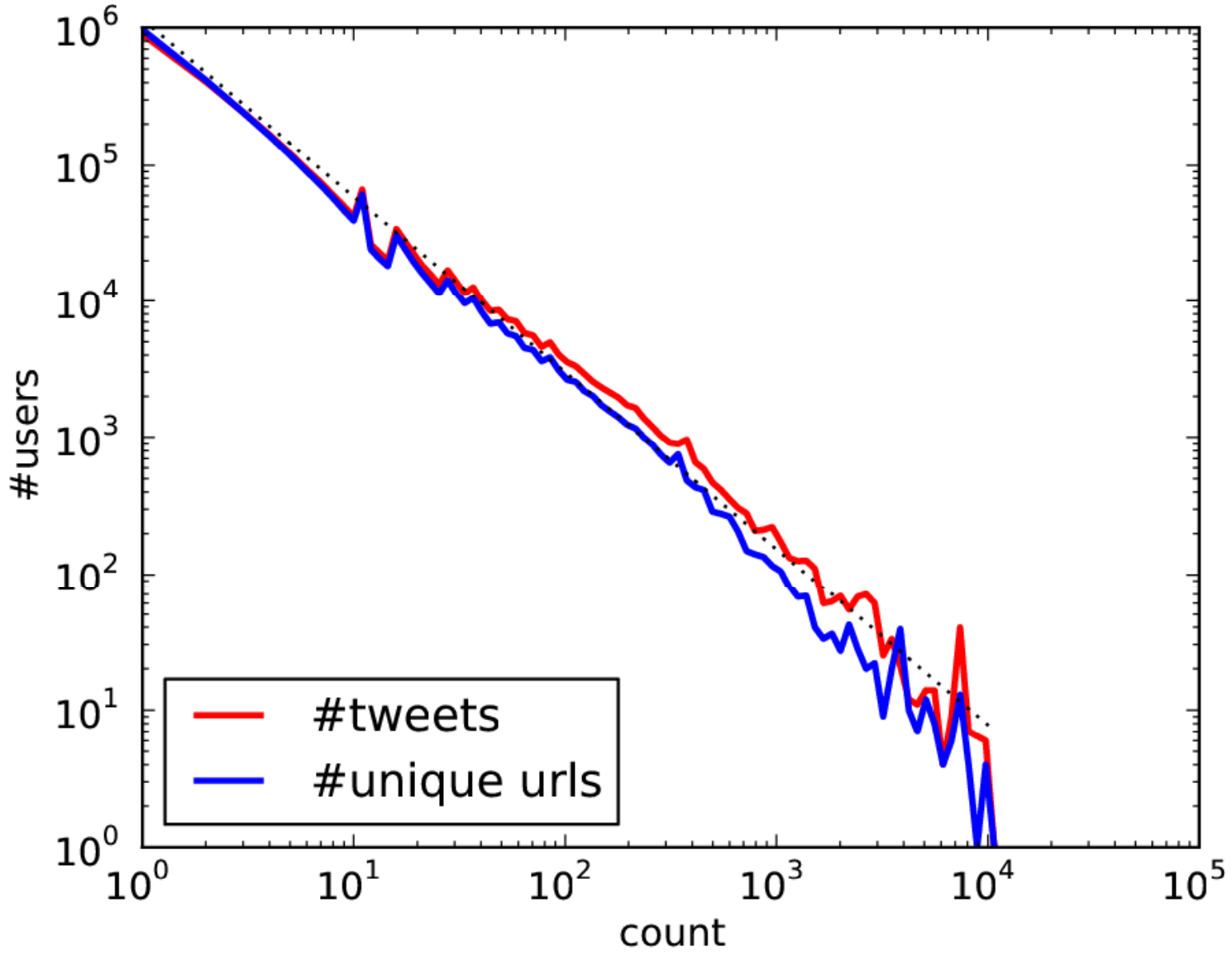
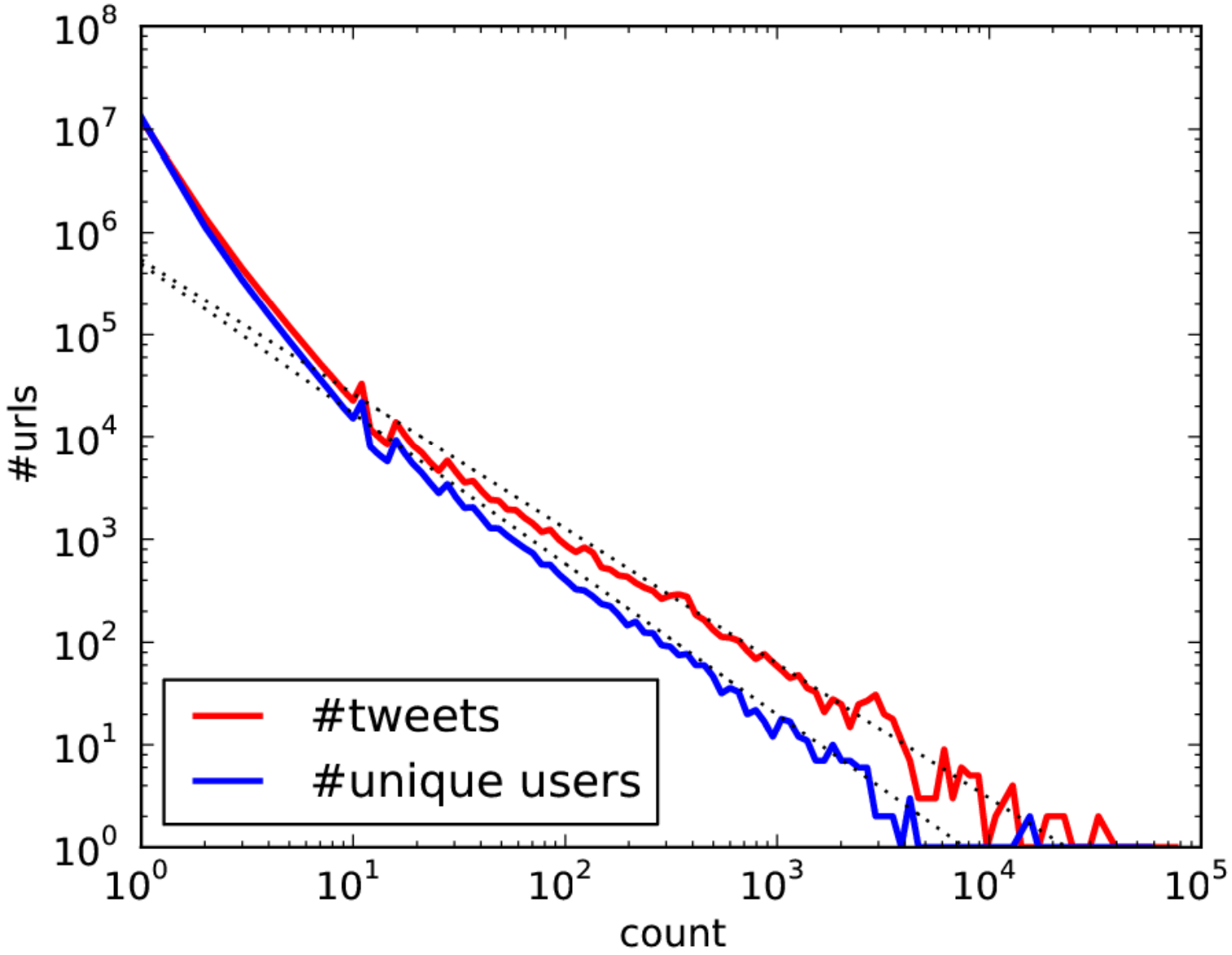
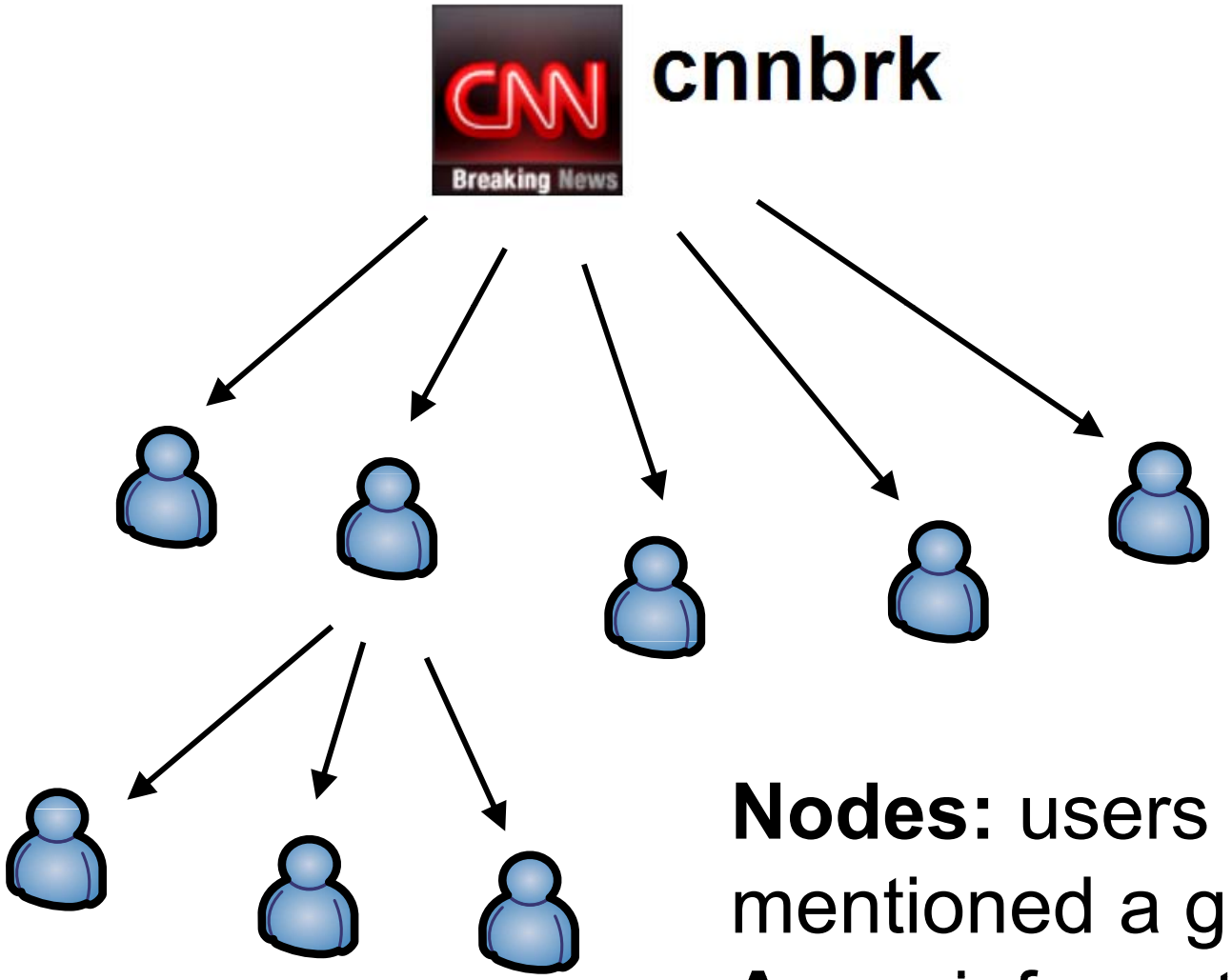
User activity



Per-URL activity



Information cascades



Nodes: users that mentioned a given URL
Arcs: information flow

Re-tweeting

cnnbrk

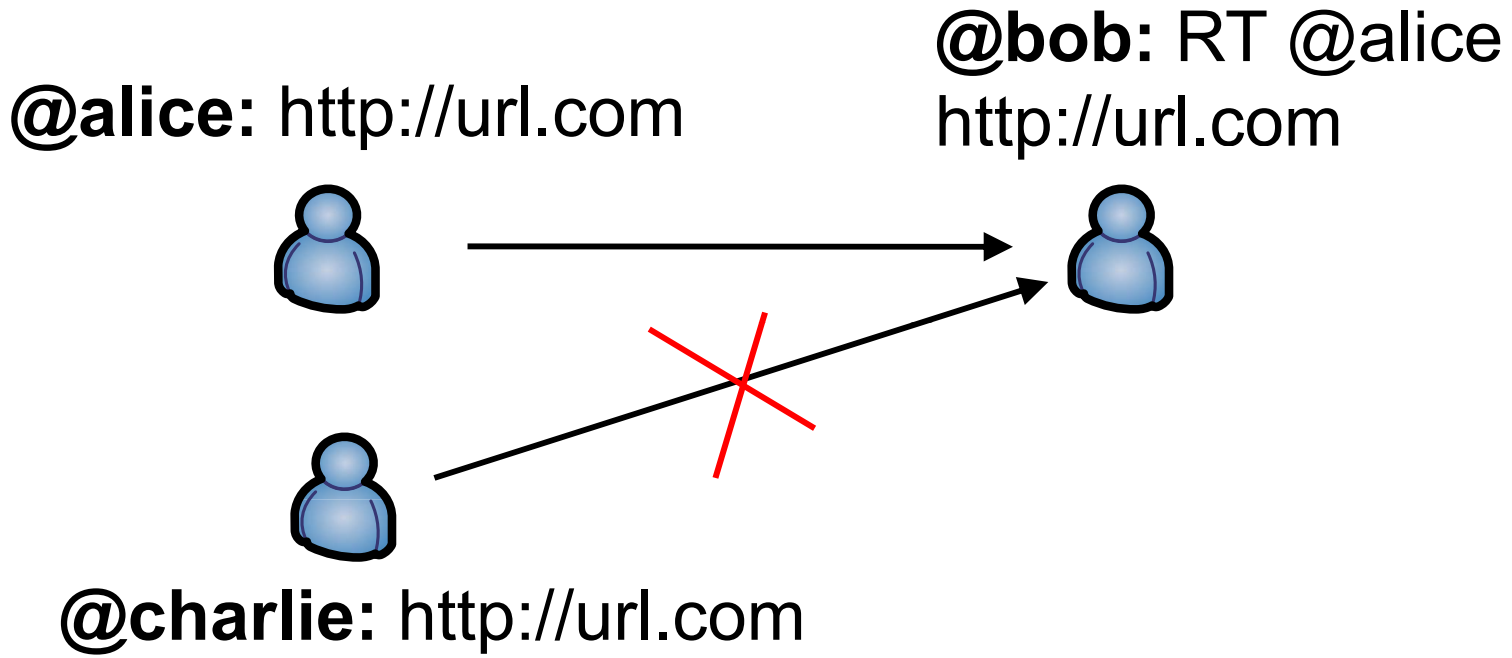
Space Shuttle Atlantis lifts off for final scheduled mission. http://on.cnn.com/cBDQEk

about 23 hours ago via web

chaunce322: RT @cnnbrk Space Shuttle **Atlantis** lifts off for final scheduled mission. http://on.cnn.com/cBDQEk

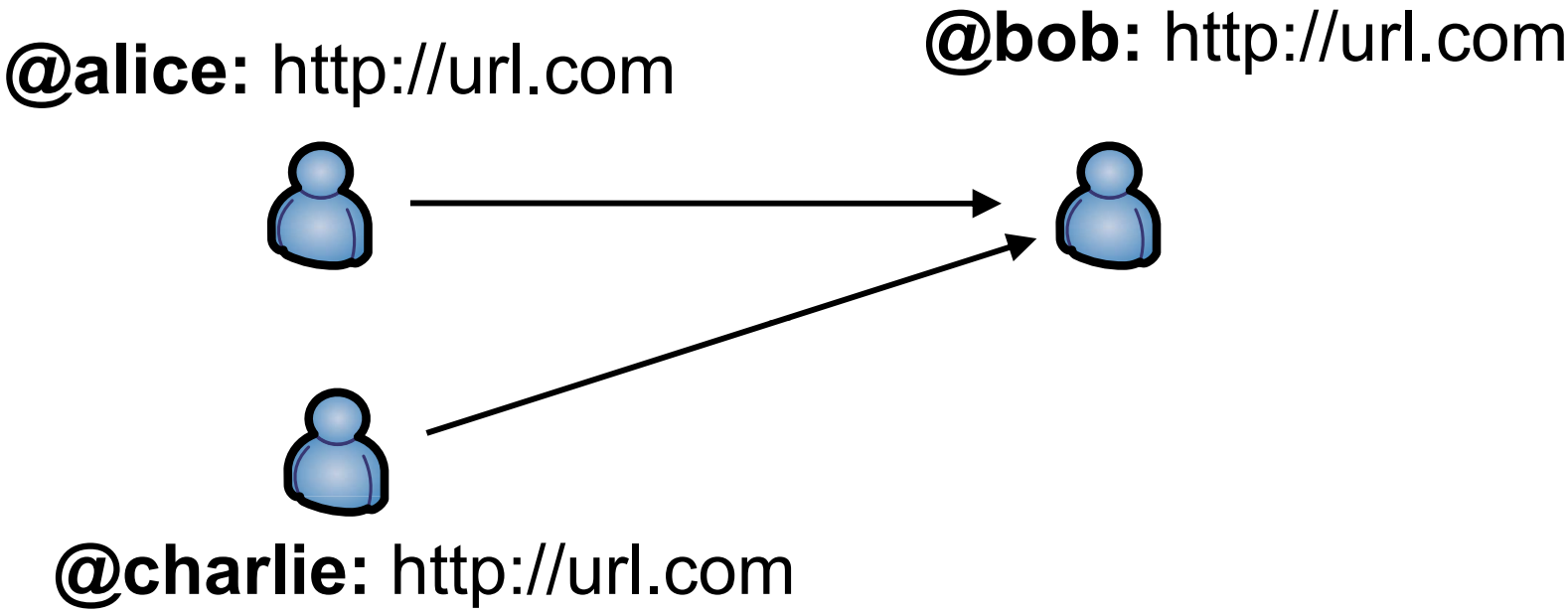
about 18 hours ago from *Twitterrific* · Reply · View Tweet

RT-cascade



- Arcs: who retweets whom
  - Irrespective of wheter users follow one another
- Single parent
  - only the user name immediately after „RT” taken into account

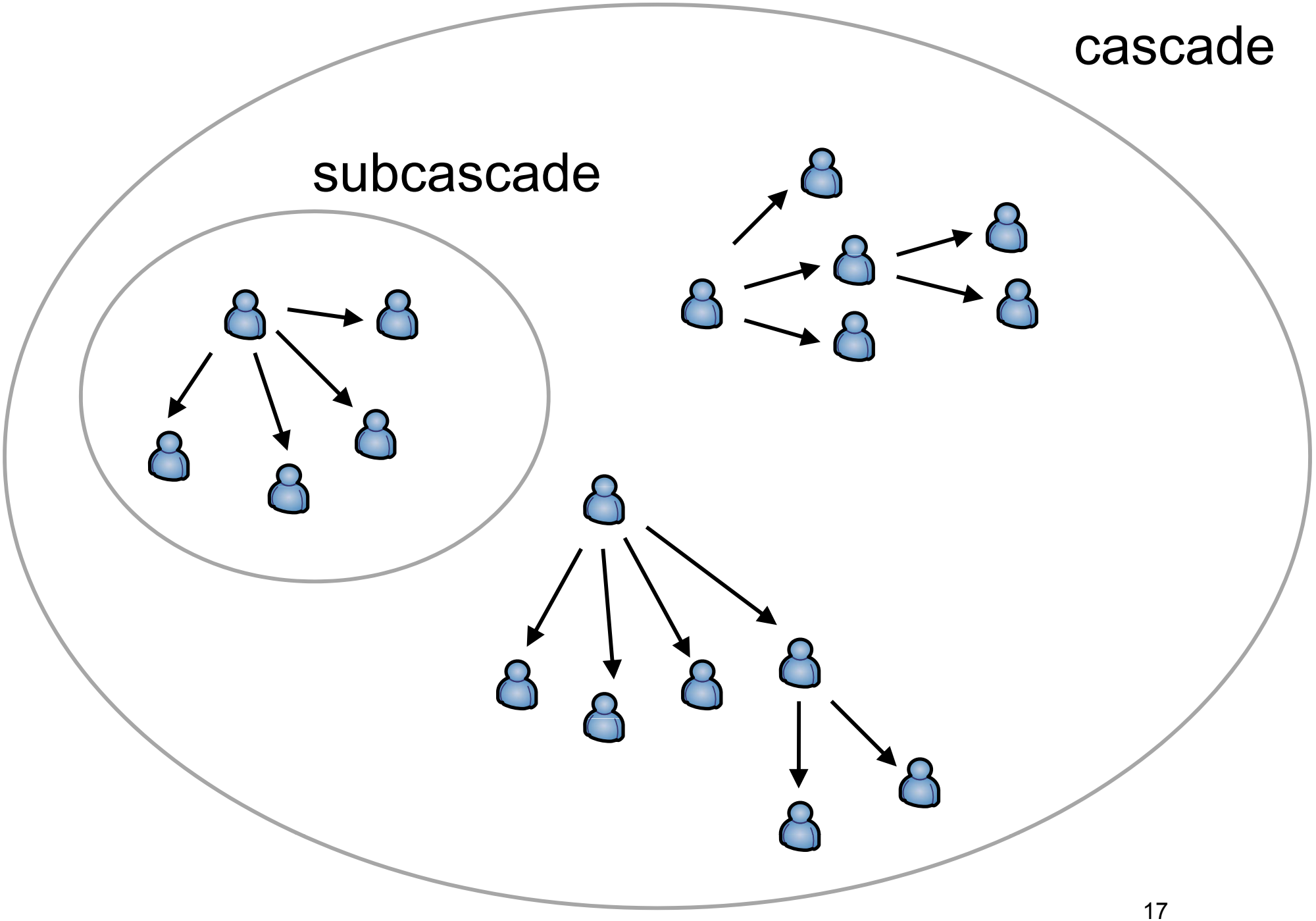
F-cascade



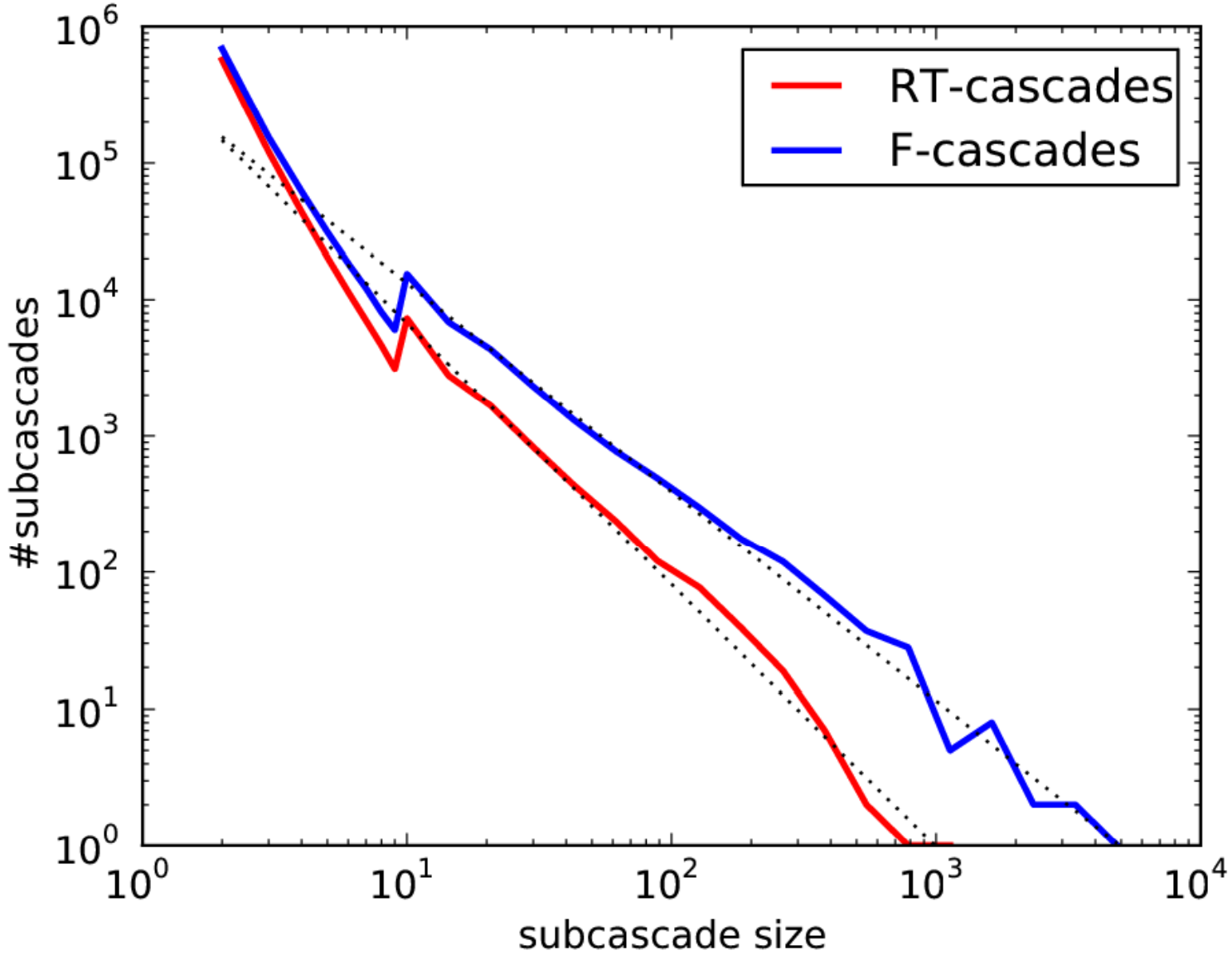
- Arc @a→@b exists if:
  - user @a mentioned URL before user @b
  - user @b **follows** user @a

RT-cascades vs. F-cascades

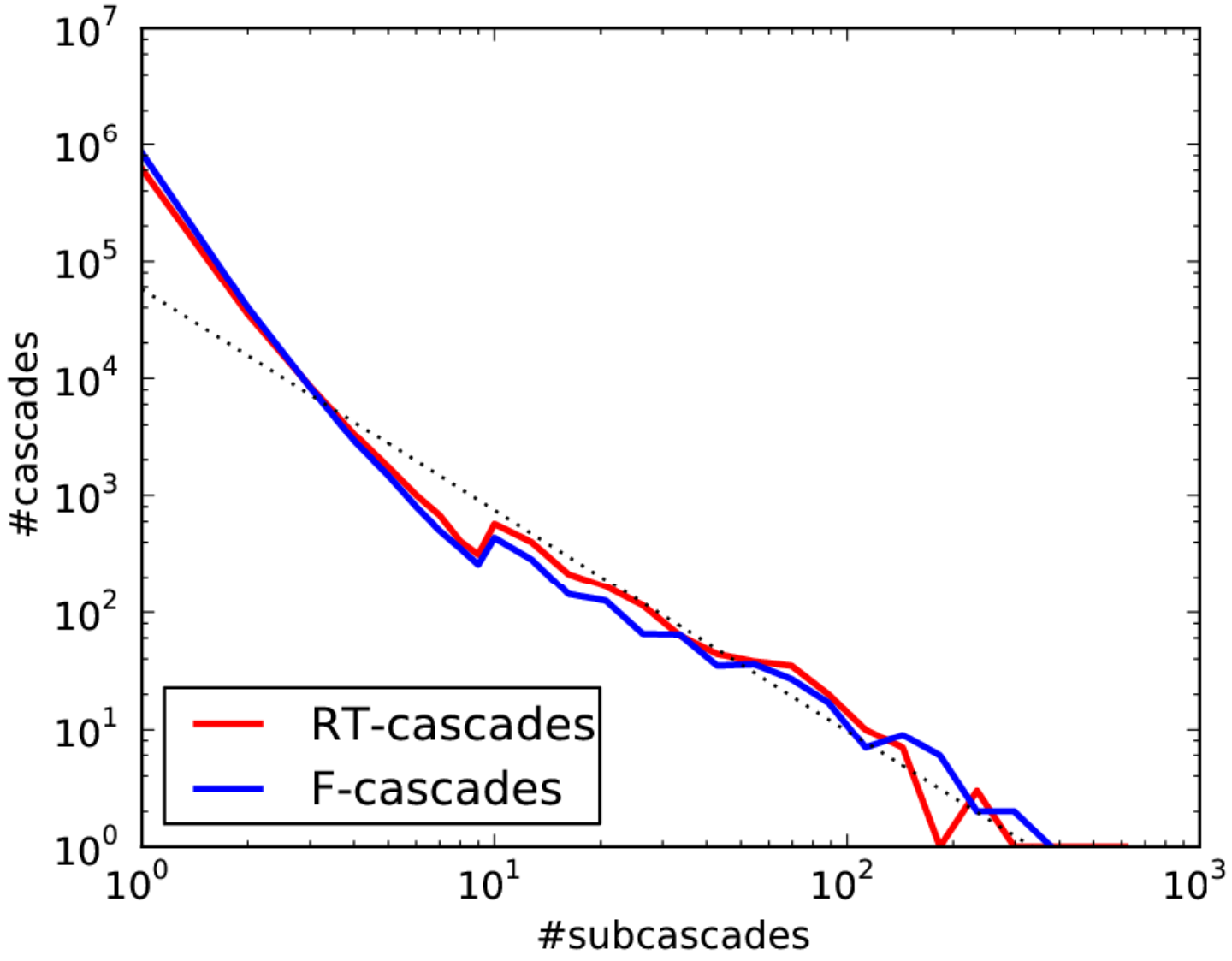
- RT-cascades are trees
- F-cascades are DAGs
- 33% of the retweets credit a source that the user does not directly follow


cascade
subcascade

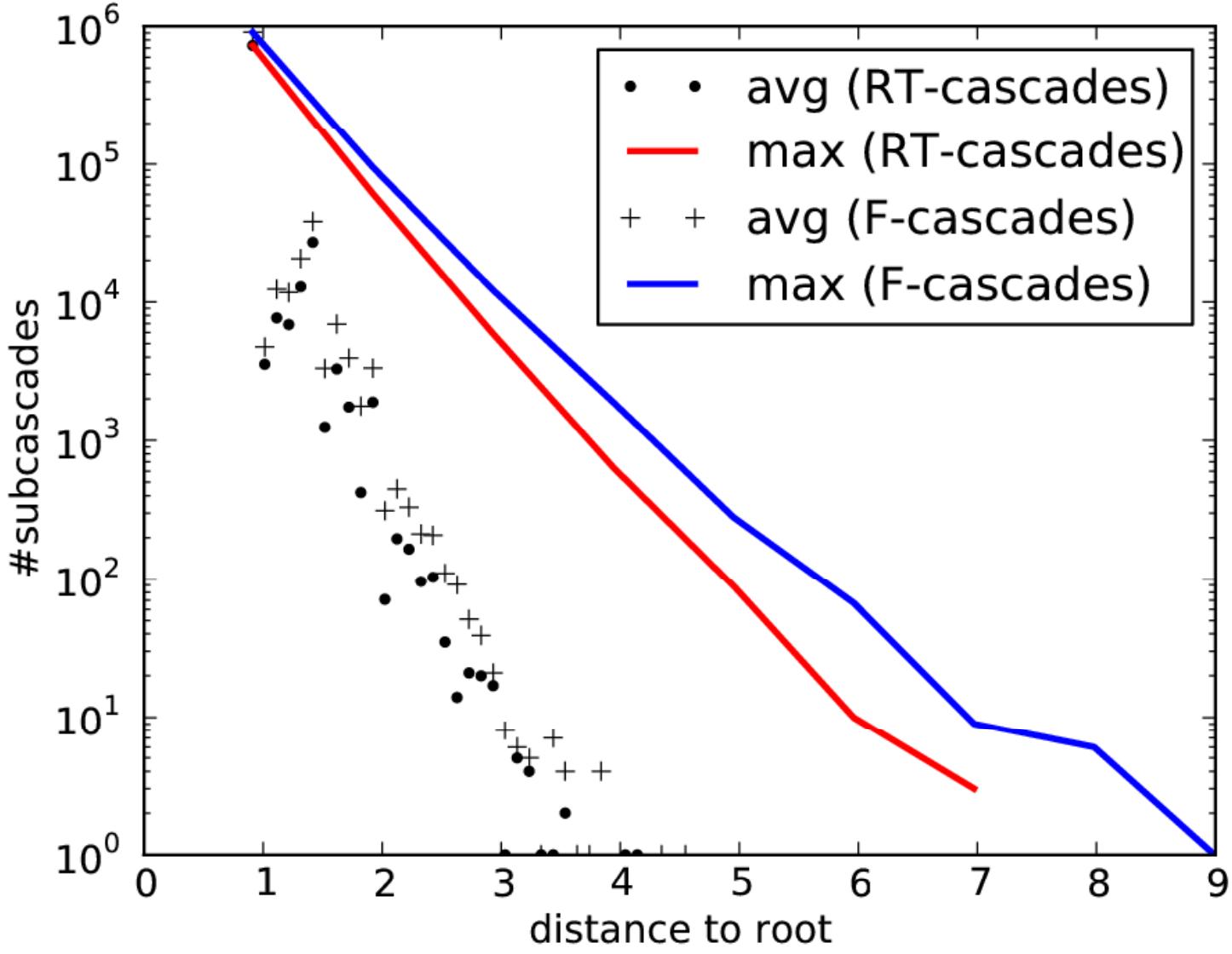
Subcascade size



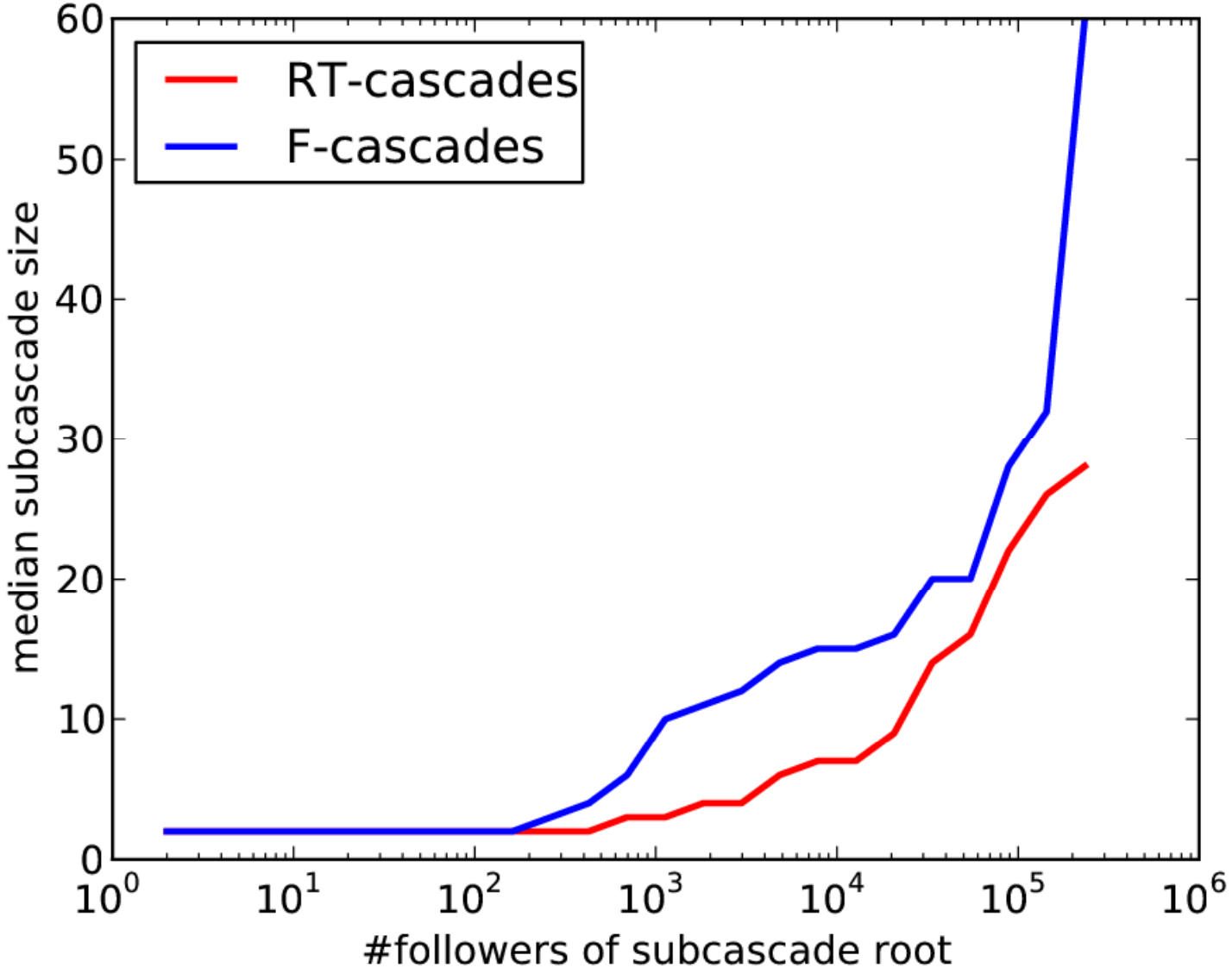
Cascade fragmentation



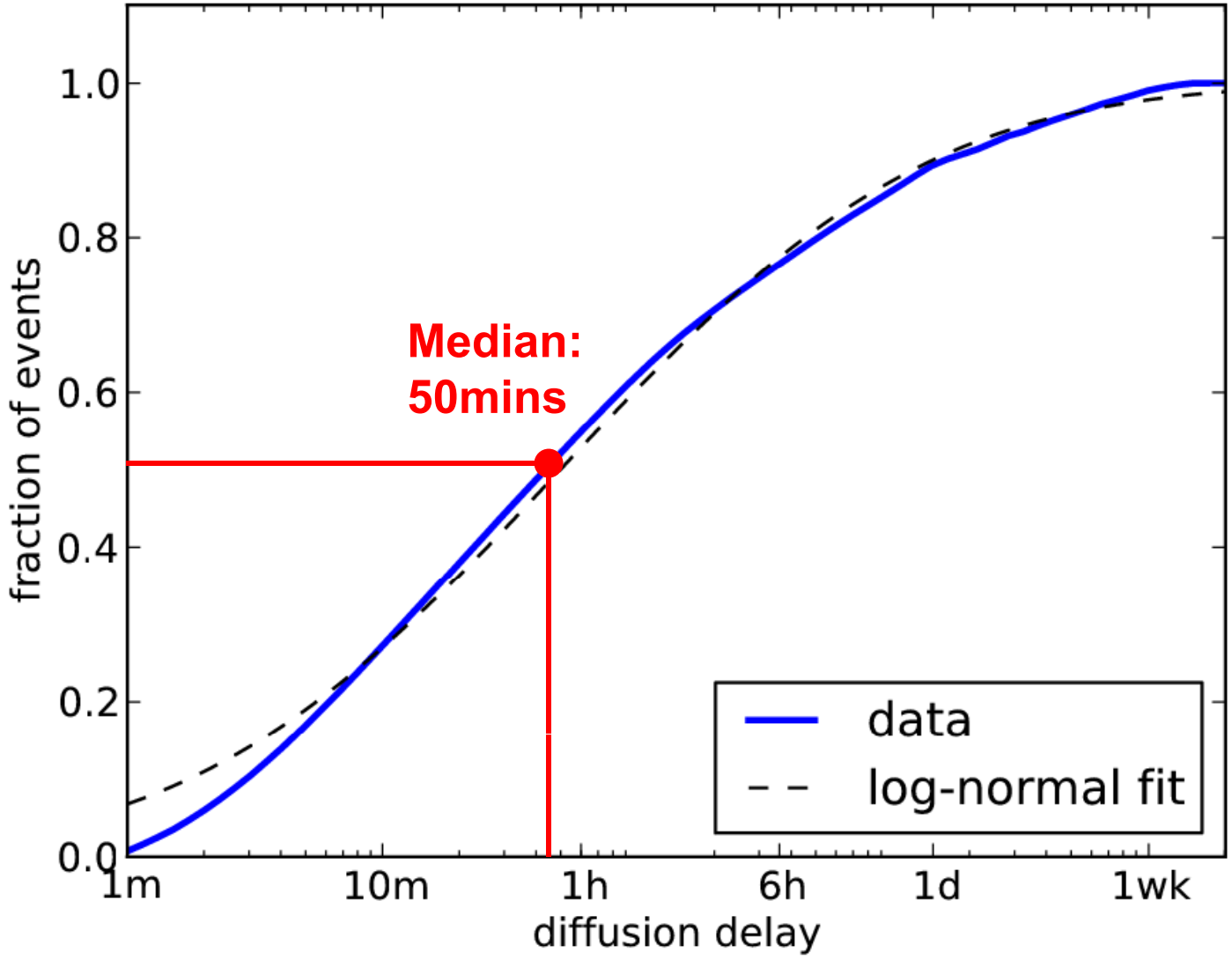
Cascade depth



Influence of the root



Information diffusion rate

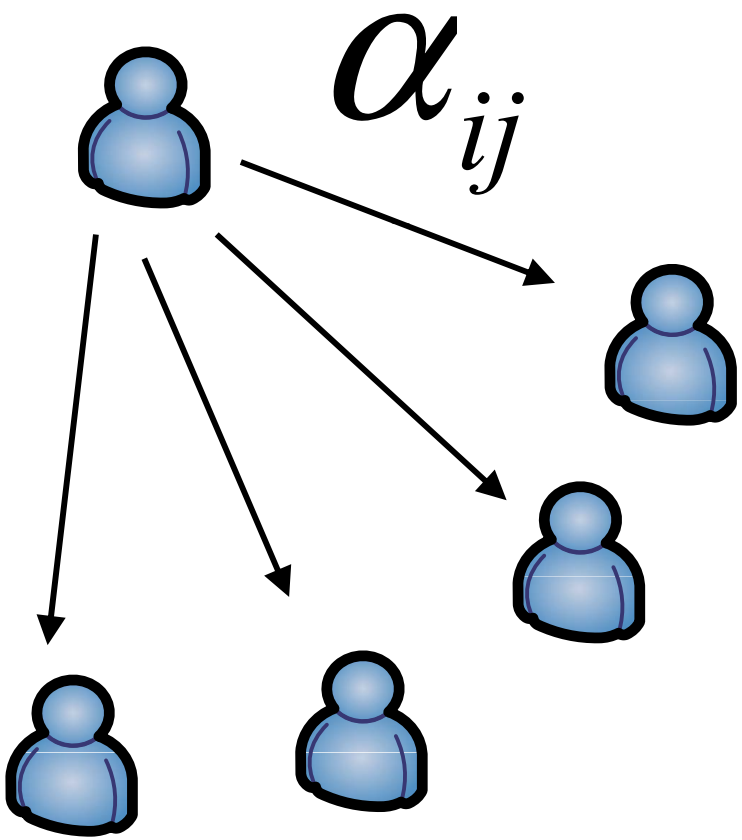


URL tweeting prediction

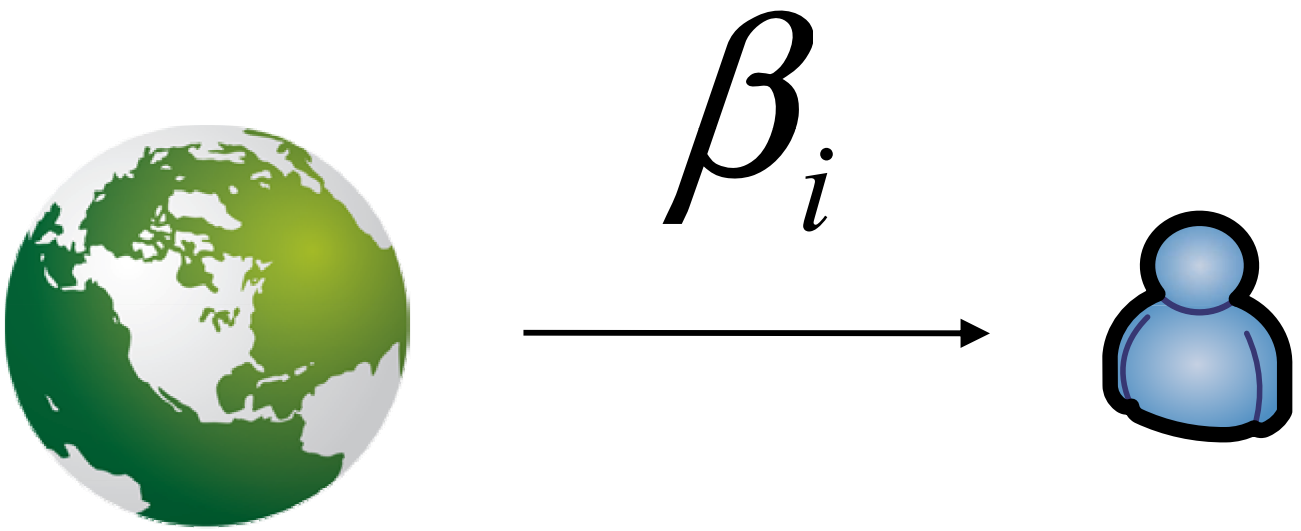
- Based on the past URL retweets by users, predict the future ones
- Find probability that user i mentions URL u

$$p_i^u = ?$$

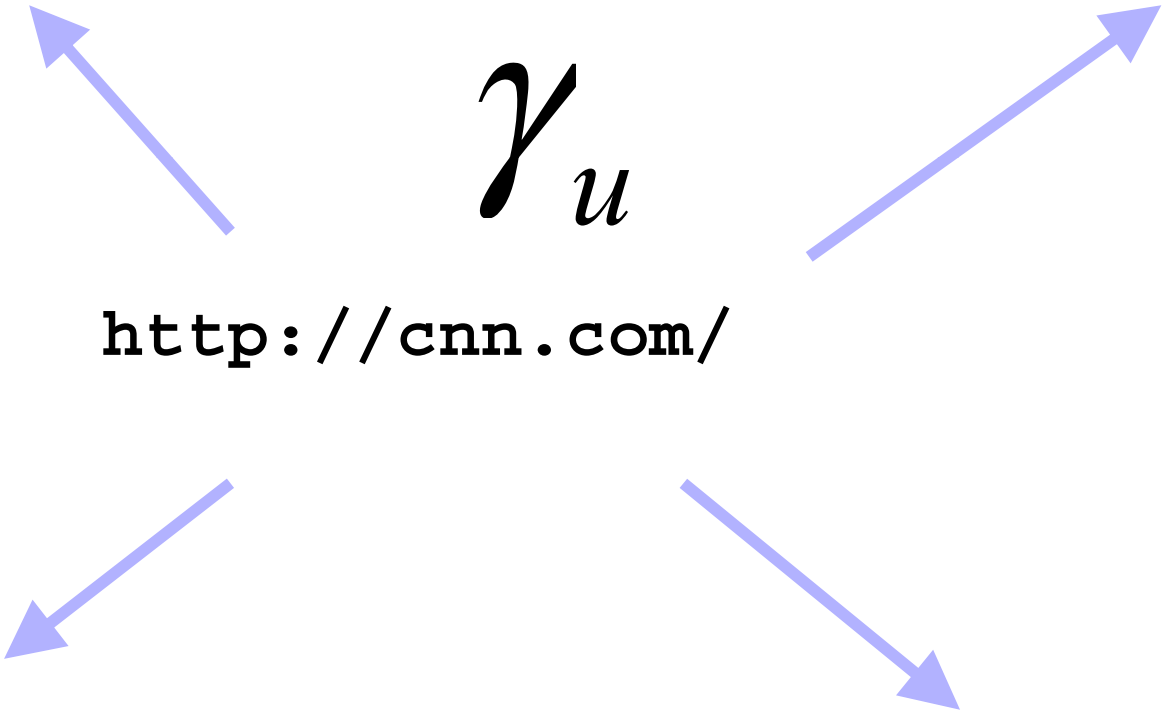
Influence



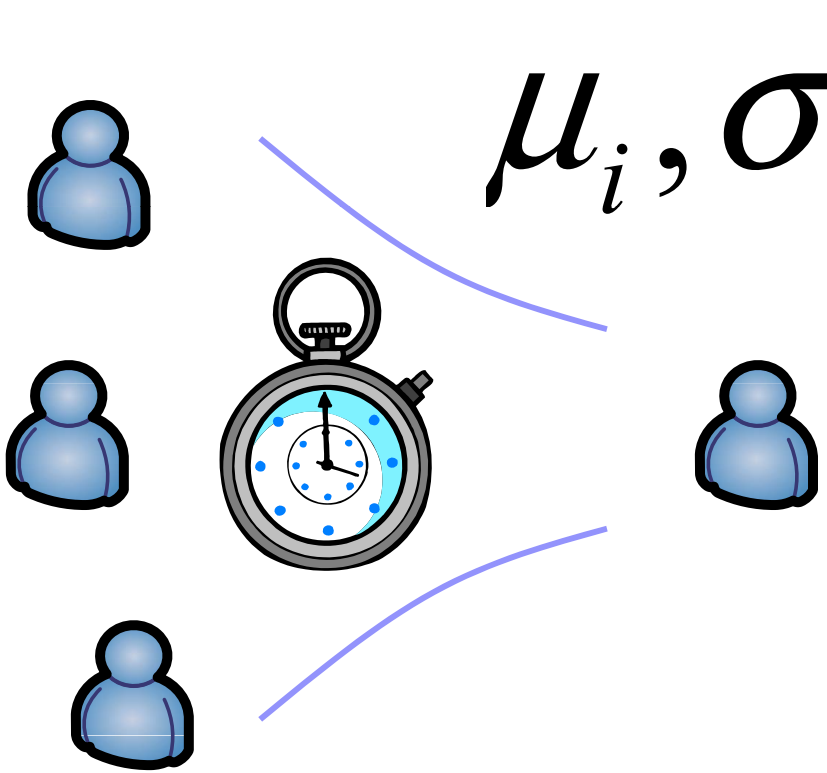
External influence



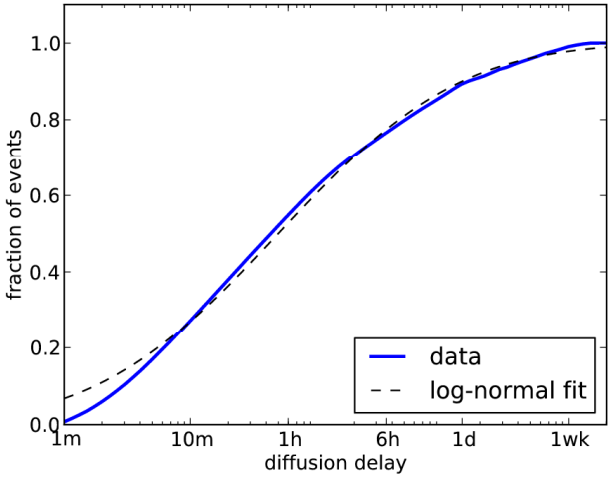
URL virality



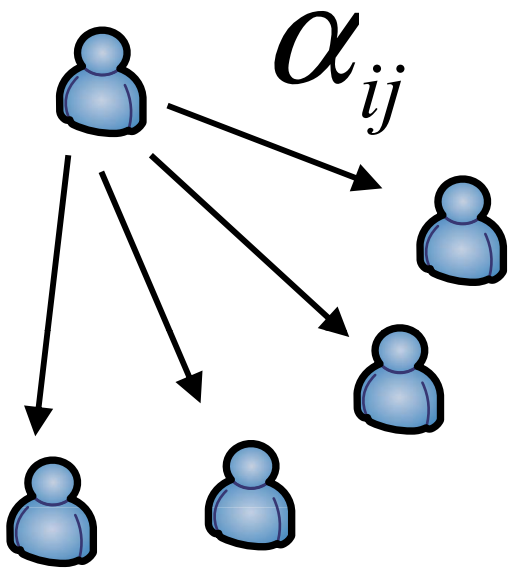
Per-user diffusion delay

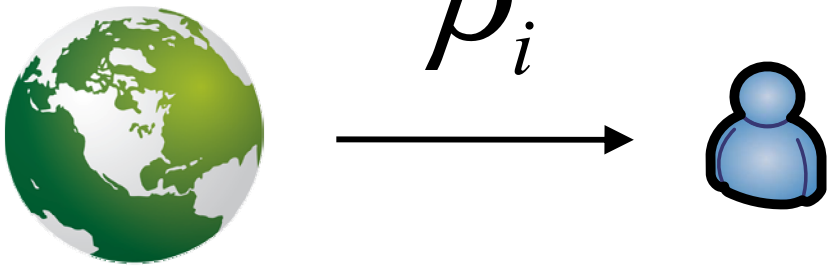


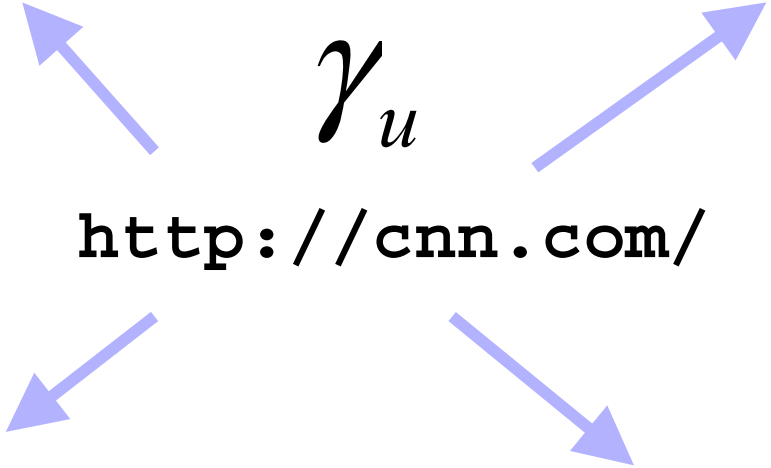
$$\mu_i, \sigma_i^2$$

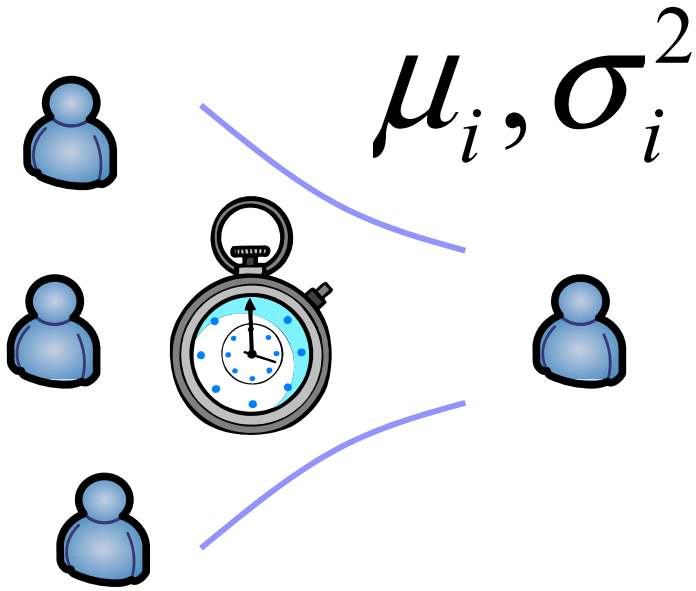


Model



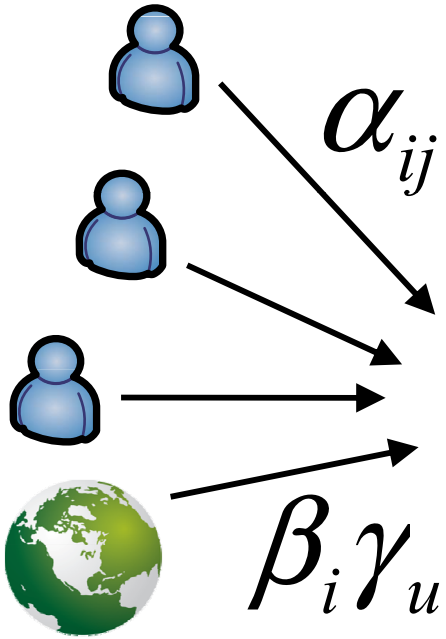






At-Least-One (ALO) model

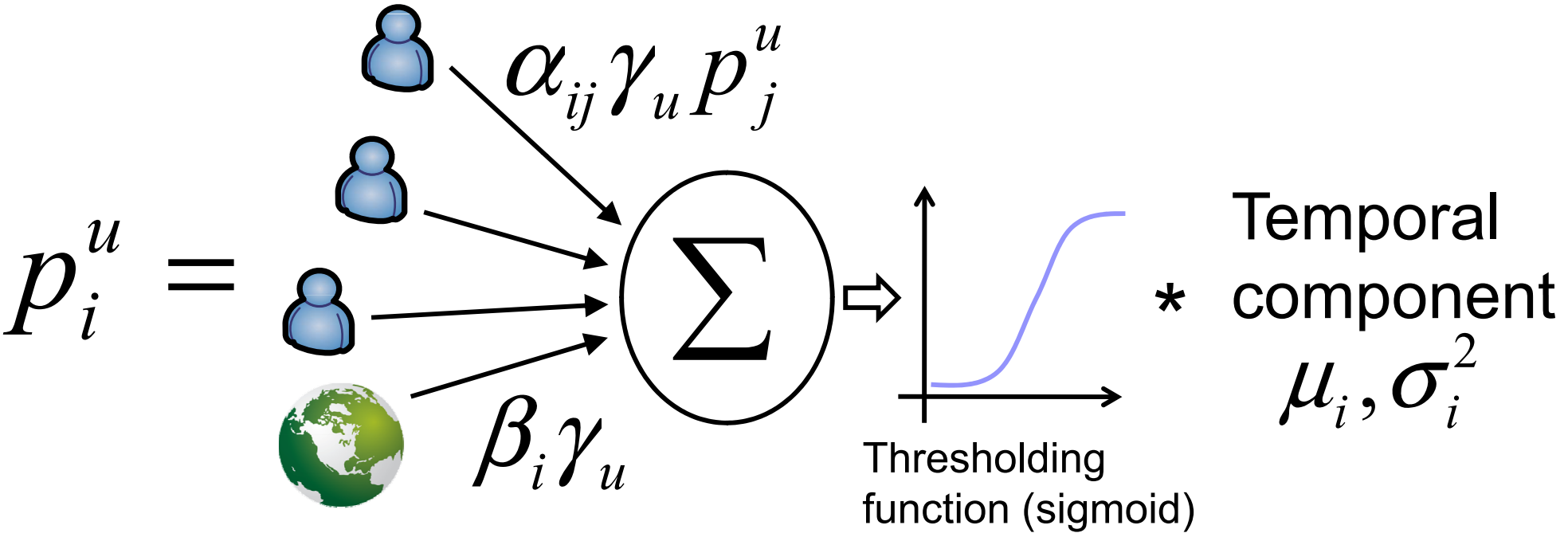
$$p_i^u = \text{P(at least one event happens)} * \text{Temporal component } \mu_i, \sigma_i^2$$



$\alpha_{ij}\gamma_u p_j^u$

$\beta_i \gamma_u$

Linear threshold (LT) model



Performance metrics

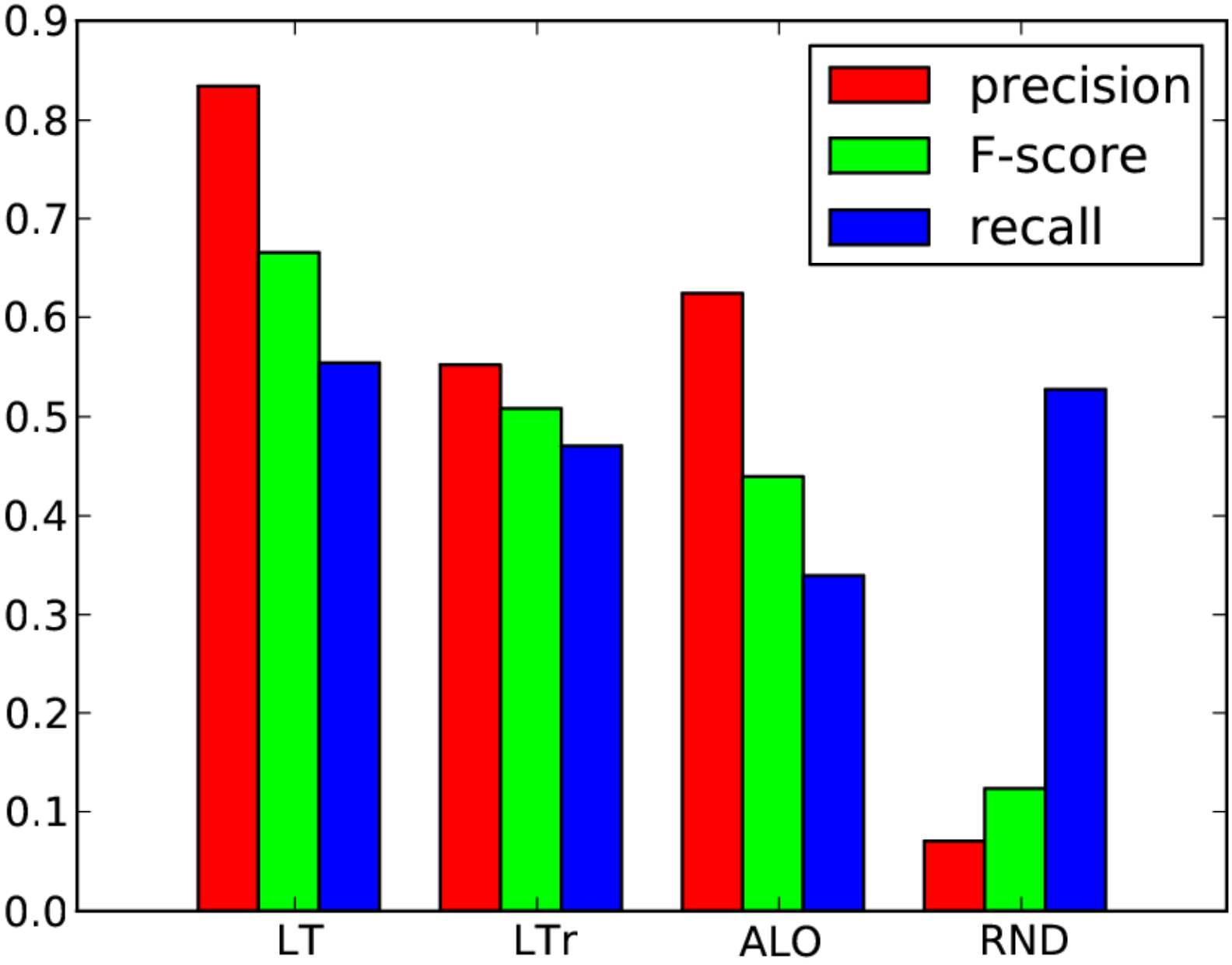
- **Recall:** fraction of tweets predicted
  - out of all tweets that happened
- **Precision:** fraction of true positives
  - out of all tweets predicted
- **F-score:** harmonic mean of recall and precision
- **F-score is the optimization goal**

Learning

- Input: a time window of tweets
- Computation: gradient ascent method
  - Parameter space: $\alpha_{ji}, \beta_i, \gamma_u, \mu_i, \sigma_i^2$
  - Goal: maximize F-score
- Output: p_i^u

Lineup

- **LT** – Linear Threshold model
- **LTr** – Linear Threshold model with α_j instead of α_{ji}
- **ALO –** At-Least-One model
- **RND** – baseline, makes random guesses about p_i^u



* training data: first 150 h, test data: next 150h,
results for 100 random URLs

Summary

- Log-normal degree distribution
- Small-world: 3.6 hops from user to user
- Power-laws in the user activity and URL mentions
- Cascades are shallow: exponential depth falloff
- Log-normally distributed diffusion delay
- The LT model:
  - predicts more than half of the URL tweets
  - with less than 15% false positive rate

Ongoing work

- Investigating mispredictions
  - URLs
  - users
- Scaling up the real-time data mining
  - continous MapReduce
  - crawler farm
- Website: personalized URL rankings for Twitter users
- **Apply to other systems**