Aggregate Estimation over a Microblog Platform

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Outline

- Motivation
- Challenges
- Subgraph Design
- Sampling Design
- Experiments

Motivation

Microblog Platforms

twitter

yammer

tumblr.

Instagram

Twitter has gone Mainstream

Aggregate Estimation over Microblogs

Aggregates	Estimands	Filters
AVERAGE	User Profile metadata	Keywords
COUNT	Tweets metadata	Time
SUM		

Motivation - I

Sociologist:

- COUNT(privacy) before and after Snowden disclosures
- COUNT(snowden, hero) Vs COUNT(snowden, traitor)

Motivation - II

Psychologist:

- What fraction of Twitter users have tweets with keywords symptomatic of depression?

Motivation - III

Companies/Investors:

- COUNT(company Name) Month-over-Month in 2013
- COUNT(android) Vs COUNT(iPhone) in 2013

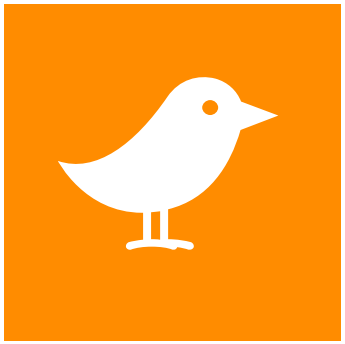
Access Model

SEARCH

Given a keyword, returns recent tweets containing keyword

USER CONNECTIONS

Given a user, returns his/her connections



USER TIMELINE

Given a user, returns profile metadata and all past tweets

Challenges

Pricing and Limits

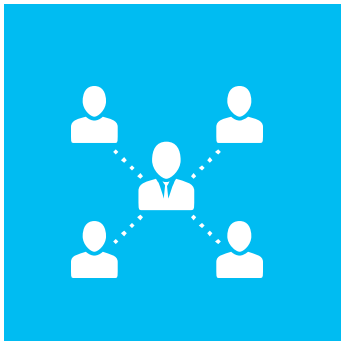
Pricing:

- Firehose access is not easy to get
- Paid access to past tweets

Limits:

- Rate limits
- API limits
- User Timeline to rescue!

Inapplicability of Prior Work



~~Aggregate Estimation over Graphs~~

Issues:

- Broad vs Specific aggregates
- Inefficiency of Random Walks in OSNs

Design Issues

Subgraph Design

Identify the best subgraph for sampling

Sampling Design

Design a topology aware random walk that leverages graph properties

Subgraph Design

Subgraph Design

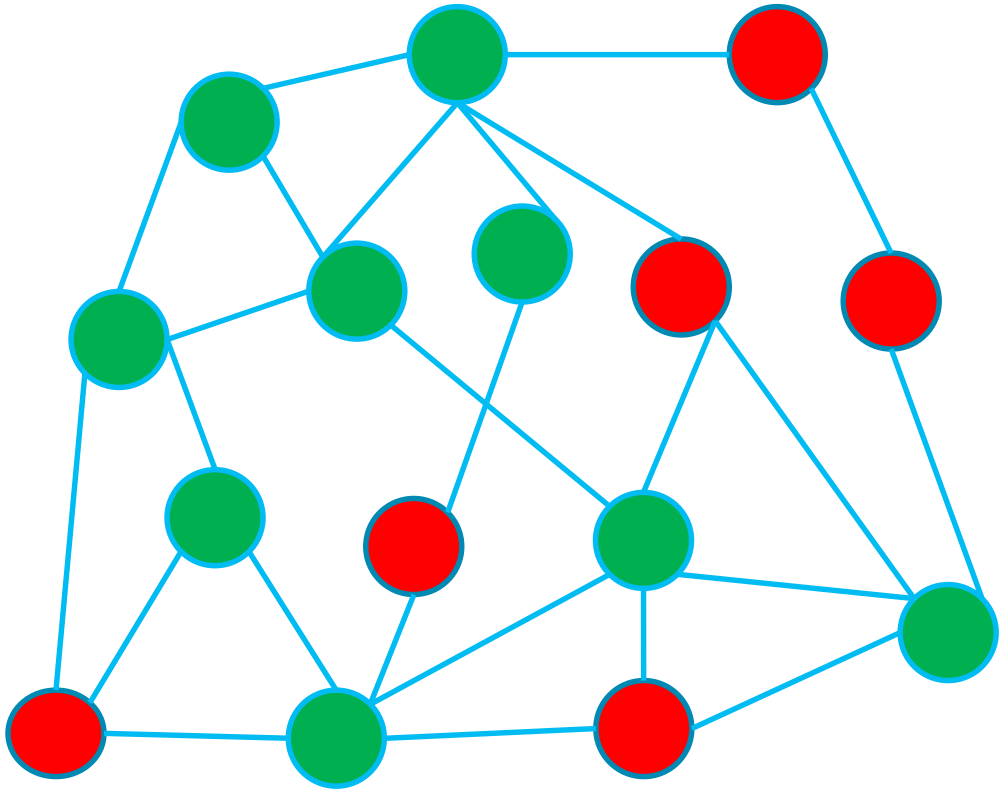
Subgraph Design

Identify the best subgraph for sampling

What is a good subgraph?

- Good Recall
- Topology efficient for sampling

Social Graph



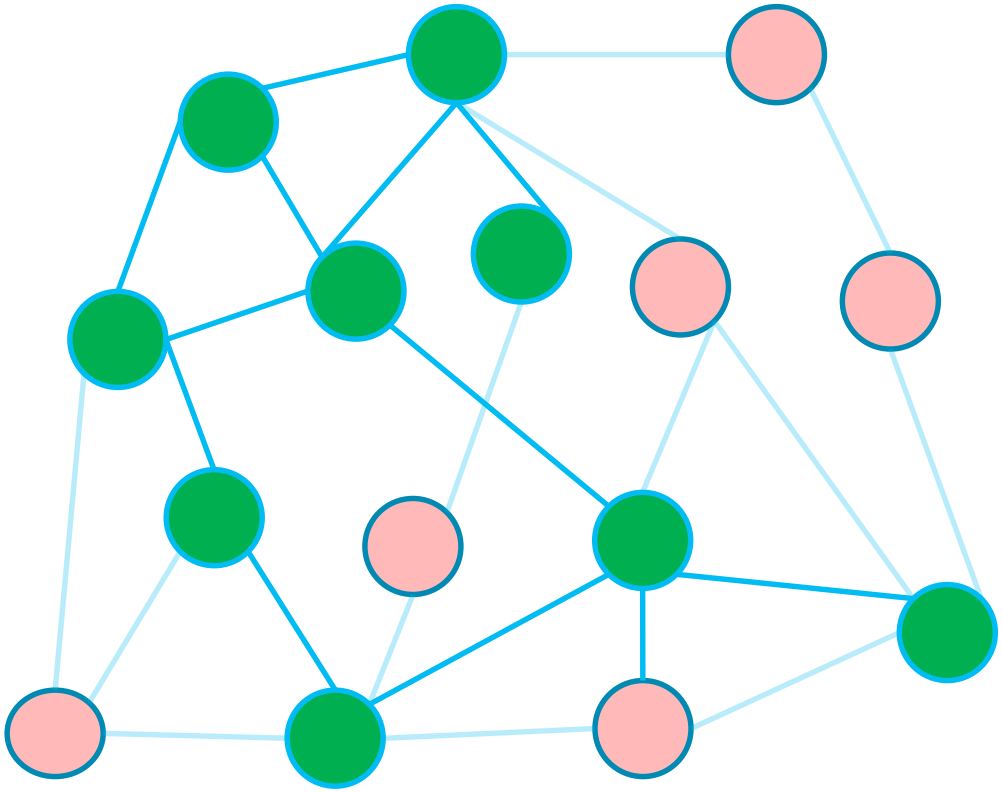
Pros

- Baseline graph
- High recall

Cons

- Very few relevant nodes
- Inefficient for sampling
- High query cost

Term Induced Subgraph



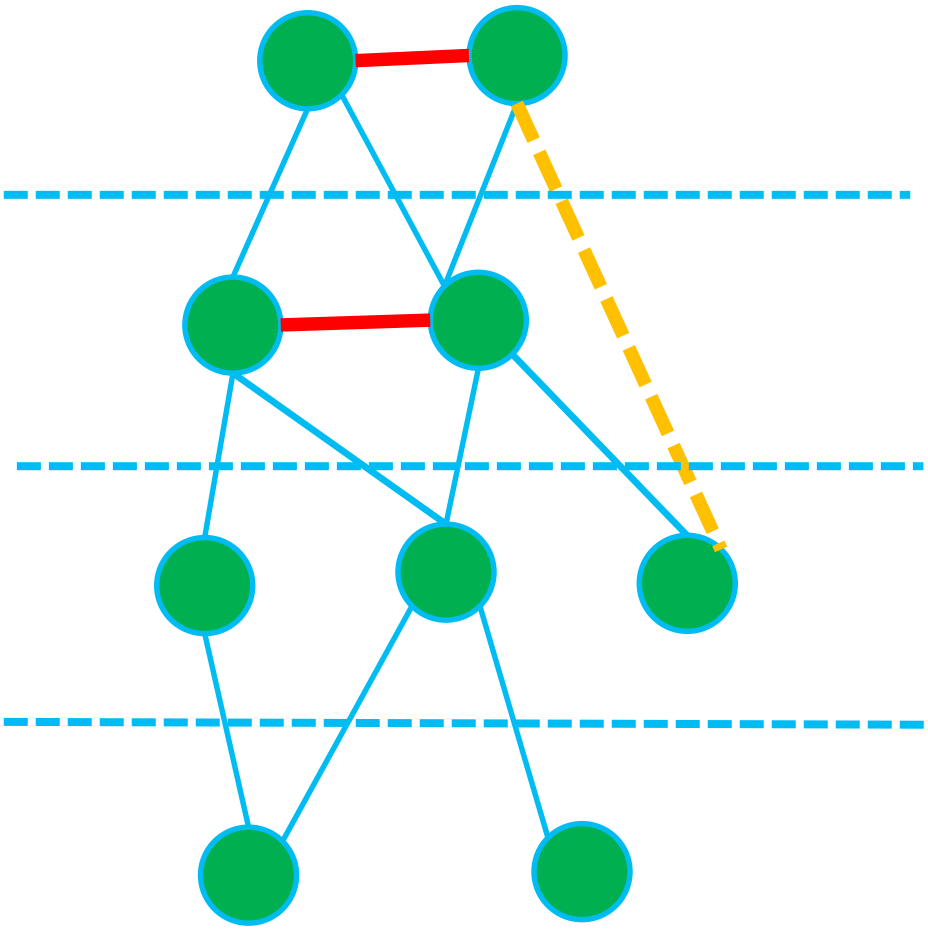
Pros

- Good recall
- Typically well connected

Cons

- Inefficient for sampling
- High query cost

Level by Level Subgraph



- Motivation
  - Communities
  - 90+% retweets within 1 hour
- Intra edges
  - Traps random walks
  - Removing improves conductance
- Inter edges
- Cross edges
- Edge taxonomy and distribution

Removal of Intra Edges

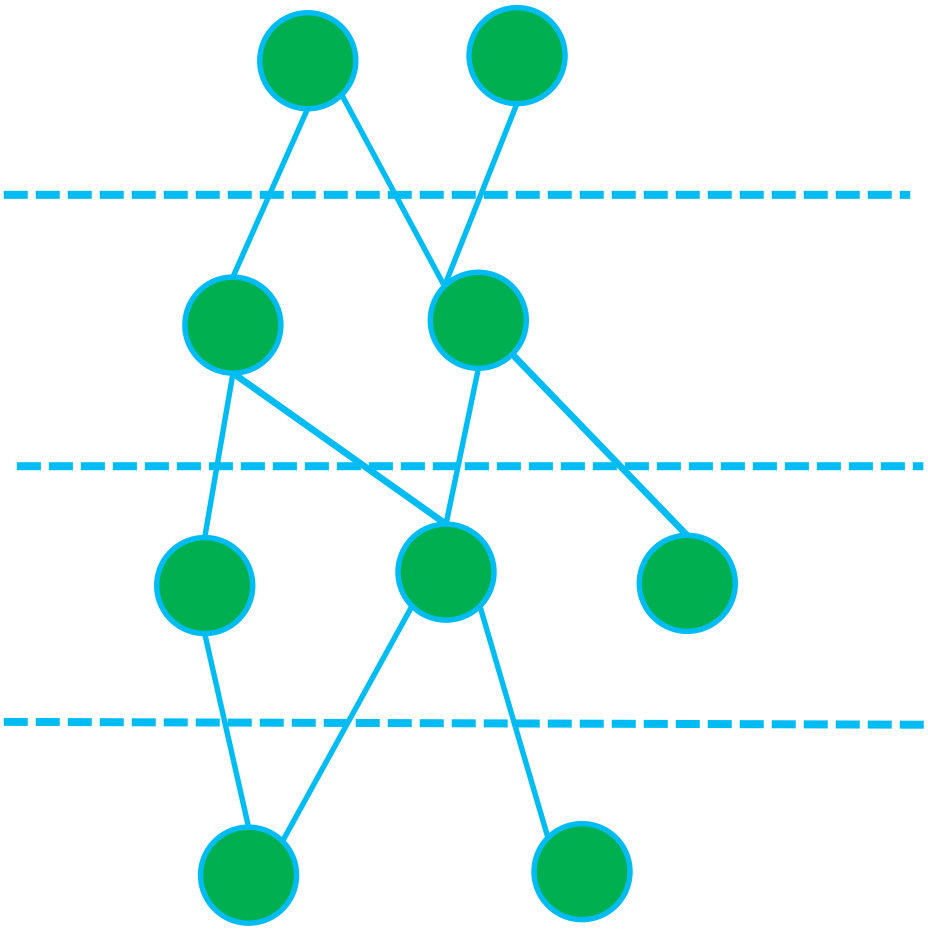
THEOREM 4.1. *The conductance for G is*

$$\varphi(G) = \begin{cases} \frac{h}{(k+d)(h-1)n} & \text{if } d \le \frac{n}{2h},\ k \le \frac{n}{2h} \\ \min\left(\frac{2kh-n}{kh+dn}, \frac{2d}{2d(h-1)+hk}\right) & \\ & \text{if } d \le \frac{n}{2h},\ \frac{n}{2h} < k < \frac{n}{h} \\ \min\left(\frac{2dh-n}{kh+dn}, \frac{2d}{2d(h-1)+hk}\right) & \\ & \text{if } \frac{n}{2h} < d < \frac{n}{h},\ k \le \frac{n}{2h} \\ \min\left((k-\frac{n}{2h})\frac{2dh-n}{kh+dn}, \frac{2d}{2d(h-1)+hk}\right) & \\ & \text{if } \frac{n}{2h} < d < \frac{n}{h},\ \frac{n}{2h} < k < \frac{n}{h} \end{cases} \tag{2}$$

After removing all intra-level edges, the conductance of G' is

$$\varphi(G') = \begin{cases} \frac{h}{nd(h-1)} & \text{if } d \le \frac{n}{2h} \\ \min\left(\frac{2hd-n}{nd}, \frac{1}{h-1}\right) & \text{if } \frac{n}{2h} < d < \frac{n}{h} \end{cases} \tag{3}$$

Level by Level Subgraph



Pros

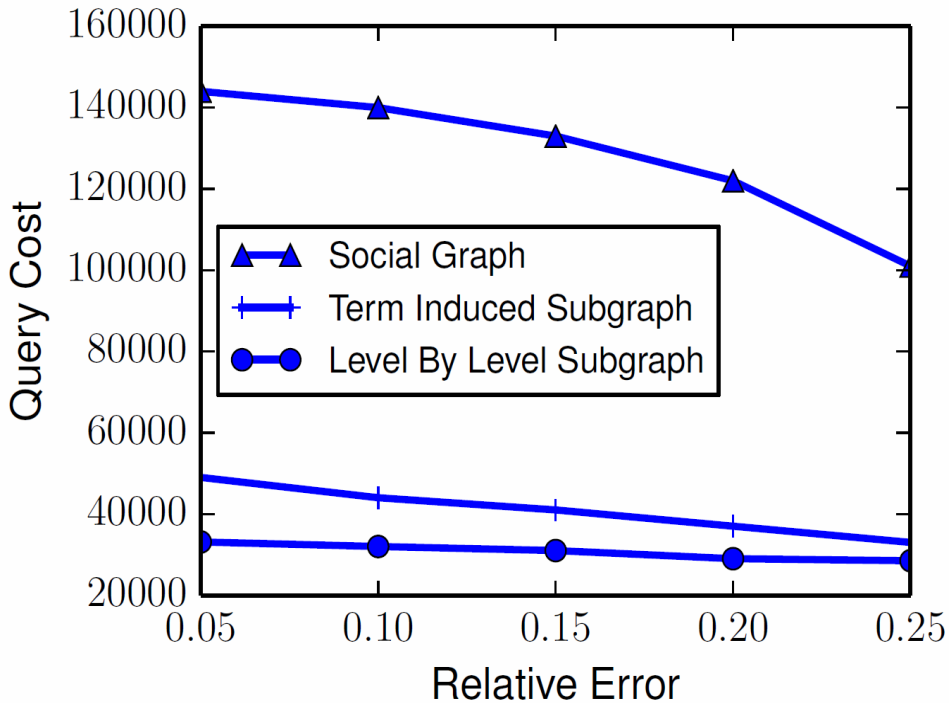
- Recall comparable to term induced subgraph
- Reasonably connected
- Better efficiency for sampling
  - Sparser graph
- Lower query cost

Algorithm So Far

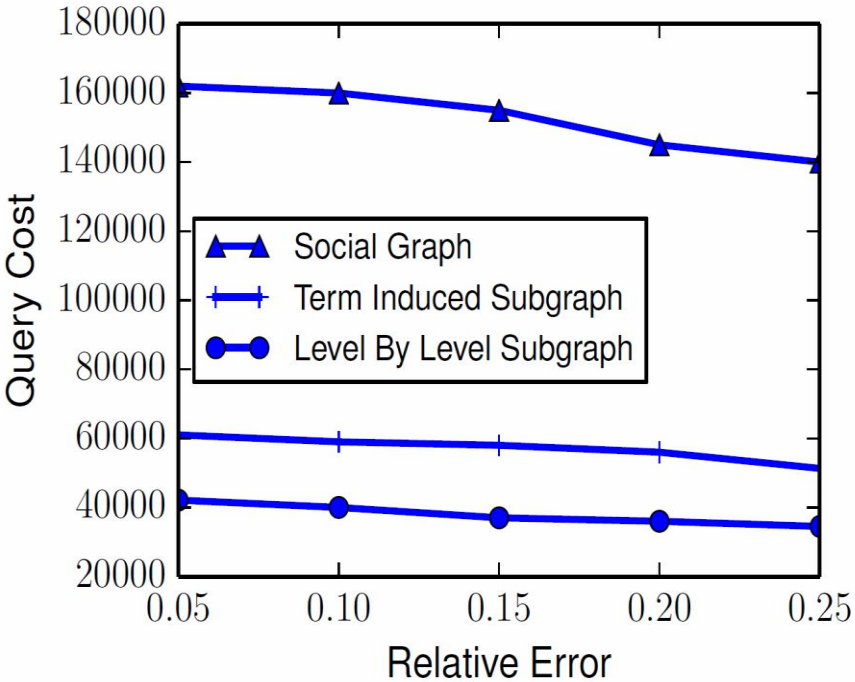
Algorithm MA-SRW

1. Get seed users
2. Repeat until budget is not exhausted
   - Retrieve samples via SRW
   - Pick only edges that belong to another level
3. Perform aggregate estimation over collected samples

MA-SRW Performance



- AVG(followers)
- Keyword=privacy
- Year=2013



- COUNT(users)
- Keyword=privacy
- Year=2013

Sampling Design

Sampling Design

Sampling Design

Design a topology aware random walk that leverages properties of Level-by-Level graph

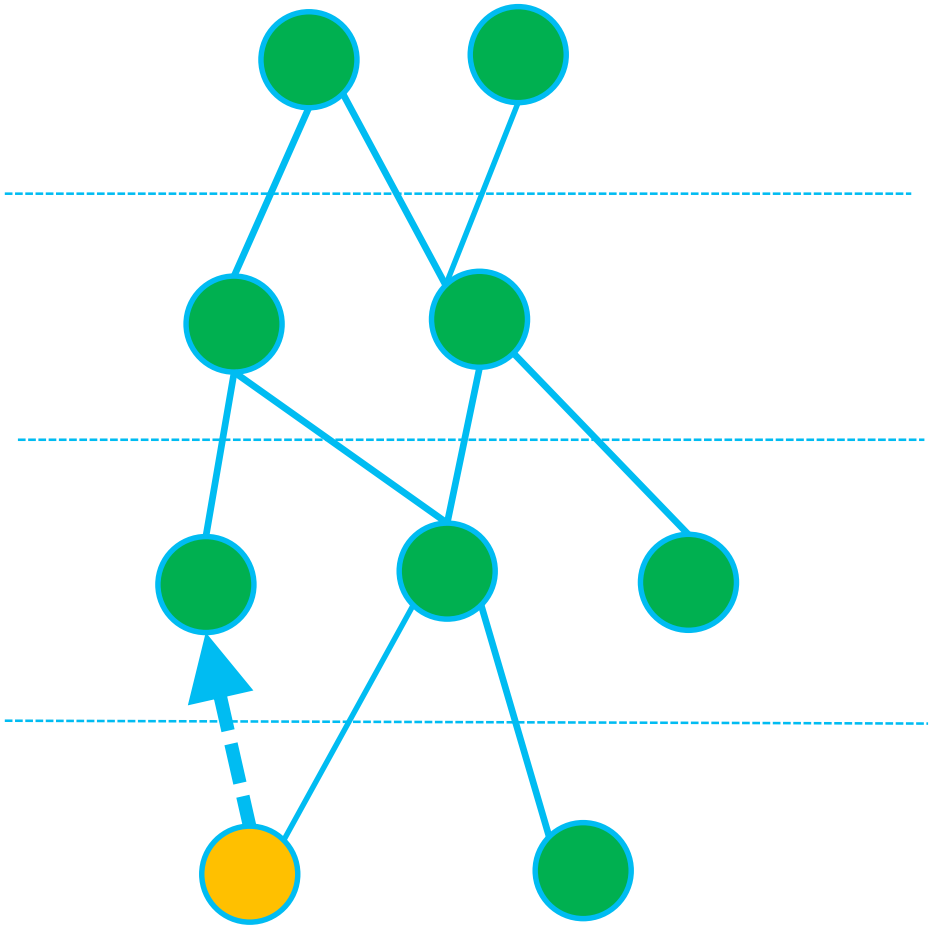
Deficiencies of Random Walks

1. High query cost for SUM/COUNT aggregates
   - Mark and recapture might require $\Omega(\sqrt{n})$ samples for one collision

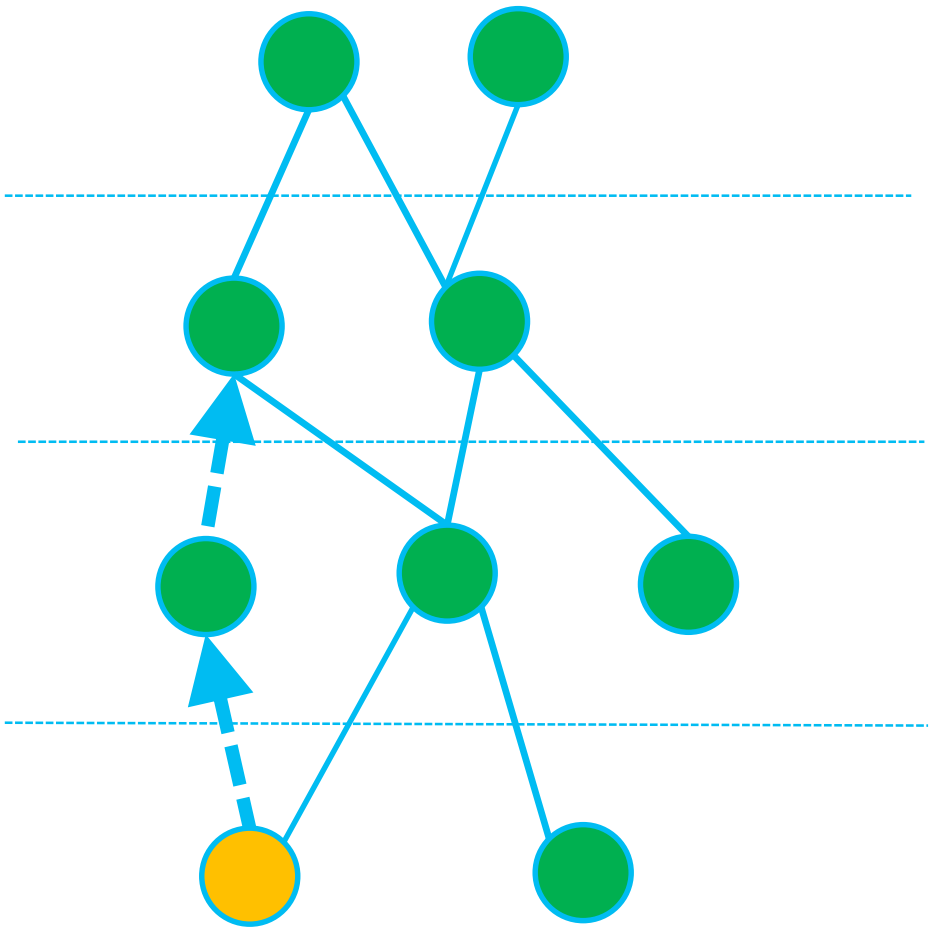
2. Large burn-in despite asymptotic unbiasedness
   - Especially bad for online social networks
   - Oblivious to topology

3. Can we compute the probabilities proactively?
   - instead of waiting till convergence to stationary distribution?

Level by Level Random Walk



Level by Level Random Walk



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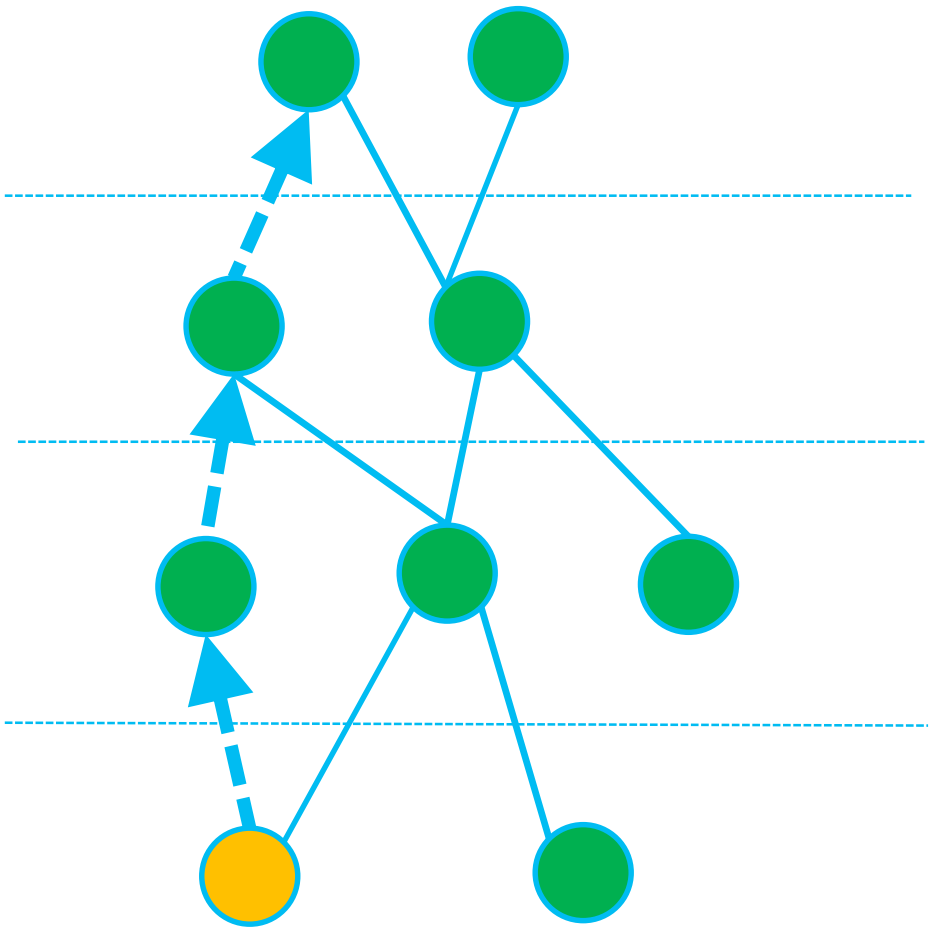

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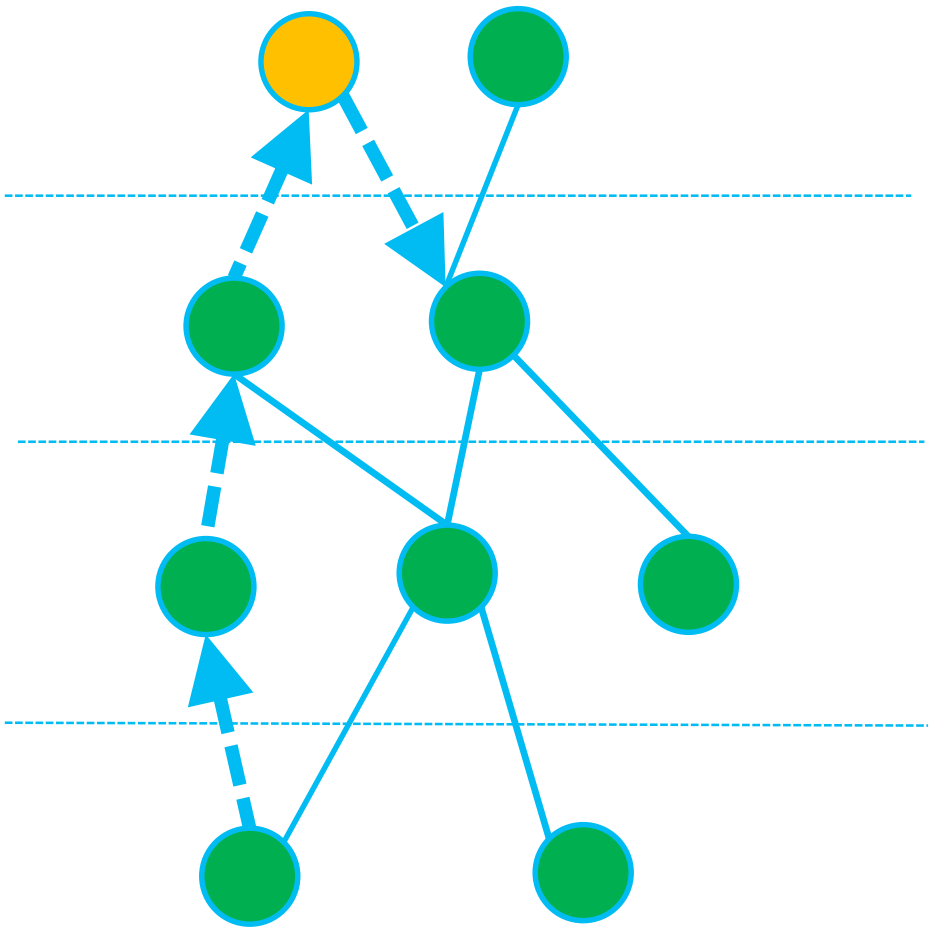
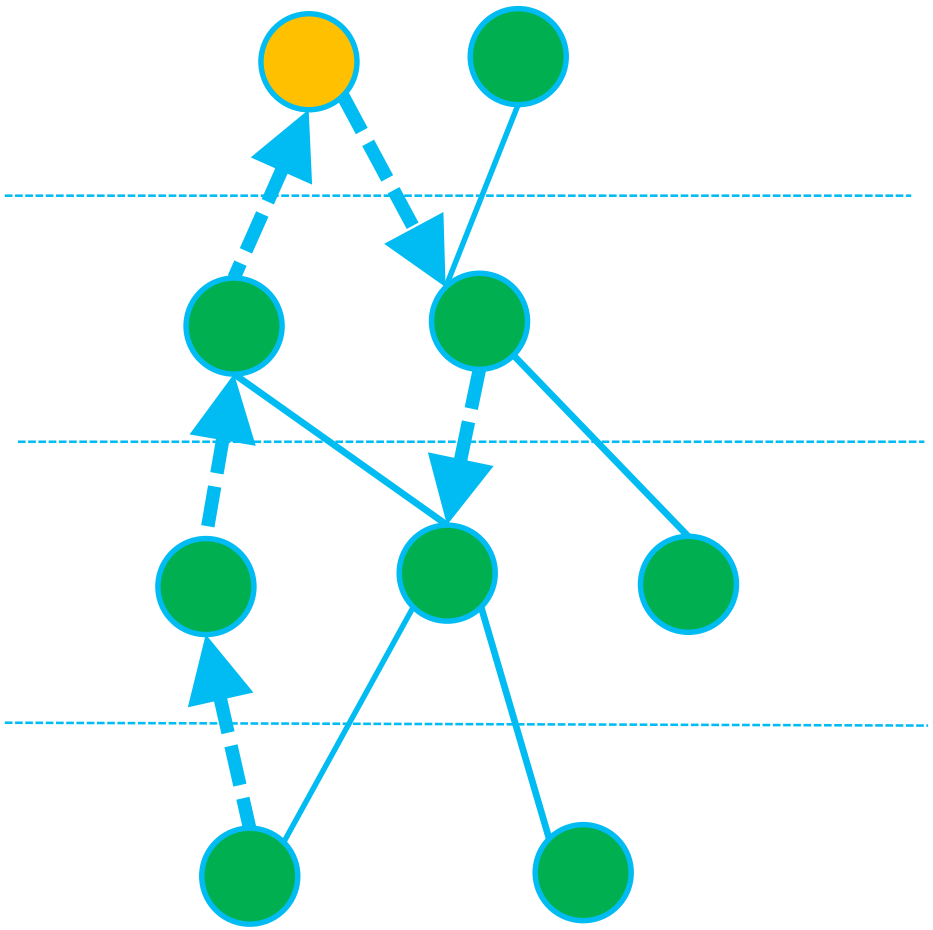
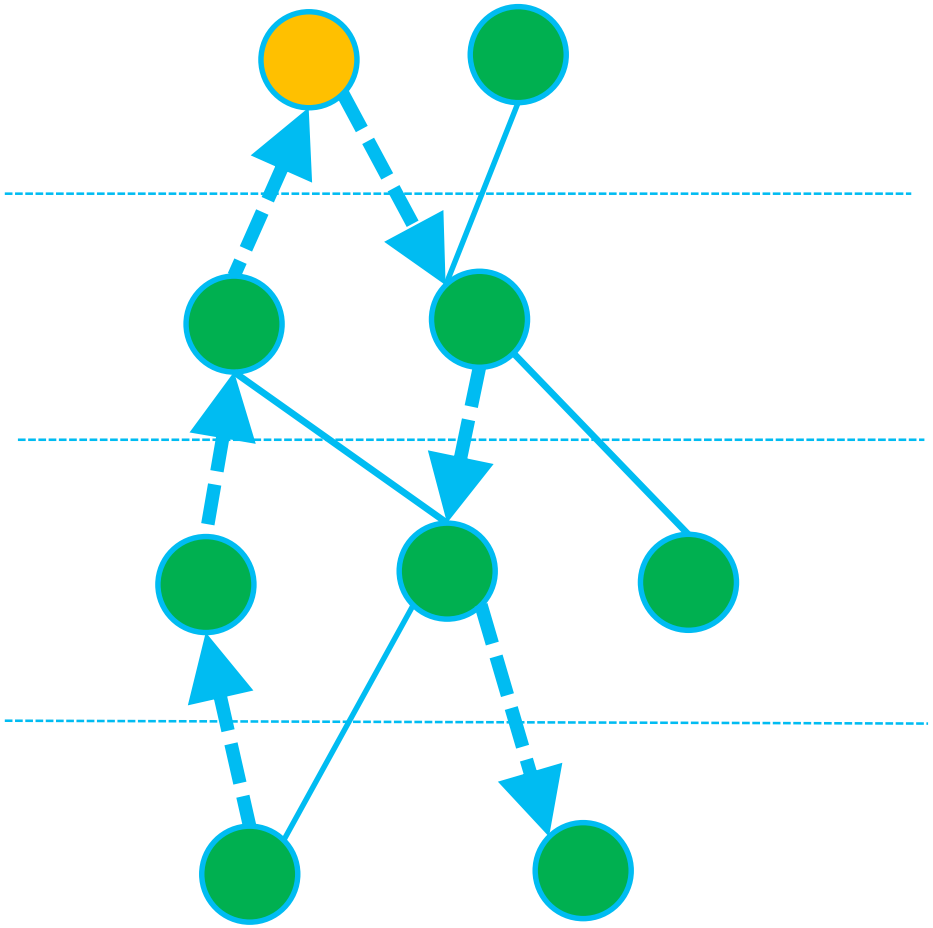


Level by Level Random Walk



Level by Level Random Walk



How to estimate probabilities?

$$\acute{p}(u) = \sum_{v \in \Delta(u)} \frac{\acute{p}(v)}{|\nabla(v)|}, \qquad \grave{p}(u) = \sum_{v \in \nabla(u)} \frac{\grave{p}(v)}{|\Delta(v)|},$$

Unbiased Estimator!

$$\omega(\acute{p}(u)) = \frac{|\Delta(u)| \cdot \acute{p}(v)}{|\nabla(v)|}$$

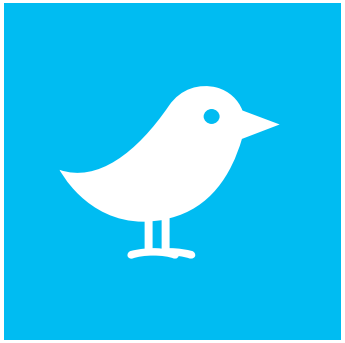
Final Algorithm

Algorithm MA-TARW

1. Get seed users
2. Repeat until budget is not exhausted
   - Perform bottom-top-bottom random walk R_i
   - Estimate sampling probabilities for all nodes in R_i
   - Estimate aggregate using all nodes in R_i via Hansen-Hurwitz estimator
3. Return average of all previous estimates

Experiments

Datasets



Twitter

Google+

Tumblr

Experiment Details

Keywords

- Privacy, New York, Boston
- Cities, Celebrities, Companies, popular and niche hashtags

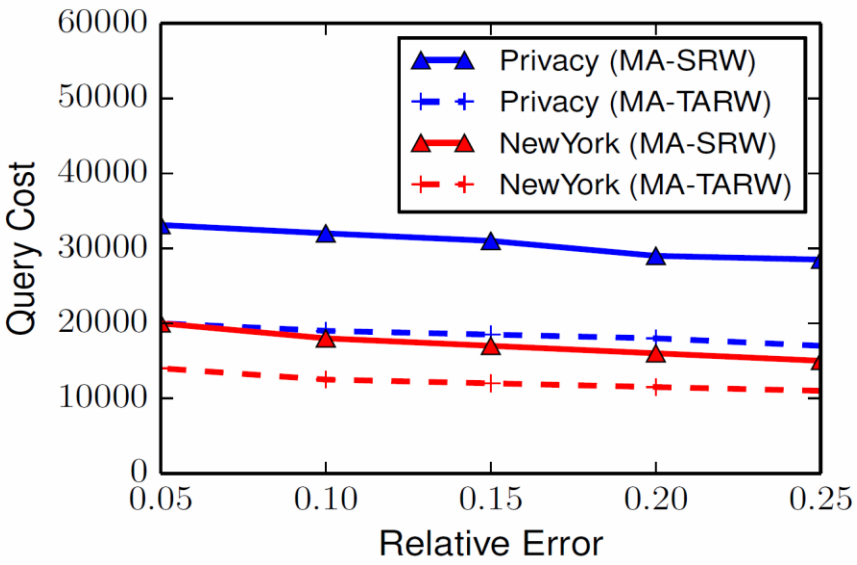
Aggregates

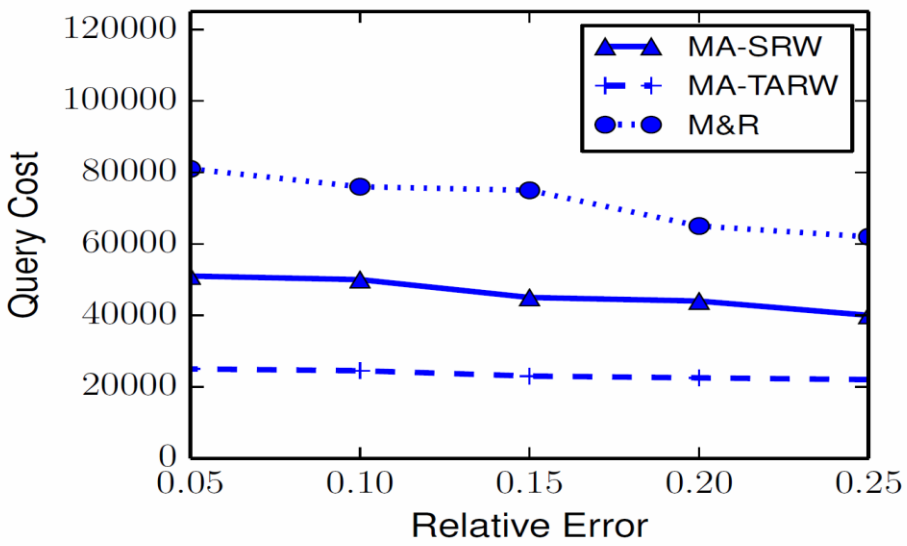
- AVG(followers)
- AVG(display name)
- COUNT(male)

Time

- Restrict tweets from 2013

Experimental Results





- AVG(followers)
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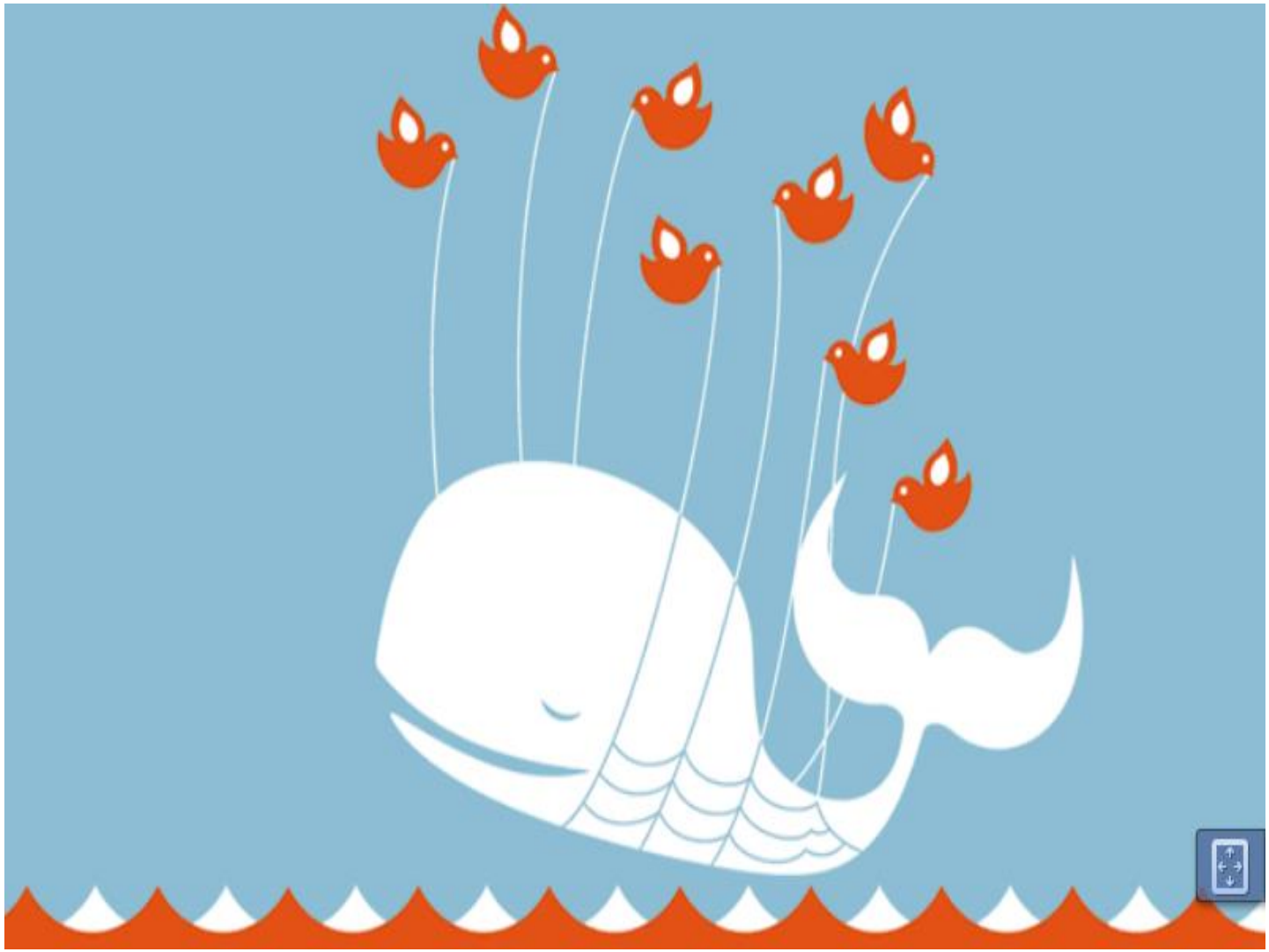
- COUNT(users)
- Keyword=privacy
- Year=2013

Summary

- Aggregate Estimation over Microblogs
- Subgraph Design
- Sampling Design

Questions?