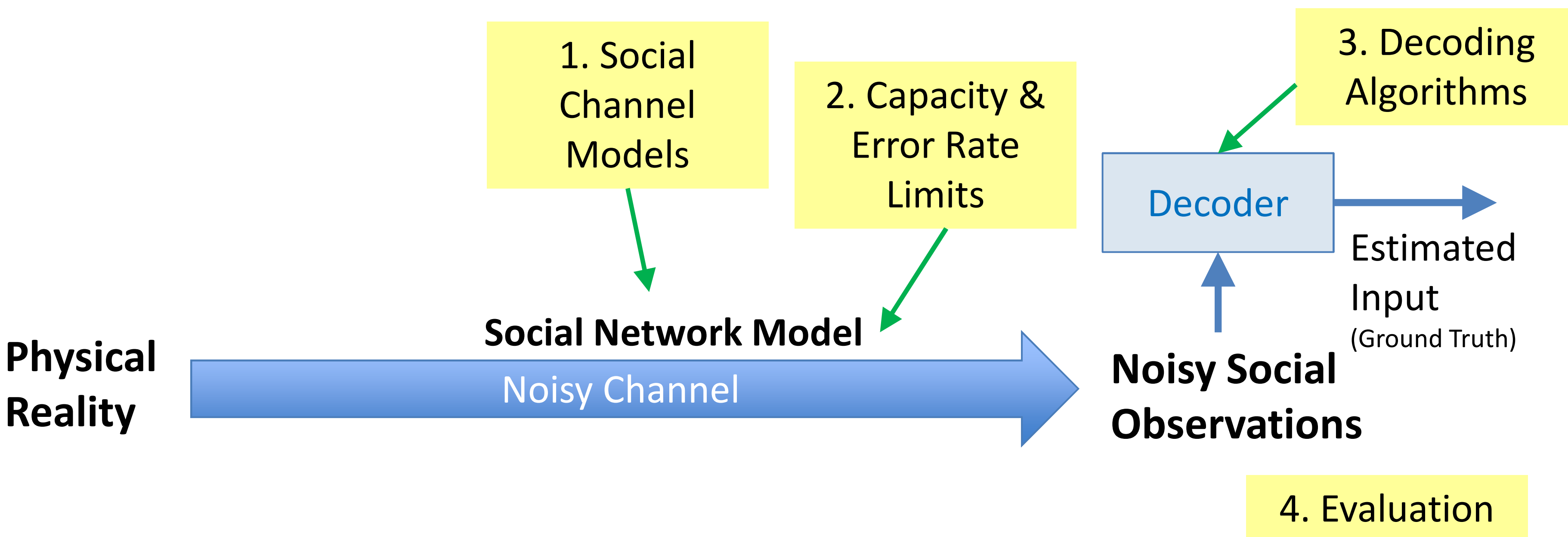
Veracity Analysis

Fact-finding Research Motivation and Approach

Goal: Develop a mathematical foundation for "*social sensing*" – the exploitation of noisy social network data to attain reliable situation awareness.

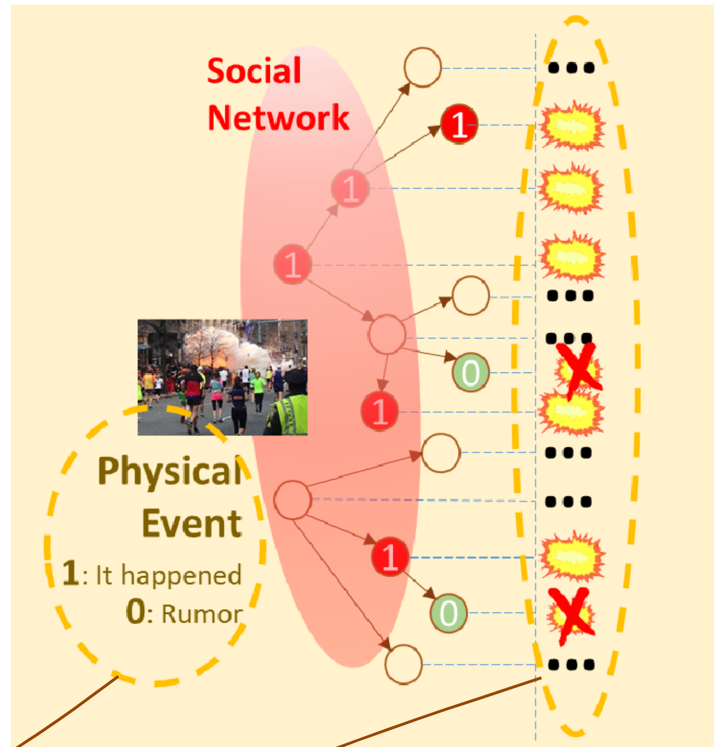
1. Construct ***models of "social channels"***
2. Establish the ***fundamental feasibility/accuracy limits*** on truth recovery from noisy social network data
3. Construct social-influence-aware fact-finding ***algorithms*** that approach these limits

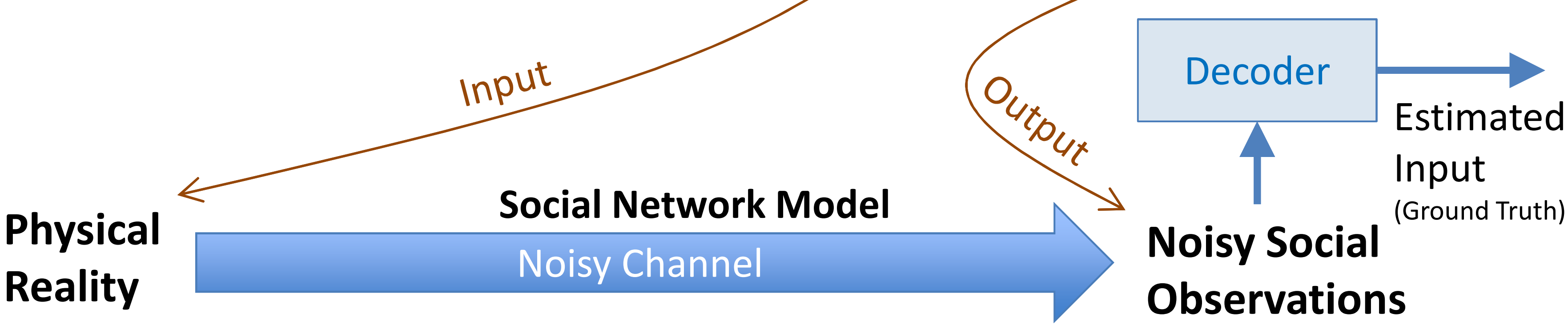


Motivation and Approach

Approach: Model the social network as a noisy channel that transforms "ground truth" into noisy observations

- Use information-theoretic results to understand its fundamental performance limits.
- Use estimation theory to build optimal fact-finders ("channel decoders" that approach these limits)





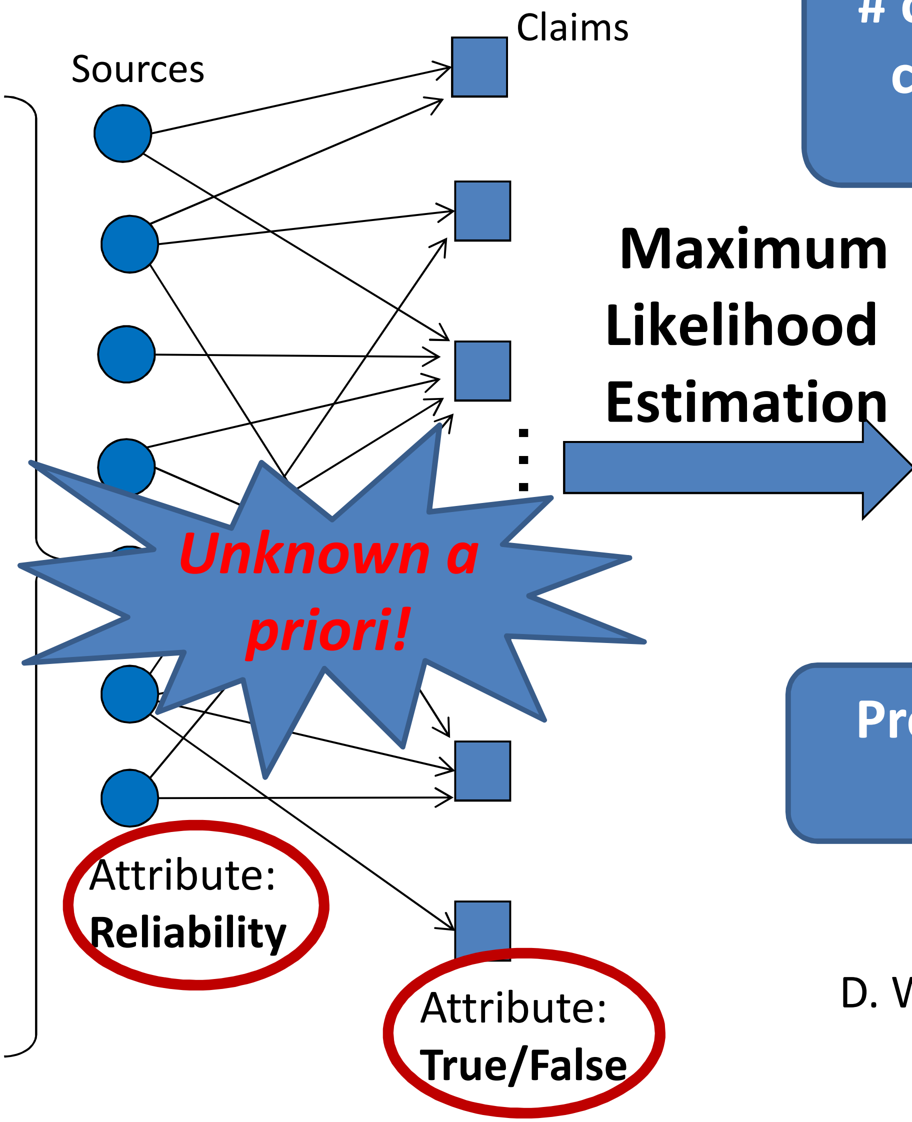
Maximum Likelihood Estimation

Events

Hurricane Sandy

Boston Marathon Explosion

Egypt President Arrest



# of True claims /Total # of claims a source makes

-*Reliability of sources*

-*Correctness of claims*

Probability a claim is true

D. Wang, et al., IPSN, 2012

Uncertain Data Provenance

Events

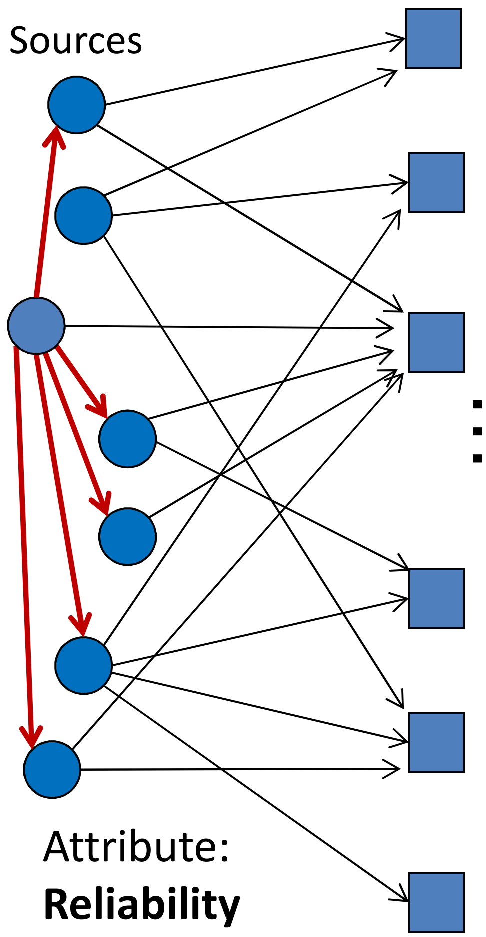
Hurricane Sandy

Boston Marathon Explosion

Egypt President Arrest

Sources

Claims



Attribute: **Reliability**

Attribute: **True/False**

Sources are not independent !

Consider the social network and source forwarding behaviors

D. Wang, et al., IPSN, 2014

Formulate the Likelihood Function

Events

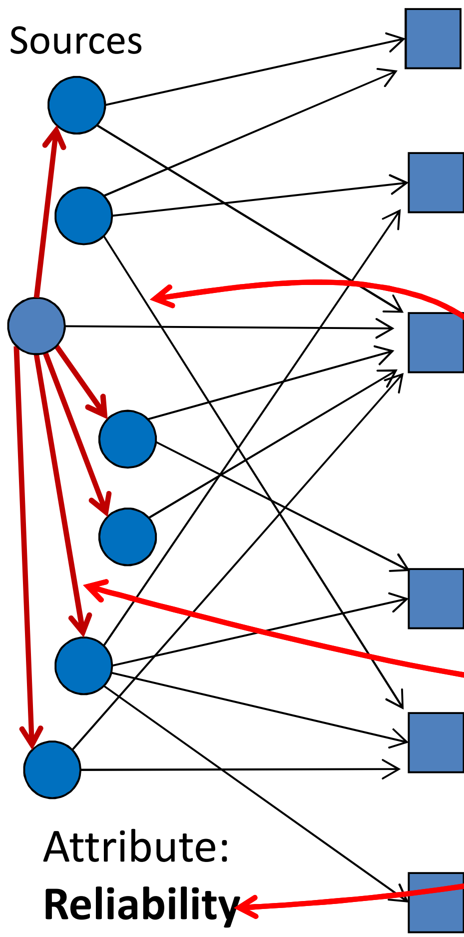
Hurricane Sandy

Boston Marathon Explosion

Egypt President Arrest

Claims

Sources



Attribute: **Reliability**

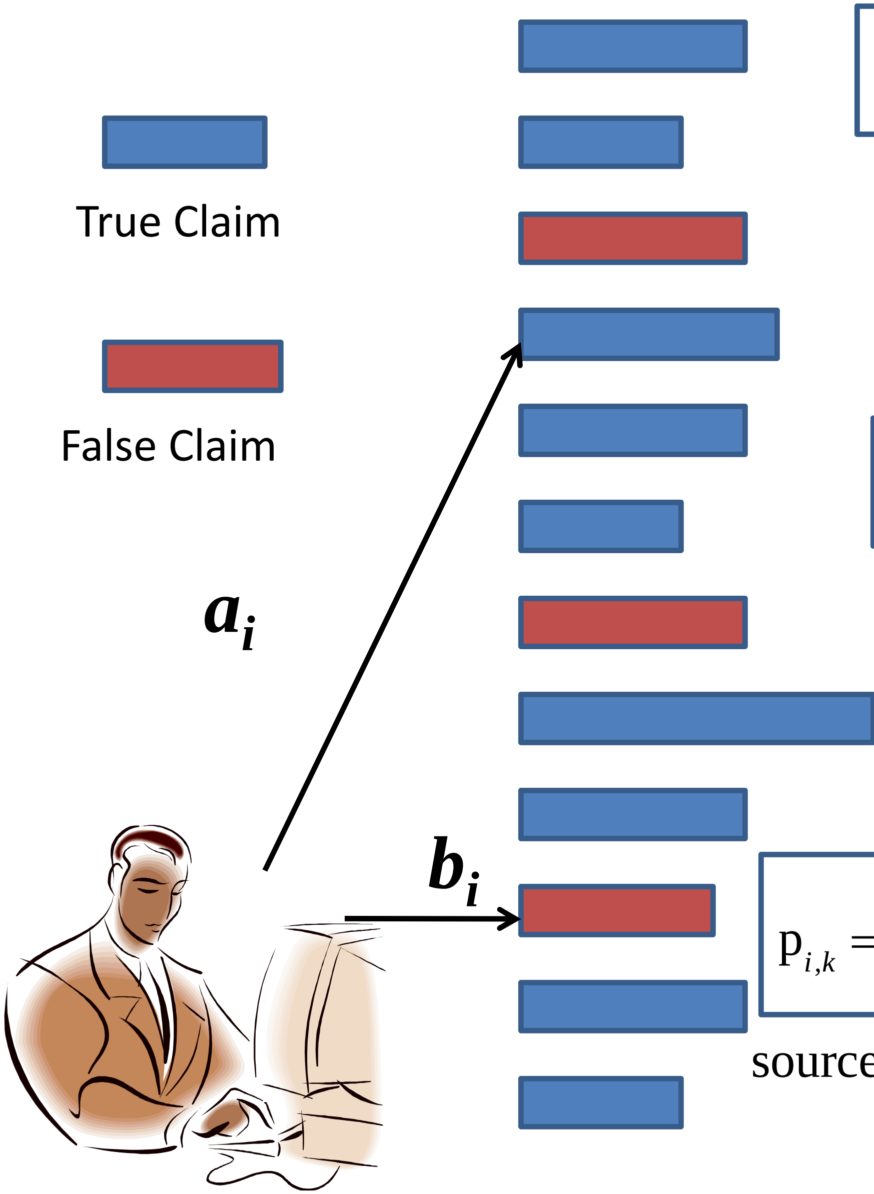
Attribute: **True/False**

SC: Source Claim Graph

SD: Social Dissemination Graph

$$P(SC|SD,\theta) = \sum_{z} P(SC, z|SD, \theta)$$

Basis Definition



$$a_i = P(S_i C_j \mid C_j = true)$$

Using Bayesian Theorem: $a_i = \frac{t_i \times s_i}{d}$

where d is the overal prior that a randomnly chozen claim is true

$$b_i = P(S_i C_j \mid C_j = false)$$

Using Bayesian Theorem: $b_i = \frac{(1 - t_i) \times s_i}{1 - d}$

where d is the overal prior that a randomnly chozen claim is true

$$p_{i,k} = \frac{\text{number of time } S_i \text{ and } S_k \text{ make the same claim}}{\text{number of claims made by } S_k}$$

source S_k is the parent node of source S_i in social network

Expectation Maximization

Expectation Maximization

$$L(\theta; X) = p(X|\theta) = \sum_{Z} p(X, Z|\theta)$$

Estimation parameter

Observed data

Hidden Variable

- Expectation Step (E-st

Apply EM

$$Q\left(\theta|\theta^{(t)}\right) = E_{Z|X,\theta^{(t)}}\left[\log L(\theta; X, Z)\right]$$

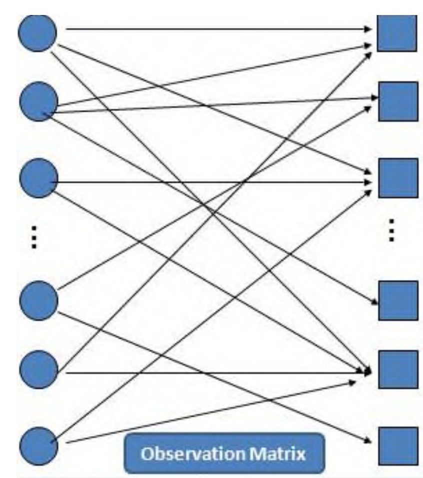
- Maximization Step (M-step)

$$\theta^{(t+1)} = \underset{\theta}{\operatorname{argmax}}\, Q\left(\theta|\theta^{(t)}\right)$$

$Z=\{z_1, z_2, \ldots z_N\}$ where z_j =1 when claim C_j is true and 0 otherwise

X

Observation Matrix



$$\theta = (a_1, a_2, \ldots a_M; b_1, b_2, \ldots b_M; d)$$

Find MLE of estimation parameter and values of hidden variables

Expectation Maximization (1/2)

Likelihood Function Incorporating Source Dependency

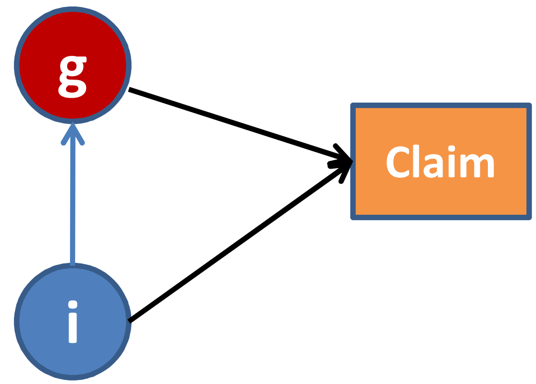
$$P(SC, z|SD, \theta) = \prod_{j=1}^{N} P(z_j) \times$$

$$\{\prod_{g \in M_j} P(S_gC_j|\theta, z_j) \prod_{i \in c_g} P(S_iC_j|S_gC_j)\}$$

$$P(z_j) = \begin{cases} d & z_j = 1 \\ (1-d) & z_j = 0 \end{cases}$$

$$P(S_gC_j|\theta, z_j) = \begin{cases} a_g & z_j = 1, S_gC_j = 1 \\ (1-a_g) & z_j = 1, S_gC_j = 0 \\ b_g & z_j = 0, S_gC_j = 1 \\ (1-b_g) & z_j = 0, S_gC_j = 0 \end{cases}$$

$$P(S_iC_j|S_gC_j) = \begin{cases} p_{ig} & S_gC_j = 1, S_iC_j = 1 \\ 1-p_{ig} & S_gC_j = 1, S_iC_j = 0 \end{cases}$$



Dependent Sources

Expectation Maximization (2/2)

E-Step

$$Q\left(\theta|\theta^{(n)}\right) = \sum_{j=1}^{N} \left\{ Z(n,j) \times \left[\left\{ \sum_{g \in M_j} \left(\log P(S_g C_j|\theta, z_j) + \sum_{i \in c_g} \log P(S_i C_j | S_g C_j) \right) \right\} + \log d \right] + (1 - Z(n,j)) \times \left[\left\{ \sum_{g \in M_j} \left(\log P(S_g C_j|\theta, z_j) + \sum_{i \in c_g} \log P(S_i C_j | S_g C_j) \right) \right\} + \log(1-d) \right] \right\} \qquad (10)$$

M-Step

$$a_g^{(n+1)} = a_g^* = \frac{\sum_{j \in SJ_g} Z(n,j)}{\sum_{j=1}^{N} Z(n,j)}$$

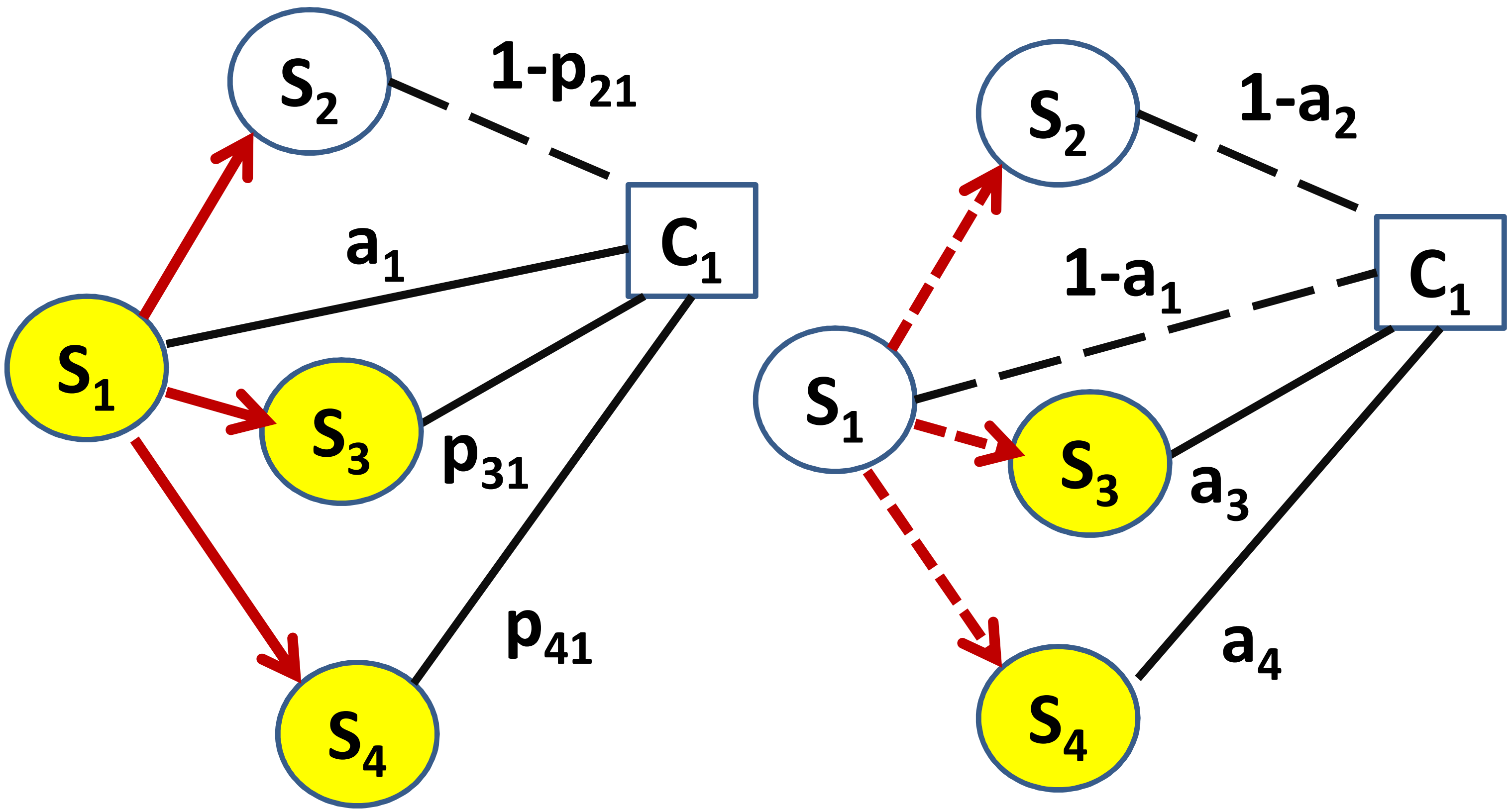
$$a_i^{(n+1)} = a_i^* = \frac{\sum_{j \in \overline{SJ}_g \cap SJ_i} Z(n,j)}{\sum_{j \in \overline{SJ}_g} Z(n,j)} \quad \text{for } i \in c_g$$

$$b_g^{(n+1)} = b_g^* = \frac{\sum_{j \in SJ_g} (1 - Z(n,j))}{\sum_{j=1}^{N} (1 - Z(n,j))}$$

$$b_i^{(n+1)} = b_i^* = \frac{\sum_{j \in \overline{SJ}_g \cap SJ_i} (1 - Z(n,j))}{\sum_{j \in \overline{SJ}_g} (1 - Z(n,j))} \quad \text{for } i \in c_g$$

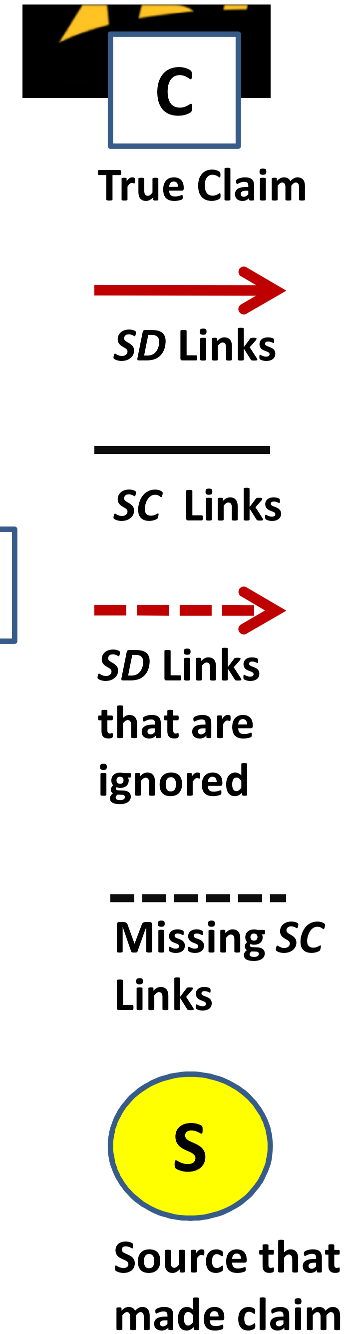
$$d^{(n+1)} = d^* = \frac{\sum_{j=1}^{N} Z(n,j)}{N}$$

Simple Illustrative Examples



Example 1

Example 2

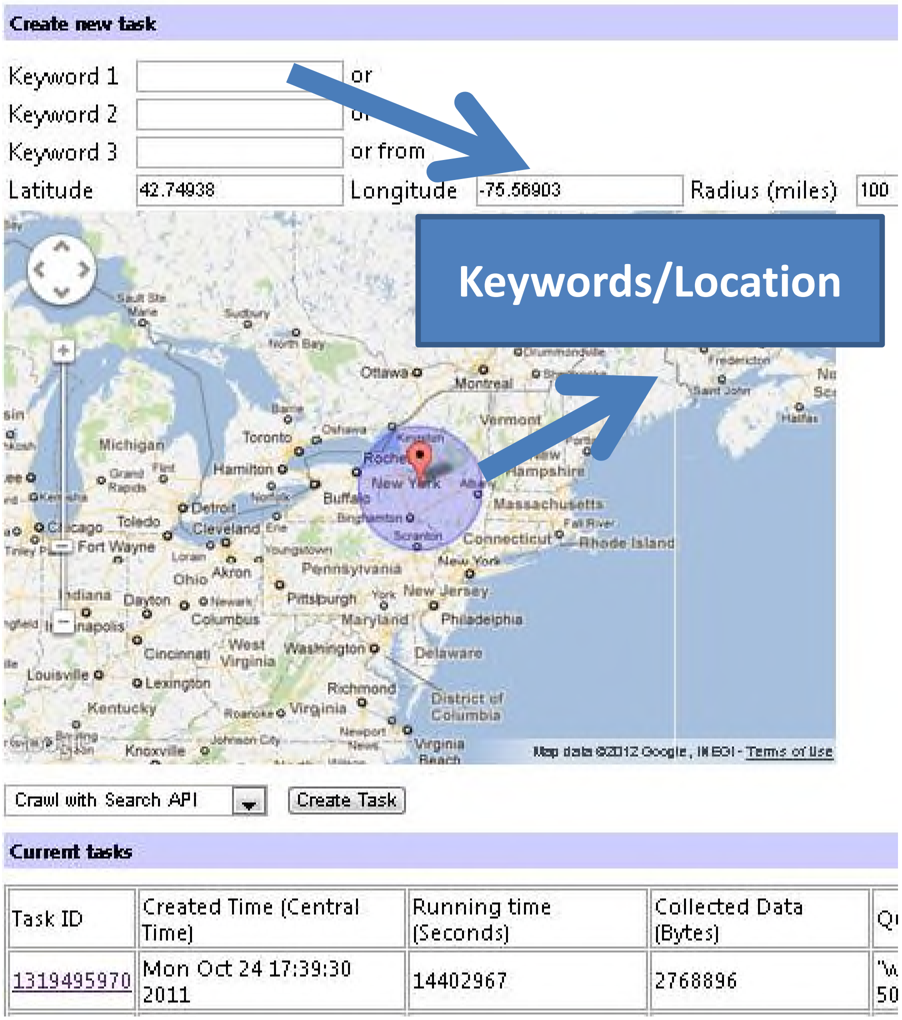


The Apollo Fact-finder

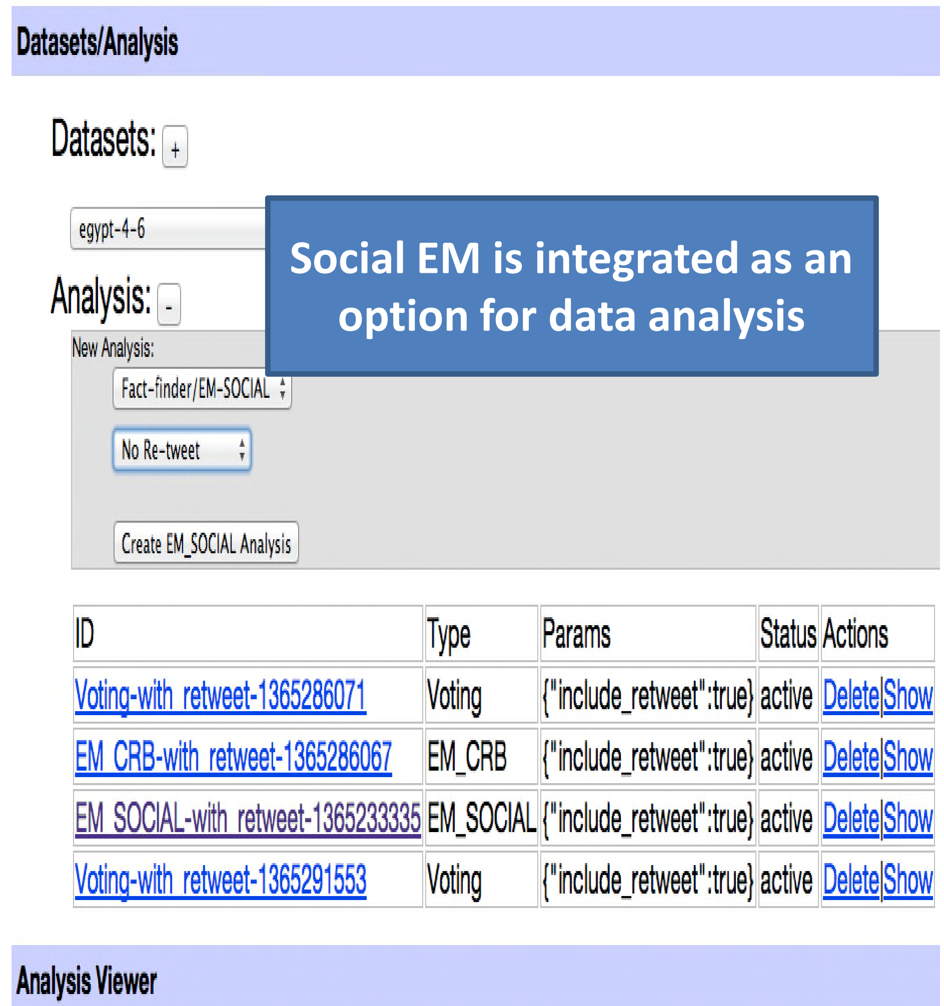
http://apollo.cs.illinois.edu/

EM is Integrated with Apollo

A Real World Application



Data Collection Frontend

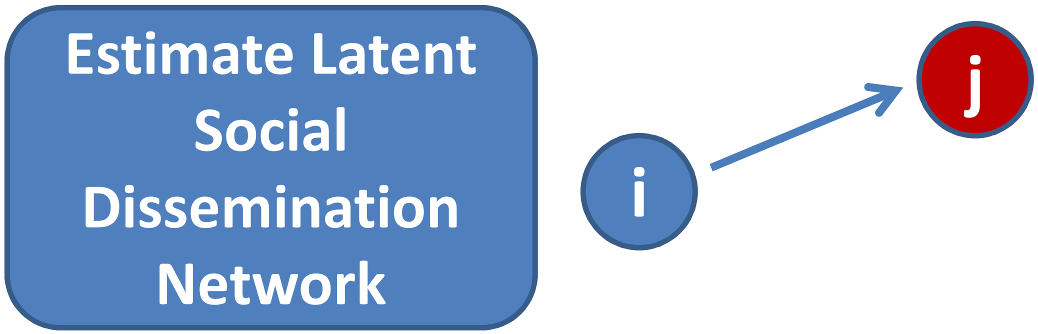


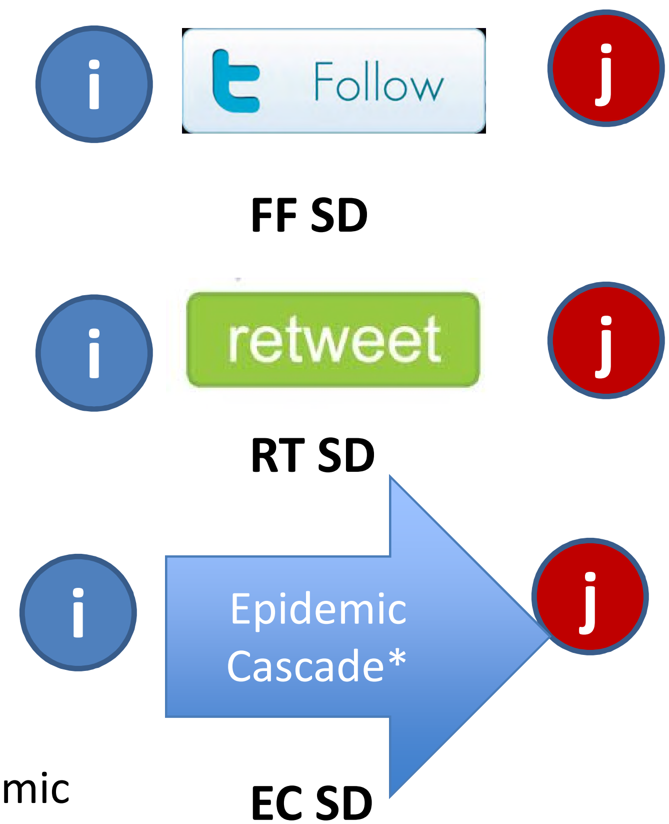
Information Analysis Frontend

NETWORK SCIENCE CTA Evaluation using Real Twitter Traces

Trace	Hurricane Sandy	Hurricane Irene	Egypt Unrest
Time duration	14 days (Nov.2-15, 2012)	8 days (Aug.26-Sept.2, 2011)	18 days (Feb.2-Feb.19,2011)
Locations	16 cities in East Coasts	New York	Cairo, Egypt
# of users tweeted	7,583	207,562	13,836
# of tweets	12,931	387,827	93,208
# of users crawled in social network	704,941	2,510,316	5,285,160
# of follower-followee links	37,597	3,902,713	10,490,098

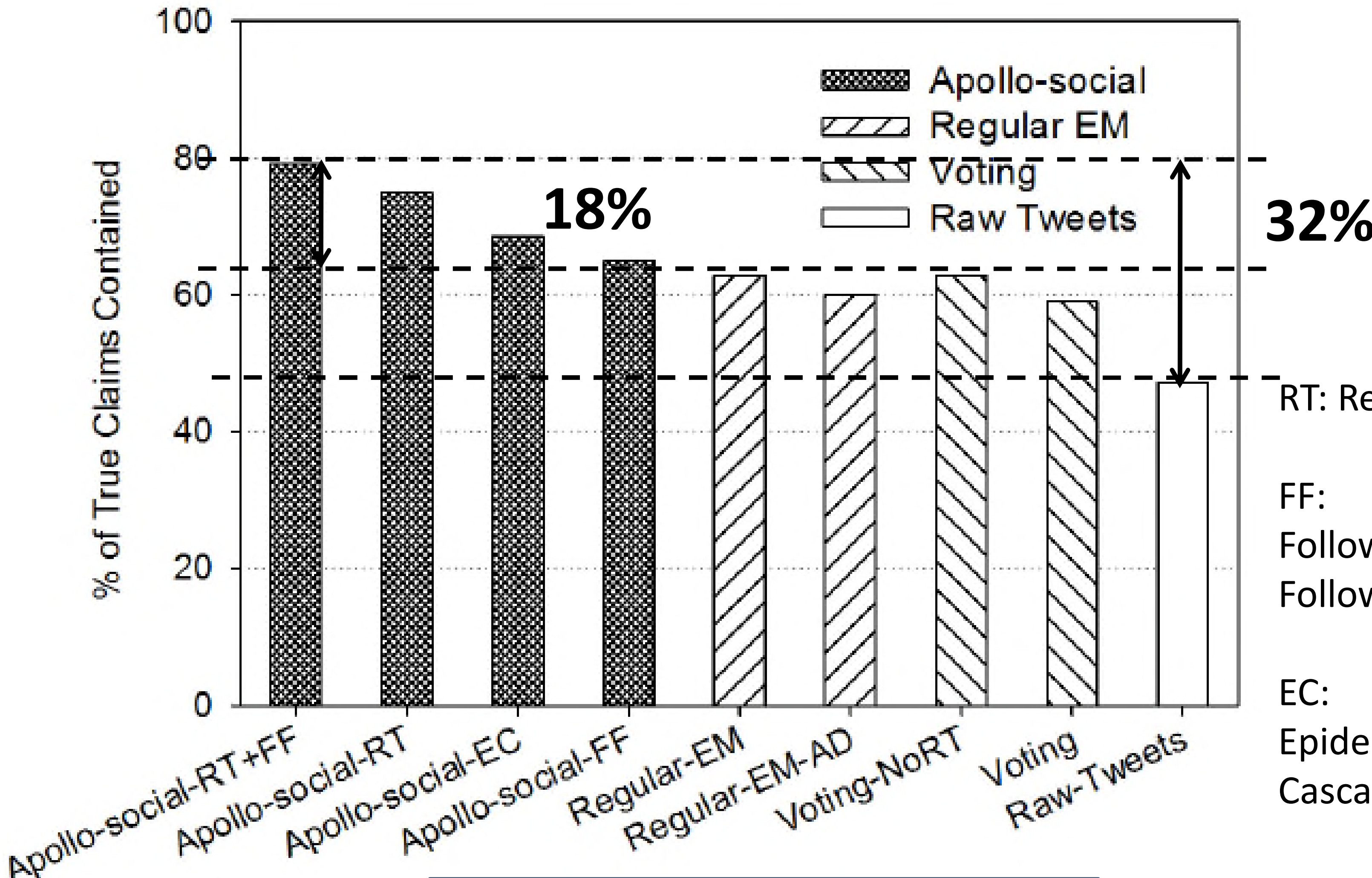
Estimate Latent Social Dissemination (SD) Network





* P. Netrapalli and S. Sanghavi. Learning the graph of epidemic cascades. SIGMETRICS '12, pages 211–222, New York, NY, USA, 2012. ACM.

Evaluation on Sandy Trace



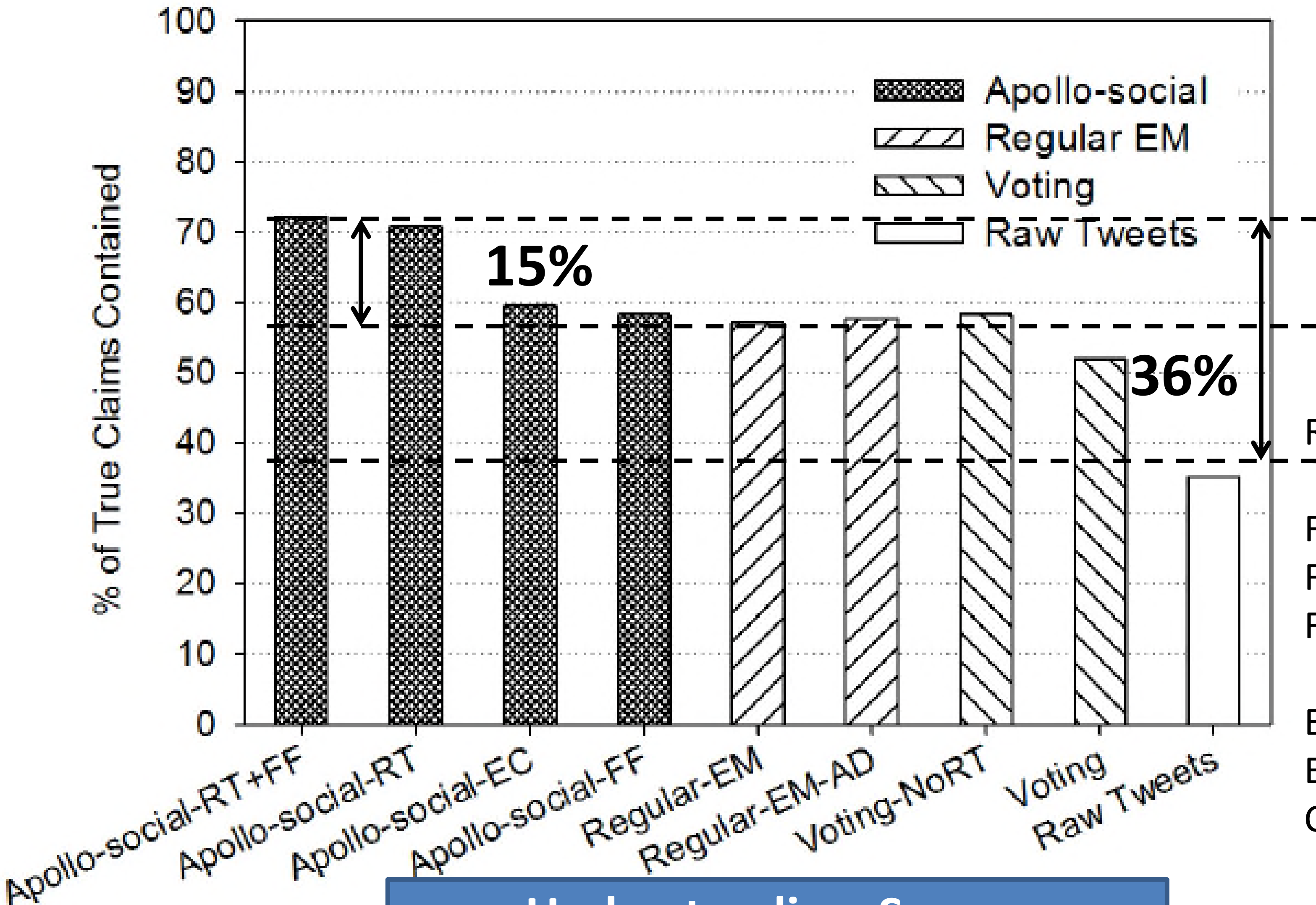
RT: Retweet

FF: Follower-Followee

EC: Epidemic Cascade

Understanding Source Dependency Helps !

Evaluation on Irene Trace



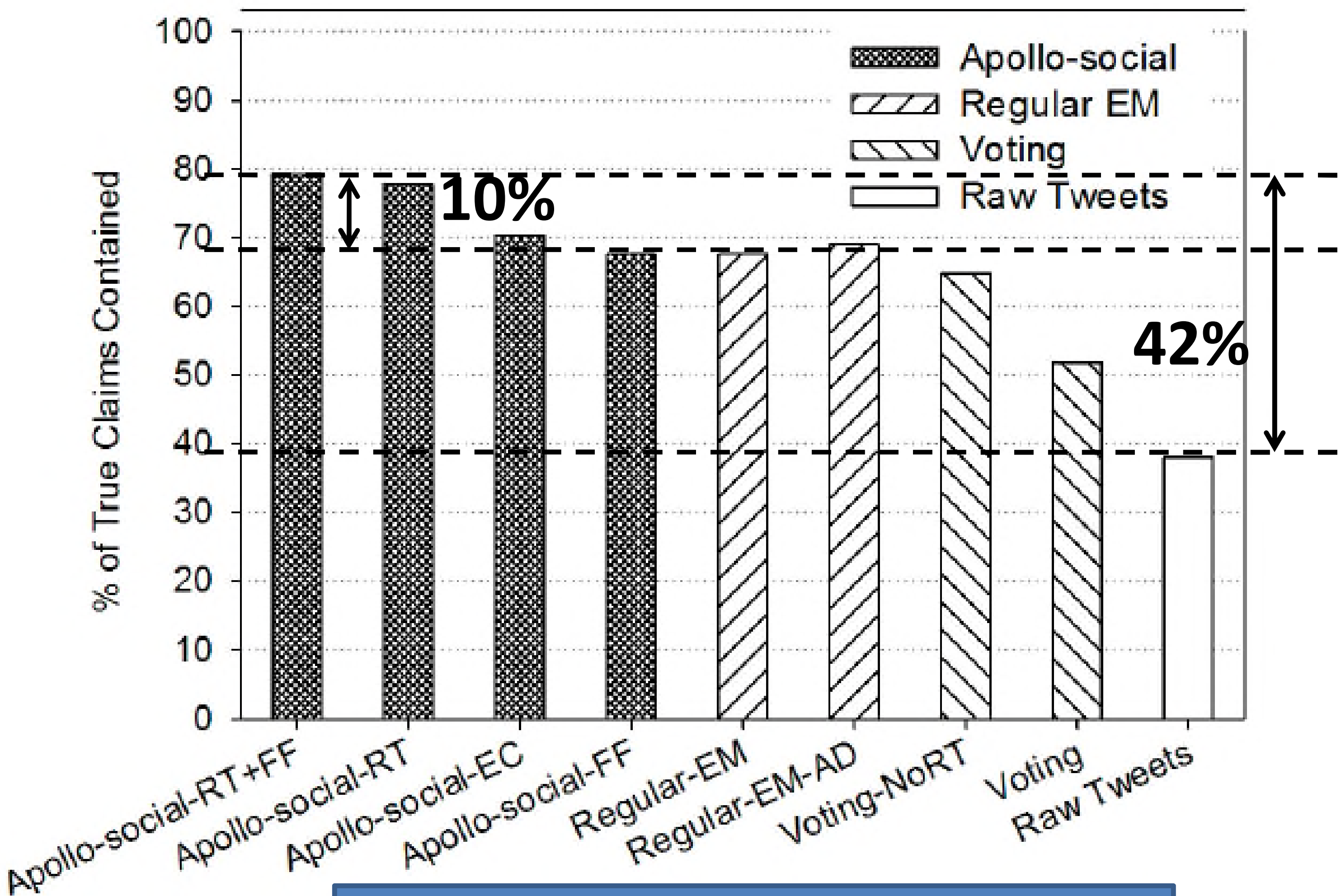
RT: Retweet

FF: Follower-Followee

EC: Epidemic Cascade

Understanding Source Dependency Helps !

Evaluation on Egypt Trace



RT: Retweet

FF: Follower-Followee

EC: Epidemic Cascade

Understanding Source Dependency Helps !

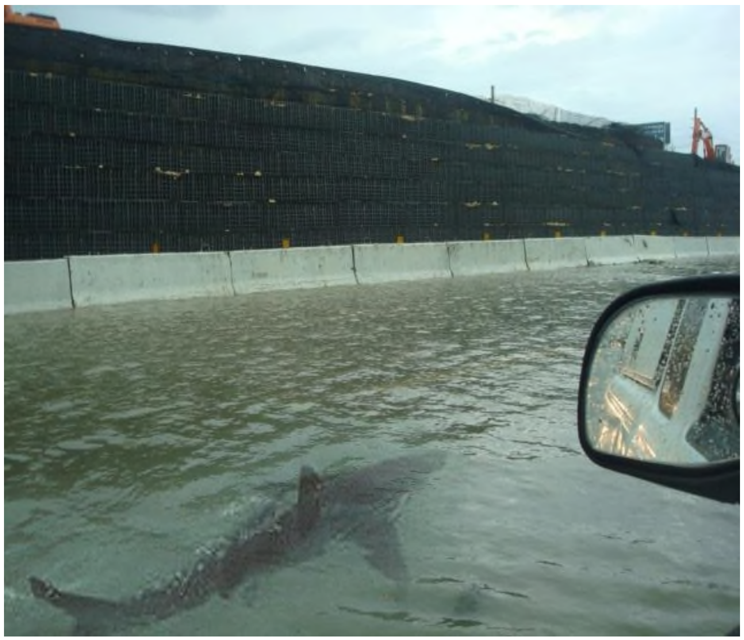
Ground Truth Events Found by Social EM vs Regular EM

#	Media	Tweet found by Apollo-social	Tweet found by Regular EM
1	Rockland County Executive C. Scott Vanderhoef is announcing a Local Emergency Order restricting the amount of fuel that an individual can purchase at a gas station.	Rockland County Orders Restrictions on Gas Sales - Nyack-Piermont, NY Patch http://t.co/cDSrqpa2	MISSING
2	New York City Mayor Michael Bloomberg has announced that the city will impose an indefinite program of gas rationing after fuel shortages led to long lines and frustration at the pump in the wake of superstorm Sandy.	Gas rationing plan set for New York City: The move follows a similar announcement last week in New Jersey to eas... http://t.co/nkmF7U9I	RT @nytimes: Breaking News: Mayor Bloomberg Imposes Odd-Even Gas Rationing Starting Friday, as Does Long Island http://t.co/eax7KMVi
3	New Jersey authorities filed civil suits Friday accusing seven gas stations and one hotel of price gouging in the wake of Hurricane Sandy.	RT @MarketJane: NJ plans price gouging suits against 8 businesses. They include gas stations and a lodging provider.	MISSING
4	The rationing system: restricting gas sales to cars with even-numbered license plates on even days, and odd-numbered on odd days will be discontinued at 6 a.m. Tuesday, Gov. Chris Christie announced on Monday.	# masdirin City Room: Gas Rationing in New Jersey to End Tuesday # news	RT @nytimes: City Room: Gas Rationing in New Jersey to End Tuesday http://t.co/pYIVOmPo
5	New Yorkers can expect gas rationing for at least five more days: Bloomberg.	Mayor Bloomberg: Gas rationing in NYC will continue for at least 5 more days. @eyewitnessnyc #SandyABC7	Bloomberg: Gas Rationing To Stay In Place At Least Through The Weekend http://t.co/mmqqjYRx

TABLE III. GROUND TRUTH EVENTS AND RELATED CLAIMS FOUND BY APOLLO-SOCIAL VS REGULAR EM IN SANDY

One Interesting Example

Shark in the street!



Suppressed by Social EM

The Washington Post

Posted at 08:53 AM ET, 08/26/2011

Hurricane Irene: 'Photo' of shark swimming in street is fake

By Sarah Anne Hughes

Holy moly! A (fake) picture of a shark swimming on a Puerto Rico street! (Reddit)

http://www.washingtonpost.com/blogs/blogpost/post/hurricane-irene-photo-of-shark-swimming-in-street-is-fake/2011/08/26/gIQABHAvfJ_blog.html

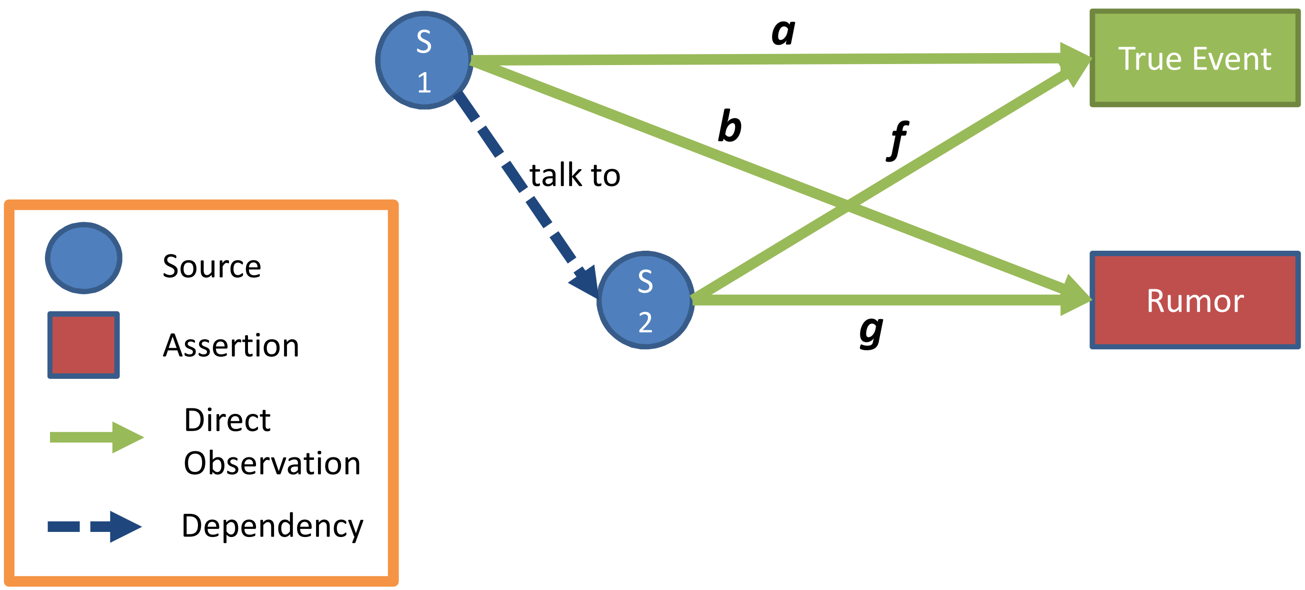
Social Sensing: Source Dependencies

- Failure of physical sensor: independent

- Failure of social sensing sensor: dependent
  - People talk and influence each other
  - Correlated errors

- We need to formulate source dependency correctly!

Estimator Parameters



Expectation-Maximization Solution

E Step

$$Q(\theta|\theta^{(t)}) = \sum_{j=1}^{m} P(C_j|SC_j;\theta^{(t)}) \sum_{C_j\in\{0,1\}} \ln(P(C_j;\theta)) \left(\sum_{i=1}^{n} \ln(P(S_iC_j|C_j;\theta,D_{ij})\right)$$

M Step

$$a_i^{(t+1)} = \frac{\sum_{C_j\in S_iC_1^{D_0}} P(C_j=1|S_iC_j;\theta^{(t)})}{\sum_{C_j\in S_iC_1^{D_0}\bigcup S_iC_0^{D_0}} P(C_j=1|S_iC_j;\theta^{(t)})}$$

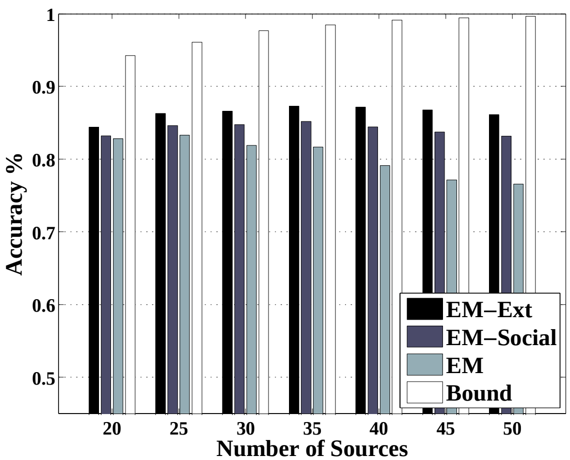
$$f_i^{(t+1)} = \frac{\sum_{C_j\in S_iC_1^{D_1}} P(C_j=1|S_iC_j;\theta^{(t)})}{\sum_{C_j\in S_iC_1^{D_1}\bigcup S_iC_0^{D_1}} P(C_j=1|S_iC_j;\theta^{(t)})}$$

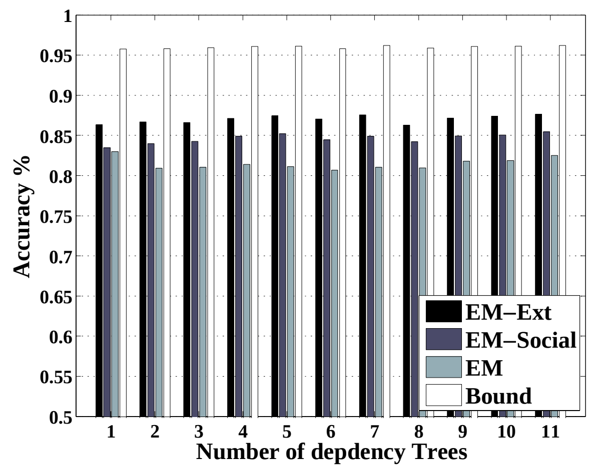
$$b_i^{(t+1)} = \frac{\sum_{C_j\in S_iC_1^{D_0}} P(C_j=0|S_iC_j;\theta^{(t)})}{\sum_{C_j\in S_iC_1^{D_0}\bigcup S_iC_0^{D_0}} P(C_j=0|S_iC_j;\theta^{(t)})}$$

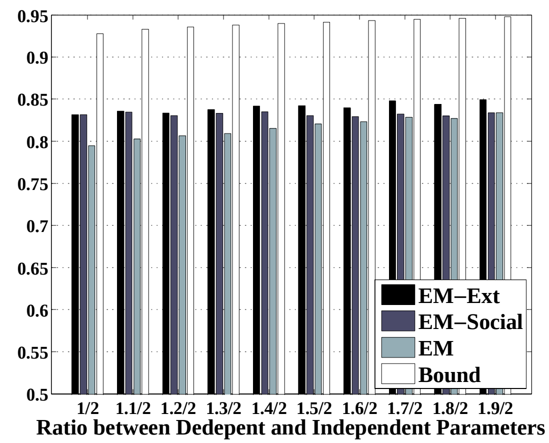
$$g_i^{(t+1)} = \frac{\sum_{C_j\in S_iC_1^{D_1}} P(C_j=0|S_iC_j;\theta^{(t)})}{\sum_{C_j\in S_iC_1^{D_1}\bigcup S_iC_0^{D_1}} P(C_j=0|S_iC_j;\theta^{(t)})}$$

$$z^{(t+1)} = \frac{\sum_{j=1}^{m} P(C_j=0|S_iC_j;\theta^{(t)})}{m}$$

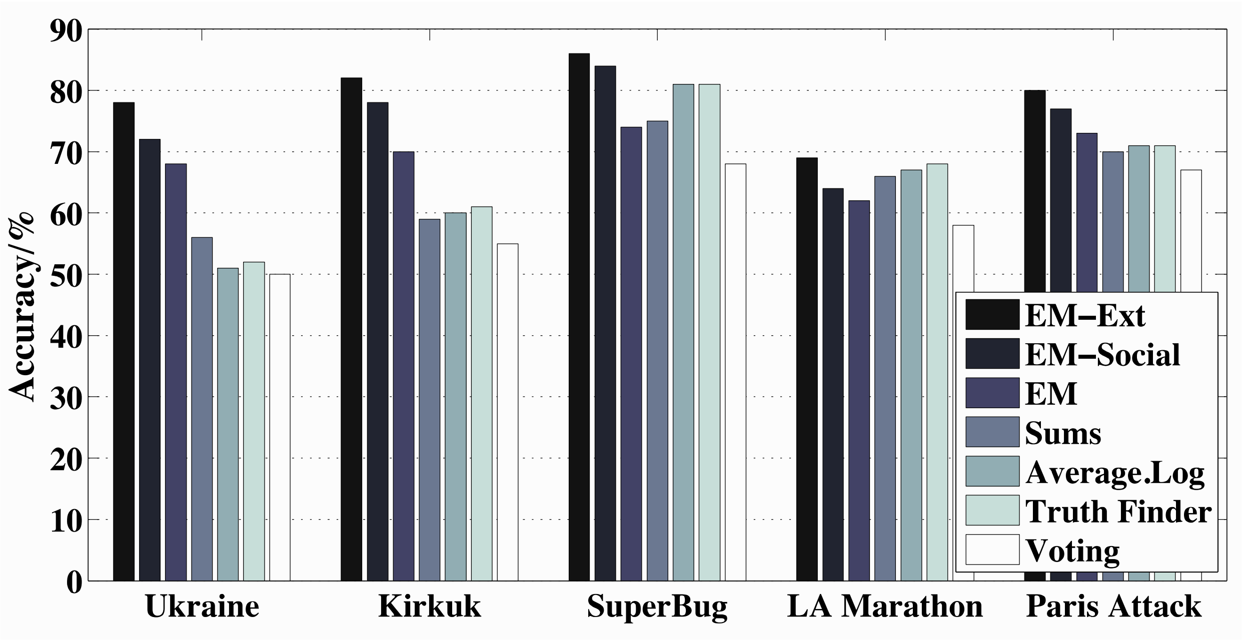
Simulation of Dependency-Aware Estimator



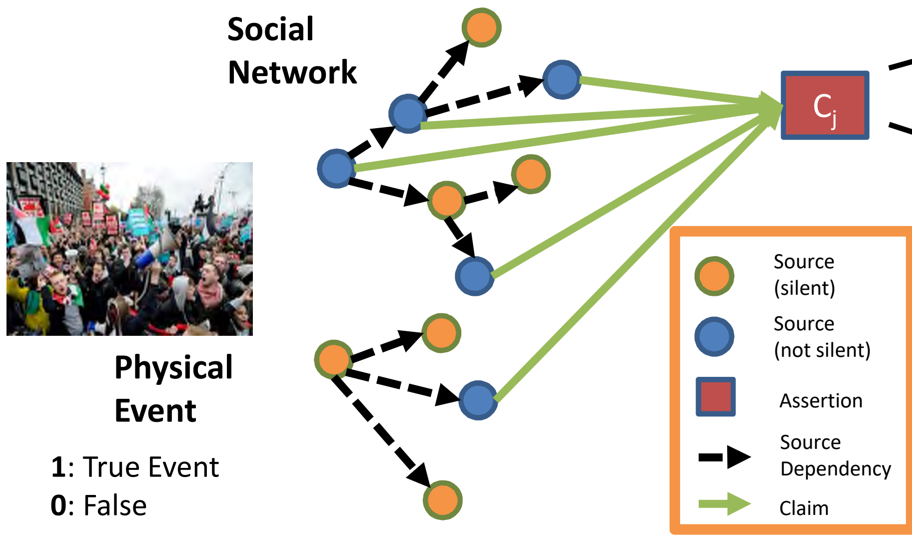




Empirical Evaluation



Optimal Estimator



Prediction

$$P(C_j\ happens \mid Observations)$$

$$P(C_j\ is\ a\ rumor \mid Observations)$$

Error

Error Bounds

- Alleged event: “France bombs Iraq”

Pravda	Jazeera	Ahram	Falsehood Probability	Truth Probability
Silent	Silent	Silent	99%	1%
Silent	Silent	Report	80%	20%
Silent	Report	Silent	90%	10%
Silent	Report	Report	40%	60%
Report	Silent	Silent	95%	5%
Report	Silent	Report	60%	40%
Report	Report	Silent	70%	30%
Report	Report	Report	5%	95%

Error Bounds

- Alleged event: “France bombs Iraq”

The odds	Pravda	Jazeera	Ahram	Falsehood Probability	Truth Probability
4%	Silent	Silent	Silent	99%	1%
10%	Silent	Silent	Report	80%	20%
10%	Silent	Report	Silent	90%	10%
20%	Silent	Report	Report	40%	60%
20%	Report	Silent	Silent	95%	5%
13%	Report	Silent	Report	60%	40%
13%	Report	Report	Silent	70%	30%
10%	Report	Report	Report	5%	95%

Error Bounds

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20%	Silent	Report	Report	40%	60%
20%	Report	Silent	Silent	95%	5%
13%	Report	Silent	Report	60%	40%
13%	Report	Report	Silent	70%	30%
10%	Report	Report	Report	5%	95%

Odds of omission = 4%

Error Bounds

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10%	Silent	Report	Silent	90%	10%
20%	Silent	Report	Report	40%	60%
20%	Report	Silent	Silent	95%	5%
13%	Report	Silent	Report	60%	40%
13%	Report	Report	Silent	70%	30%
10%	Report	Report	Report	5%	95%

Odds of omission = 4%
Odds of error = 0.1 * 0.2 + …

Error Bounds

- Alleged event: "France bombs Iraq"

The odds	Pravda	Jazeera	Ahram	Falsehood Probability	Truth Probability
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10%	Silent	Silent	Report	80%	20%
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20%	Report	Silent	Silent	95%	5%
13%	Report	Silent	Report	60%	40%
13%	Report	Report	Silent	70%	30%
10%	Report	Report	Report	5%	95%

Odds of omission = 4%
Odds of error = 0.1 * 0.2 + 0.1 * 0.1 + …

Error Bounds

- Alleged event: “France bombs Iraq”

The odds	Pravda	Jazeera	Ahram	Falsehood Probability	Truth Probability
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10%	Silent	Silent	Report	80%	20%
10%	Silent	Report	Silent	90%	10%
20%	Silent	Report	Report	40%	60%
20%	Report	Silent	Silent	95%	5%
13%	Report	Silent	Report	60%	40%
13%	Report	Report	Silent	70%	30%
10%	Report	Report	Report	5%	95%

Odds of omission = 4%
Odds of error = 0.1 * 0.2 + 0.1 * 0.1 + 0.2 * 0.4 + …

Error Bounds

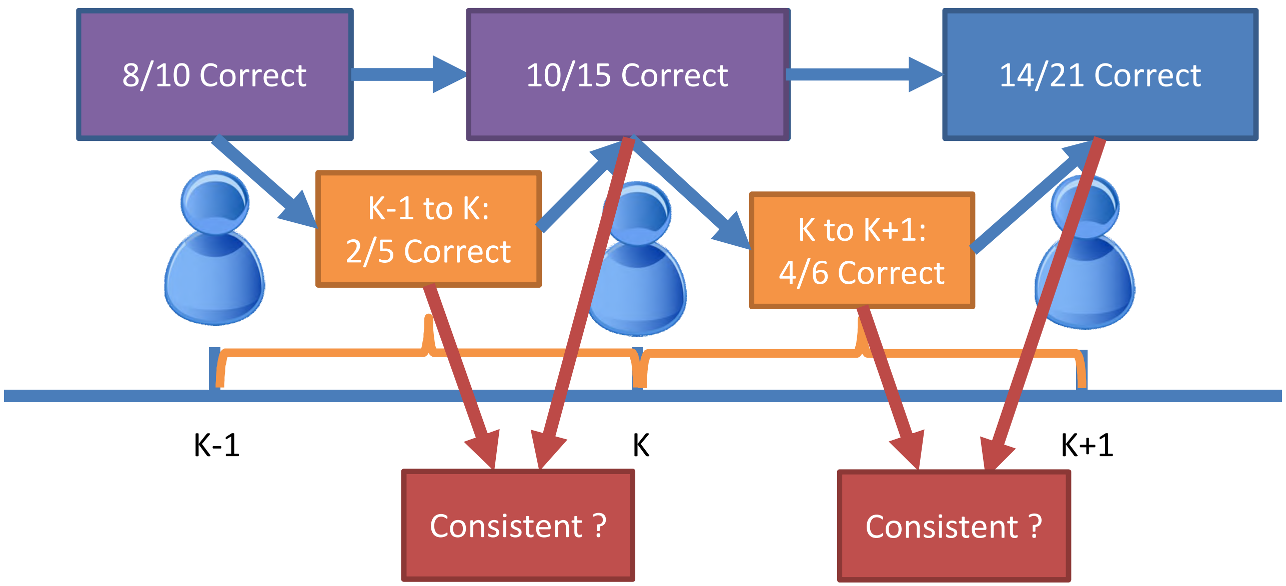
- Alleged event: “France bombs Iraq”

The odds	Pravda	Jazeera	Ahram	Falsehood Probability	Truth Probability
4%	Silent	Silent	Silent	99%	1%
10%	Silent	Silent	Report	80%	20%
10%	Silent	Report	Silent	90%	10%
20%	Silent	Report	Report	40%	60%
20%	Report	Silent	Silent	95%	5%
13%	Report	Silent	Report	60%	40%
13%	Report	Report	Silent	70%	30%
10%	Report	Report	Report	5%	95%

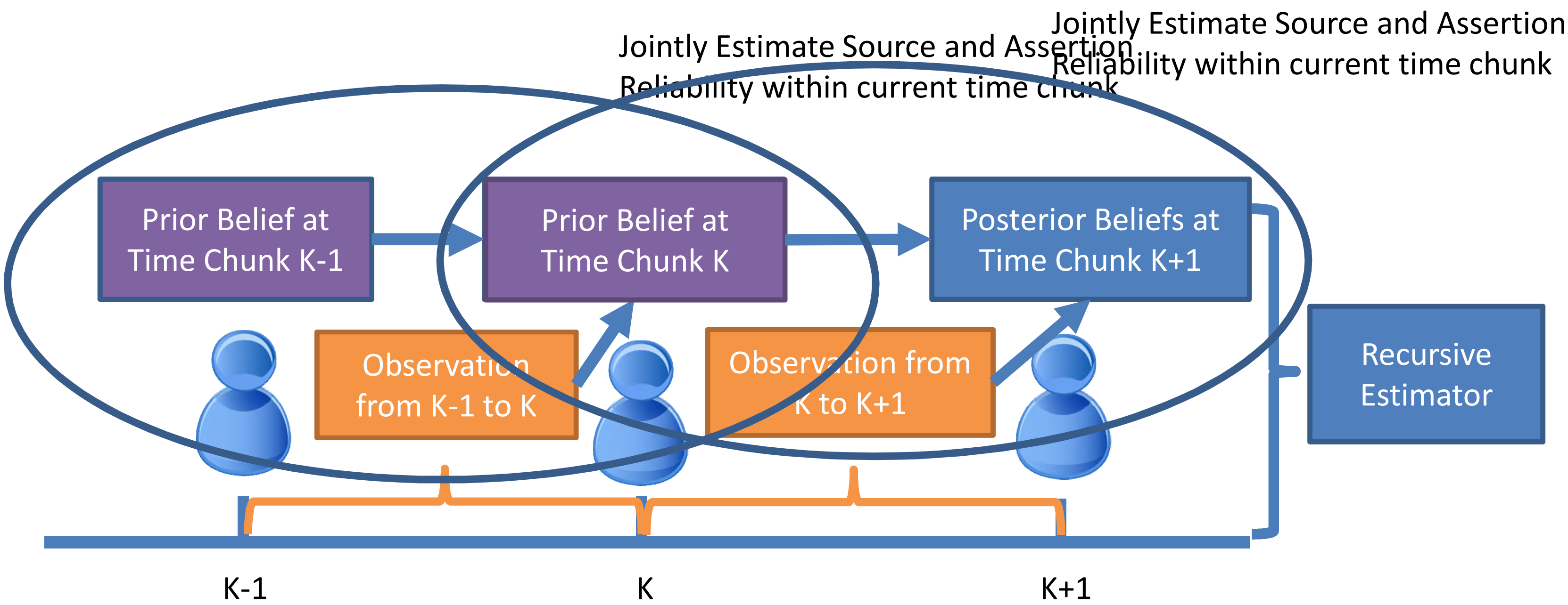
Odds of omission = 4%

Odds of error = 0.1 * 0.2 + 0.1 * 0.1 + 0.2 * 0.4 + 0.2 * 0.05 + 0.4 * 0.13 + 0.3 * 0.13 + 0.05 * 0.1 = 23.6%

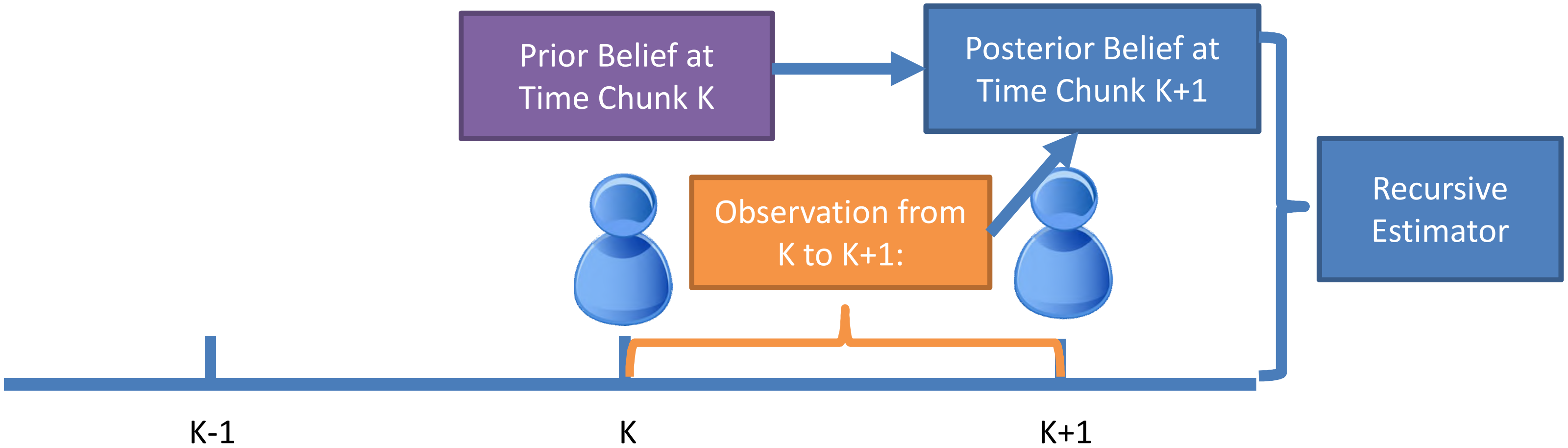
Example


8/10 Correct
10/15 Correct
14/21 Correct
K-1 to K:
2/5 Correct
K to K+1:
4/6 Correct
K-1
K
K+1
Consistent ?
Consistent ?

Overview


Jointly Estimate Source and Assertion Reliability within current time chunk
Jointly Estimate Source and Assertion Reliability within current time chunk
Prior Belief at Time Chunk K-1
Prior Belief at Time Chunk K
Posterior Beliefs at Time Chunk K+1
Recursive Estimator
Observation from K-1 to K
Observation from K to K+1
K-1
K
K+1

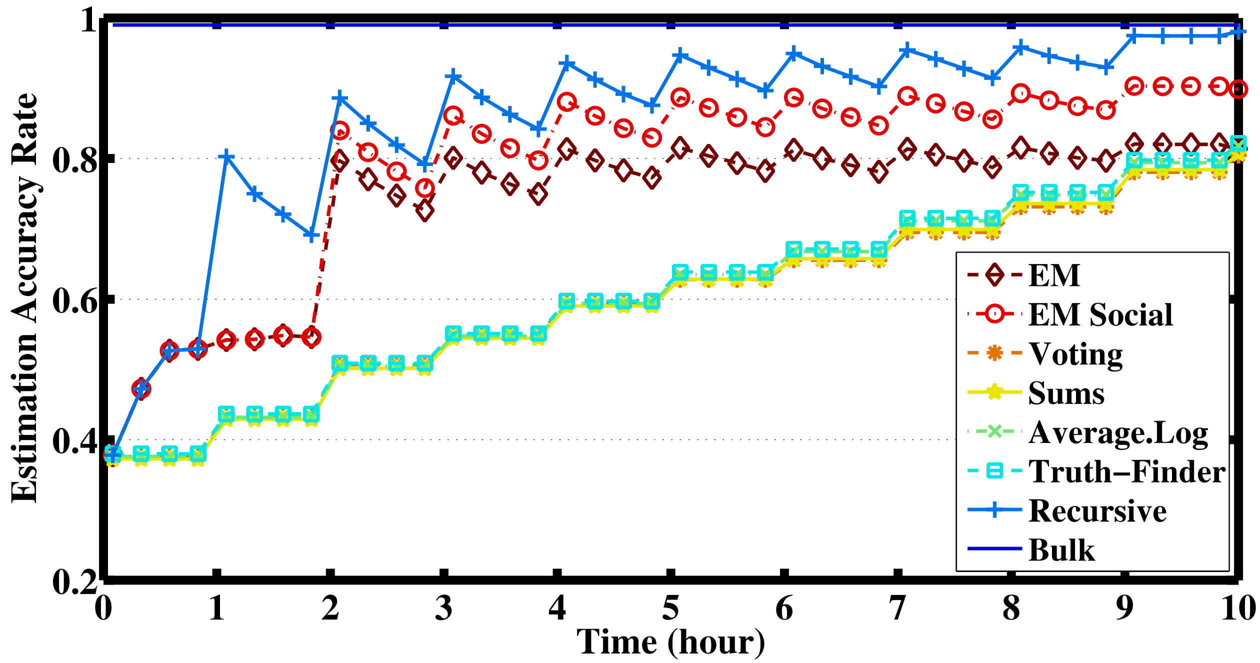
Recursive Estimator



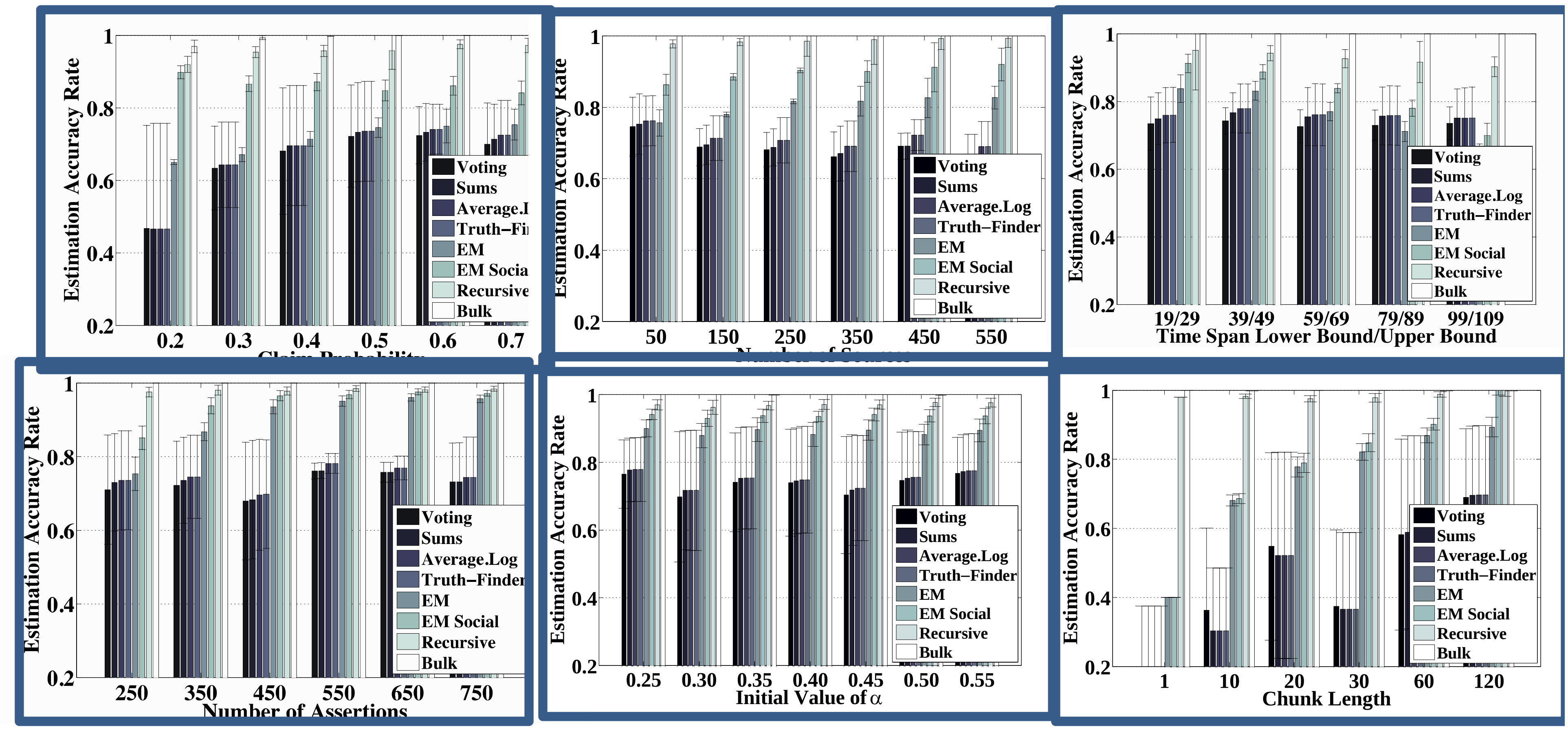
Recursive Estimator

- Recursively update the belief of reliability distribution:
  - Compute mean reliability (Compute 1st Moment)
    - source reliability parameters, θi
    - probability of correctness, P (t(C) = 1|SCk, D, θ)
  - Computing the error variance (Compute 2nd Moment)
    - error variance of source reliability parameters, θi
  - Computing the posterior belief (Update Distribution with Moment Matching)
    - updated belief in source reliability

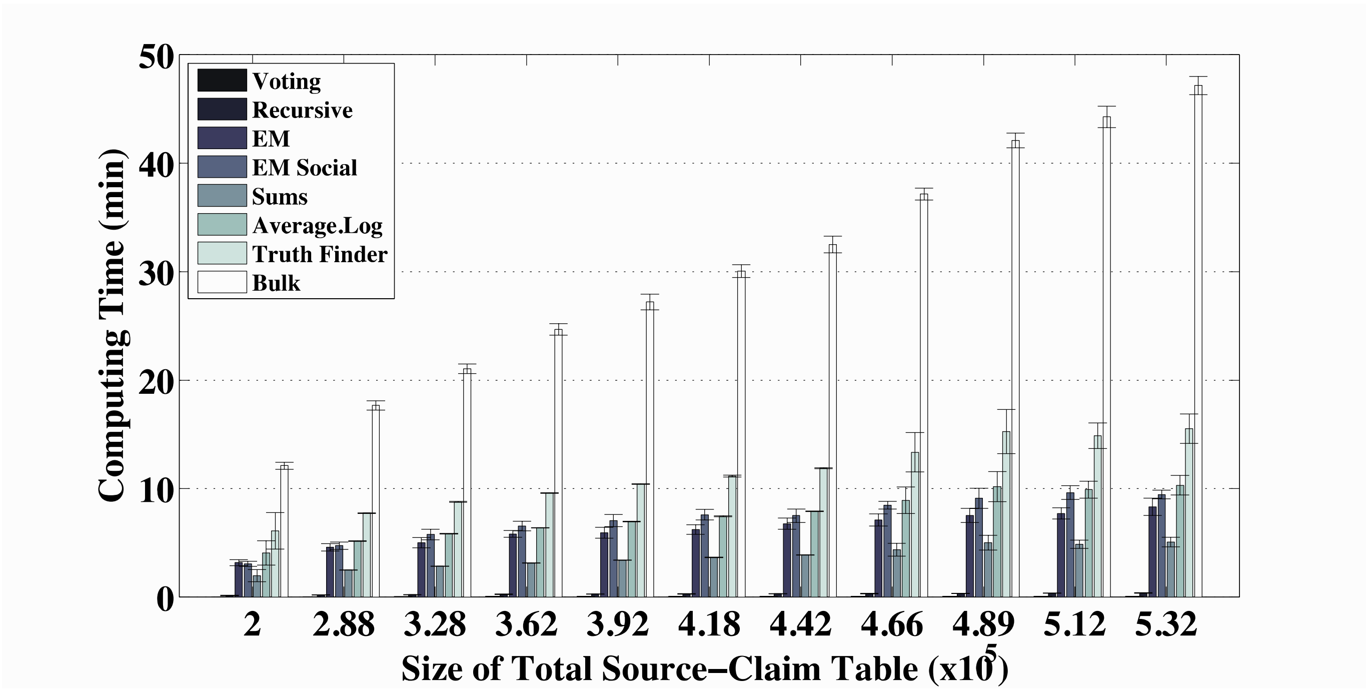
Synthetic Data: estimation accuracy of 10-hour trace



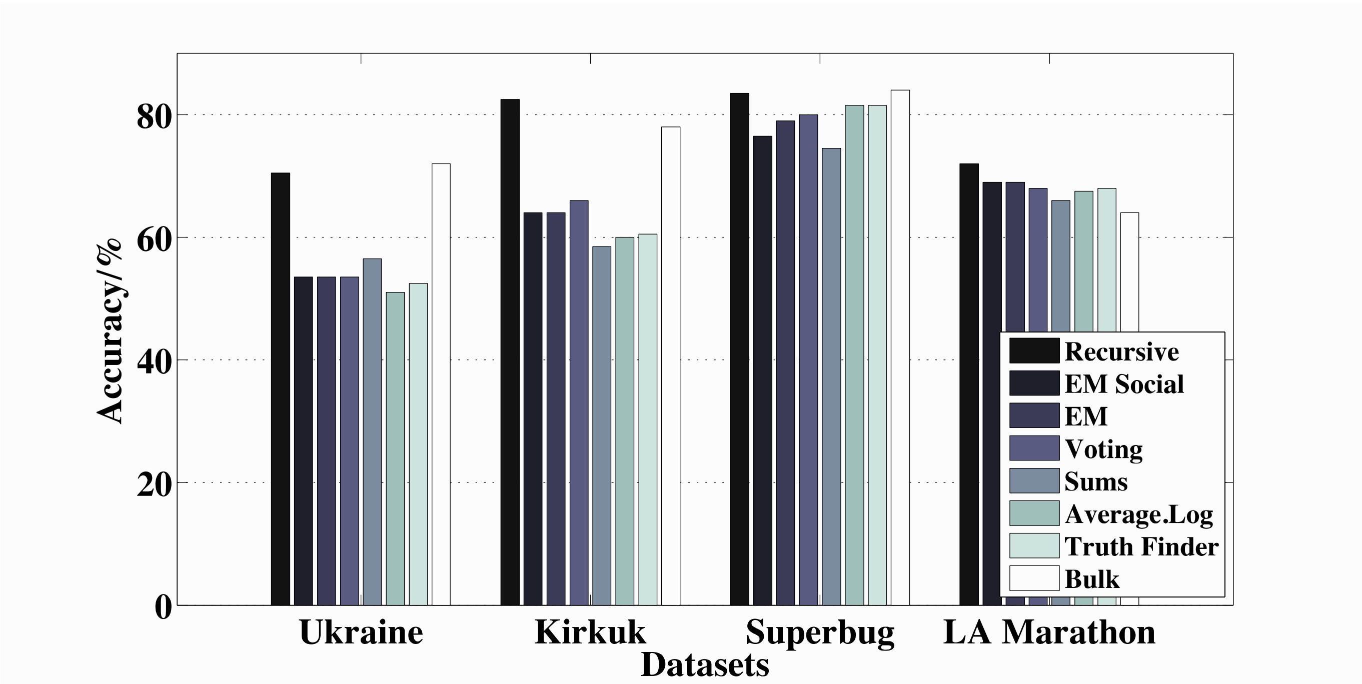
Synthetic Data: effect of changing Simulation parameters



Synthetic Data: computation time



Empirical Evaluation: Empirical Accuracy Results



Empirical Evaluation: empirical execution time