Large-scale Social Sensing (with Humans as Sensors)

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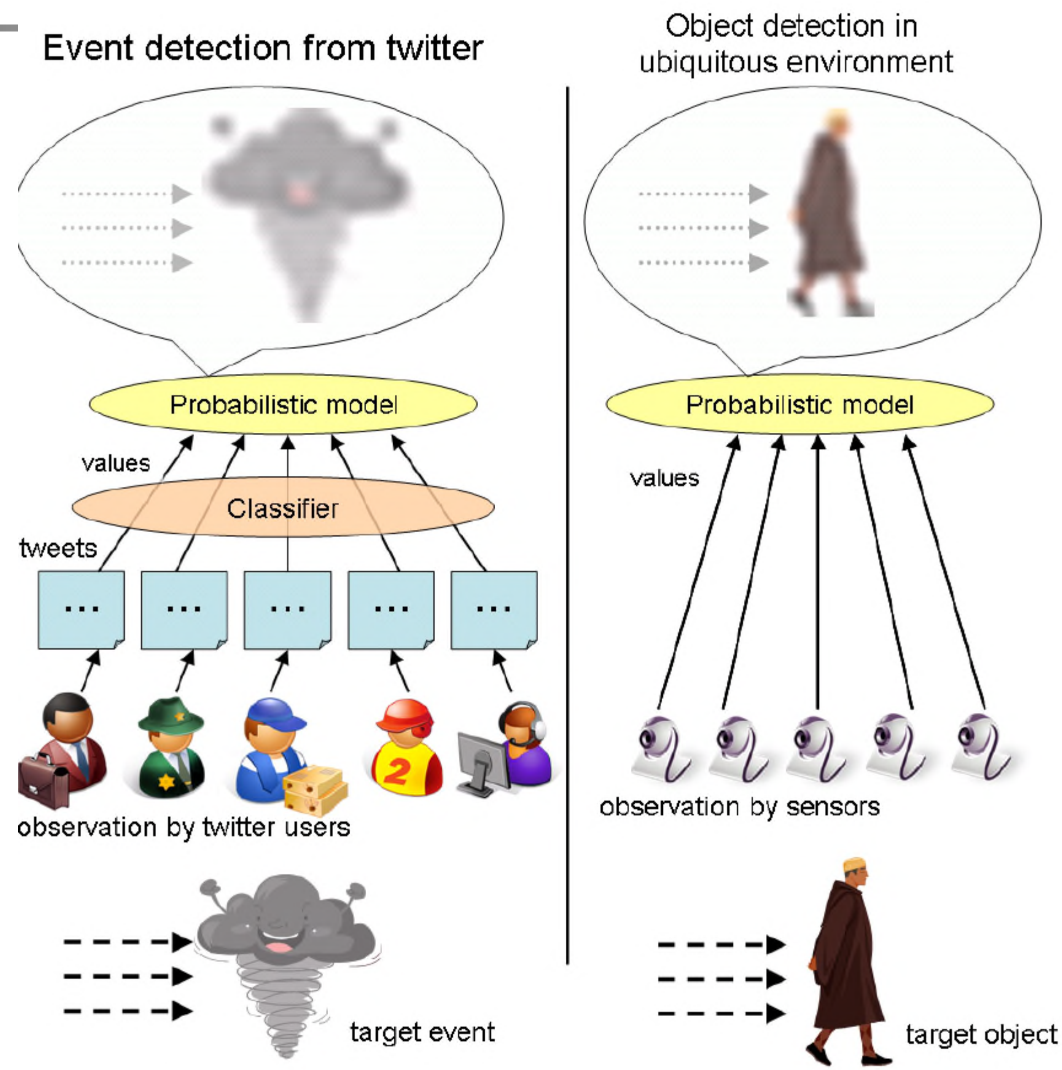
Earthquake Shakes Twitter Users

Using Humans as Sensors:

- Assumption: Each Twitter user is regarded as a sensor. A sensor detects a target event and makes a report probabilistically
- Assumption: Each tweet is associated with a time and location, which is a set of latitude and longitude

Earthquake Shakes Twitter Users

Using Humans as Sensors:

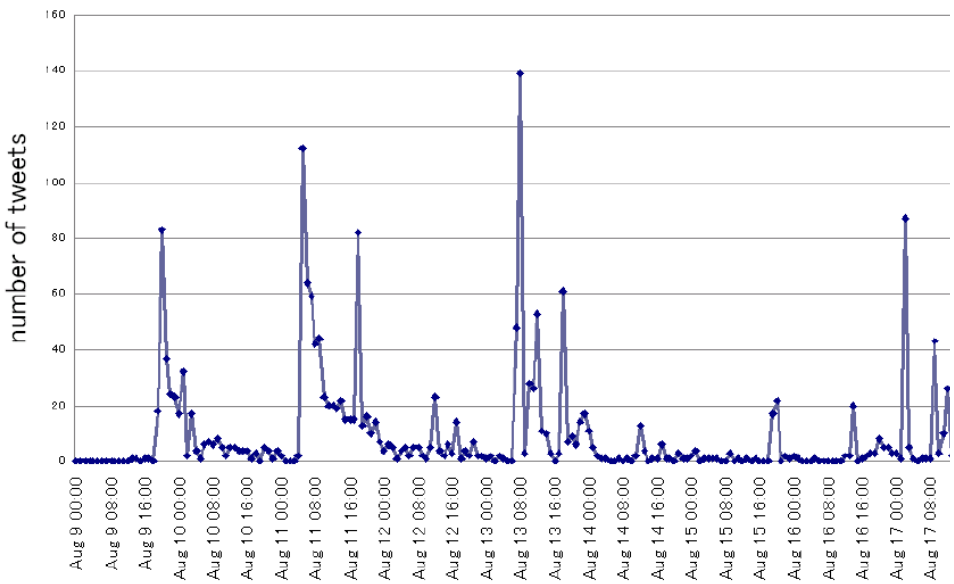


Event Detection: The Classifier

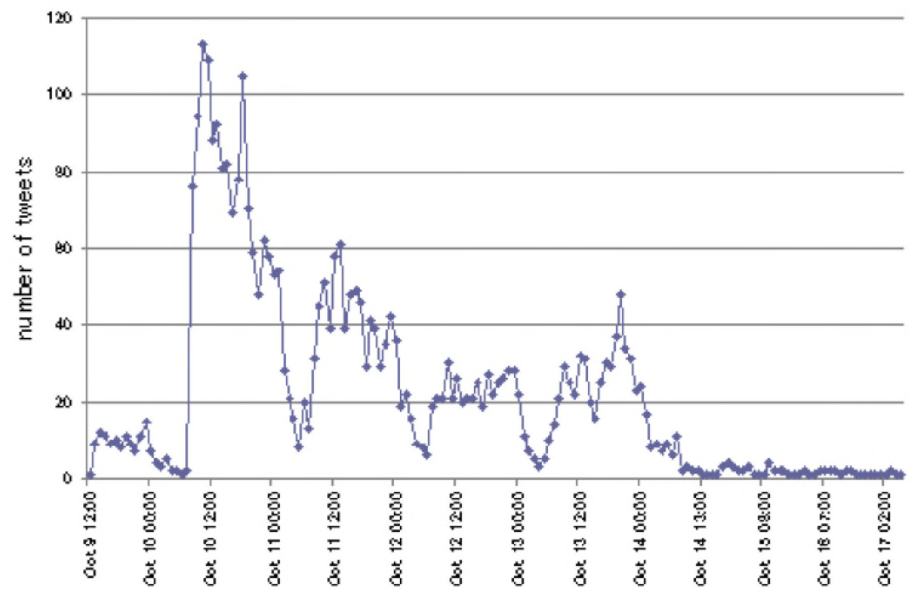
- Not all occurrences of a keyword (e.g., "earthquake" or "shaking" is about an ongoing event:
  - I am afraid of earthquakes
  - Shaking hands with boss
- How to solve this? (How to classify occurrences that constitute *"sensing" of an ongoing event* from others?)

Event Detection: A Probabilistic Model

- Spikes in occurrence of related keywords help detect corresponding events:



Earthquake-related keywords



Typhoon-related keywords

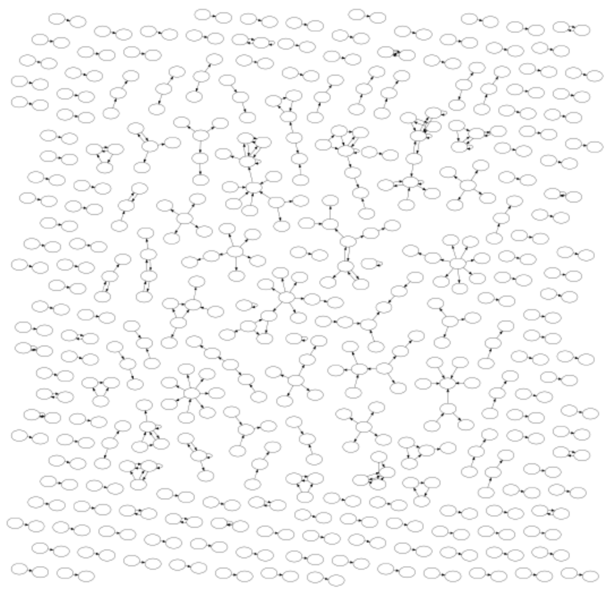
When a user detects an event at time 0, the time to make a tweet follows and exponential distribution.

Event Tracking

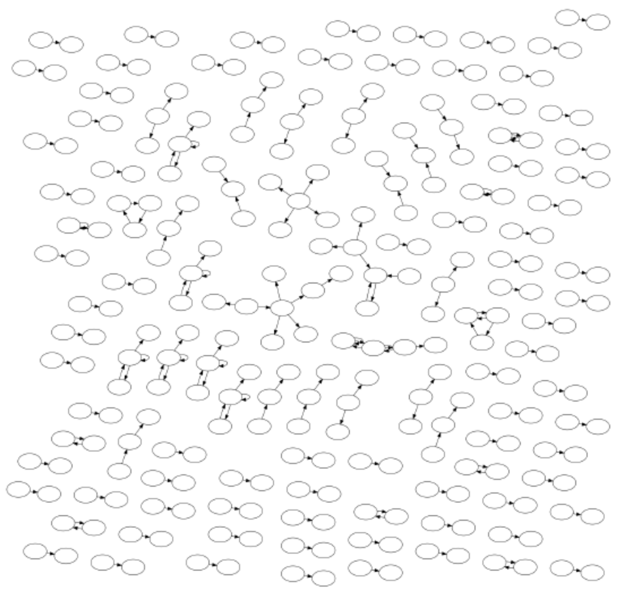
- Given (i) detected noisy location of the event at each point in time and a (ii) mobility model for the event, compute the most likely trajectory
- Multiple tracking techniques available in literature:
  - Kalman filter
  - Particle filter

Information Diffusion

- Assuming little/no diffusion (no retweets)



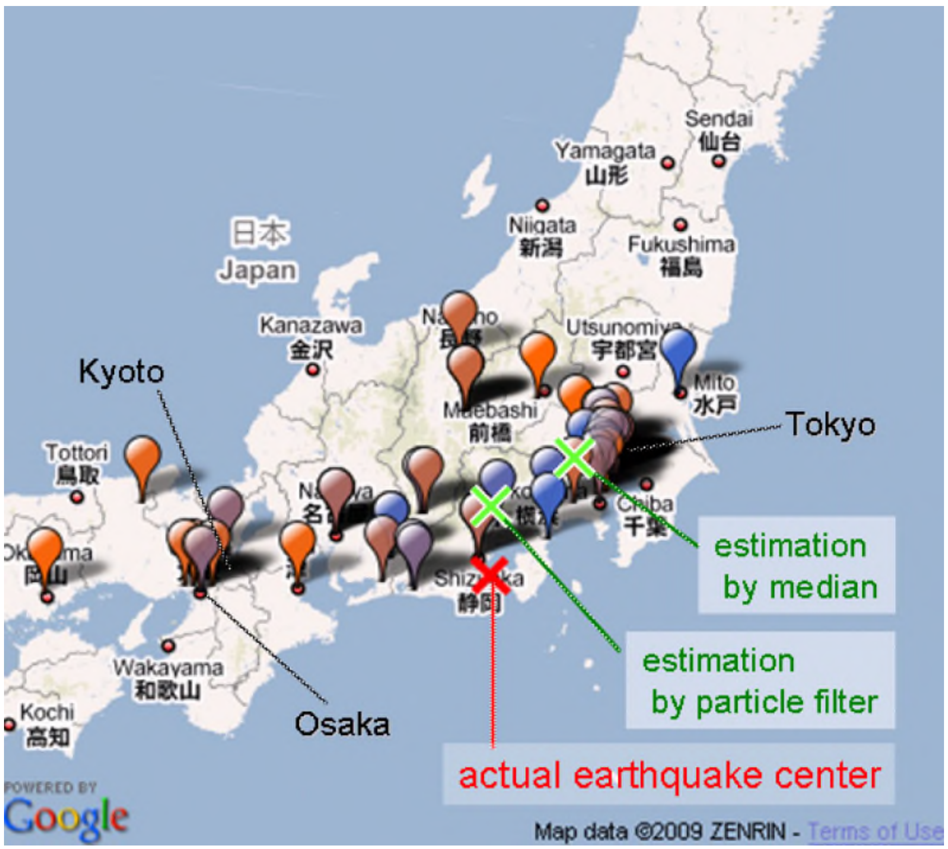
Diffusion of Earthquake tweets



Diffusion of Typhoon tweets

Evaluation

- Detection of an Earthquake



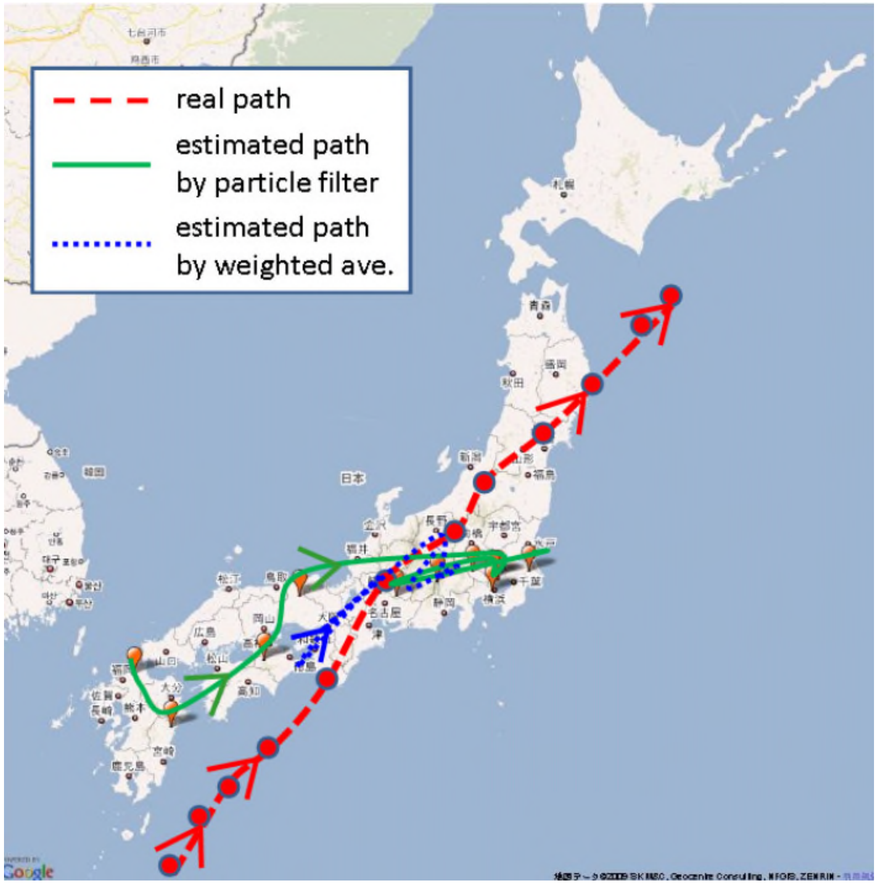
Evaluation

- Detection of an Earthquake

Date	Actual center		Median (baseline)			Weighted ave. (baseline)			Kalman filters			**Particle filters**		
	lat.	long.	lat.	long.	dist.	lat.	long.	dist.	lat.	long.	dist.	lat.	long.	dist.
Aug. 10 01:00	33.10	138.50	3.40	-0.80	3.49	2.70	-0.10	2.70	2.67	-0.50	2.72	2.60	0.50	**2.65**
Aug. 11 05:00	34.80	138.50	0.90	-0.90	1.27	0.70	-0.30	0.76	0.60	-0.20	**0.63**	0.30	-0.90	0.95
Aug. 13 07:50	33.00	140.80	1.30	-9.60	9.69	2.30	-2.30	**3.25**	1.63	-3.75	4.09	2.70	-2.70	3.82
Aug. 17 20:40	33.70	130.20	4.60	6.00	7.56	0.90	3.20	3.32	1.63	4.35	4.65	0.10	-0.80	**0.81**
Aug. 18 22:17	23.30	123.50	7.80	9.90	12.60	8.70	10.90	13.95	8.32	10.13	13.11	5.60	8.10	**9.85**
Aug. 21 08.51	35.70	140.00	0.50	-4.40	4.43	0.10	-1.00	1.00	0.00	-0.60	**0.60**	-0.80	0.48	0.93
Aug. 24 13:30	37.50	138.60	-0.40	0.00	**0.40**	-0.50	0.40	0.64	-0.50	0.30	0.58	2.40	0.70	2.50
Aug. 24 14:40	41.10	140.30	-1.90	1.10	2.20	-1.30	0.50	**1.39**	-1.50	0.50	1.58	3.10	2.00	3.69
Aug. 25 02:22	42.10	142.80	-2.90	-3.90	4.86	-6.10	-3.80	7.19	-5.20	-3.70	6.38	-1.80	-1.90	**2.62**
Aug. 25 20:19	35.40	140.40	1.60	-1.80	2.41	2.20	-0.70	2.31	0.70	-1.60	1.75	1.40	0.10	**1.40**
Aug. 31 00:46	37.20	141.50	-0.40	-3.60	3.62	-1.10	-2.30	2.55	-1.30	-2.20	2.56	-0.30	-0.30	**0.42**
Aug. 31 21:11	33.40	130.90	-4.50	-3.60	5.76	0.50	2.10	2.16	0.70	1.90	2.02	-0.20	-1.70	**1.71**
Sep. 3 22:26	31.10	130.30	6.20	-0.10	6.20	4.00	5.00	6.40	4.90	7.20	8.71	2.40	2.10	**3.19**
Sep. 4 11:30	35.80	140.10	3.10	-1.70	3.54	0.20	-0.90	**0.92**	0.00	-1.00	1.00	0.80	1.40	1.61
Sep. 05 10:59	37.00	140.20	-2.70	-8.30	8.73	-1.40	-3.10	**3.40**	-1.30	-3.30	3.55	-2.10	-5.80	6.17
Sep. 08 01:24	42.20	143.00	-3.60	-8.90	9.60	-2.50	-3.90	4.63	-4.50	-6.00	7.50	1.30	-3.60	**3.83**
Sep. 10 18:29	43.20	146.20	-5.90	-10.20	11.78	-4.90	-7.10	8.63	-4.50	-7.20	8.49	-0.90	-7.00	**7.06**
Sep. 16 21:38	33.40	130.90	1.10	-0.20	**1.12**	0.90	2.10	2.28	0.50	1.40	1.49	-0.20	-2.50	2.51
Sep. 22 20:40	47.60	141.70	-11.10	-7.50	13.40	-10.80	-3.10	11.24	-11.30	-3.80	11.92	-7.80	-3.00	**8.36**
Oct. 1 19:43	36.40	140.70	0.70	-3.80	3.86	-0.60	-1.80	1.90	-0.30	-1.50	1.53	-0.70	0.30	**0.76**
Oct. 5 09:35	42.40	141.60	-3.70	-3.10	4.83	-2.70	-2.00	3.36	-2.60	-1.60	3.05	1.10	-1.70	**2.02**
Oct. 6 07:49	35.90	137.60	0.50	1.20	1.30	-0.20	0.80	0.82	-0.10	0.90	0.91	0.30	0.50	**0.58**
Oct. 10 17:43	41.80	142.20	-3.50	-5.40	6.44	-1.40	-2.10	**2.52**	-2.20	-2.60	3.41	2.40	-1.30	2.73
Oct. 12 16:10	35.90	137.60	2.80	0.50	2.84	0.80	1.20	**1.44**	0.80	1.60	1.79	3.60	1.40	3.86
Oct. 12 18:42	37.40	139.70	-2.00	-4.40	4.83	-1.50	-0.90	1.75	-1.70	-1.40	2.20	-1.00	-0.60	**1.17**
Average distance					5.47			3.62			3.85			**3.01**

Evaluation

- Detection and tracking of a Typhoon



Evaluation

- Detection and tracking of a Typhoon

Date	Location		Median (baseline)			Weighted ave. (baseline)			Kalman filters			**Particle filters**		
	lat.	long.	lat.	long.	dist.	lat.	long.	dist.	lat.	long.	dist.	lat.	long.	dist.
Oct. 7 12:00	29.00	131.80	-1.90	-1.90	**2.69**	-5.20	-3.60	6.32	-3.90	-1.10	4.05	-4.70	1.10	4.83
Oct. 7 15:00	29.90	132.50	-3.70	-2.60	4.52	-3.80	-2.40	4.49	3.20	3.10	4.46	-2.70	0.90	**2.85**
Oct. 7 18:00	30.80	133.20	-4.10	-1.90	4.52	-4.40	-3.50	5.62	-6.40	5.40	8.37	-3.20	-0.70	**3.28**
Oct. 7 21:00	31.60	134.30	-3.90	-3.50	5.24	-3.60	-3.30	4.88	-10.90	-1.60	11.02	-3.70	-0.50	**3.73**
Oct. 8 0:00	32.90	135.60	-2.30	-0.10	**2.30**	-2.30	-0.90	2.47	-12.60	-20.40	23.98	-2.90	-3.50	4.55
Oct. 8 6:00	35.10	137.20	1.60	3.00	3.40	0.80	1.70	**1.88**	4.20	16.00	16.54	-0.60	-2.50	2.57
Oct. 8 9:00	36.10	138.80	-0.60	3.60	3.65	0.00	0.50	**0.50**	0.50	2.60	2.65	0.70	-0.80	1.06
Oct. 8 12:00	37.10	139.70	1.70	3.90	4.25	1.50	1.20	1.92	2.10	1.60	2.64	1.40	0.10	**1.40**
Oct. 8 15:00	38.00	140.90	2.30	3.20	3.94	2.40	2.20	**3.26**	1.70	7.60	7.79	2.40	2.70	3.61
Oct. 8 18:00	39.00	142.30	3.20	7.30	7.97	3.50	5.10	**6.19**	2.10	-18.80	18.92	3.70	5.10	6.30
Oct. 8 21:00	40.00	143.60	4.30	3.90	5.81	4.00	5.30	6.64	1.60	4.50	4.78	4.20	3.10	**5.22**
Average distance					4.39			4.02			9.56			**3.58**

The Human Sensor Model

- Humans are better at binary observations. For measurements on a scale, use sensors
- Examples of actual Twitter feeds that can be thought of as "binary observations":
  - "Crash blocking lanes on I-5S @ McBean Pkwy in Santa Clarita"
  - "105E past LakewoodB: traffic stopped to clear tire debris out of lanes"
  - "@BostonGlobe: BREAKING NEWS: Shots fired in Watertown; source says Boston Marathon terror bomb suspect has been pinned down."
  - "The police chief of Afghanistan's southern Kandahar province has died in a suicide attack on his headquarters."
  - "Yonkers mayor has lifted his gas rationing order. Fill it up! #SandyABC7"

Dow Jones Hickup

- Dow Jones lost 150 points on a rumor of two explosions in the White House on April 23rd, 2013

Reconstructing Event Timelines
The Apollo Fact-finder

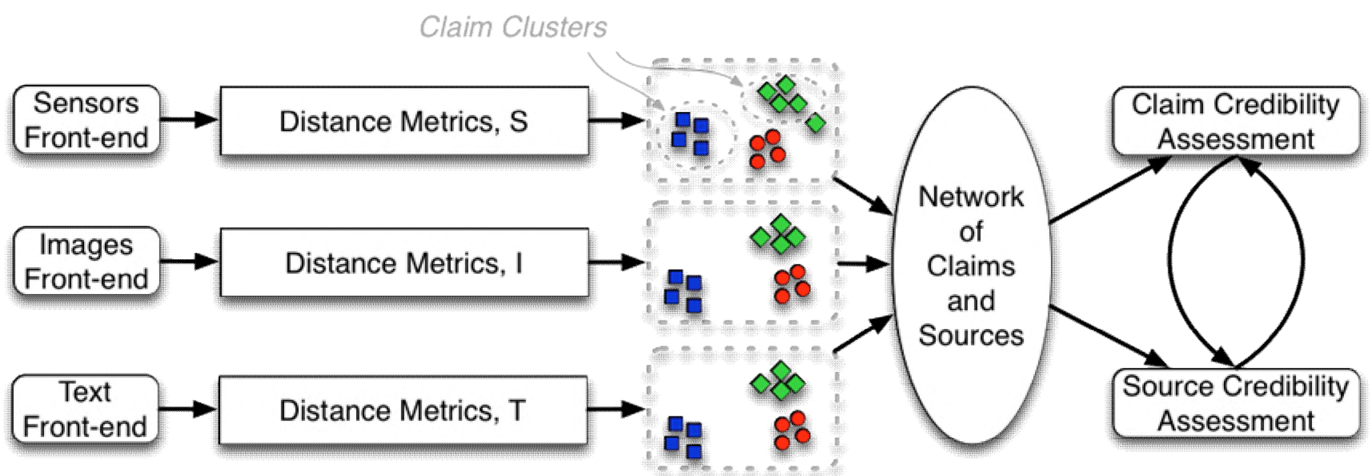
Boston Bombing

Hurricane Sandy

Egypt unrest

People

Clean Event Summary?



The Apollo Fact-finder

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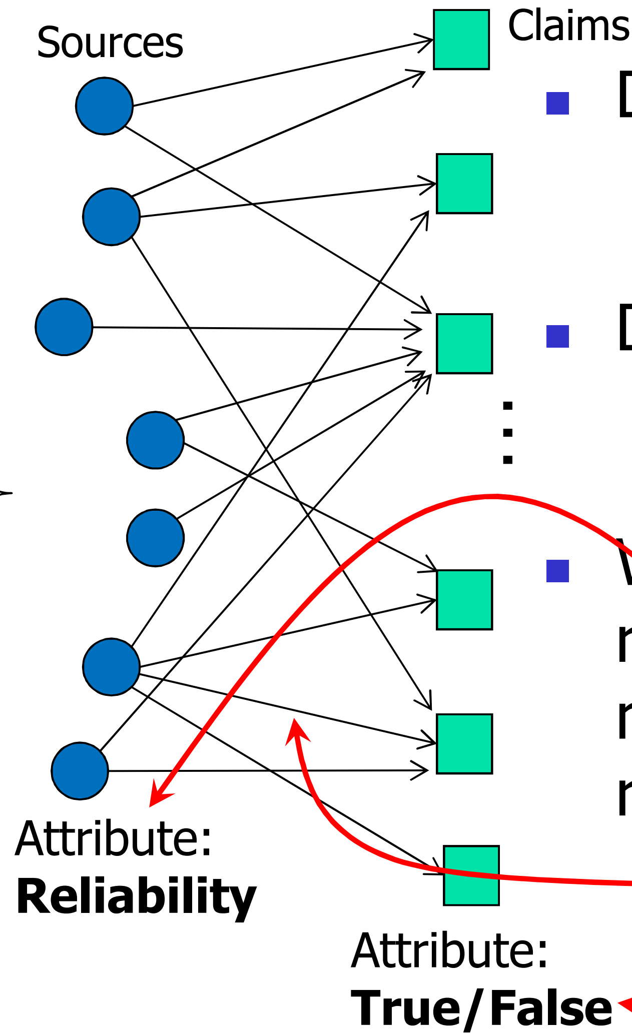


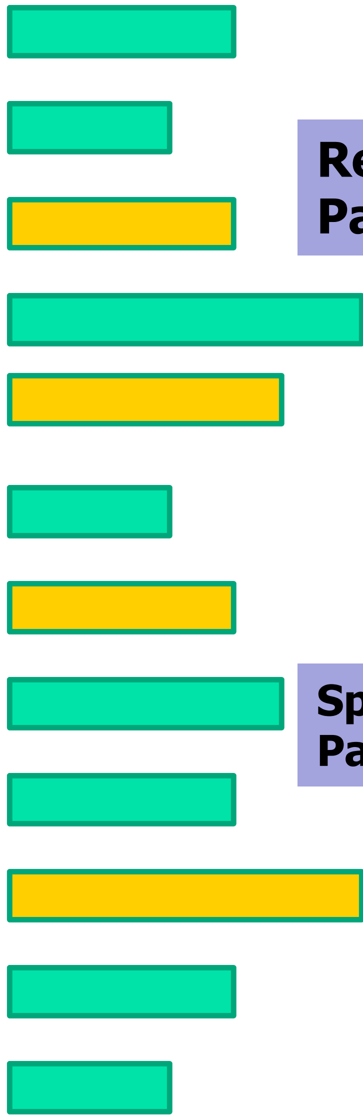
- Define a_i as:
  - P (source$_i$ makes an original observation | it is true)
- Define b_i as:
  - P (source$_i$ makes an original observation | it is false)
- What are the source reliability parameters that maximize the probability of received observations?

$$P(SC|\theta) = \sum_z P(SC, z|\theta)$$

Humans as Sensors

True Assertion

False Assertion



Reliability of Participant *i* $=$ $\dfrac{i}{i + i}$

Participant Reliability

$t_i = P(C_j^t \mid S_i C_j)$

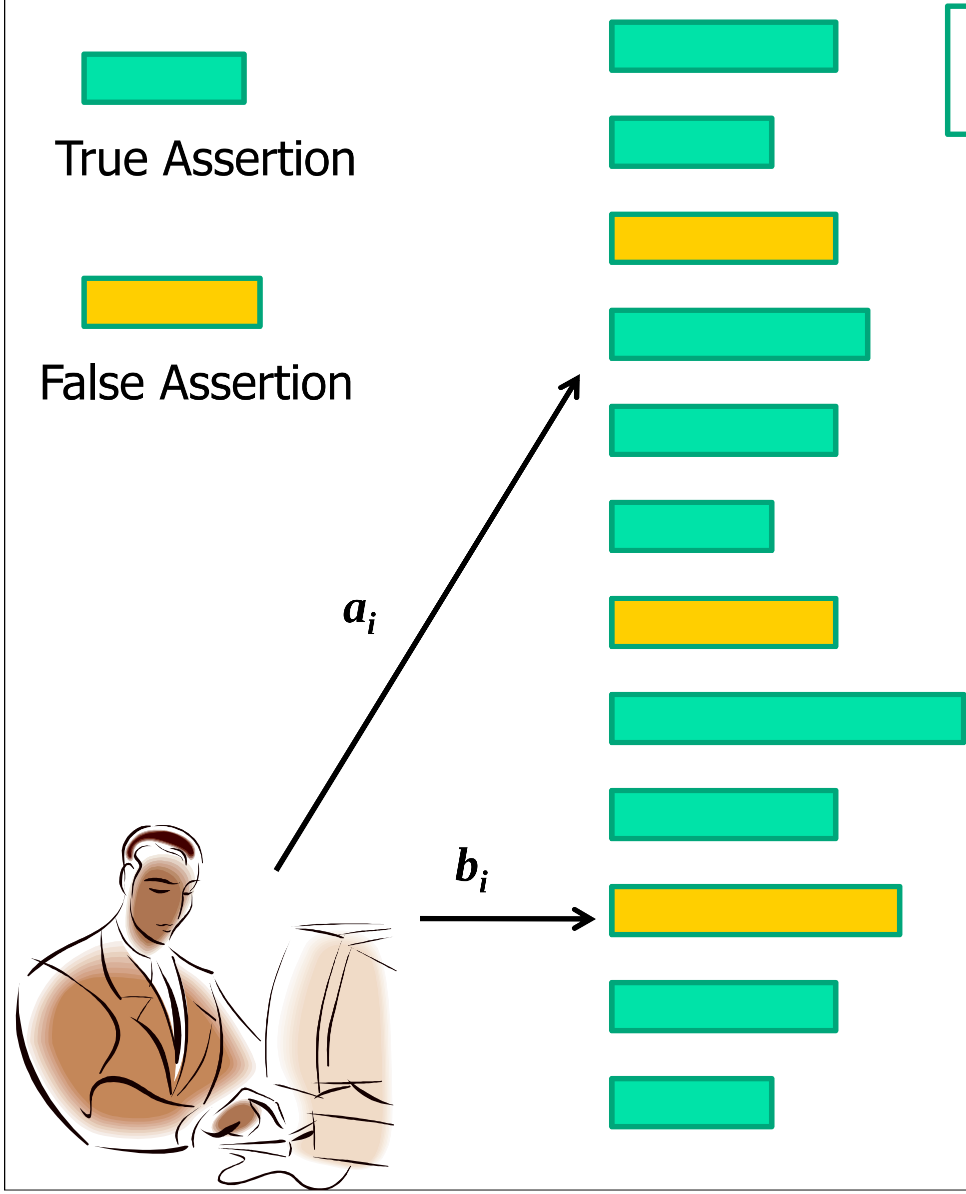
$S_i C_j$: participant i claims assertion j

Speak Rate of Participant *i* $\propto$ $\dfrac{i + i}{All + All}$

Participant i speak with rate s_i

$s_i = P(S_i C_j)$

Expectation Maximization



$$\boxed{a_i = P(S_i C_j \mid C_j^t)}$$

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

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

$$\boxed{b_i = P(S_i C_j \mid C_j^f)}$$

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

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

Expectation Maximization

Expectation Maximization

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

Estimation parameter

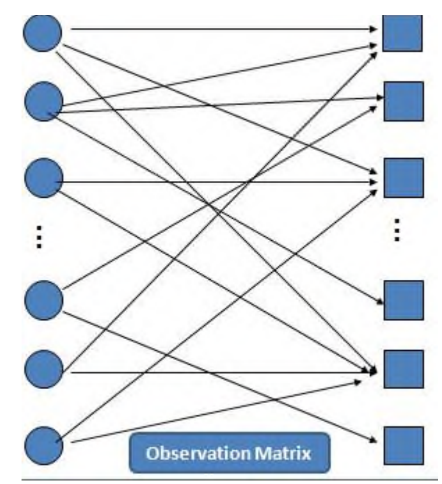
Observed data

Hidden Variable

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

X

Observation Matrix



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

Apply EM

Expectation Step (E-step)

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

Maximization Step (M-step)

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

Find MLE of estimation parameter and values of hidden variables

Expectation Maximization

Likelihood function of EM

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

$$= \prod_{j=1}^{N} \left\{ \prod_{i=1}^{M} a_i^{S_i C_j} (1 - a_i)^{(1 - S_i C_j)} \times d \times z_j + \prod_{i=1}^{M} b_i^{S_i C_j} (1 - b_i)^{(1 - S_i C_j)} \times (1 - d) \times (1 - z_j) \right\}$$

Expectation Step (E-Step)

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

$$Z(t, j) = f(a^{(t)}, b^{(t)}, d^{(t)} j)$$

$$= \sum_{j=1}^{N} \left\{ p(z_j = 1|X_j, \theta^{(t)}) \times \left[\sum_{i=1}^{M} (S_i C_j \log a_i + (1 - S_i C_j) \log(1 - a_i) + \log d) \right] \right.$$

$$\left. + p(z_j = 0|X_j, \theta^{(t)}) \times \left[\sum_{i=1}^{M} (S_i C_j \log b_i + (1 - S_i C_j) \log(1 - b_i) + \log(1 - d)) \right] \right\}$$

Maximization Step (M-Step)

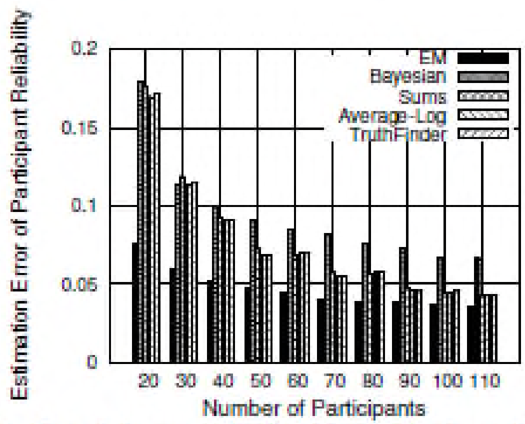
$$a_i^{(t+1)} = a_i^* = \frac{\sum_{j \in SJ_i} Z(t, j)}{\sum_{j=1}^{N} Z(t, j)}$$

$$b_i^{(t+1)} = b_i^* = \frac{K_i - \sum_{j \in SJ_i} Z(t, j)}{N - \sum_{j=1}^{N} Z(t, j)}$$

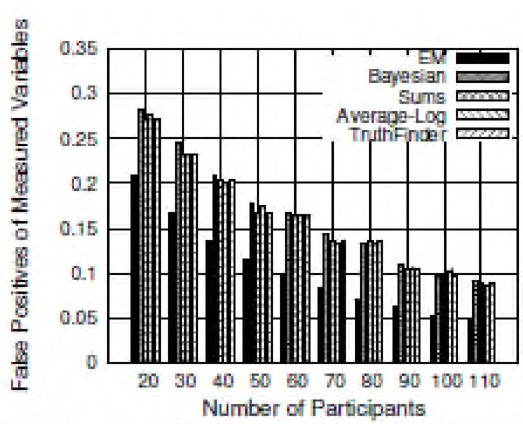
$$d_i^{(t+1)} = d_i^* = \frac{\sum_{j=1}^{N} Z(t, j)}{N}$$

Iterate

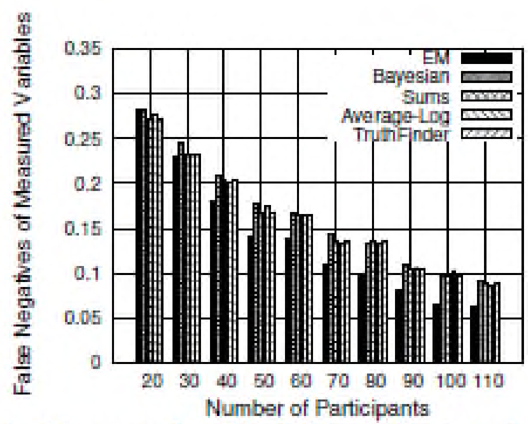
Simulation



(a) Participant Reliability Estimation Accuracy



(b) Measured Variable Estimation: False Positives



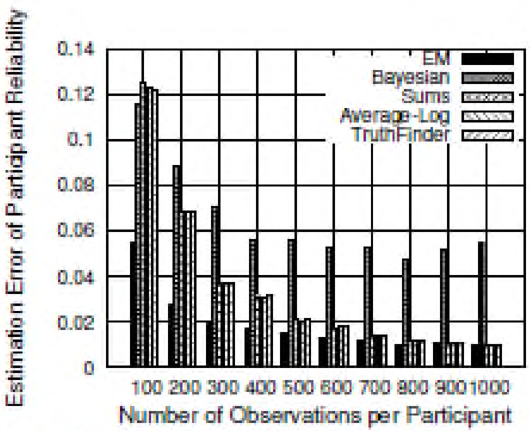
(c) Measured Variable Estimation: False Negatives

EM outperforms state-of-art heuristics

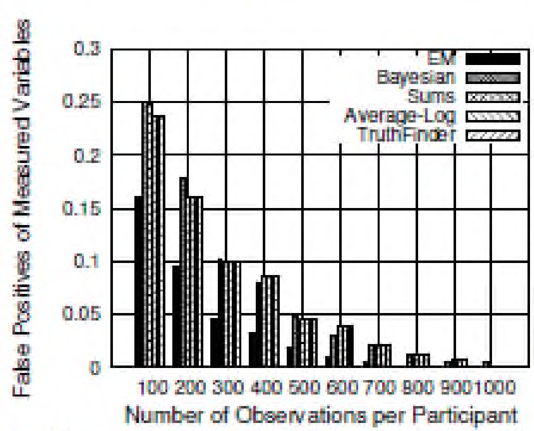
Parameters:

Number of Participants: 20-110, Number of True Assertions: 1000, Number of False Assertions: 1000, Average Number of Claims per Participant: 100

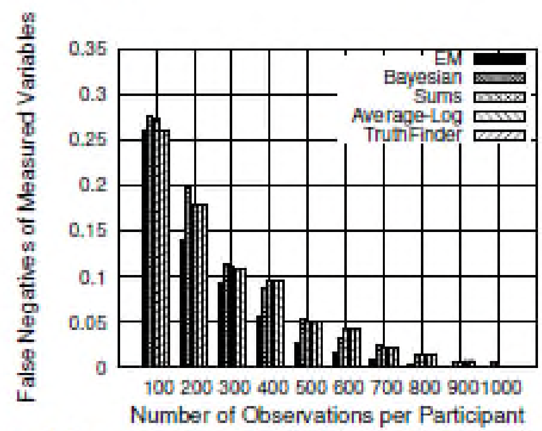
Simulation



(a) Participant Reliability Estimation Accuracy



(b) Measured Variable Estimation: False Positives



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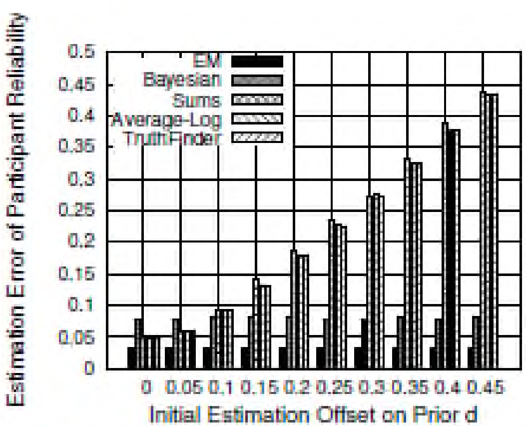
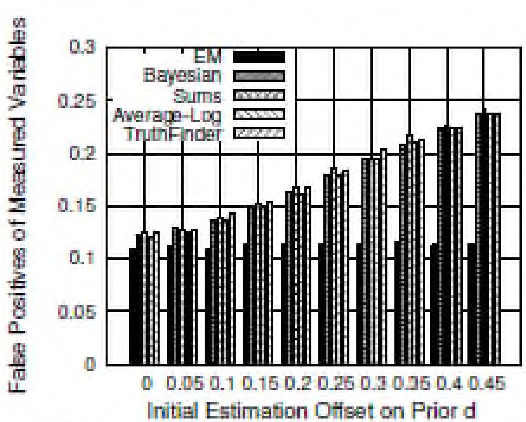
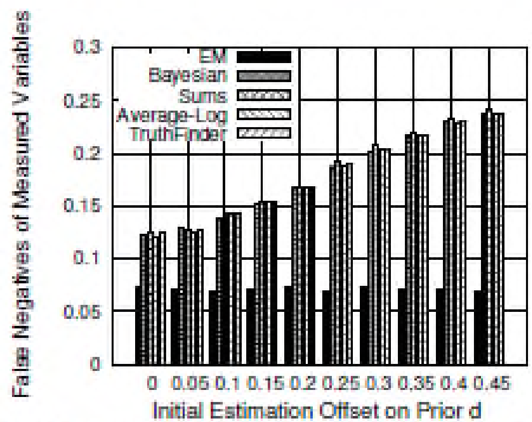


(a) Participant Reliability Estimation Accuracy



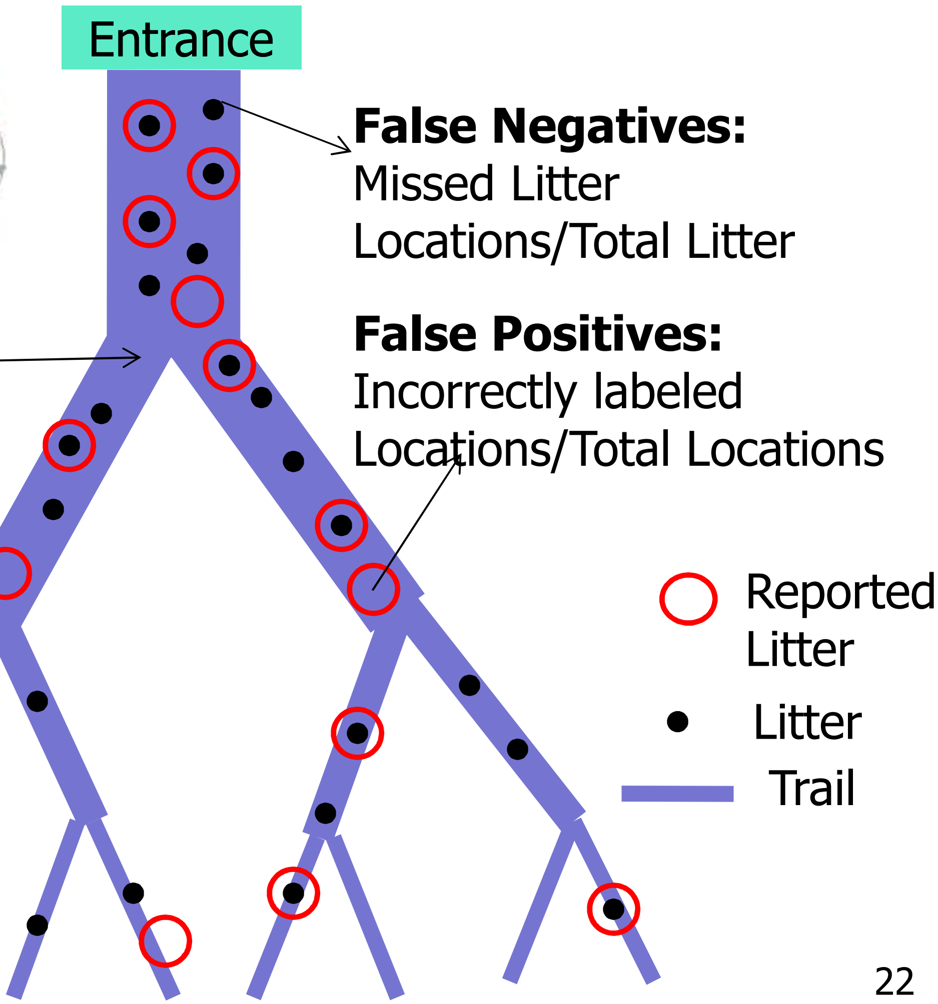
(b) Measured Variable Estimation: False Positives



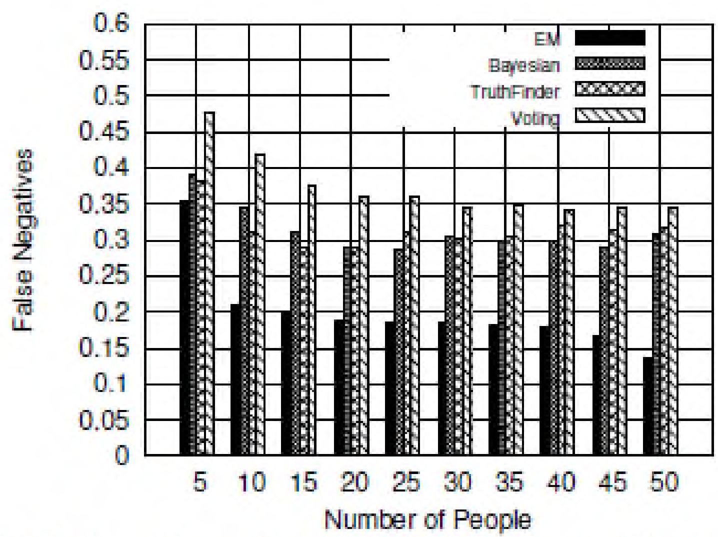
(c) Measured Variable Estimation: False Negatives

Simulated Geotagging

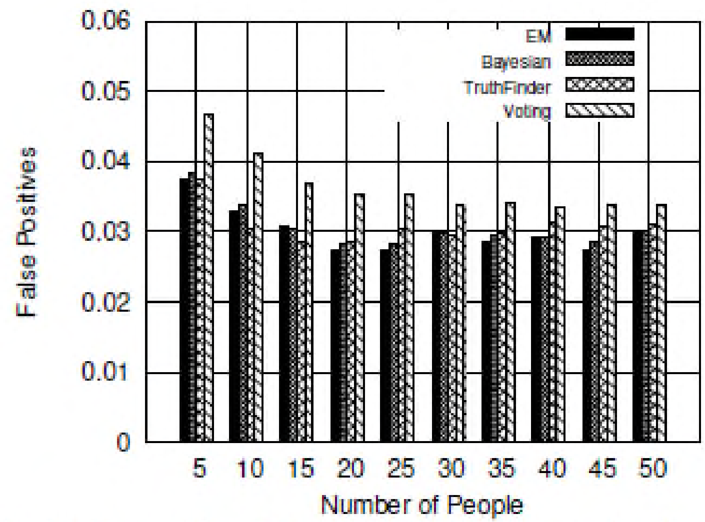
P_c:
probability to continue



Simulated Geotagging



(a) False Negatives (missed/total litter)



(b) False Positives (false/total locations)

Litter Geotagging Accuracy <u>versus Number of People</u>

Twitter-based Evaluation (Hurricane Irene)

#	Media	Tweet found by EM
1	East Coast Braces For Hurricane Irene; Hurricane Irene is expected to follow a path up the East Coast	@JoshOchs A #hurricane here on the east coast
2	Hurricane Irene's effects begin being felt in NC, The storm, now a Category 2, still has the East Coast on edge.	Winds, rain pound North Carolina as Hurricane Irene closes in http://t.co/0gVOSZk
3	Hurricane Irene charged up the U.S. East Coast on Saturday toward New York, shutting down the city, and millions of Americans sought shelter from the huge storm.	Hurricane Irene rages up U.S. east coast http://t.co/u0XiXow
4	The Wall Street Journal has created a way for New Yorkers to interact with the location-based social media app Foursquare to find the nearest NYC hurricane evacuation center.	Mashable - Hurricane Irene: Find an NYC Evacuation Center on Foursquare ... http://t.co/XMtpH99
5	Following slamming into the East Coast and knocking out electricity to more than a million people, Hurricane Irene is now taking purpose on largest metropolitan areas in the Northeast.	2M lose power as Hurricane Irene moves north - Two million homes and businesses were without power ... http://t.co/fZWkEU3
6	Irene remains a Category 1, the lowest level of hurricane classification, as it churns toward New York over the next several hours, the U.S. National Hurricane Center said on Sunday.	Now its a level 1 hurricane. Let's hope it hits NY at Level 1
7	Blackouts reported, storm warnings issued as Irene nears Quebec, Atlantic Canada.	DTN Canada: Irene forecast to hit Atlantic Canada http://t.co/MjhmeJn
8	President Barack Obama declared New York a disaster area Wednesday, The New York Times reports, allowing the release of federal aid to the state's government and individuals.	Hurricane Irene: New York State Declared A Disaster Area By President Obama
9	Hurricane Irene's rampage up the East Coast has become the tenth billion-dollar weather event this year, breaking a record stretching back to 1980, climate experts said Wednesday.	Irene is 10th billion-dollar weather event of 2011.
10	WASHINGTON- On Sunday, September 4, the President will travel to Paterson, New Jersey, to view damage from Hurricane Irene.	White House: Obama to visit Paterson, NJ Sunday to view damage from Hurricane Irene

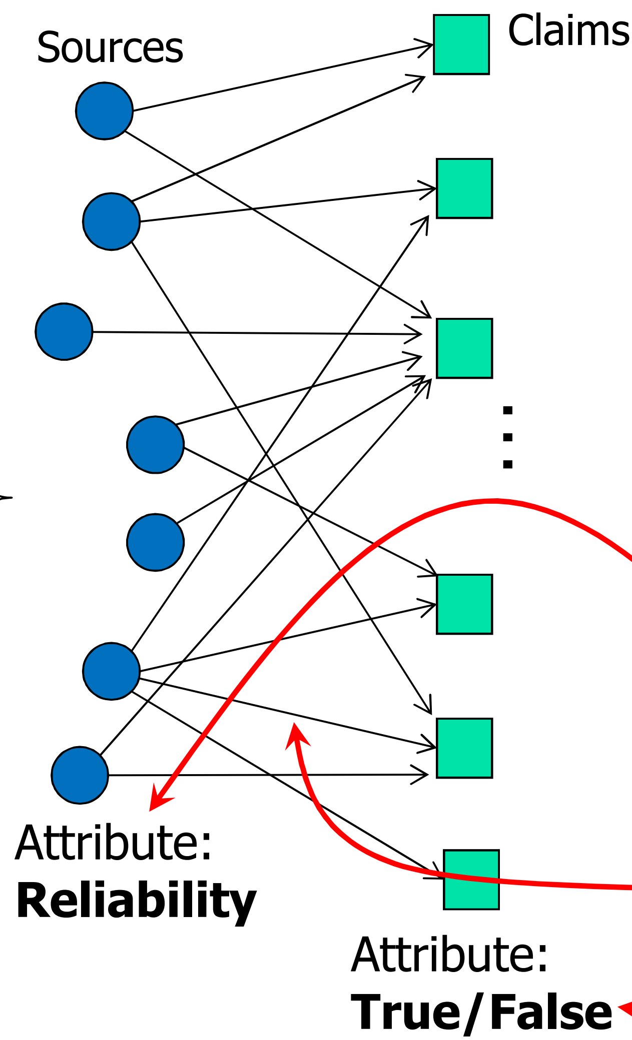
Top correct tweets found by EM matches well with Media Reports

A Maximum Likelihood Estimation Problem

Boston Bombing

Hurricane Sandy

Egypt unrest



- Joint estimation of
  - Source reliability
  - True/false value of each observation
- Given
  - Who said what

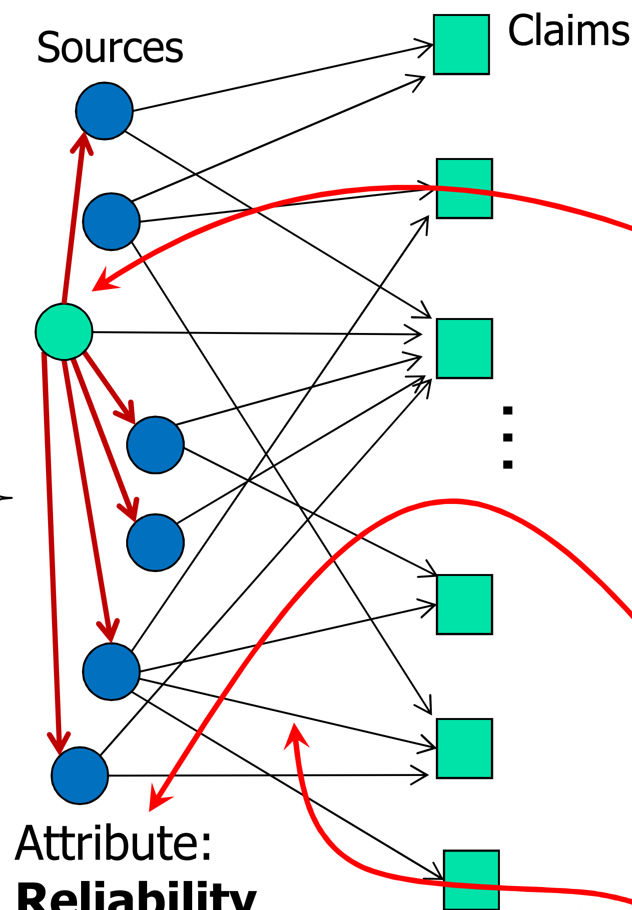
$$P(SC|\theta) = \sum_z P(SC, z|\theta)$$

Source Dependencies

Boston Bombing

Hurricane Sandy

Egypt unrest



- Joint estimation of
  - Source reliability
  - True/false value of each observation
- Given
  - Who said what, and
  - Correlations between sources

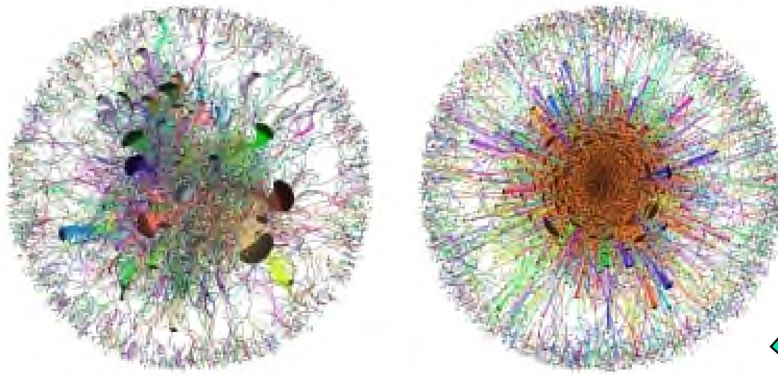
Attribute: **True/False** $P(SC|SD,\theta) = \sum_z P(SC,z|SD,\theta)$

Reconstructing Event Timelines
A Twitter Example


Boston Bombing


Hurricane Sandy


Egypt unrest



Social Network

People

Information (consistency) Network

Clean Event Summary?

Expectation Maximization

Likelihood Function Incorporating Source Dependency

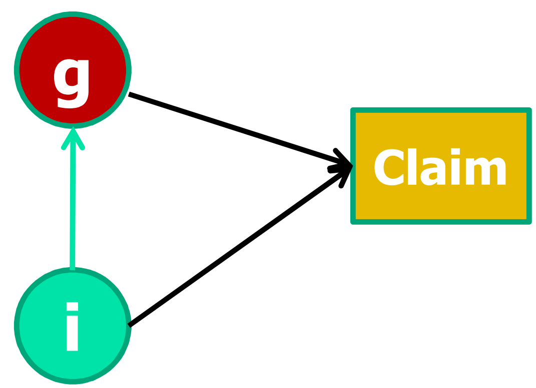
$$P(SC, z|SD, \theta) = \prod_{j=1}^{N} P(z_j) \times$$

$$\{ \prod_{g \in M_j} P(S_g C_j|\theta, z_j) \prod_{i \in c_g} P(S_i C_j|S_g C_j) \}$$

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

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

$$\boxed{P(S_i C_j|S_g C_j) = \begin{cases} p_{ig} & S_g C_j = 1, S_i C_j = 1 \\ 1-p_{ig} & S_g C_j = 1, S_i C_j = 0 \end{cases}}$$



Dependent Sources

Expectation Maximization

E-Step

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

M-Step

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

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

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

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

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

Collected Data 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

The Experiments

- Run the maximum likelihood estimator on Twitter data to determine the probability of correctness of different tweets
- Sort tweets by probability of correctness.
- Give the top N tweets to a human for "grading"
- Human must investigate each tweet to determine if it is true.
- Any tweet that cannot be shown to be true is considered "unconfirmed"
- Compare the percentages of unconfirmed tweets across different credibility estimation algorithms

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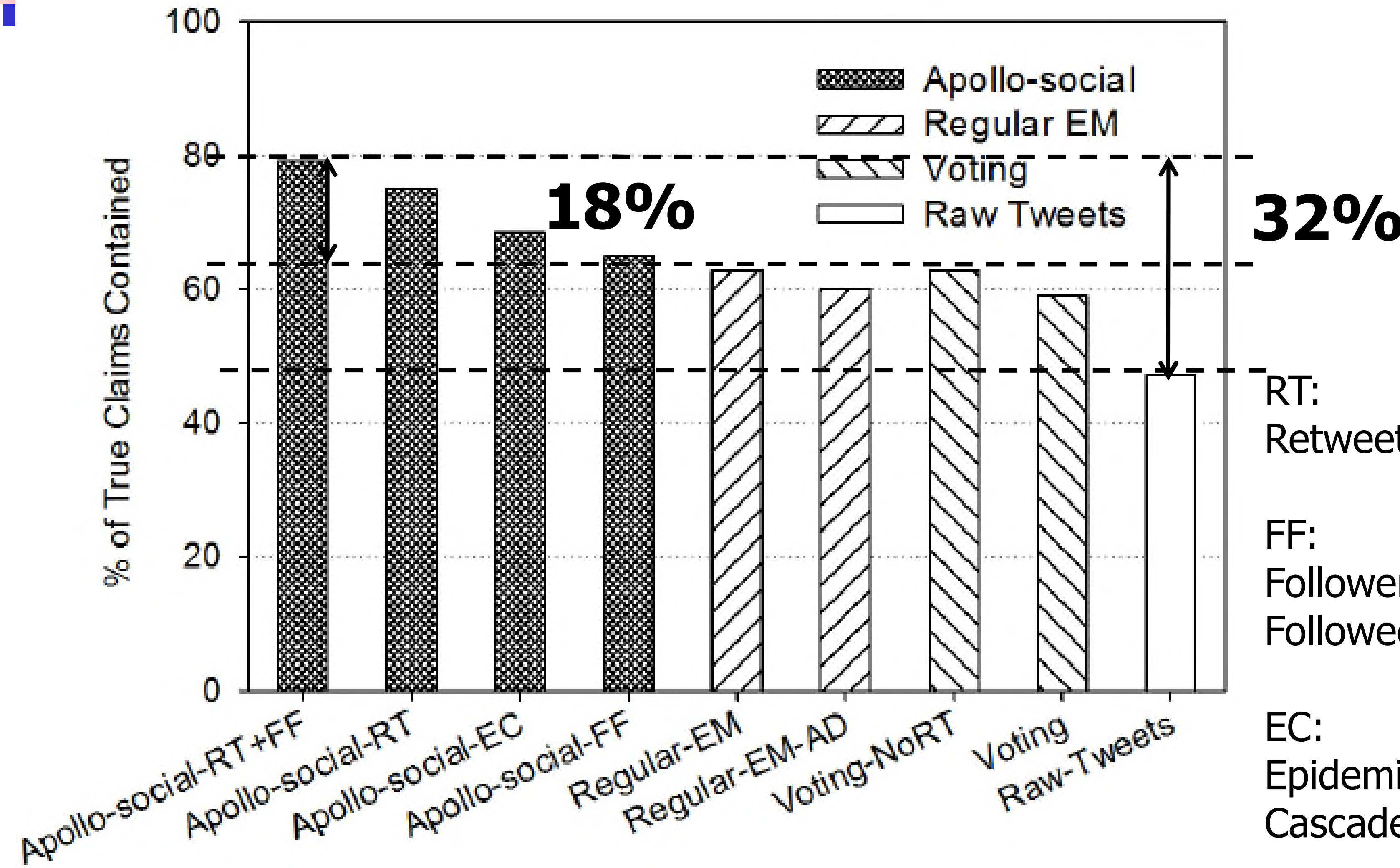
Note: To remove bias, the grader was not told which algorithm "believed" which tweet.

Evaluation: Sandy Trace
A Comparison of Confirmed True Tweets



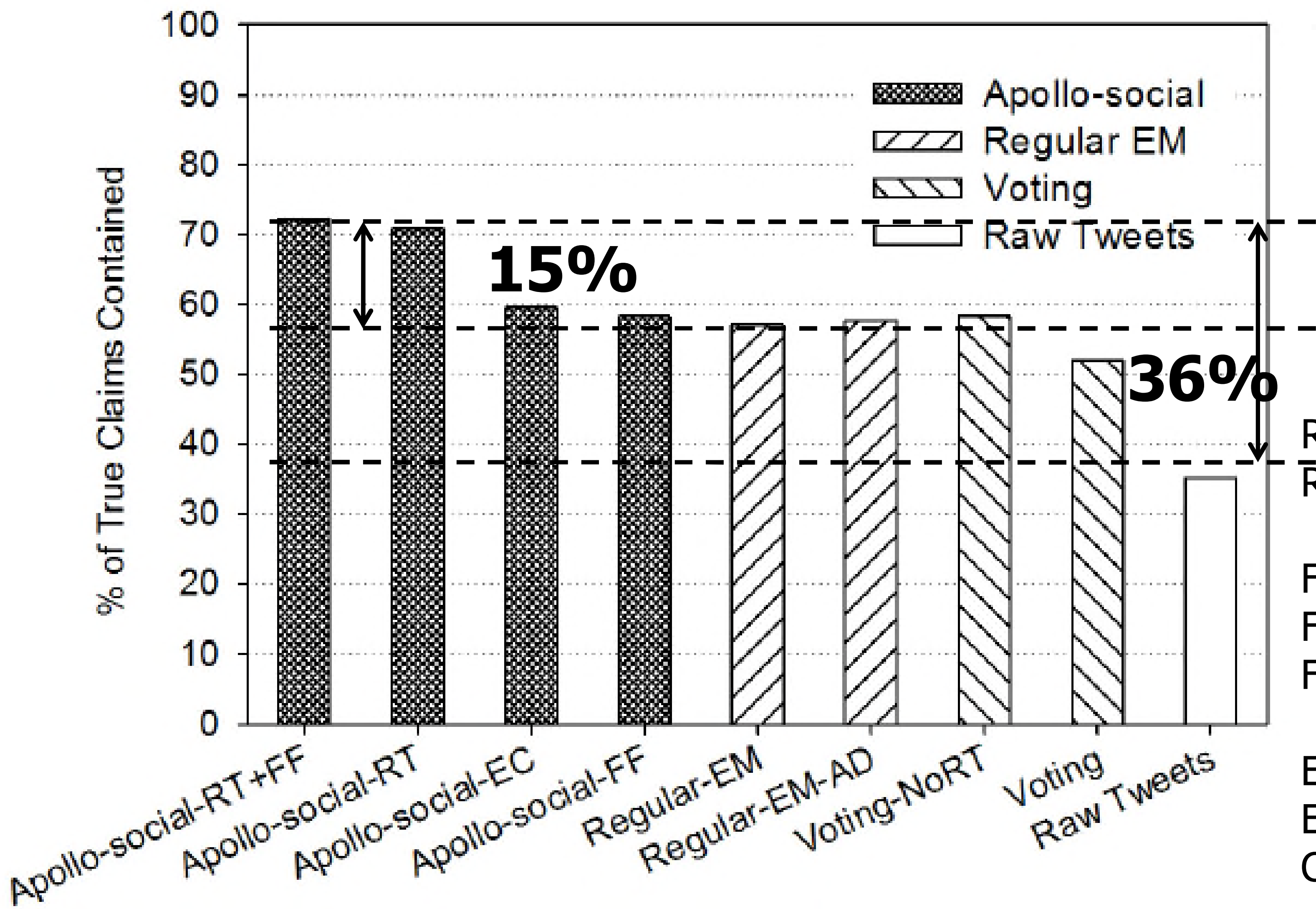
RT: Retweet

FF: Follower-Followee

EC: Epidemic Cascade

Evaluation: Irene Trace

A Comparison of Confirmed True Tweets



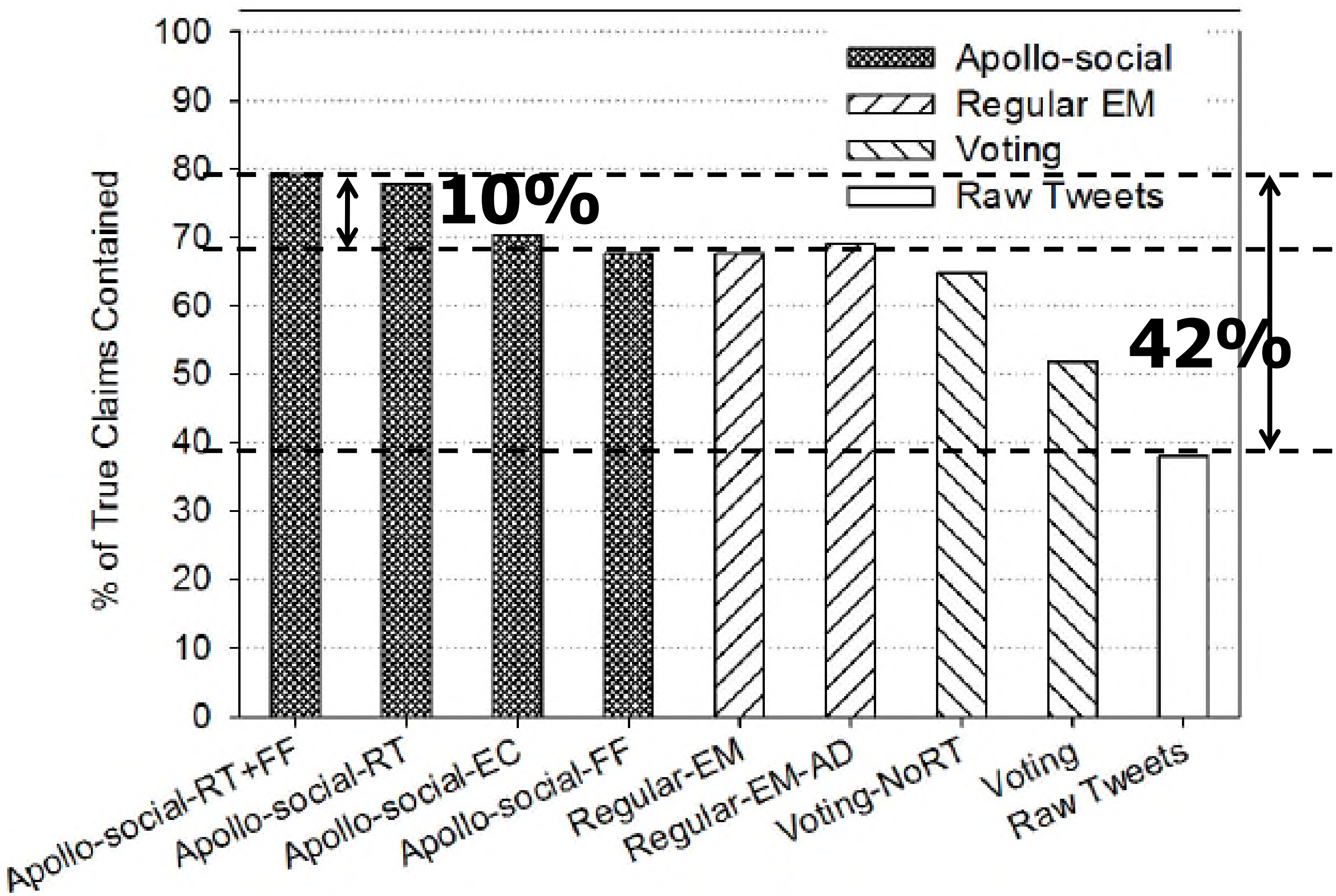
RT: Retweet

FF: Follower-Followee

EC: Epidemic Cascade

Evaluation: Egypt Trace

A Comparison of Confirmed True Tweets



RT: Retweet

FF: Follower-Followee

EC: Epidemic Cascade

Example

#	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

Another Example

The Washington Post

Another Example