معهد قطر لبحوث الحوسبة
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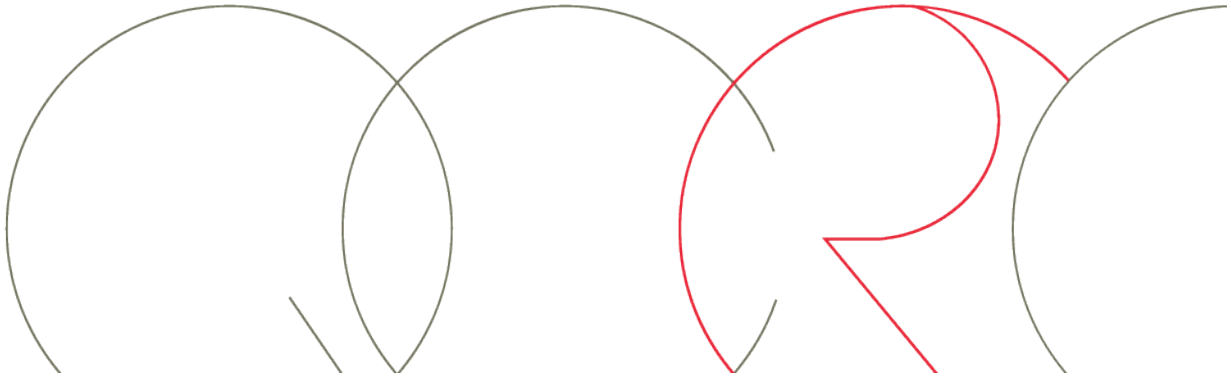
Scaling Up Truth Discovery



May 17, 2016

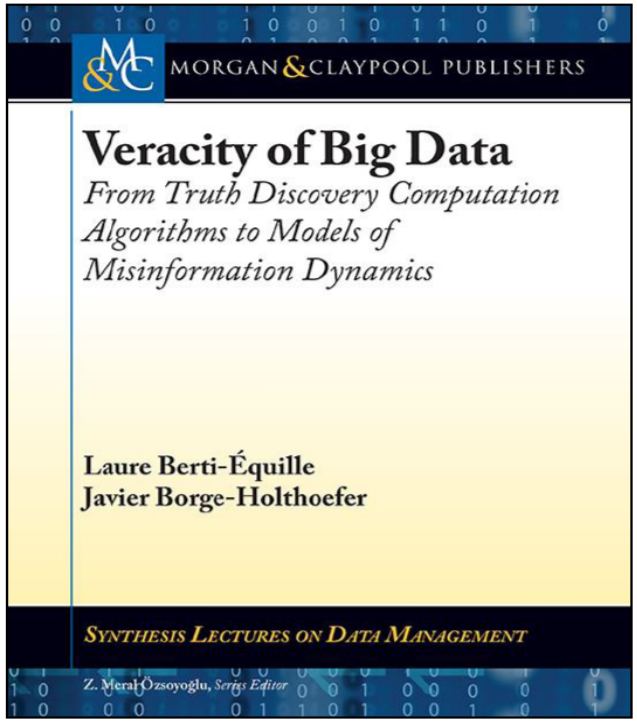
Disclaimer

Aim of the tutorial: Get the big picture

The algorithms of the main approaches will be sketched

Please don't mind if your favorite algorithm is missing

The revised version of the tutorial will be available at:
http://daqcri.github.io/dafna/



So many sources of information…

Accurate?

Deep Web data quality is low

FlightView

American Airlines Flight Number 119 (AA119)

FLIGHT TRACKER

Departure

Airport:
Scheduled Time: 6:15 PM, Dec 08
Takeoff Time: 6:53 PM, Dec 08
Terminal - Gate: Terminal A - 32

ArrivalStatus: In Air

Airport:
Scheduled Time: 9:40 PM, Dec 08
9:42 PM, Dec 08

Estimated Time:
Track This Flight Live!

Time Remaining: 25 min
Terminal - Gate: Terminal 4 - 42B
Baggage Claim: 4

FlightAware

AAL119 (Track inbound flight)
(web site) (all flights)
American Airlines "American"

Aircraft	Boeing 737-800 (twin-jet) (B738/Q - track or photos)
Origin	Terminal A / Gate 32 / Newark Liberty Intl (KEWR - tr
Destination	Terminal 4 / Gate 42B / Los Angeles Intl (KLAX - track
	Other flights between these airports
Route	ZIMMZ Q42 BTRIX Q480 AIR J80 VHP J80 MCI J24 SLN J102 ALS J44 RSK J (Decode)
Date	2011年 12月 08日 (
Duration	5 hours 43 minutes
Progress	20 minutes left 5 hours 23 minutes
Status	En Route (2,284 sm (
Distance	Direct: 2,451 sm Pl
Fare	$51.99 to $3,561.11
Cabin	First: Dinner / Econor
	Scheduled 7-day
Departure	06:15PM EST 07:08I
Arrival	08:33PM PST 09:17I

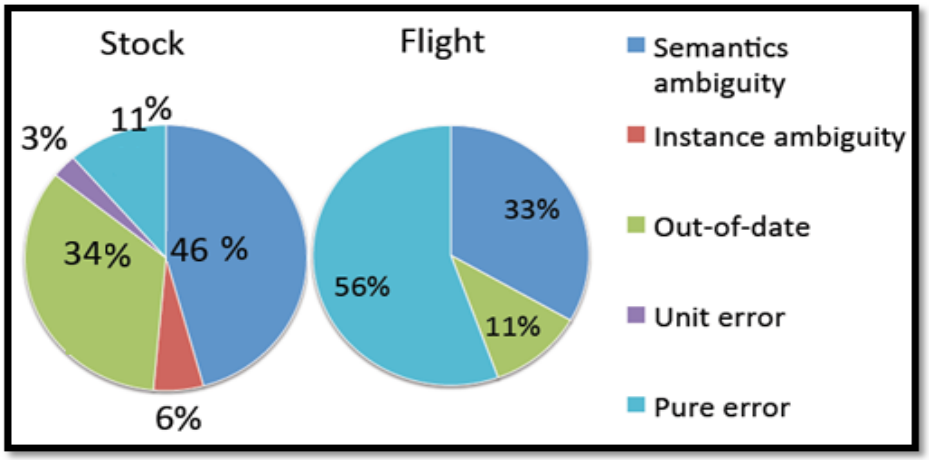
Orbitz

American Airlines # 119

Leg 1: In Transit

Departs: Newark (EWR) View real-time airpo

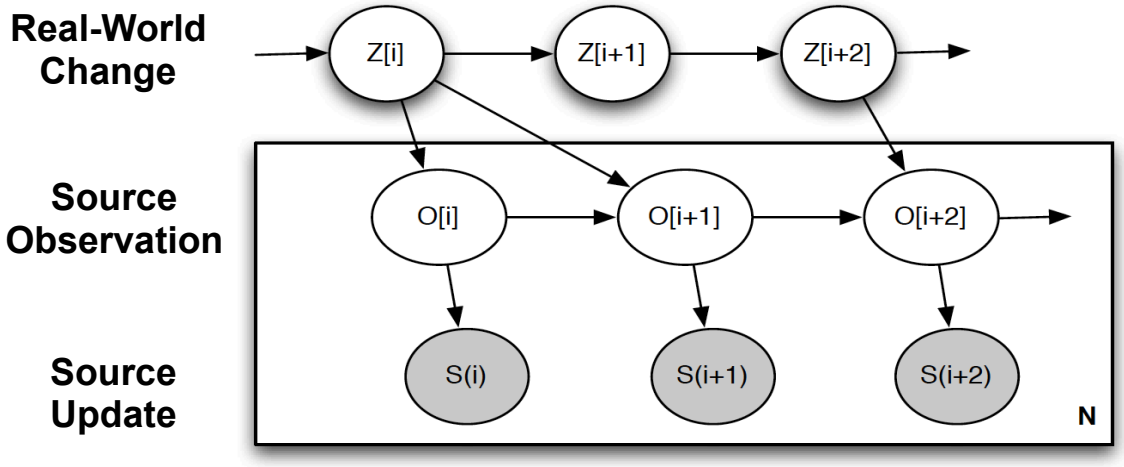
Gate: 32



X. Li, X. L. Dong, K. Lyons, W. Meng, and D. Srivastava. Truth Finding on the Deep Web: Is the Problem Solved? PVLDB, 6(2):97–108, 2012.

Up-to-date?

Real-world entities evolve over time, but sources can delay, or even miss, reporting some of the real-world updates.



Research: 80% fund giants publish out of date fund data

15 September 2015 | By Valentina Romeo

Tweet 9 Share 5 Print Email Comments (3)

Eight out of ten of the biggest fund groups are handing investors outdated performance information, a new survey finds.

According to fintech company Instinct Studios, 80 per cent of the largest asset managers have fund factsheets that are six weeks out of date.

A. Pal, V. Rastogi, A. Machanavajjhala, and P. Bohannon. Information integration over time in unreliable and uncertain environments. Proceedings of WWW '12, p. 789-798.

Trustworthy?
WikiTrust

Computed based on edit history of the page and reputation of the authors

- *B.T. Adler, L. de Alfaro, A Content-Driven Reputation System for the Wikipedia, Proceedings of the 16th International World Wide Web Conference, 2007.*
- *L. de Alfaro, B. Adler. Content-Driven Reputation for Collaborative Systems. Proceedings of Trustworthy Global Computing 2013.Lecture Notes in Computer Science, Springer, 2013.*

Information can still be trustworthy

Authoritative sources can be wrong

YAHOO! NEWS

AFP apologises to French industrialist after death reported

AFP February 28, 2015 2:42 PM

AFP issued an apology to French industrialist Martin Bouygues, chairman and CEO of the conglomerate Bouygue...

© REUTERS/ BENOIT TESSIER

French TV Denies Reports of Bouygues Conglomerate CEO's Death

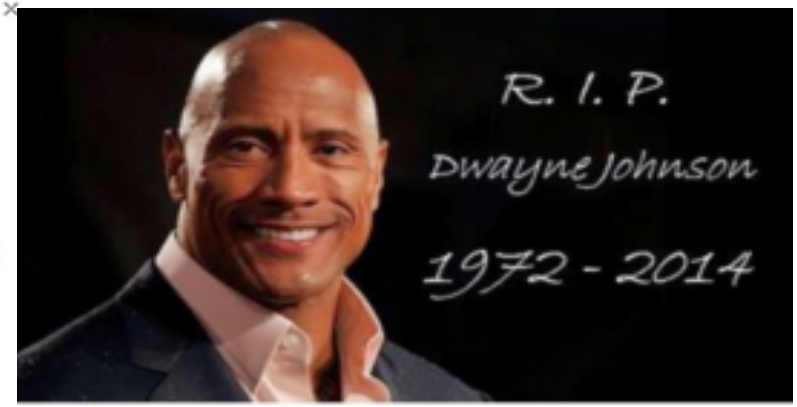
Rumors: Celebrity Death Hoaxes

成龍 Jackie Chan
June 21

Hi everybody! Yesterday, I got on a 3am flight from India to Beijing. I didn't get a chance to sleep and even had to clean my house when I got home. Today, everybody called to congratulate me on my rumored engagement. Afterward, everybody called me to see if I was alive.

If I died, I would probably tell the world! I took a photo with today's date, just in case you don't believe me! However, thank you all for your concern. Kiss kiss and love you all!

P.S. My dog is healthy, just like me! He doesn't need surgery! By the way, my dogs are golden retrievers, not Labradors.



DWAYNE JOHNSON died while filming a dangerous stunt for FAST & FURIOUS 7

REAL RUMOR

4 tweets

retweet

Russell Crowe is NOT dead.

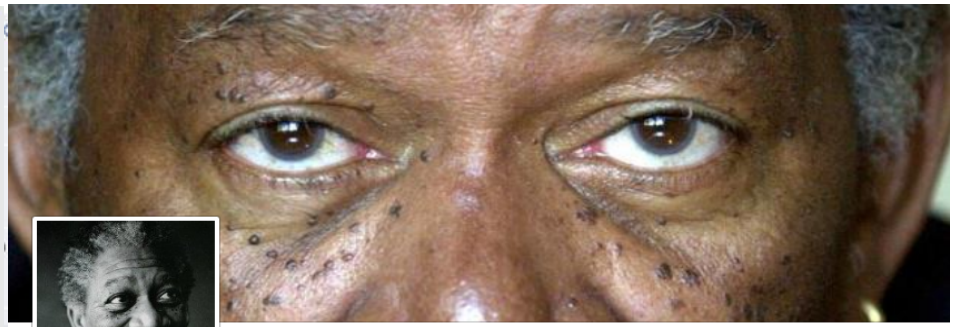
Another heinous celebrity death hoax took root online this morning with Crowe as the victim.

As was the case with previous "deaths," the actor was said to have suffered a fatal fall while filming in a remote location. Specifically, in the Hahnenkamm mountains of Austria.

New York radio station Z100 and other outlets reported the news as fact.

Fortunately, it's just another **vile, disgusting FAKE**.

The Crowe hoax comes from **FakeAWish.com**, the same disturbed "death" generator that's claimed previous victims such as **George**



R.I.P Morgan Freeman
860,689 likes · 972,460 talking about this

Like Message

Community
At about 5 p.m. ET on Thursday, our beloved actor Morgan Freeman passed away due to a artery rupture. Morgan was born on June 1, 1937. He will be missed but not forgotten. Please show your sympathy and condolences by commenting on and liking this page.

About

Photos

860k

Likes

(Manual) Fact Verification Web Sites

Global Summit of Fact-Checking in London, July 2015	2015	2014
Active fact-checking sites (tracking politicians' campaign promises)	64 (21)	44
Percentage of sites that use rating systems such as meters or labels	80	70
Sites that are affiliated with news organizations	63%	

http://reporterslab.org/snapshot-of-fact-checking-around-the-world-july-2015/

FACTCHECK.ORG

OpenSecrets.org
Center for Responsive Politics

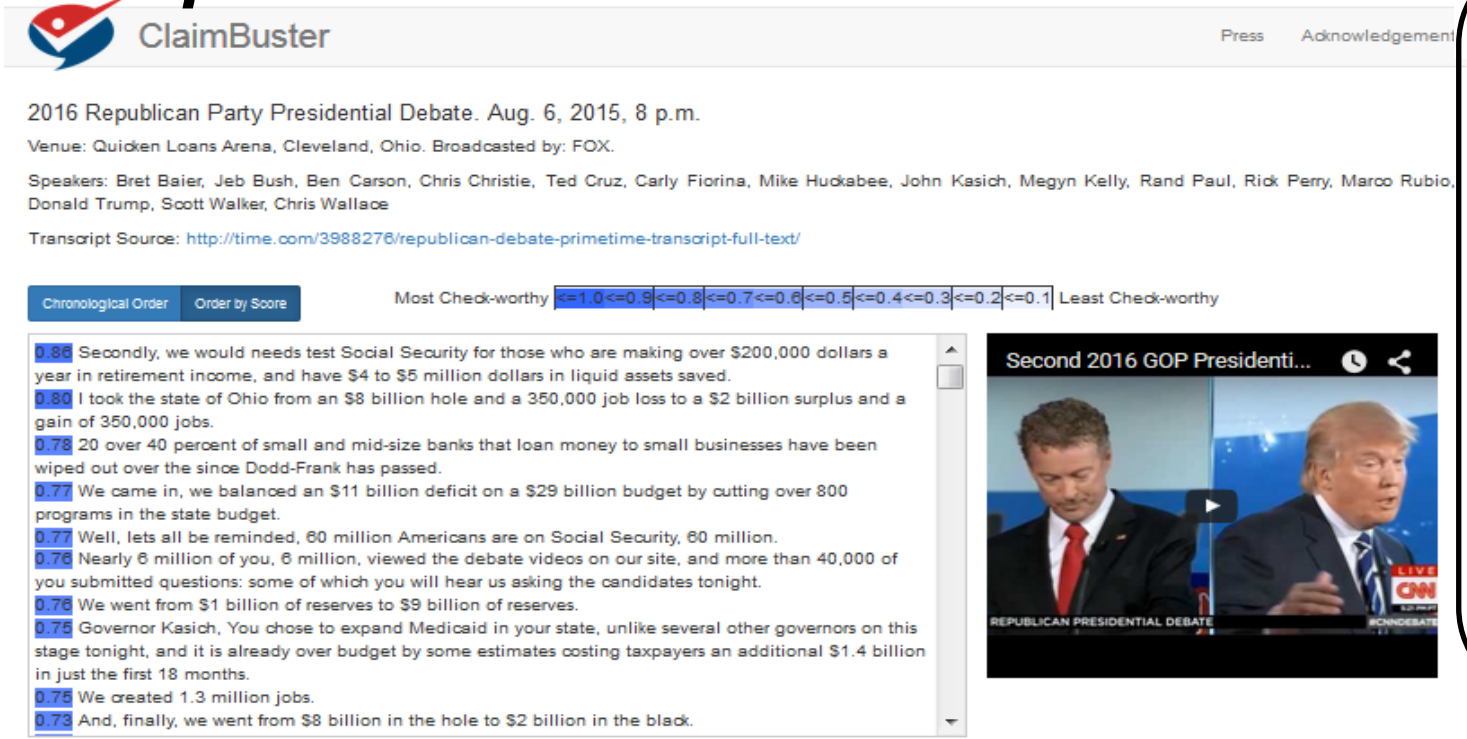
PPRuNe
Professional Pilots
Rumour Network

TruthOrFiction.com

UYCheck.com
¿nos dicen la verdad?

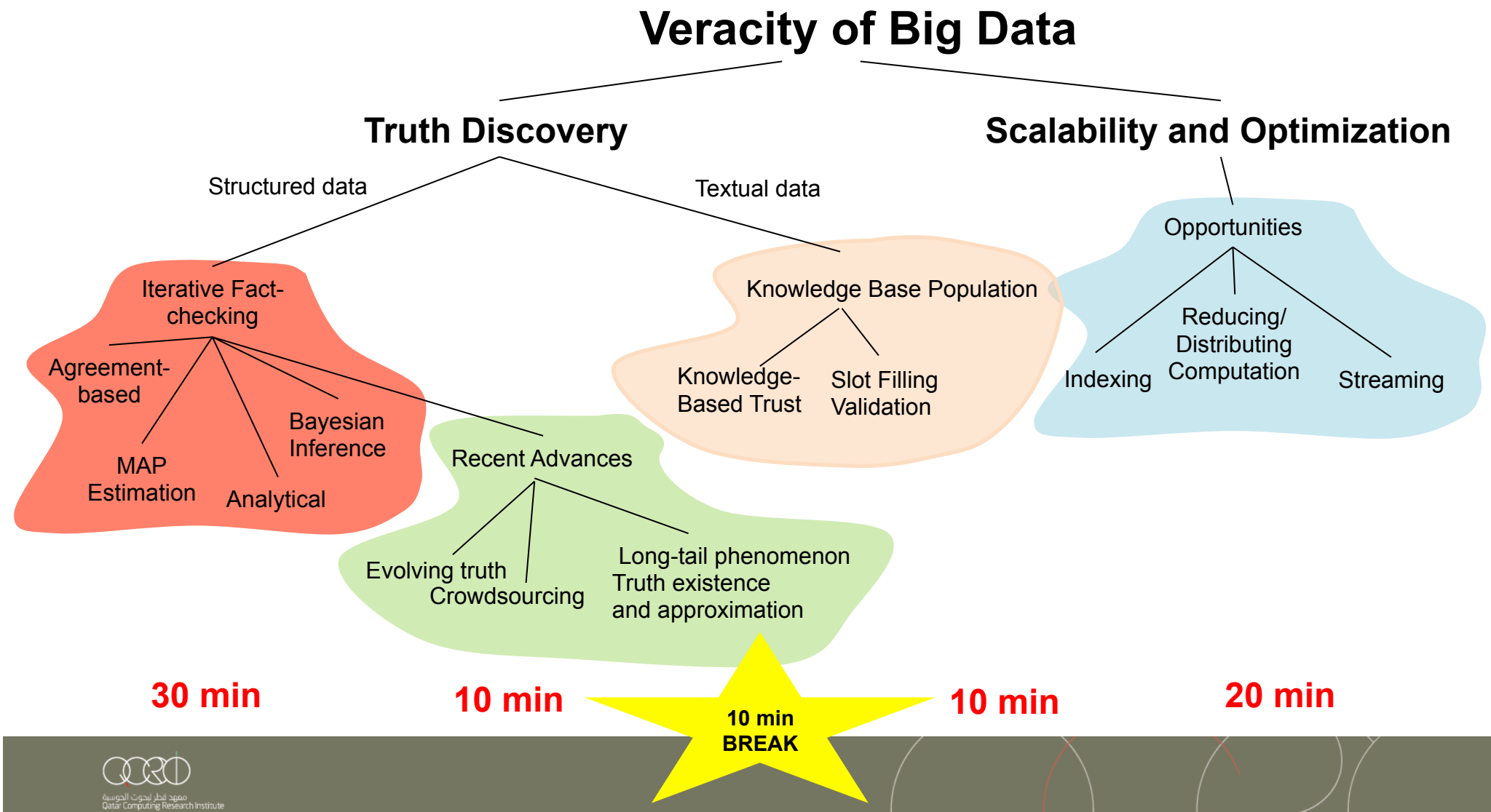
Scaling Fact-Checking

Computational Journalism



S. Cohen, J. T. Hamilton, and F. Turner. Computational journalism. CACM, 54(10):66–71, Oct. 2011.
N. Hassan, C. Li, and M. Tremayne. Detecting check-worthy factual claims in presidential debates. In CIKM, 2015.
N.Hassan, B. Adair, J. T. Hamilton, C. Li, M. Tremayne, J. Yang, C. Yu , The Quest to Automate Fact-Checking, C+J Symposium 2015
http://towknight.org/research/thinking/scaling-fact-checking/ http://blog.newstrust.net/2010/08/truthsquad-results.html

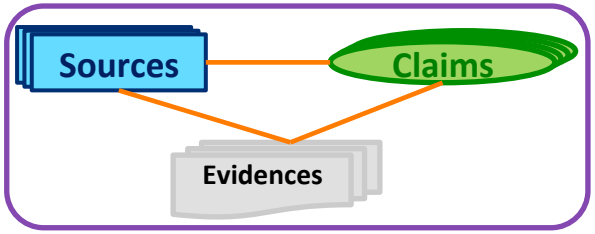
Tutorial Organization



Outline

1. Motivation
2. Truth Discovery from Structured Data
3. Truth Discovery from Extracted Information
4. Opportunities for Scalability Improvement
5. Conclusions

Terminology



Truth Discovery Method: INPUT

Claims (s_i, d_j, v_k)

OUTPUT

Ground Truth

d_1	*USA.CurrentPresident*		
v_1	*Obama*	false	true
v_2	*Clinton*	true	false
d_2	*Russia.CurrentPresident*		
v_3	*Putin*	true	true
v_4	*Medvedev*	false	false
v_5	*Yeltsin*	false	false
d_3	*France.CurrentPresident*		
v_6	*Hollande*	false	true
v_7	*Sarkozy*	true	false

s_1 s_2 s_3

$C(v_k) \forall k$ Confidence of the values

$T(s_i) \forall i$ Trustworthiness of the sources

s_i Source

d_j Data item

v_k Value

Mutual exclusive set

true claim Fact

false claim Allegation

Outline

1. Motivation
2. Truth Discovery from Structured Data
   - Agreement-based Methods
   - MAP Estimation-based Methods
   - Bayesian Methods
   - Analytical Methods

Agreement-Based Methods

Source Reputation Models

Source-Claim Iterative Models

Agreement-Based Methods

Source Reputation Models

Based on Web Link Analysis

Compute the importance of a source in the Web graph based on the probability of landing on the source node by a random surfer

Hubs and Authorities (HITS)	[Kleinberg, 1999]
PageRank	[Brin and Page, 1998]
SourceRank	[Balakrishnan, Kambhampati, 2009]

Trust Metrics: See R. Levien, Attack resistant trust metrics, PhD Thesis UC Berkeley LA, 2004

Hubs and Authorities (HITS)

Agreement

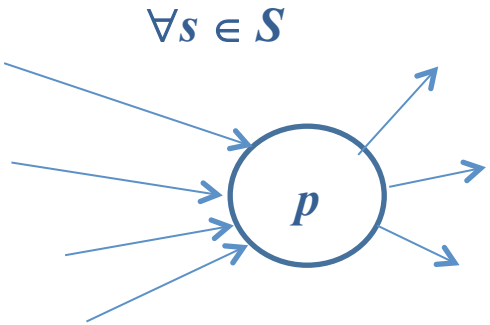
Source Reputation

- Identify Hub and Authority pages
- Each source p in S has two scores (at iteration *i*)
  - Hub score: Based on "outlinks", links that point to other sources
  - Authority score: Based on "inlinks", links from other sources

$$Hub^0(s) = 1$$

$$Hub^i(p) = \frac{1}{Z_h} \sum_{s \in S; p \to s} Auth^i(s)$$

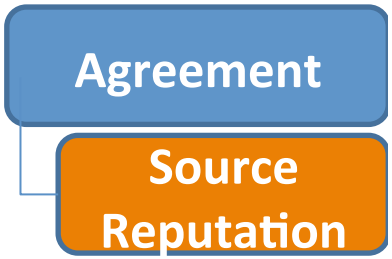
$$Auth^i(p) = \frac{1}{Z_a} \sum_{s \in S; s \to p} Hub^{i-1}(s)$$



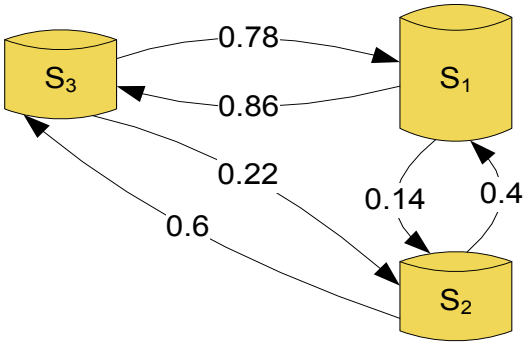
Z_a and Z_h are normalizers (L_2 norm of the score vectors)

J. M. Kleinberg. Authoritative sources in a hyperlinked environment. Journal of the ACM, 46(5):604–632, 1999.

SourceRank



- Agreement graph: Markov chain with edges as the transition probabilities between the sources
- Source reputation is computed by a Markov random walk

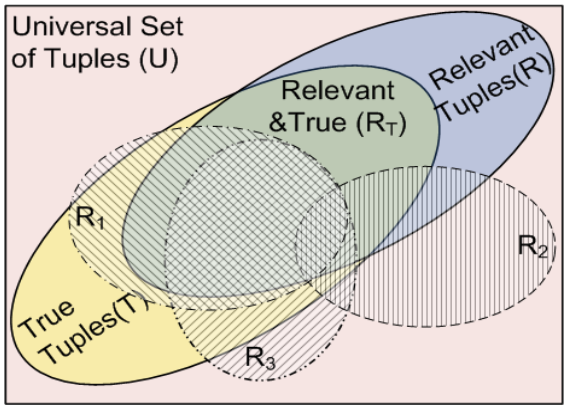


Probability of agreement of two independent false tuples

$$P_a(f_1, f_2) = \frac{1}{|U|}$$

Probability of agreement of two independent true tuples

$$P_a(r_1, r_2) = \frac{1}{|R_T|}$$



$$|U| >> |R_T| \Rightarrow P_a(r_1, r_2) >> P_a(f_1, f_2)$$

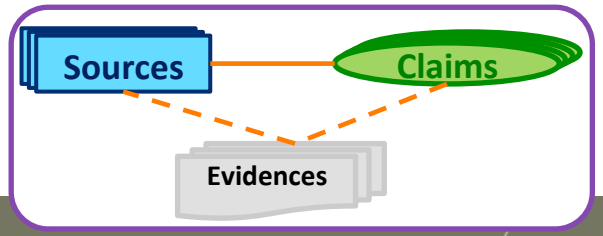
R. Balakrishnan, S. Kambhampati, SourceRank: Relevance and Trust Assessment for DeepWeb Sources Based on InterSource Agreement, In Proc. WWW 2009.

Agreement-Based Methods

Source Reputation Models

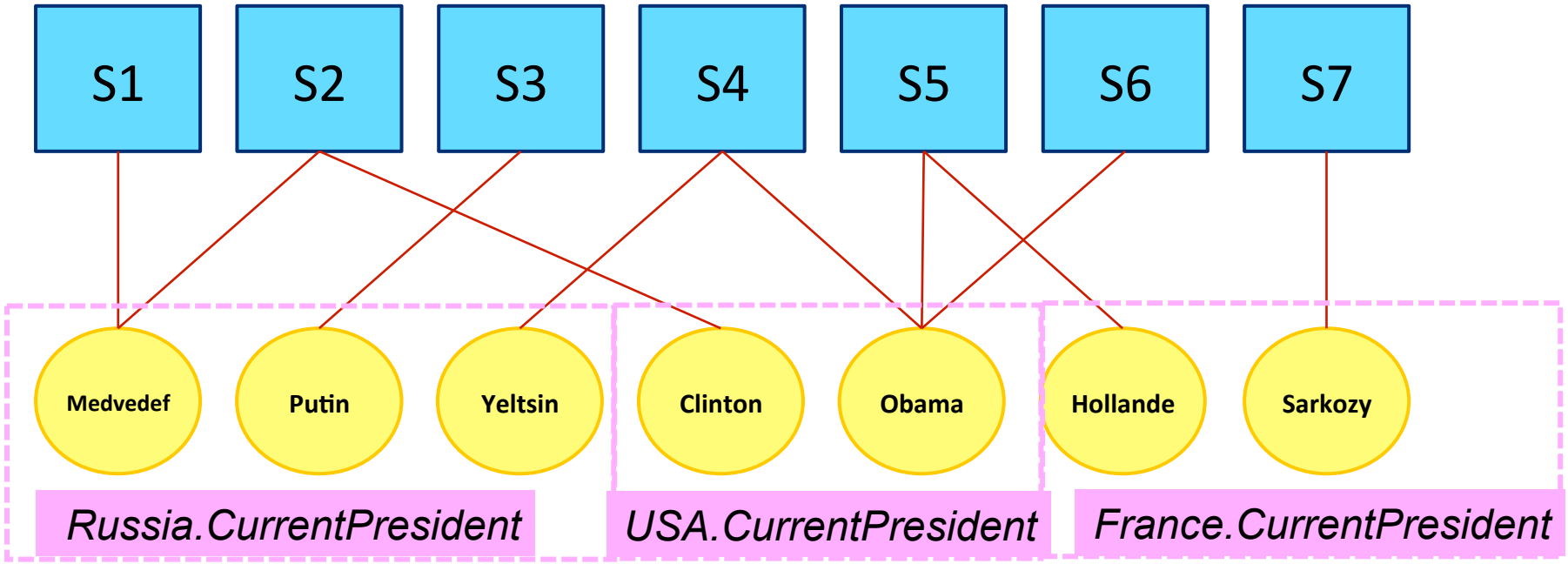
Only rely on source credibility is not enough

Source-Claim Iterative Models



Example

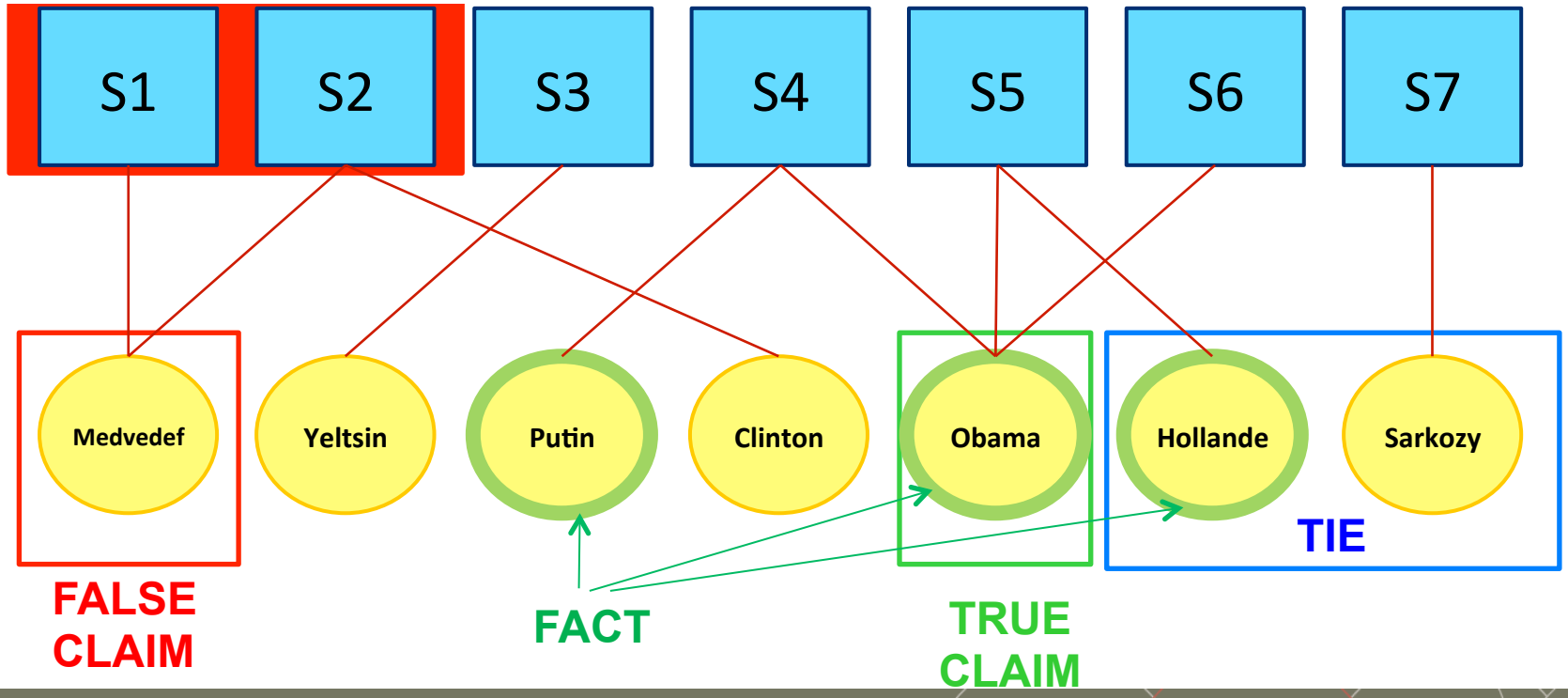
Seven sources disagree on the current president of Russia, Usa, and France
Can we discover the true values?



Solution: Majority Voting

Seven sources disagree on the current president of Russia, USA, and France
Can we discover the true values?

Majority can be wrong!
What if these sources are not independent?



Majority Voting Accuracy : 1.5 out of 3 correct

Limit of Majority Voting Accuracy

Condorcet Jury Theorem (1785)

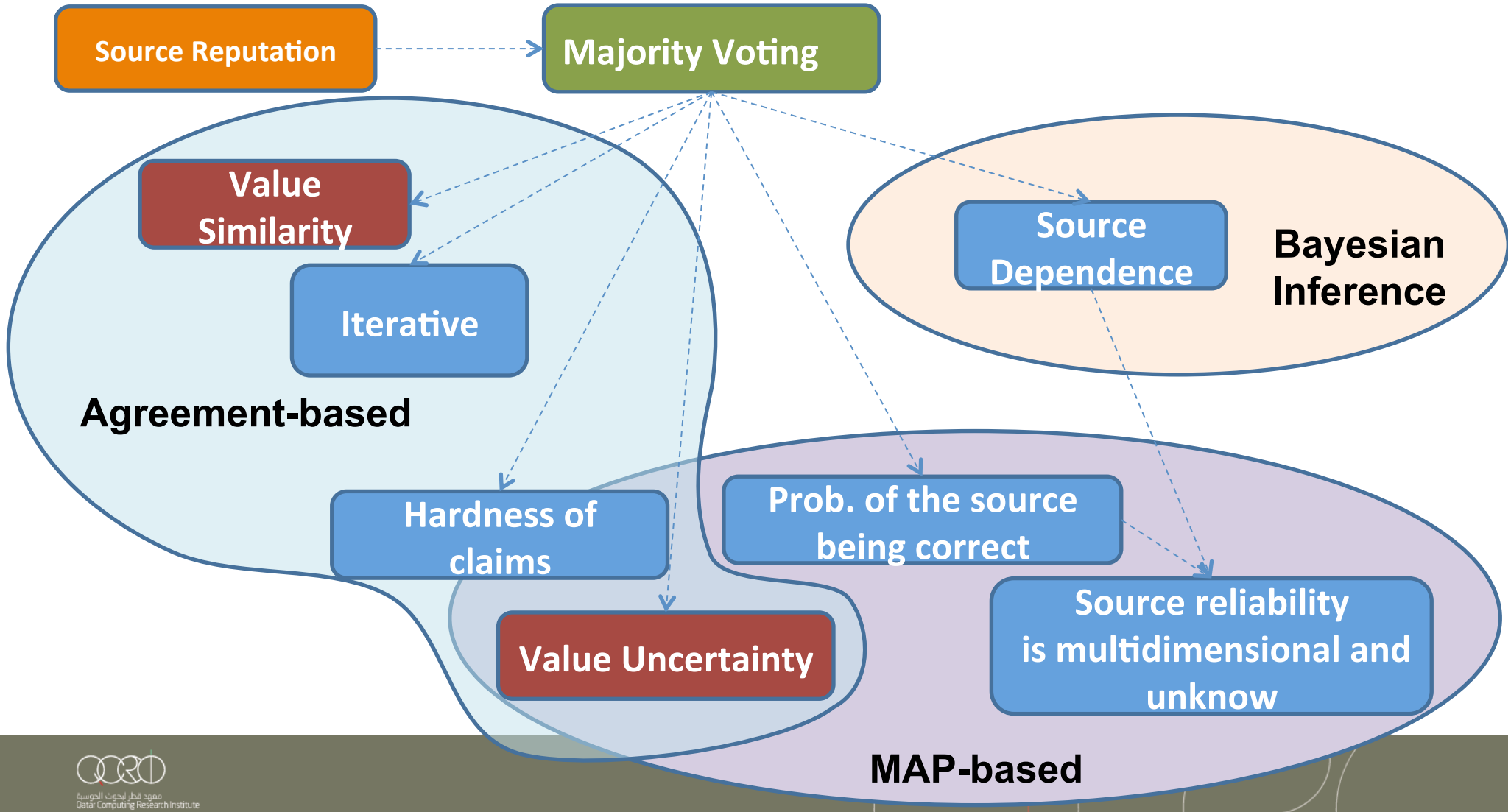
Originally written to provide theoritical basis of democracy

The majority vote will give an accurate value if at least $\lfloor S/2 + 1 \rfloor$ independent sources give correct claims.
If each voter has a probability p of being correct, then the probability of the majority of voters being correct P_{MV} is

$$P_{MV} = \sum_{m=\lfloor S/2+1 \rfloor}^{S} \binom{S}{m} p^m (1-p)^{S-m}$$

- If $p > 0.5$, then P_{MV} is monotonically increasing, $P_{MV} \to 1$ as $S \to \infty$
- If $p < 0.5$, then P_{MV} is decreasing and $P_{MV} \to 0$ as $S \to \infty$
- If $p = 0.5$, then $P_{MV} = 0.5$ for any S

Roadmap of Modeling Assumptions

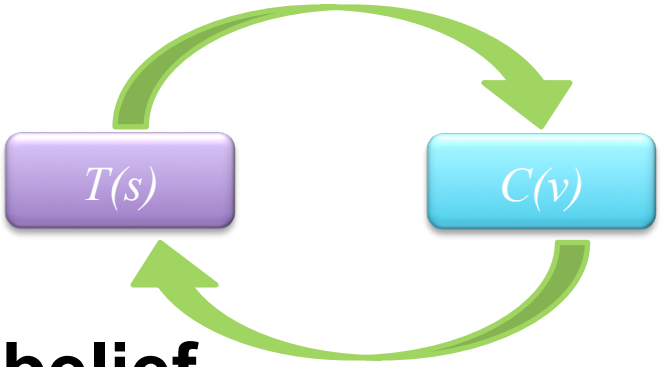


Agreement-Based Methods

Agreement

Source-Claim

Source-Claim Iterative Models



Based on iterative computation of source trustworthiness and claim belief

- Sums (adapted from HITS) *(1)*
- Average.Log, Investment, Pooled Investment *(1)*
- TruthFinder *(2)*
- Cosine, 2-Estimates, 3-Estimates *(3)*

(1) J. Pasternack and D. Roth. Knowing what to believe (when you already know something). In COLING, pages 877–885, 2010.

(2) X. Yin, J. Han, and P. S. Yu. Truth Discovery with Multiple Conflicting Information Providers on the Web. TKDE, 20(6):796–808, 2008.

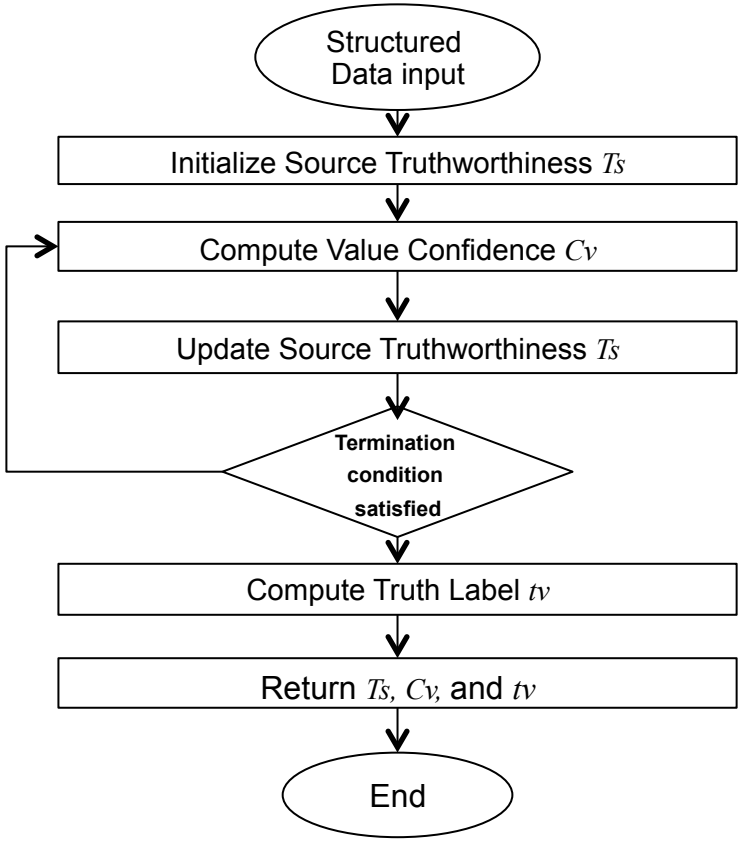
(3) A. Galland, S . Abiteboul, A. Marian, P. Senellart. Corroborating Information from Disagreeing Views. In Proc. of the ACM International Conference on Web Search and Data Mining (WSDM), pages 131–140, 2010.

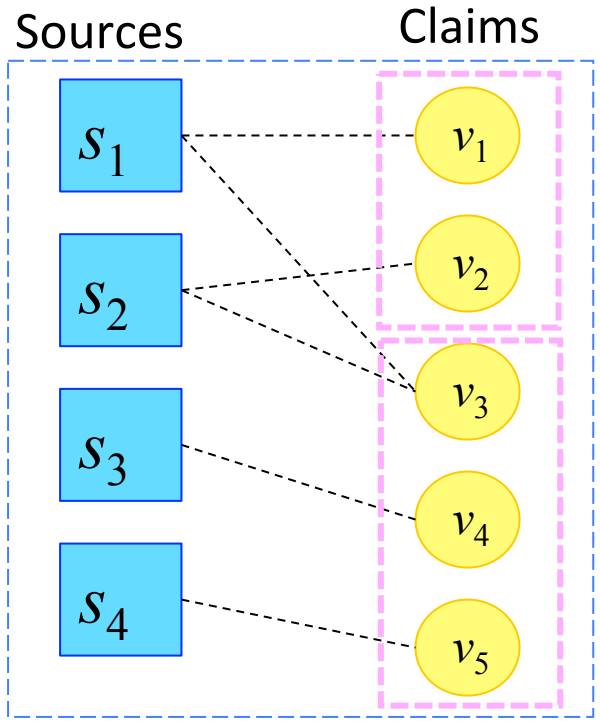
Basic Principle

Agreement

Source-Claim

Iterative and transitive voting algorithm





Bipartite graph

$T(s)$ $C(v)$

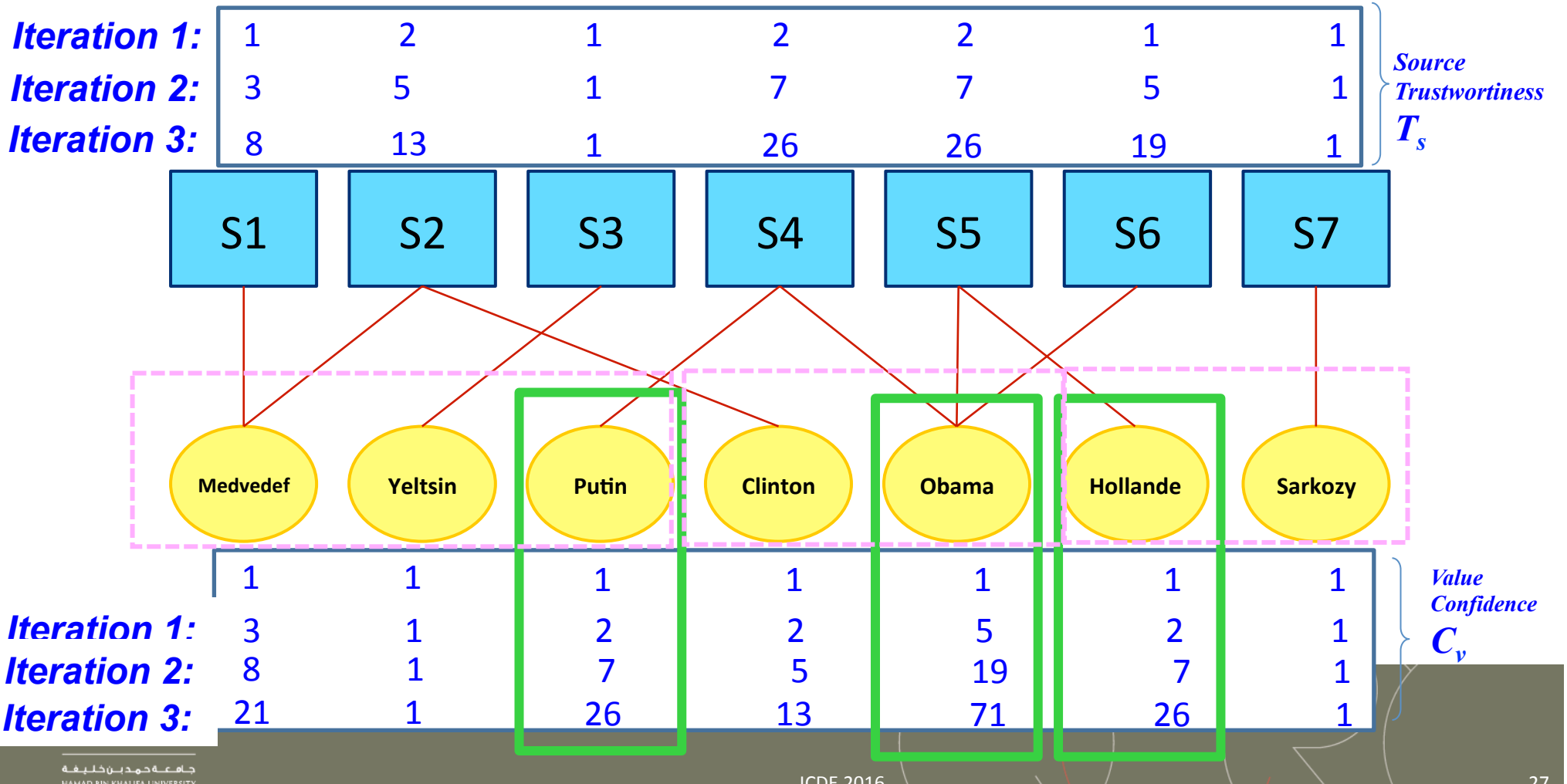
Example (cont'd)

Agreement

Source-Claim

Sums Fact-Finder: $T^i(s) = \sum_{v \in V_s} C^{i-1}(v)$ $\quad C^i(v) = \sum_{s \in S_v} T^i(s)$

Initialization: We believe in each claim equally



Iterative Methods

Value Uncertainty

Agreement

Source-Claim

- Sums (adapted from HITS)

$$T^i(s) = \sum_{v \in V_s} \omega(s,v) C^{i-1}(v)$$

$$C^i(v) = \sum_{s \in S_v} \omega(s,v) T^i(s)$$

uncertainty

- Average.Log

$$T^i(s) = \log\left(\sum_{v \in V_s} \omega(s,v)\right) \cdot \frac{\sum_{v \in V_s} \omega(s,v) C^{i-1}(v)}{\sum_{v \in V_s} \omega(s,v)}$$

- Generalized Investment

$$T^i(s) = \sum_{v \in V_s} \frac{\omega(s,v) C^{i-1}(v) T^{i-1}(s)}{\sum_{v \in V_s} \omega(s,v) \cdot \sum_{r \in S_v} \frac{\omega(r,v) T^{i-1}(r)}{\sum_{b \in V_r} \omega(r,b)}}$$

$$C^i(v) = G\left(\sum_{s \in S_v} \frac{\omega(s,v) T(s)}{\sum_{v \in V_s} \omega(s,v)}\right) \quad \text{with } G(x)=x^{1.2}$$

J. Pasternack and D. Roth. Knowing what to believe (when you already know something). In COLING, pages 877–885, 2010.

TruthFinder

Value Similarity

Agreement

Source-Claim

Initialization. $\forall s \in S : T_s \leftarrow 0.8$ ← We believe in each source equally (optimistic)

repeat

  for each $d \in D$

    do

      for each $v \in V_d$:

        do

$$\sigma_v \leftarrow -\sum_{s \in S_v} \ln(1 - T_s)$$ ← Probability to be true

$$\sigma_v^\star \leftarrow \sigma_v + \rho \sum_{v' \in V_d} \sigma_{v'} . sim(v, v')$$ ← Mutually supportive, similar values; Control parameter ρ

$$C_v \leftarrow \frac{1}{1+e^{-\gamma \sigma_v^\star}}$$ ← Confidence of each value; Dampening factor γ to compensate dependent similar values

  for each $s \in S$

    do $T_s \leftarrow \frac{1}{|V_s|} \sum_{v \in V_s} C_v$ ← Trustworthiness of each source

until $Convergence(T_S, \delta)$ ← Thresholded cosine similarity of Ts between two successive iterations (δ)

for each $d \in D$

  do $trueValue(d) \leftarrow \operatorname{argmax}_{v \in V_d}(C_v)$

X. Yin, J. Han, P. S. Yu. Truth Discovery with Multiple Conflicting Information Providers on the Web. TKDE, 20(6):796–808, 2008.

A Fine-grained Classification

1. Method Characteristics

- Initialization and parameter settings
- Repeatability
- Convergence and stopping criteria
- Complexity
- Scalability

Mono-valued: C1 (Source1,USA.CurrentPresident,Obama)
Multi-valued: C2 (Source1,Australia.PrimeMinitersList,
(Turnbull, Abott, Rudd, Gillard…))
Boolean: C3 (Source1,USA.CurrentPresident.Obama,Yes)

2. Input Data

- Type of data: categorical, string/text, continuous
- Mono- or multi-valued claims
- Similarity of claims
- Correlations between attributes or objects

3. Prior Knowledge and Assumptions

- Source Quality: Constant/evolving, non-/uniform across sources, homogeneous/ heterogeneous over data items
- Dependence of sources
- Hardness of certain claims

4. Output

- Single versus multiple true values per data item
- At least one or none true claim
- Enrichment with explanations and evidences

TruthFinder Signature

Agreement

Source-Claim

1. Method Characteristics

- ❑ Initialization and parameter settings — T_s, δ, γ, ρ
- ❑ Repeatability — Yes
- ❑ Convergence and stopping criteria — δ for Cosine similarity of T_s
- ❑ Complexity — $O(Iter.SV)$
- ❑ Scalability — Yes

2. Input Data

- ❑ Type of value — String, categorical, numeric
- ❑ Mono-/multi-valued claims — Mono- and Multi-valued claims
- ❑ Similarity of claims — Yes
- ❑ Correlations between attributes or objects — No

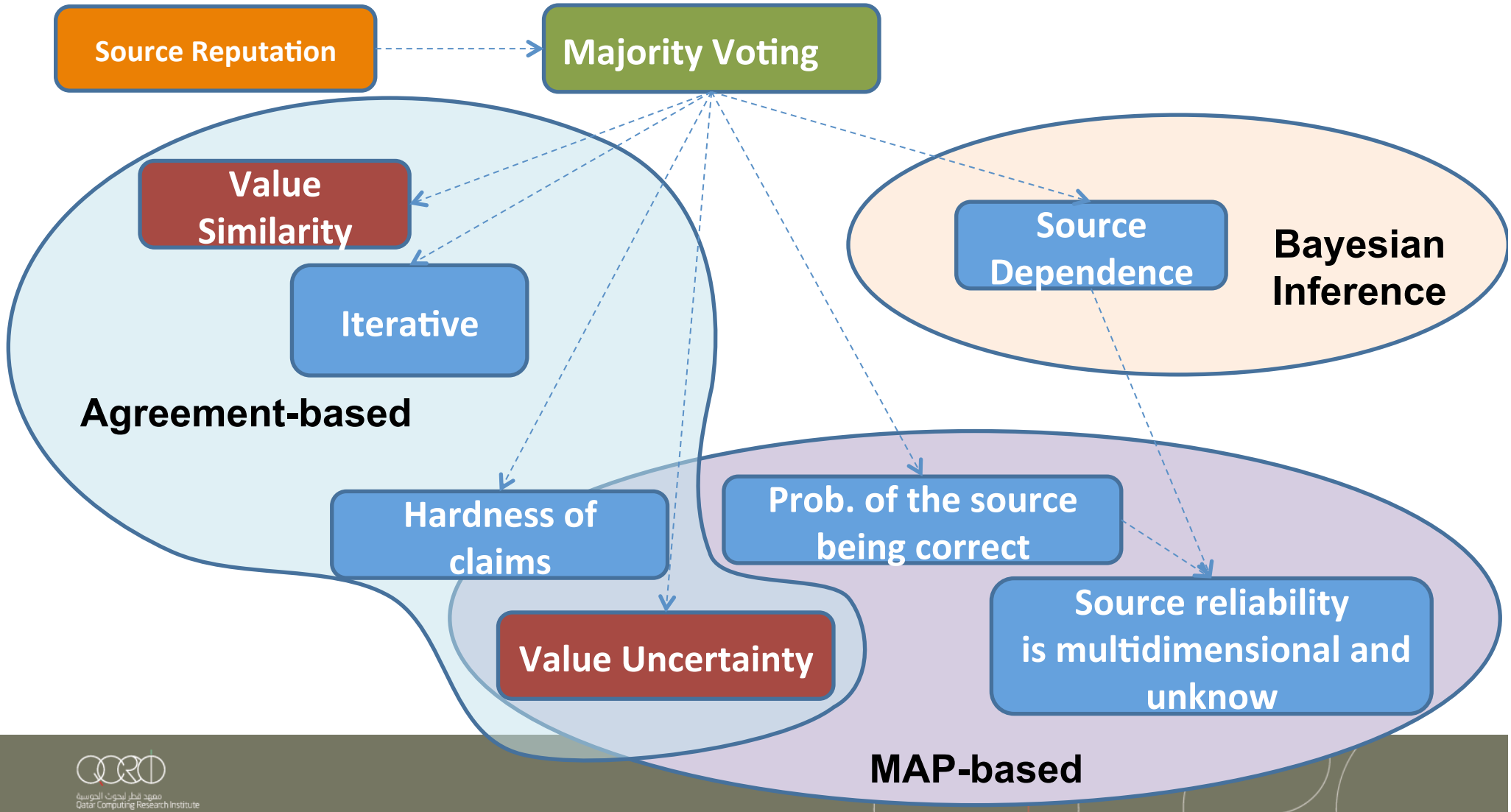
3. Prior Knowledge

- ❑ Source Quality — Constant, uniform, homogeneous
- ❑ Dependence of sources — Yes (dampening factor)
- ❑ Hardness of certain claims — No

4. Output

- ❑ Single/multiple truth per data item — Single true value per data item
- ❑ At least one or none true claim — At least one
- ❑ Enrichment (explanation/evidence) — No

Roadmap of Modeling Assumptions



Outline

1. Motivation
2. Truth Discovery from Structured Data
   - Agreement-based Methods
   - MAP-Estimation-based Methods
   - Bayesian Methods
   - Analytical Methods

Latent Credibility Analysis

MAP

EM

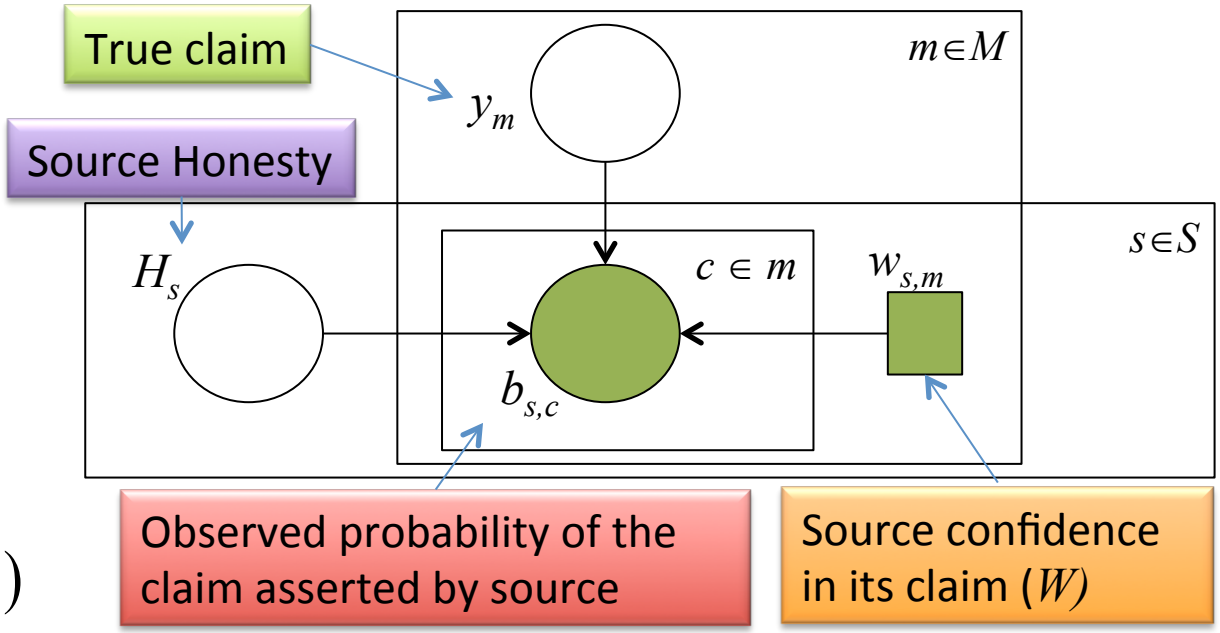
SimpleLCA, GuessLCA, MistakeLCA, LieLCA

Expectation-Maximization to find the maximum a posteriori (MAP) point estimate of the parameters

$$\theta^* = \arg\max_\theta P(X|\theta)P(\theta)$$

Then compute:

$$P(Y_U|X,Y_L,\theta^*) = \frac{P(Y_U,X,Y_L|\theta^*)}{\sum_{Y_U} P(Y_U,X,Y_L|\theta^*)}$$



Latent variables θ

- H_s: probability s makes honest, accurate claim
- D_m: probability s knows the true claims in m

J. Pasternack, D. Roth. Latent credibility analysis. In Proceedings of the 22nd International Conference on WWW 2013.

LCA Signature

MAP

EM

1. Method Characteristics

- ❑ Initialization and parameter settings
- ❑ Repeatability
- ❑ Convergence and stopping criteria
- ❑ Complexity
- ❑ Scalability

2. Input Data

- ❑ Type of value
- ❑ Mono-/multi-valued claims
- ❑ Similarity of claims
- ❑ Correlations between attributes or objects

3. Prior Knowledge

- ❑ Source Quality
- ❑ Dependence of sources
- ❑ Hardness of certain claims

4. Output

- ❑ Single/multiple truth per data item
- ❑ At least one or none true claim
- ❑ Enrichment (explanation/evidence)

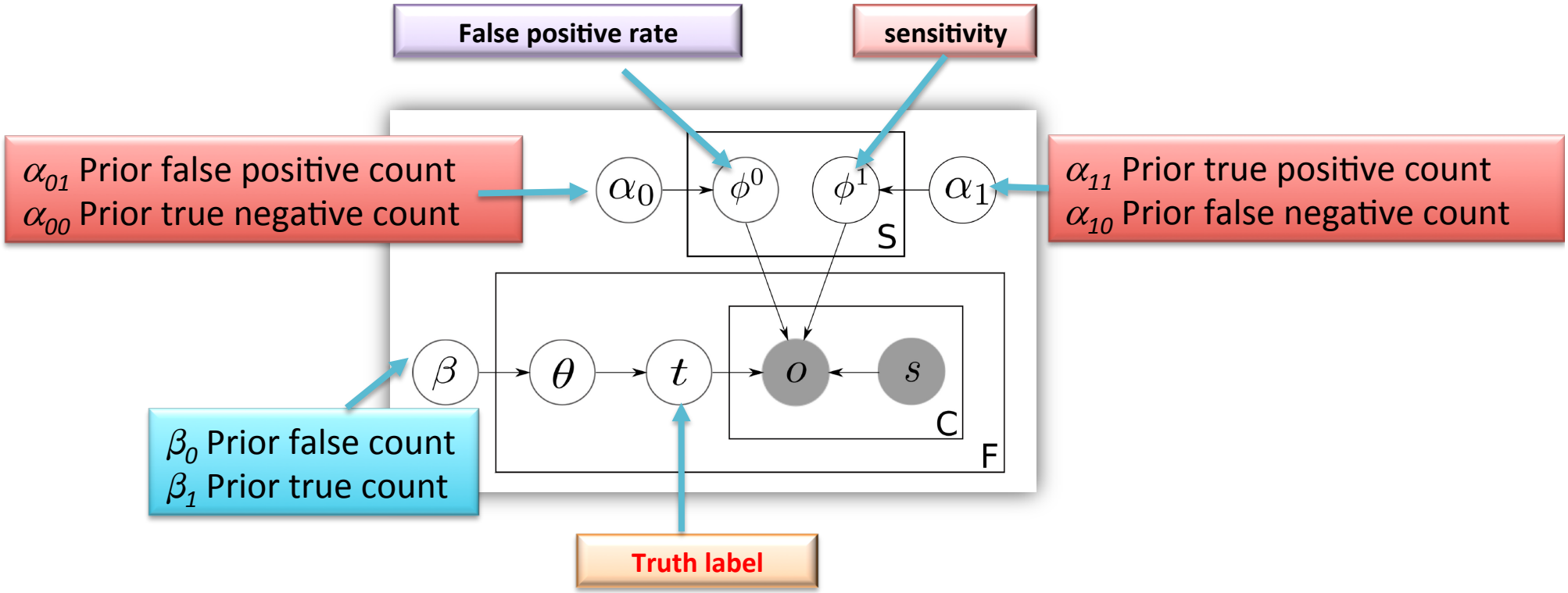
W, K, β_1 *(prior truth prob./claim)*
Yes
K **iterations**
$O(KSD)$
Yes
String, categorical
Multi-valued
Yes (as joint probability)
No
Constant, source- and entity-specific
No
Yes
Single true value per data item
At least one
No

Latent Truth Model (LTM)

MAP

Gibbs Sampling

Collapsed Gibbs sampling to get MAP estimate for t



B. Zhao, B. I. P. Rubinstein, J. Gemmell, and J. Han. A Bayesian approach to discovering truth from conflicting sources for data integration. Proceedings of the VLDB Endowment, 5(6):550-561, 2012.

LTM Signature

MAP

Gibbs Sampling

1. Method Characteristics

- ❑ Initialization and parameter settings
- ❑ Repeatability
- ❑ Convergence and stopping criteria
- ❑ Complexity
- ❑ Scalability

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3. Prior Knowledge

- ❑ Source Quality
- ❑ Dependence of sources
- ❑ Hardness of certain claims

4. Output

- ❑ Single/multiple truth per data item
- ❑ At least one or none true claim
- ❑ Enrichment (explanation/evidence)

$(T_s, \mathbf{K}, Burn\text{-}in, Thin, \alpha_{00},\beta_{00}, \alpha_{01},\beta_{01}, \alpha_{10},\beta_{10}, \alpha_{11},\beta_{11})$
No (Gibbs sampling)
***K* iterations**
$O(KSV)$
Yes
String, categorical
Mono-valued (multiple claims/per source)
No
No
Incremental, source-specific, homog./entity
No
No
Multiple true values per data item
At least one
No

Outline

1. Motivation
2. Truth Discovery from Structured Data
   - Agreement-based Methods
   - MAP Estimation-based Methods
   - Bayesian Methods
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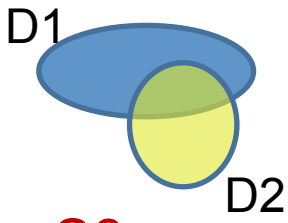
Bayesian

Source Dependence



- Sharing the same errors is unlikely if sources are independent
- Accuracy differences give the copying direction

  Acc(D1 ∩ D2)-Acc(D1-D2) > Acc(D1 ∩ D2)-Acc(D2-D1)⇒ S1→S2

Source Accuracy

$$Acc(S) = \underset{v \in V_S}{Avg}\left(P(V_s)\right)$$

Value Probability

$$\Pr(v \text{ true} \mid \Phi) = \frac{e^{C(v)}}{\sum_{v_0 \in V_d} e^{C(v_0)}}$$

Source Vote Count

$$A'(S) = \ln\left(\frac{n_f Acc(S)}{1 - Acc(S)}\right)$$

Consider value similarity

$$C''(v) = C(v) + \rho \sum_{v' \neq v} C(v') \cdot sim(v, v')$$

ValueVote Count

$$C(v) = \sum_{S \in S_v} A'(S).I(S)$$

Consider dependence

I(S) Prob. of independently providing value *v*

X. L. Dong, L. Berti-Equille, D. Srivastava. Integrating conflicting data: the role of source dependence. In VLDB, 2009

X. L. Dong, L. Berti-Equille, Y. Hu, D. Srivastava. Global detection of complex copying relationships between sources. In VLDB, 2010

Depen Signature

Bayesian

1. Method Characteristics	
❑ Initialization and parameter settings	T_s, n_f (nb false value), ε (error rate), α (a priori prob.), c (copying prob.), δ
❑ Repeatability	Yes
❑ Convergence and stopping criteria	δ
❑ Complexity	$O(Iter.S^2V^2)$
❑ Scalability	**No**(1)
2. Input Data	
❑ Type of value	String, categorical, numerical
❑ Mono-/multi-valued claims	Multi-valued
❑ Similarity of claims	Yes
❑ Correlations between attributes or objects	**No**(2)
3. Prior Knowledge	
❑ Source Quality	Contant, uniform across sources , homogeneous across objects
❑ Dependence of sources	Yes
❑ Hardness of certain claims	No
4. Output	
❑ Single/multiple truth per data item	Single true values per data item
❑ At least one or none true claim	At least one
❑ Enrichment (explanation/evidence)	No

(1) X. Li, Xin Luna Dong, Kenneth Lyons, Weiyi Meng, and Divesh Srivastava. Scaling up Copy Detection. In ICDE, 2015.
(2) R. Pochampally, A. Das Sarma, X. L. Dong, A. Meliou, D. Srivastava. Fusing data with correlations. In SIGMOD, 2014.

Outline

1. Motivation
2. Truth Discovery from Structured Data
   - Agreement-based Methods
   - MAP Estimation-based Methods
   - Bayesian Methods
   - Analytical Methods

Analytical Solutions

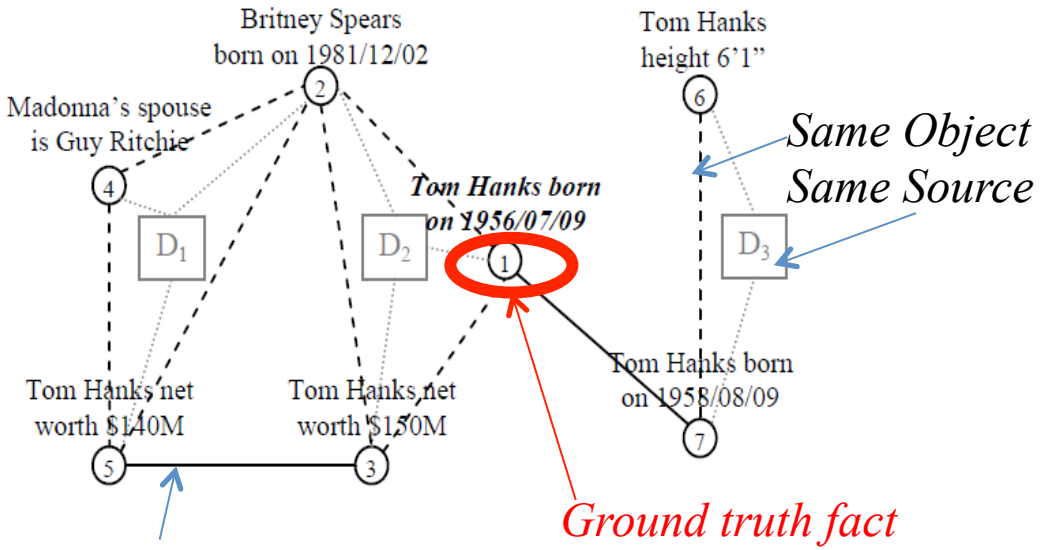
Matrix Diagonalization

Semi-Supervised Truth Discovery (SSTF)

Minimize loss funtion

$$E(\mathrm{C}) = \frac{1}{2}\sum_{i,j}\left|w_{ij}\right|(c_i - s_{ij}c_j)^2$$

$$\text{where } s_{ij} = \begin{cases} 1 \text{ if } w_{ij} \geq 0 & \text{Supportive claims} \\ -1 \text{ if } w_{ij} < 0 & \text{Claims in conflict} \end{cases}$$



w_{ij} relationship between confidence scores

$$\left.\frac{\partial E}{\partial c}\right|_{c=c^*} = 0 \Leftrightarrow (D_{uu} - W_{uu})C_u - W_{ul}C_l = 0$$

Weight Matrices

Matrix of unlabeled claim confidence scores

X. Yin, W. Tan. Semi-supervised Truth Discovery. In Proceedings of the 20th international conference WWW '11, 2011.

Related Work: L. Ge, J. Gao, X. Yuy, W. Fanz and A. Zhang, Estimating Local Information Trustworthiness via Multi-Source Joint Matrix Factorization, Proc. of ICDM 2012

Recap of the methods

	Truthfinder	MLE	LCA	LTM	Depen+	SSTF
Data Type	String, Categorical Numerical	**Boolean**	String, Categorical	String, Categorical	String, Categorical Numerical	String, Categorical Numerical
Mono/multi-valued claim	**Mono & Multi**	Mono	**Multi**	Mono	**Mono & Multi**	Mono
Similarity	Yes	No	Yes	No	Yes	Yes
Correlations	No	No	No	No	Yes+	Yes
Source Quality	Constant, uniform	Constant, Source-specific	Constant, **Source- and data item specific**	**Incremental, source-specific**	Constant, uniform	Constant, uniform
Source Dependence	No	No	No	No	Yes	No
Claim hardness	No	No	Yes	No	No	No
Single/multi-truth	Single	Single	Single	**Multi-truth**	Single	Single
Trainable	No	No	No	No	No	Yes

D. A. Waguih and L. Berti-Equille. Truth discovery algorithms: An experimental evaluation. arXiv preprint arXiv:1409.6428, 2014.

Limits of Modeling Assumptions

Sources

(*)**Relaxed in**

- Sources are **self-consistent**: a source does not claim conflicting claims
- The probability a source asserts a claim is independent of the truth of the claim
- Sources make their claims **independently**(1)
- A source has **uniform confidence** to all the claims it expresses(2)
- **Trust the majority**
- **Optimistic scenario :** $S_{True} >> S_{False}$

(1)[Dong et al, VLDB'09]

(2)[Pasternack Roth, WWW'13]

Claims

- Only claims with a **direct source attribution** are considered
  e.g., "S 1 claims that S2 claims A" is not condidered
- Claims are assumed to be **positive** and usually certain:
  e.g., "S claims that A is false", "S does not claim A is true" are not considered
  or "S claims that A is true with 15% uncertainty" (2)
- Claims claimed by only one source are true
- Correlations between claims/entity are not considered(3)
- One single true value exists(4)

(3)[Pochampally et al. SIGMOD'14]

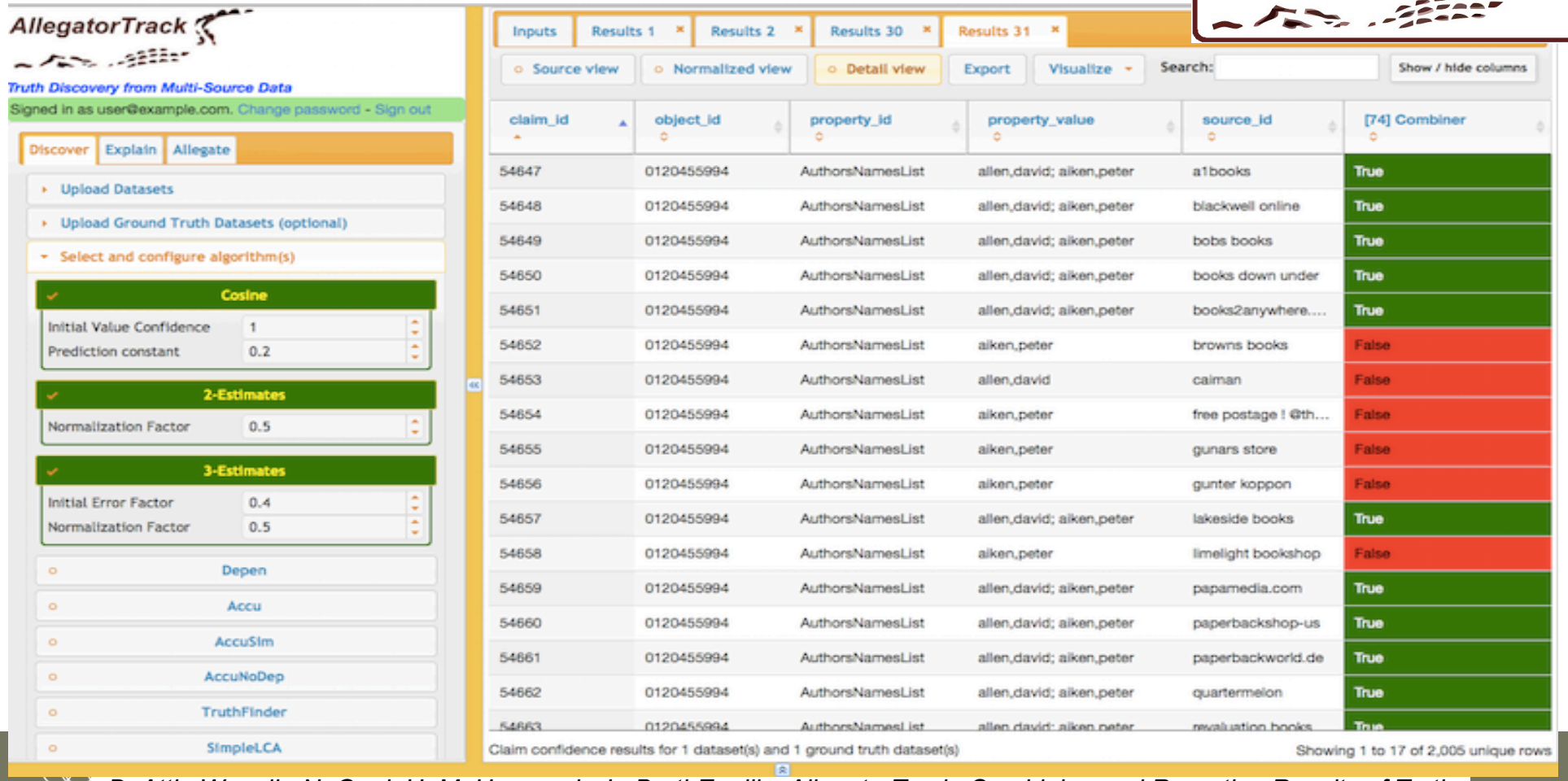
(4)[Zhi et al., KDD'15]

Further Testing

API

AllegatorTrack

http://daqcri.github.io/dafna/

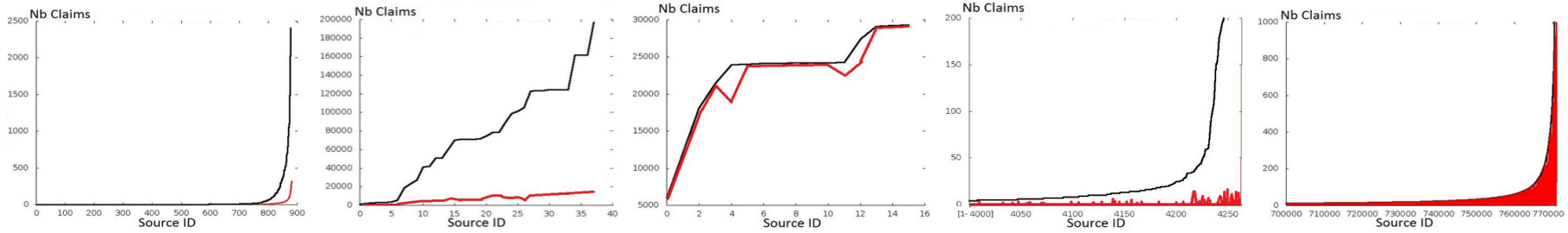


D. Attia Waguih, N. Goel, H. M. Hammady, L. Berti-Equille. AllegatorTrack: Combining and Reporting Results of Truth Discovery from Multi-source Data. In ICDE 2015.

Further Testing

http://daqcri.github.io/dafna/

- Datasets and Synthetic Data Generator



Ground Truth (GT)	R (Random) U.25; U.75 (Uniform) FP (Fully Pessimistic) FO (Fully Optimistic) 80-P (80-Pessimistic) 80-O (80-Optimistic) E (Exponential)
Conflict Distribution (Conf)	U (Uniform) E (Exponential)
Number of Distinct Values	2...20

Experimental Results (1/2)

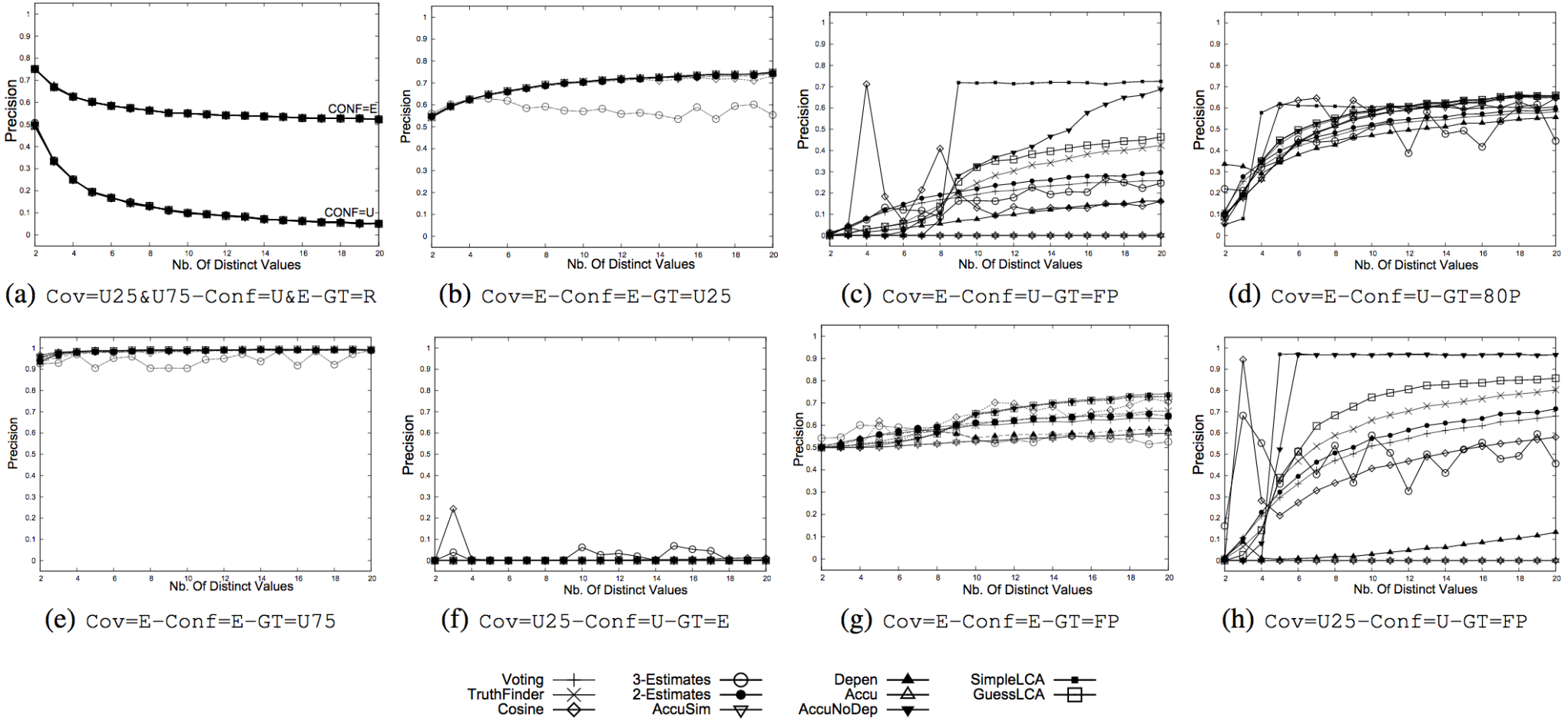


Figure 1: Precision Average for Various Truth Discovery Scenarios with $|S| = 50$ and $|D| = 1,000$

D. Attia Waguih, N. Goel, H. M. Hammady, L. Berti-Equille. AllegatorTrack: Combining and Reporting Results of Truth Discovery from Multi-source Data. In ICDE 2015.

Experimental Results (2/2)

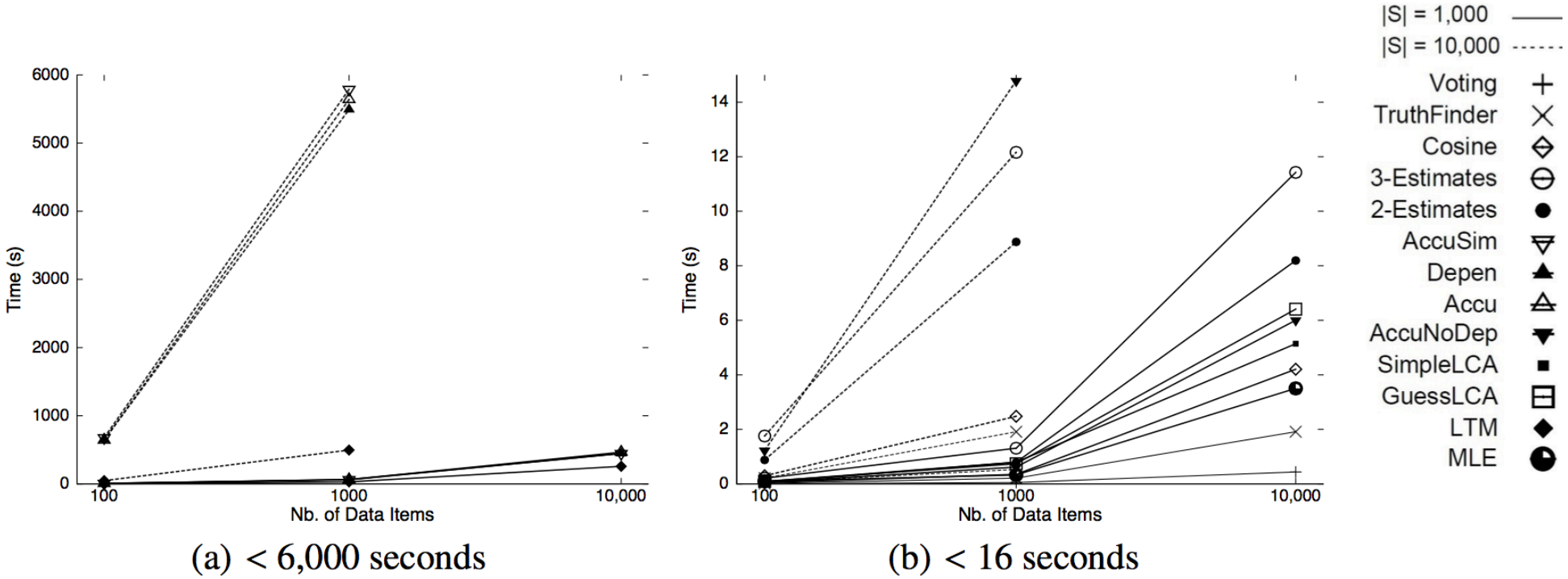


Figure 2: Scalability Experiments: Runtime for scaling-up the numbers of sources and data items

D. Attia Waguih, N. Goel, H. M. Hammady, L. Berti-Equille. AllegatorTrack: Combining and Reporting Results of Truth Discovery from Multi-source Data. In ICDE 2015.

Outline

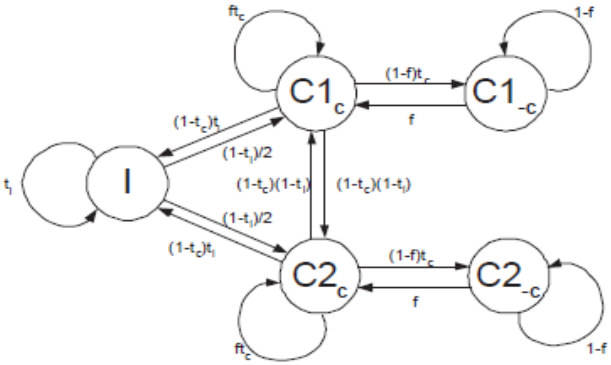
1. Motivation
2. Truth Discovery from Structured Data

Recent Advances

- Evolving Truth
- Truth Finding from Crowdsourced Data
- Long-Tail Phenomenon
- Truth Existence and Approximation

Evolving Truth

- **Truth can evolve over time**
  - Lifespan of objects
  - Coverage, Exactness, Freshness of source
  - HMM model to detect lifespan and copying relationships



X. L. Dong, L. Berti-Equille, D. Srivastava. Truth discovery and copying detection in a dynamic world. In VLDB 2009.

- **Source quality changes over time**
  - MAP estimation of the source weights

Y. Li, Q. Li, J. Gao, L. Su, B. Zhao, W.Fan, J. Han. On the discovery of evolving truth. In KDD 2015.

- **New sources can be added**
  - Incremental voting over multiple trained classifiers
  - Concept drift

L. Jia, H. Wang, J. Li, H. Gao, Incremental Truth Discovery for Information from Multiple Sources. In WAIM 2013 workshop, LNCS 7901, p. 56-66, 2013

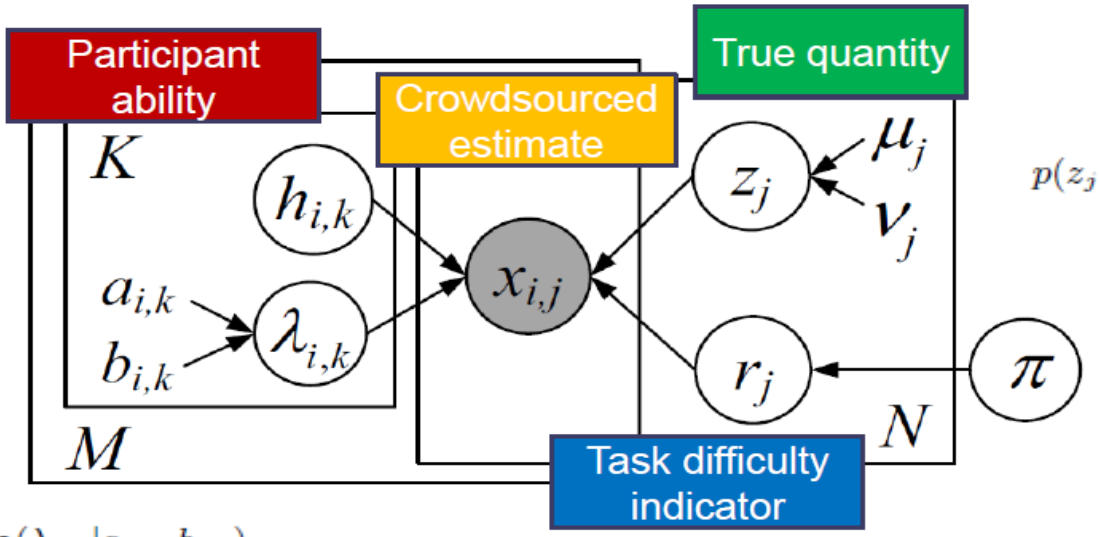
Truth discovery from crowdsourced data

Expectation Maximization

TBP (Truth Bias and Precision)

Likelihood of observing a crowdsourced estimate (given model parameters only) follows a mixture distribution

$$p(x_{i,j}|\boldsymbol{\pi}, z_j, h_{i,k}, \lambda_{i,k}) = \sum \pi_k \mathcal{N}(x_{i,j}|z_j + h_{i,k}, 1/\lambda_{i,k})$$



$$p(z_j|\mu_j, \nu_j) = \mathcal{N}(z_j|\mu_j, 1/\nu_j)$$

$$p(r_{j,k}|\pi) = \text{Mul}(\mathbf{r}_j|\pi)$$

$$p(\lambda_{i,k}|a_{i,k}, b_{i,k}) = \text{Gamma}(\lambda_{i,k}|a_{i,k}, b_{i,k})$$

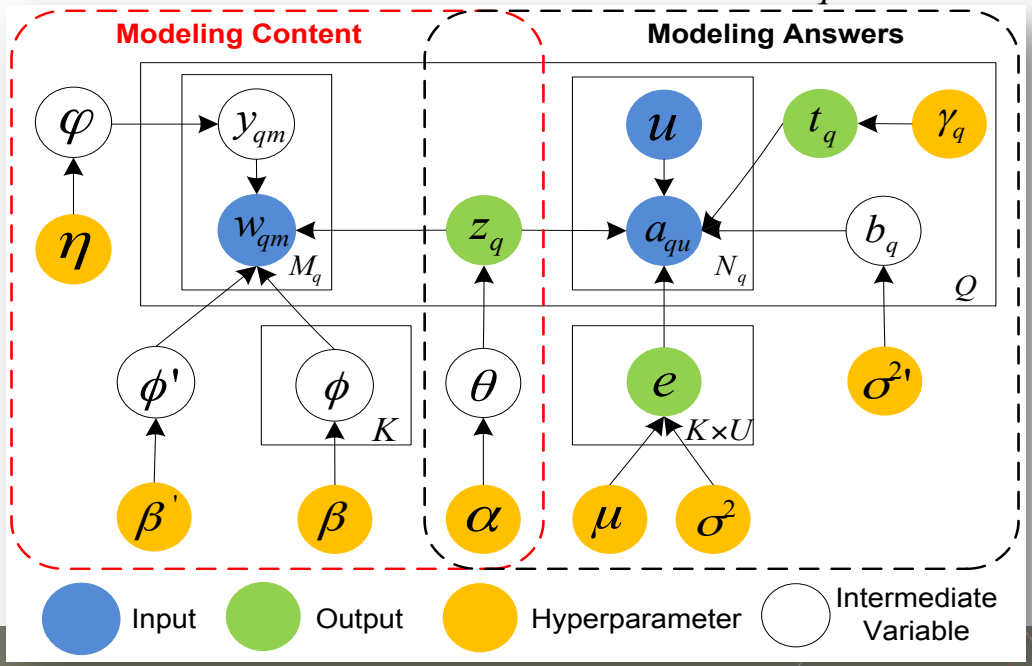
R. W. Ouyang, L. Kaplan, P. Martin, A. Toniolo, M. Srivastava, and T. J. Norman. Debiasing crowdsourced quantitative characteristics in local businesses and services. Proc. of IPSN ACM/IEEE, pp. 190-201, 2015.

Truth discovery from crowdsourced data

Optimization

Faitcrowd

- **Input:** Q questions, K topics, M_q words and N_q answers per question provided by U users, hyperparameters
- **Output**: User expertise ***e***, true answers t_q, question topic labels z_q



$$t_q \sim U(\gamma_q)$$

$$b_q \sim N(0, \sigma^{2'})$$

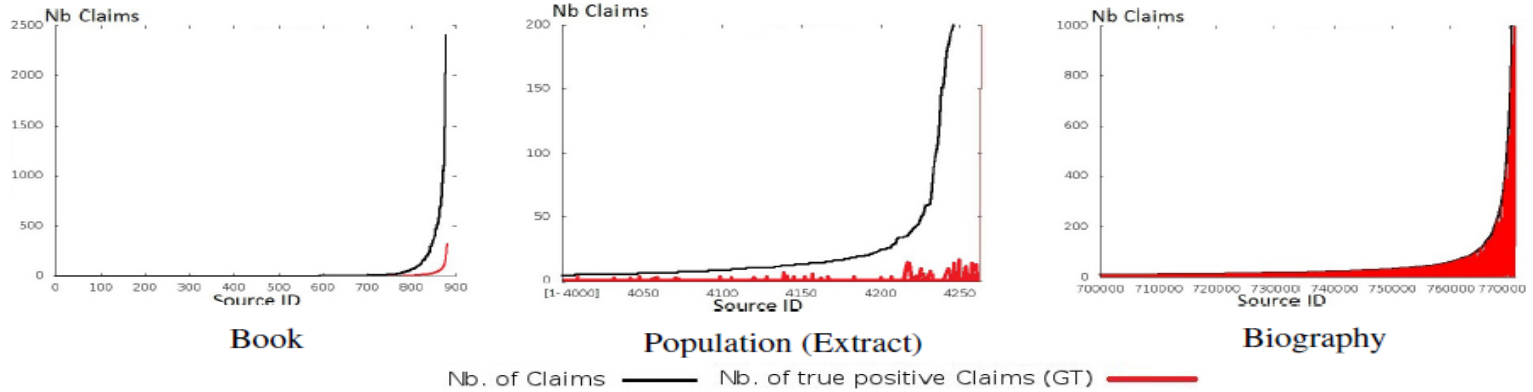
$$a_{qu}|t_q \sim logistic(e_{z_q u}, b_q)$$

$$e_{z_q u} \sim N(\mu, \sigma^2)$$

F. Ma, Y. Li, Q. Li, M. Qui, J. Gao, S. Zhi, L. Su, B. Zhao, H. Ji, and J. Han. Faitcrowd: Fine grained truth discovery for crowdsourced data aggregation. In Proc. of KDD 2015.

Long-Tail Phenomenon

Variance Minimization



CADT Method for Independent and Benevolent Sources

Goal : Minimize the Variance of Source Reliability $\varepsilon_s \propto N(0,\sigma_s^2)$ $\varepsilon_{combined} = \dfrac{\sum_{s\in S} w_s \varepsilon_s}{\sum_{s\in S} w_s}$

$$\min_{w_s} \sum_{s\in S} w_s^2 \sigma_s^2 \quad \text{s.t.} \sum_{s\in S} w_s = 1, w_s \geq 0, \forall s \in S$$

$$w_s \propto \frac{\chi^2_{(\alpha/2,N_s)}}{\sum_{n\in N_s} \left(x_n^s - x_n^{*(0)}\right)^2}$$

Reliability of source s

Number of claims by source s

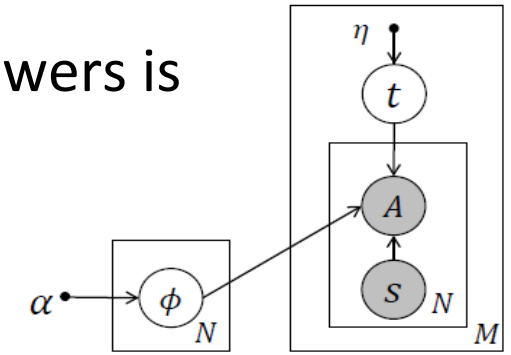
Chi-squared probability at (1-α) confidence interval

Initial value confidence for entity n

Q. Li, Y. Li, J. Gao, L. Su, B. Zhao, M.Demirbas, W. Fan, and J. Han. 2014. A confidence-aware approach for truth discovery on long-tail data. Proc. VLDB Endow. 8, 4 (December 2014), 425-436.

Recent contributions

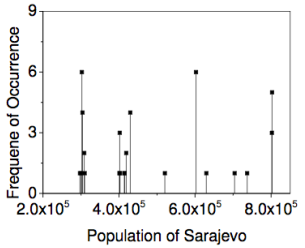
- **Modeling Truth Existence**
  - Problem of *No-truth* questions: none of the answers is true
  - EM-based algorithm similar to MLE
  - Silent rate, false and true spoken rates



S. Zhi, B. Zhao, W. Tong, J. Gao, D. Yu, H. Ji, J. Han. Modeling Truth Existence in Truth Discovery. In Proc. of KDD 2015

- **Multi-Truth Discovery**
  - Bayesian model with inter-value mutual exclusion, source/value grouping

X. Wang, X. Xu, X. Li. An Integrated Bayesian Approach for Effective Multi-Truth Discovery. In CIKM 2015



- **Approximate Truth Discovery**

X. Wang, Q. Z. Sheng, X. S. Fang, X. Xu, X. Li, L. Yao. Approximate Truth Discovery Via Problem Scale Reduction. In CIKM 2015

Outline

1. Motivation
2. Truth Discovery from Structured Data
3. Truth Discovery from Extracted Information
    - Knowledge-Based Trust
    - Slot Filling Validation

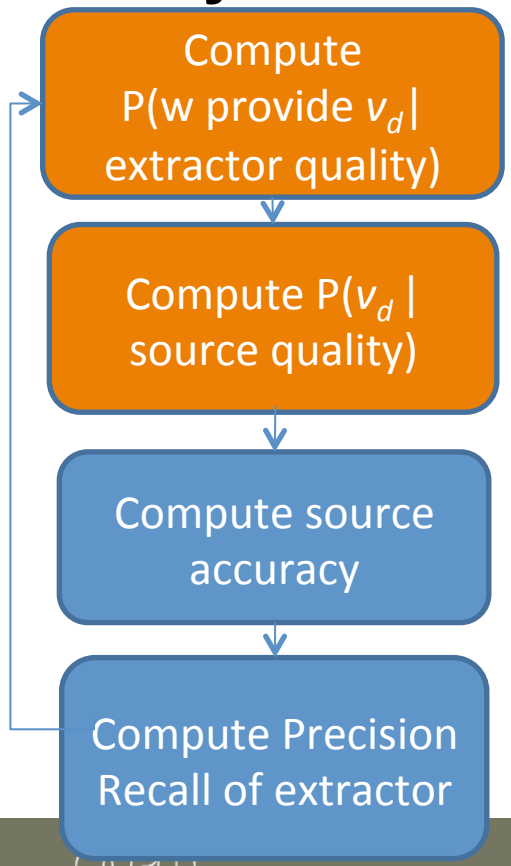
Knowledge-Based Trust

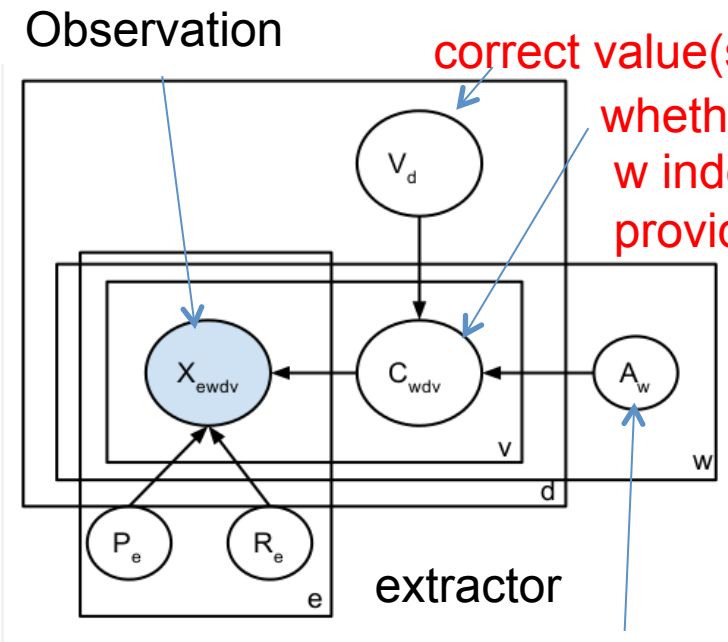
Bayesian

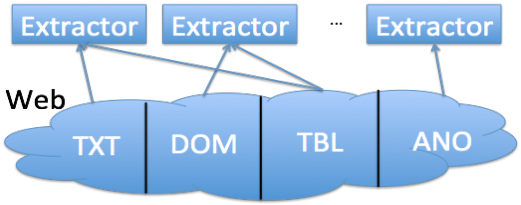
EM

Distinguish extractor errors from source errors

Multi-Layer Model based on EM







#Triples	3.0B (0.3B w. pr>=0.7)
#URLs	2.5B (28M Websites)
#Extractors	16

As of 2014

X. L. Dong, K. Murphy, E. Gabrilovich, G. Heitz, W. Horn, N. Lao, W. Zhang. Knowledge Vault: A Web-scale approach to probabilistic knowledge fusion, In VLDB 2015

Slot Filling Validation

Method **extending Co-HITS** [Deng *et al.* 2009] over **heterogeneous networks**

Credibility Propagation

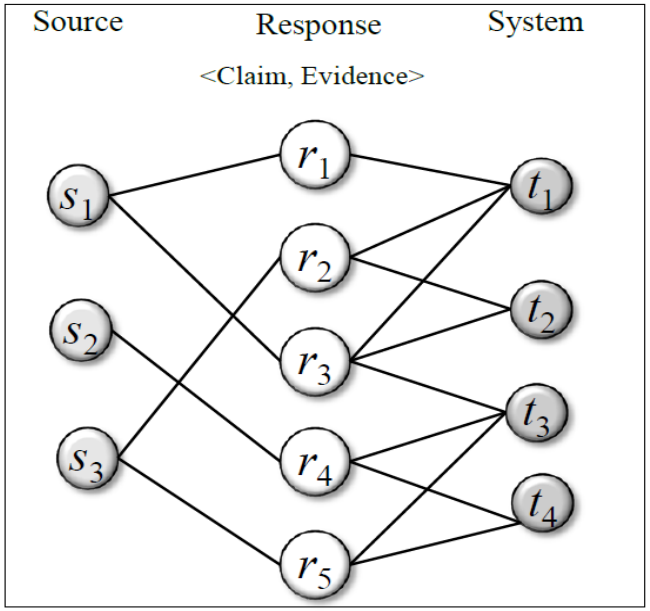
1. Initialize credibility scores c^0 for S to 1, for T with TextRank [Mihalcea 2004] and for R using linguistic indicators

2. Construct heterogeneous networks across R, S and T with transition prob.

$$p_{ij}^{rs} = \frac{w_{ij}^{rs}}{\sum_k w_{ik}^{rs}}$$

3. Compute:

$$\begin{cases} c(s_i) = (1-\lambda_{rs})c^0(s_i) + \lambda_{rs}\sum_{r_j \in R} p_{ji}^{rs} c(r_j) \\ c(t_k) = (1-\lambda_{rt})c^0(t_k) + \lambda_{rt}\sum_{r_j \in R} p_{jk}^{rt} c(r_j) \\ c(r_j) = (1-\lambda_{sr}-\lambda_{tr})c^0(r_j) \\ \quad + \lambda_{sr}\sum_{s_i \in S} p_{ij}^{sr} c(s_i) + \lambda_{tr}\sum_{t_k \in T} p_{kj}^{tr} c(t_k) \end{cases}$$



W^{sr} W^{rt} Weight matrices

D. Yu, H. Huang, T. Cassidy, H. Ji, C. Wang, S. Zhi, J. Han, C. R. Voss, M. Magdon-Ismail. The wisdom of minority: Unsupervised slot filling validation based on multi-dimensional truth-finding. In COLING 2014, p. 1567–1578, 2014

Outline

1. Motivation
2. Truth Discovery from Structured Data
3. Truth Discovery from Extracted Information
4. Opportunities for Scalability Improvement
5. Conclusions

Main scalability issues

Information Extraction

Bottleneck of the extraction and data curation pipeline

→ *Agichtein and Sarawagi, Scalable Information Extraction and Integration. Tutorial KDD 2006*

Agreement-based and Source Dependence

1. Pairwise comparisons of the sources covering the same data items
2. Pairwise comparisons of the similar values in each data item

→ *X. Li, Xin Luna Dong, Kenneth Lyons, Weiyi Meng, and Divesh Srivastava. Scaling up Copy Detection. In ICDE, 2015.*

EM-based Approaches

1. Each update needs all the data set: "out-of-memory" problem
2. The algorithms need to iterate over the whole dataset several times until convergence
3. In M-step, optimal hidden variables do not have a closed-form solutions and joint optimization is required

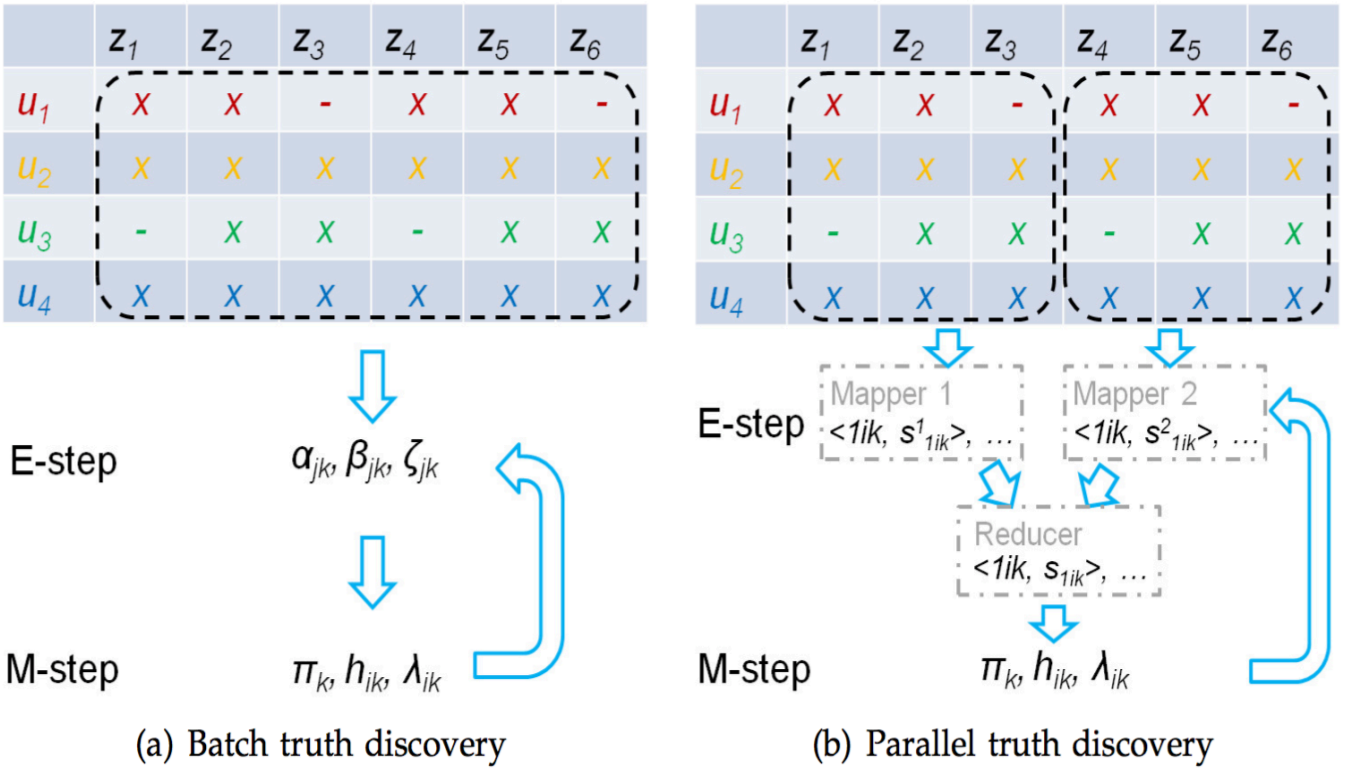
Iterative Optimization

Large-scale matrix factorization (e.g. SGD is not embarrassingly parallel)

Reducing and Distributing Computation (1/2)

MapReduce Framework for parallel TBP model

Each mapper and each reducer process 1/C and 1/D of all data.



(a) Batch truth discovery (b) Parallel truth discovery

Time Complexity

Original: *O(TK(1+X))*

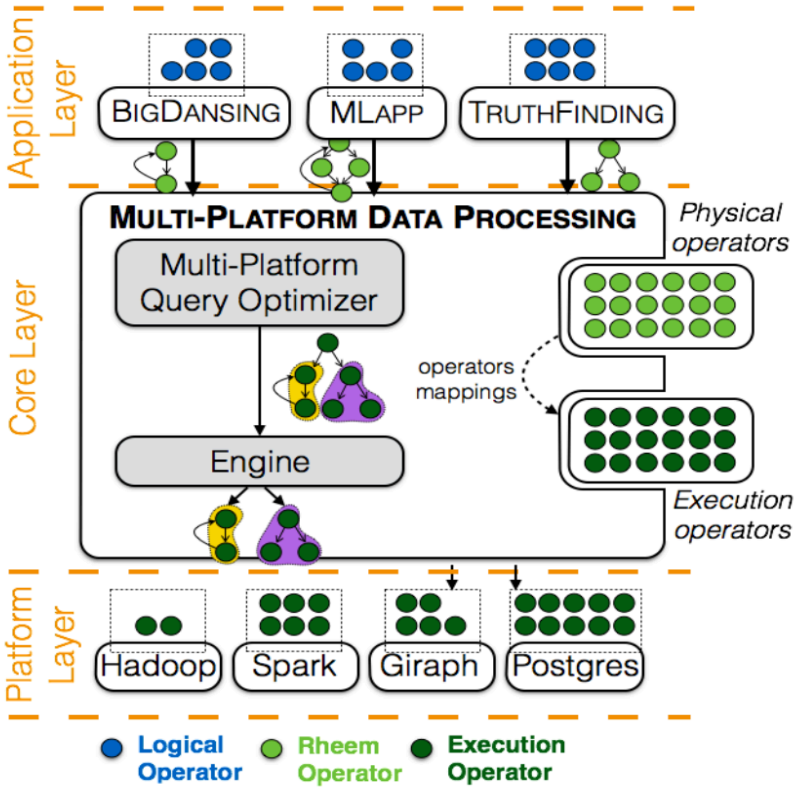
Parallel:
- Mapper: *O(K/C(X+N))*
- Reducer: *O(K/D(CM+M))*

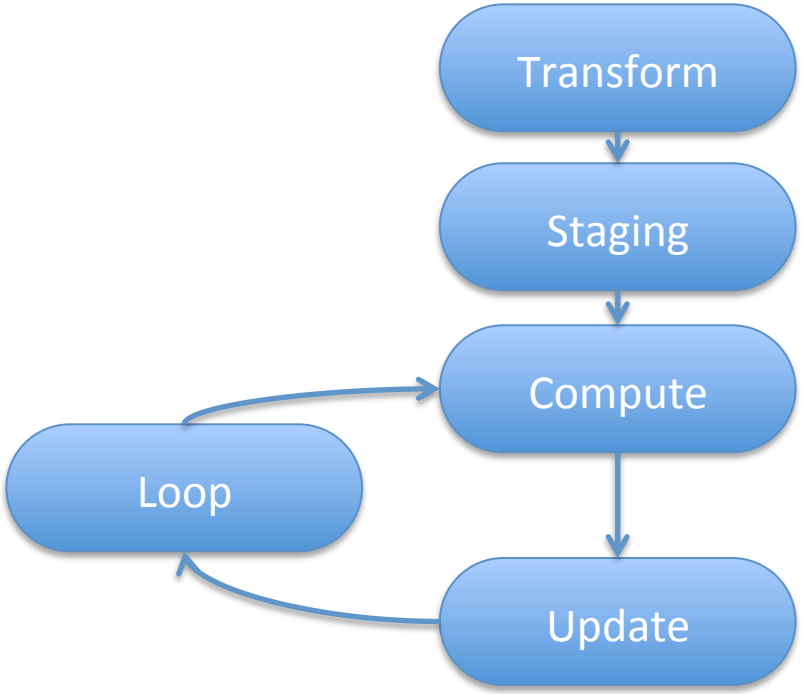
Total:
O(TK(1+C+Mapper+Reducer))

R. Wentao Ouyang, L. M. Kaplan, A.Toniolo, M. Srivastava, T. J. Norman, Parallel and Streaming Truth Discovery in Large-Scale Quantitative Crowdsourcing. IEEE Transactions on Parallel & Distributed Systems, doi:10.1109/TPDS.2016.2515092

Reducing and Distributing Computation (2/2)

RHEEM/ ML4ALL Framework for distributed TruthFinder





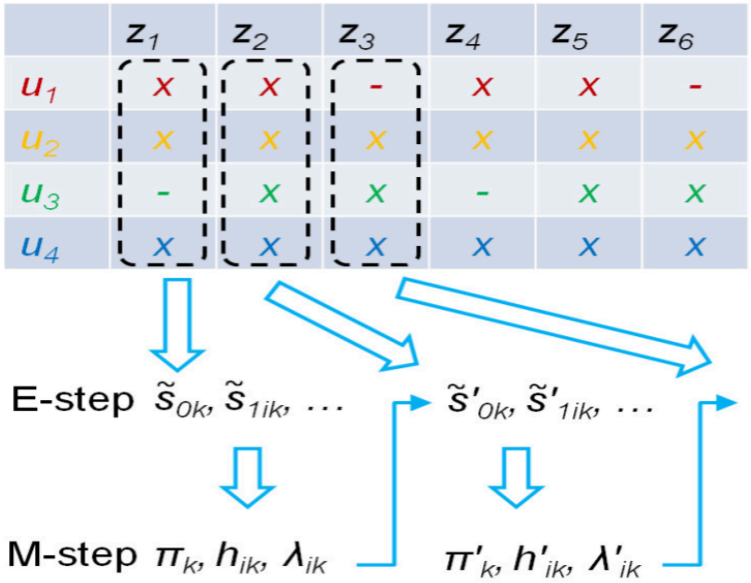
Agrawal et. al., Rheem: Enabling Multi-Platform Task Execution. SIGMOD 2016 (Demo Paper)

Streaming Truth Discovery

- **Further step: Streaming TBP**

Time Complexity

Original: *O(TK(1+X))*
Streaming: O(K(N+X))



- ***StreamTF***

One-pass algorithm with stochastic natural gradient algorithm

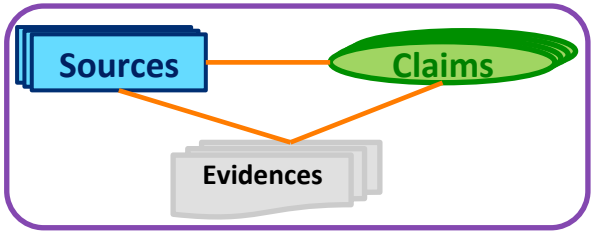
$$\mathcal{L}(q) = \sum_{t=1}^{T} \ell(O^t, \eta^t, \theta^t, \lambda_0, \lambda_1)$$

Z. Zhao, J. Cheng, W. Ng, Truth Discovery in Data Streams: A Single-Pass Probabilistic Approach, Proc. of CIKM'14.

Outline

1. Motivation
2. Truth Discovery from Structured Data
3. Truth Discovery from Extracted Information
4. Opportunities for Scalability Improvement
5. Conclusions

Truth Discovery Challenges

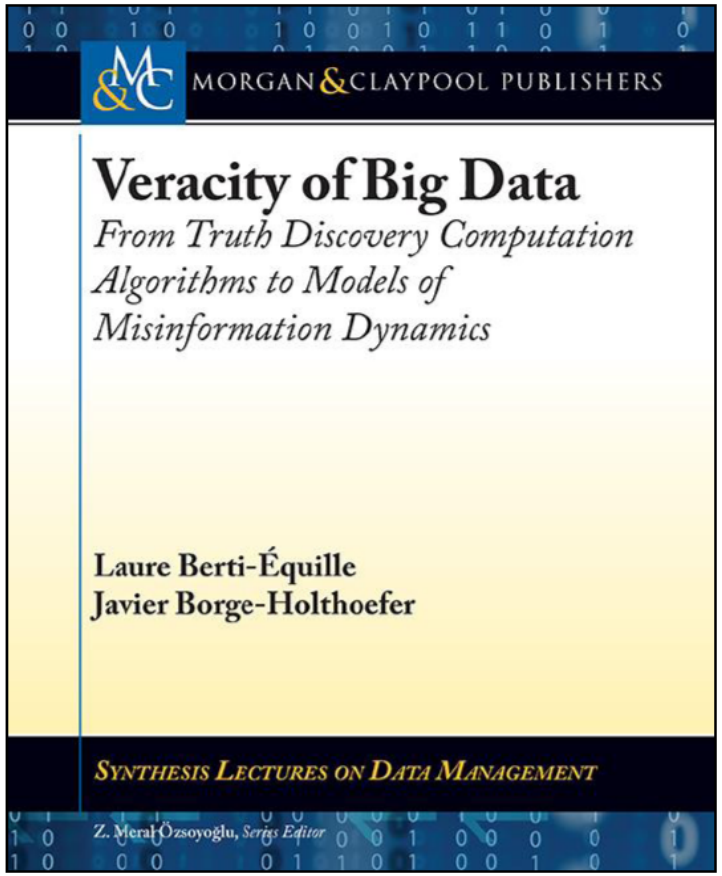


- **Data Veracity is Multidimensional**
  - Source: Coverage, Accuracy, Trustworthiness, Freshness, Reputation, Dependence…
  - Claims: Popularity (i.e., supported by many or few sources) (long-tail phenomena)
  - Truth: Trivial truths (hardeness), sensitive truths, uncertain, rapidly evolving
  - Data items: Information entropy (many (or few) conflicting information)
- **Truth Discovery Modeling**
  - Voting only works with benevolent sources. What about adversarial/pessimistic scenarios?
  - Need to incorporate evidences and contextual metadata (hidden agenda of sources)
  - Need to address truth discovery in the context of source/content networks
- **Algorithmic Framework**
  - Bane complex parameter setting
  - Quality performance: Ground truth data set size should be statistically significant
  - No "one-size fits all" solution
  - Need for benchmarks
- **Build a complete Truth Discovery pipeline/system**

Summary

- We presented an overview of the techniques proposed for truth discovery with some opportunities for scalability and optimization improvement
- Many scientific and technical obstacles:
  - Relax modeling assumptions
  - Solve algorithmic issues related to scalability, repeatability, and complex parameter settings
  - Integrate theoretical and applied work from complex networked systems to better capture the multi-layered dynamics of misinformation
- Still a lot needs to be done for automating truth discovery for realistic and actionable scenarios
- But what about cross-modal truth discovery from a mixture of images, videos, texts, and tweets?

Further Reading



Veracity of Big Data (Morgan & Claypool)

Surveys

- M. Gupta and J. Han. Heterogeneous network-based trust analysis: A survey. *ACM SIGKDD Explorations Newsletter*, 13(1):54–71, 2011.
- K. Thirunarayan, P. Anantharam, C. A. Henson, and A. P. Sheth. Comparative trust management with applications: Bayesian approaches emphasis. Future Generation Comp. Syst., 31:182–199, 2014.

Tutorials

- Jing Gao, Qi Li, Bo Zhao, Wei Fan, Jiawei Han Truth Discovery and Crowdsourcing Aggregation: A Unified Perspective. In VLDB 2015
- Xin Luna Dong and Divesh Srivastava. Big Data Integration. In VLDB 2013
- Barna Saha and Divesh Srivastava. Data Quality: the Other Face of Big Data. In VLDB 2014
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- Carlos Castillo, Wei Chen, Laks V. S. Lakshmanan. Information and Influence Spread in Social Networks. In KDD 2012
- Jure Leskovec. Social Media Analytics. In KDD 2011

Experimental Study

- D. A. Waguih and L. Berti-Equille. Truth discovery algorithms: An experimental evaluation. *arXiv preprint arXiv:1409.6428*, 2014.

Thanks!

Questions?