# Truth Discovery and Veracity Analysis

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# Outline

- Motivation: Why Truth Finding?
- TruthFinder:  A Source-Claim-Object Network Framework
- Truth Finding: Variations and Extensions
- LTM: Latent Truth Model (Modeling Multi-Valued Truth and Two-sided Errors)
- GTM: A Gaussian Truth Model for Finding Truth among Numerical Data
- Conclusions and Future Research

# Why Truth Finding?

- We are in the Web and "Big Data" age
  - Lots of information:  Also, lots of errors and false information!
  - Lots of information providers: Not every one is 100% reliable
- When encountering conflicting information on the same entities
  - Which piece of info is correct?
  - Which sources are trustable?
- Challenges:  We want to get trusted information!
  - Training on millions of pieces of information?
    - Too expensive, unrealistic!
  - Trust on "trusted" sources?
    - Everyone can make mistakes, even for the majority

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# Truth Validation by Info Network Analysis

- The trustworthiness problem of the web (according to a survey):
  - 54% of Internet users trust news web sites most of time
  - 26% for web sites that sell products
  - 12% for blogs
- TruthFinder: Truth discovery on the Web by link analysis
  - Among multiple conflict results, can we automatically identify which one is likely the true fact?
- Veracity (conformity to truth):
  - Given a large amount of conflicting information about many objects, provided by multiple web sites (or other information providers), how to discover the true fact about each object?
- Our first work: Xiaoxin Yin, Jiawei Han, Philip S. Yu, "Truth Discovery with Multiple Conflicting Information Providers on the Web", TKDE'08

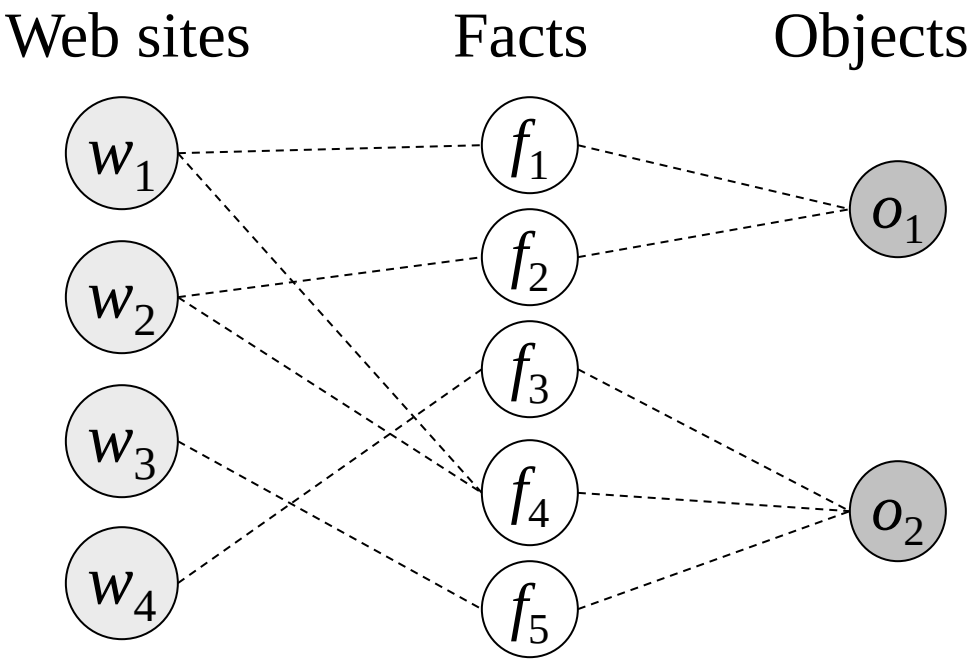
# Conflicting Information on the Web

- Different websites often provide conflicting info. on a subject, e.g., Authors of *"Rapid Contextual Design"*

| ***Online Store*** | ***Authors*** |
|---|---|
| Powell's books | Holtzblatt, Karen |
| Barnes & Noble | Karen Holtzblatt, Jessamyn Wendell, Shelley Wood |
| A1 Books | Karen Holtzblatt, Jessamyn Burns Wendell, Shelley Wood |
| Cornwall books | Holtzblatt-Karen, Wendell-Jessamyn Burns, Wood |
| Mellon's books | Wendell, Jessamyn |
| Lakeside books | WENDELL, JESSAMYNHOLTZBLATT, KARENWOOD, SHELLEY |
| Blackwell online | Wendell, Jessamyn, Holtzblatt, Karen, Wood, Shelley |

# Our Setting: Info. Network Analysis

- Each object has a set of ***conflictive*** facts
  - E.g., different author names for a book
- And each web site provides some facts
- How to find the true fact for each object?



# Basic Heuristics for Problem Solving

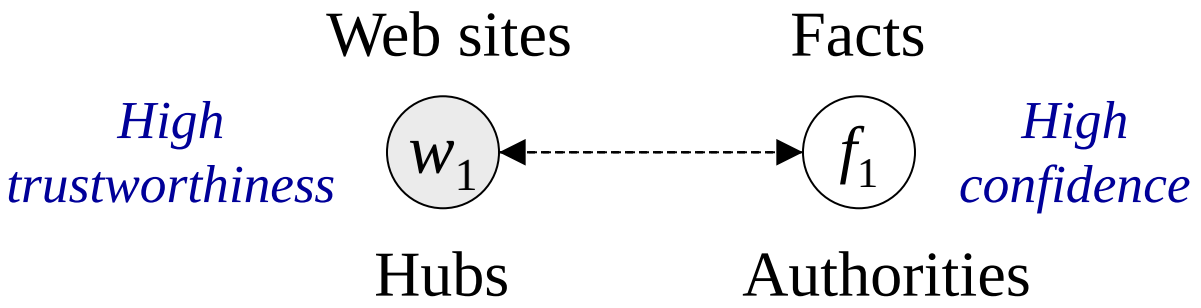
1. There is usually only one true fact for a property of an object
2. This true fact appears to be the same or similar on different web sites
   - E.g., “Jennifer Widom” vs. “J. Widom”
3. **The false facts on different web sites are less likely to be the same or similar**
   - False facts are often introduced by random factors
4. **A web site that provides mostly true facts for many objects will likely provide true facts for other objects**

# Overview of the TruthFinder Method

- *Confidence of facts* ↔ *Trustworthiness of web sites*
  - A fact has *high confidence* if it is provided by (many) trustworthy web sites
  - A web site is *trustworthy* if it provides many facts with high confidence
- The TruthFinder mechanism, an overview:
  - Initially, each web site is equally trustworthy
  - Based on the above four heuristics, infer fact confidence from web site trustworthiness, and then backwards
  - Repeat until achieving stable state

# Analogy to Authority-Hub Analysis

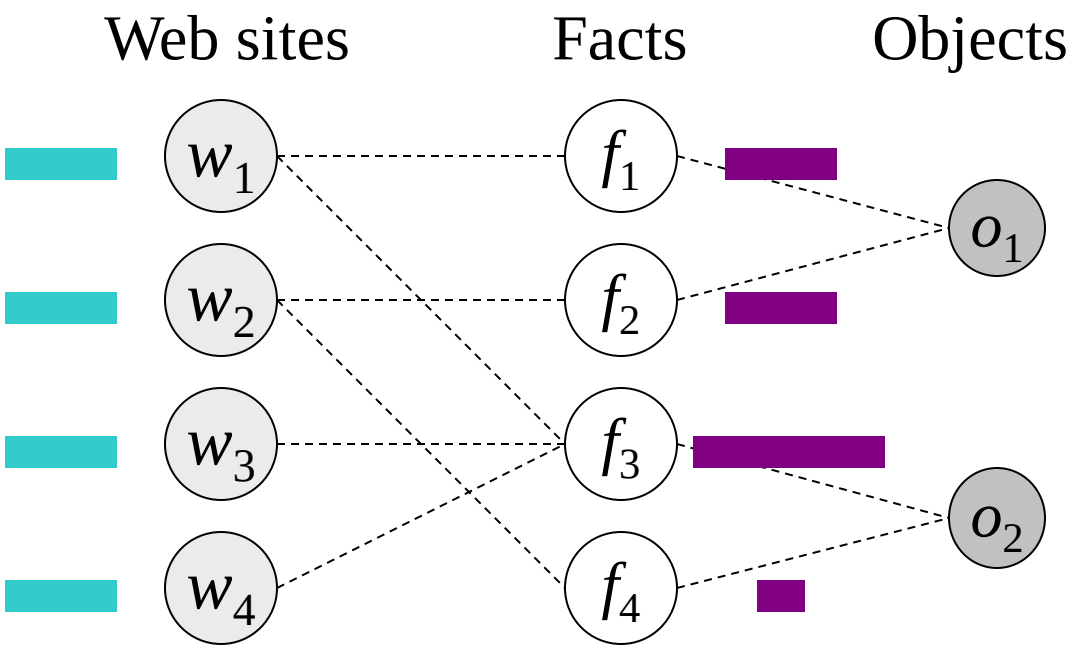
- Facts ↔ Authorities, Web sites ↔ Hubs




- Difference from authority-hub analysis
  - Linear summation cannot be used
    - A web site is trustable if it provides accurate facts, instead of many facts
    - Confidence is the probability of being true
  - Different facts of the same object influence each other

# Inference on Trustworthness

- Inference of web site trustworthiness & fact confidence




- True facts and trustable web sites will become apparent after some iterations

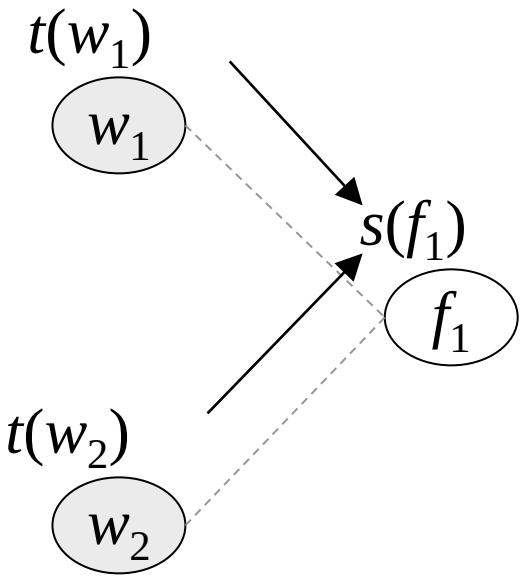
# Computation Model: t(w) and s(f)

- **The trustworthiness of a web site *w*: *t*(*w*)**
  - Average confidence of facts it provides

$$t(w) = \frac{\sum_{f \in F(w)} s(f)}{|F(w)|}$$

*Sum of fact confidence*

*Set of facts provided by w*




- **The confidence of a fact *f*: *s*(*f*)**
  - One minus the probability that all web sites providing *f* are wrong

$$s(f) = 1 - \prod_{w \in W(f)} (1 - t(w))$$

*Probability that w is wrong*

*Set of websites providing f*

# Experiments: Finding Truth of Facts

- Determining authors of books
  - Dataset contains 1265 books listed on abebooks.com
  - We analyze 100 random books (using book images)

| Case | *Voting* | *TruthFinder* | *Barnes & Noble* |
|---|---|---|---|
| Correct | 71 | 85 | 64 |
| Miss author(s) | 12 | 2 | 4 |
| Incomplete names | 18 | 5 | 6 |
| Wrong first/middle names | 1 | 1 | 3 |
| Has redundant names | 0 | 2 | 23 |
| Add incorrect names | 1 | 5 | 5 |
| No information | 0 | 0 | 2 |

# Experiments: Trustable Info Providers

- Finding trustworthy information sources
  - Most trustworthy bookstores found by TruthFinder vs. top-ranked bookstores by Google (query “bookstore”)

**TruthFinder**

| Bookstore | *trustworthiness* | *#book* | *Accuracy* |
|---|---|---|---|
| TheSaintBookstore | 0.971 | 28 | 0.959 |
| MildredsBooks | 0.969 | 10 | 1.0 |
| Alphacraze.com | 0.968 | 13 | 0.947 |

**Google**

| Bookstore | *Google rank* | *#book* | *Accuracy* |
|---|---|---|---|
| Barnes & Noble | 1 | 97 | 0.865 |
| Powell’s books | 3 | 42 | 0.654 |

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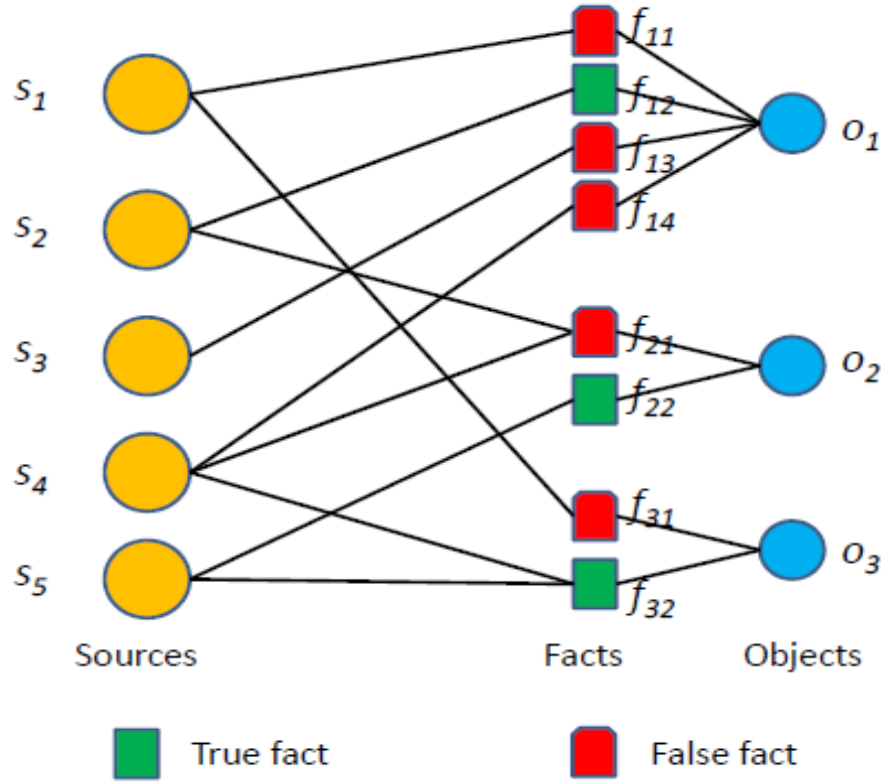
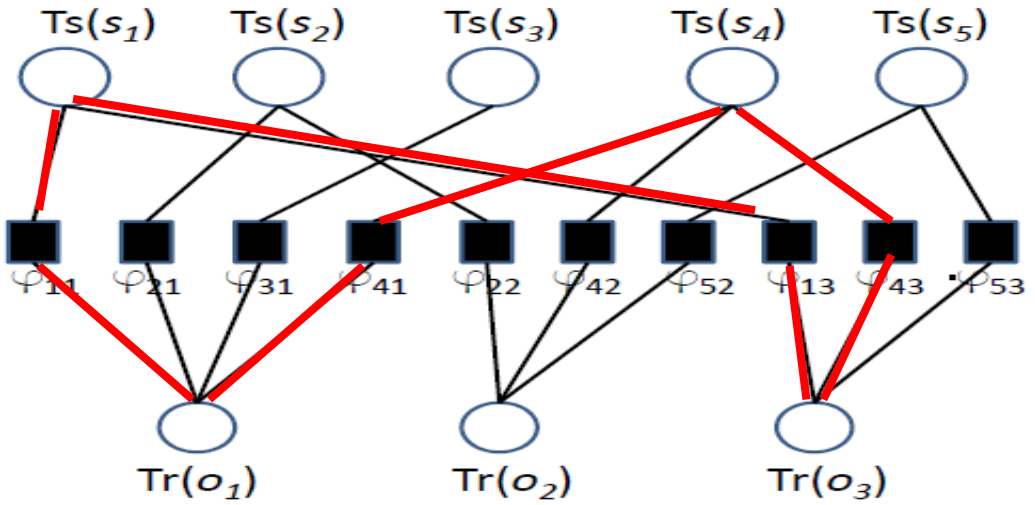
# Mining Collective Intelligence in Groups: Latent Dirichlet Truth Discovery



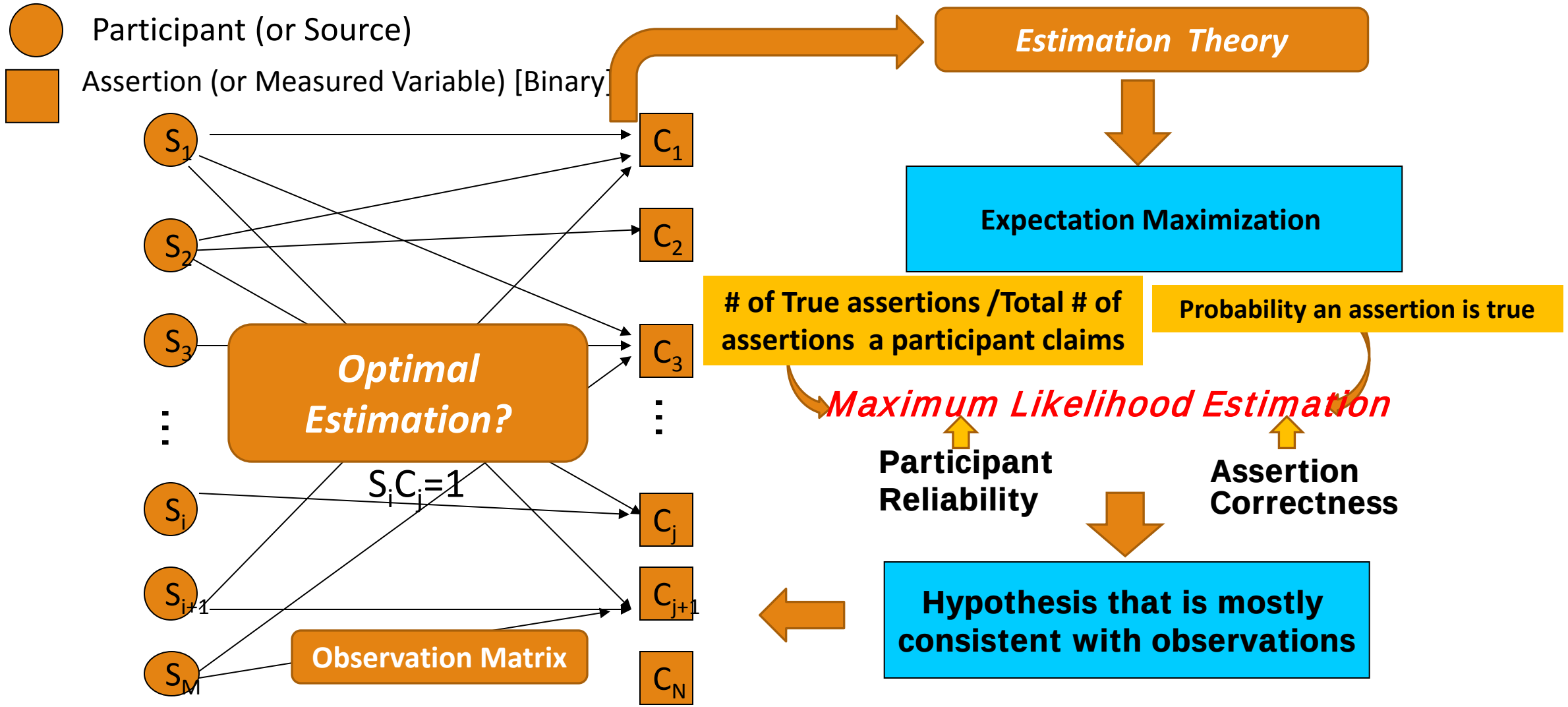

**A Source-Claim-Object Framework**




- Explicitly exploit the fact-object hierarchy
- Considers all the facts as a whole for each object
- Model the behavior of both trustworthy and untrustworthy sources explicitly

Guo-Jun Qi, Charu C. Aggarwal, Jiawei Han, and Thomas Huang, "Mining Collective Intelligence in Groups", WWW'13, May 2013

# An Expectation Maximization Framework




D. Wang, L. Kaplan and T. Abdelzaher, "On Truth Discovery in Social Sensing with Conflicting Observations: A Maximum Likelihood Estimation Approach", ACM Transaction on Sensor Networks (TOSN), 2014

# Generalized Fact-Finding: Considering Additional Information

- Ex: *"Obama was born in Hawaii" vs. "Obama was born in Kenya"*
  - **Uncertainty in the claims:** "I'm 90% sure Obama was born in Hawaii"
  - **Attributes of sources:** The source making the first claim is Authority
  - **Similarity between claims:** A source claiming "Kenya" implicitly prefers neighboring "Uganda" over "Hawaii"
- Key Features: J. Pasternack and D. Roth, "Making Better Informed Trust Decisions with Generalized Fact-Finding", IJCAI'11
  - Consider **Additional/Background Knowledge** in Fact-finding (e.g., source uncertainty, claim similarity, group information)
  - Model Additional Knowledge **as Link Weights** to Generalize Fact-finding algorithms
  - Generalize bi-partite graph to **k-partite graph** to consider source groups or attributes

# Truth Discovery and Copying Detection in a Dynamic World

- Luna Dong's series work on truth discovery and data integration
- Find true values and determine the copying relationship between sources (VLDB'09)
- Quality of sources over time: coverage, exactness and freshness
- Use hidden Markov model (HMM) to decide whether a source is a copier of another and identifies the specific moments it copies
- Use a Bayesian model that aggregates info from sources to decide the true value for a data items and the evolution of the true value over time
- Further study on truth finding on the Web (e.g., VLDB'13)
  - Lot of inconsistencies on even deep web, in some highly "trusted" domains, e.g., stock and flight
  - For 70% of data items, > 1 value is provided: Widely open!

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# From TruthFinder to Latent Truth Model (LTM)

- HITS-like Random Walk methods (e.g., TruthFinder(KDD'08), 3-Estimate(WSDM'10), Invest(COLING'10), …)
  - Higher Quality Sources ↔ More Probable Facts
- Limitations
  - Quality as a single value: Precision or Accuracy
  - In practice, some sources tend to ignore true attributes (False Negatives), while some others tend to produce false attributes (False Positives).
  - FN ǂ FP when there are multiple truths per entity!
- LTM (Latent Truth Model): Bo Zhao, Benjamin I. P. Rubinstein, Jim Gemmell, and Jiawei Han, "A Bayesian Approach to Discovering Truth from Conflicting Sources for Data Integration", VLDB'12
- LTM: A Principled Probabilistic Model
- Model negative claims and two-sided source quality with Bayesian regularization

# What Is Latent Truth Model?

- Different but real situations (new assumptions)
  - Multiple facts can be true for each entity (object)
    - One book may have 2+ authors
  - A source can make multiple claims per entity, where more than one of them can be true
    - A source may claim a book w. 3 authors
  - Sources and objects are independent respectively
    - Assume book websites and books are independent
  - The majority of data coming from many sources are not erroneous
    - Trust the majority of the claims

**Table 1: An example raw database of movies.**

| *Entity (Movie)* | *Attribute (Cast)* | *Source* |
|---|---|---|
| Harry Potter | Daniel Radcliffe | IMDB |
| Harry Potter | Emma Waston | IMDB |
| Harry Potter | Rupert Grint | IMDB |
| Harry Potter | Daniel Radcliffe | Netflix |
| Harry Potter | Daniel Radcliffe | BadSource.com |
| Harry Potter | Emma Waston | BadSource.com |
| Harry Potter | Johnny Depp | BadSource.com |
| Pirates 4 | Johnny Depp | Hulu.com |
| ... | ... | ... |

# Challenge: Why Voting Does Not Work?

- Input:
  - Facts = (Entity, Attribute)
  - Claims = (Relation, Source, Observation)
- Output: Truth(Relation) → {1, 0}

- Many sources are not of high quality: Cannot trust all sources in voting
- Movie: Harry Potter and the Deathly Hallows
  - IMDB: Daniel Radcliffe, Emma Watson
  - Nexflix: Daniel Radcliffe
  - BadSource.Com: Daniel Radcliffe, Johnny Depp

| RID | Entity | Attribute |
|---|---|---|
| 1 | HP7 | Daniel Radcliffe |
| 2 | HP7 | Emma Watson |
| 3 | HP7 | Johnny Depp |

Input: Fact Table

| RID | Source | Obs. |
|---|---|---|
| 1 | IMDB | 1 |
| 2 | IMDB | 1 |
| 3 | IMDB | 0 |
| 1 | Netflix | 1 |
| 2 | Netflix | 0 |
| 3 | Netflix | 0 |
| 1 | BadSource | 1 |
| 2 | BadSource | 0 |

Input: Claim Table

False Negative (threshold = 0.5)

False Positive (threshold = 0.3)

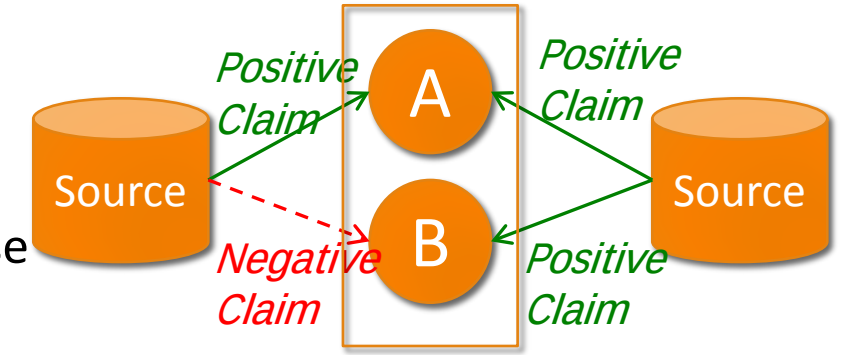
Optimal Threshold?

| RID | Truth |
|---|---|
| 1 | 1 |
| 2 | 1 |
| 3 | 0 |

Output: Truth Table

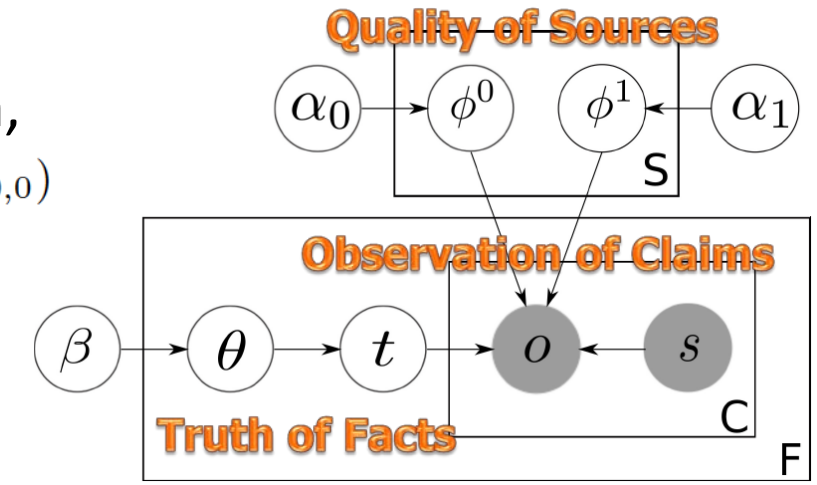
# Multiple Truths for Same Entities

- Implicit negative claims by source s:
  - For those facts not claimed true by source s, but by some other sources
- Modeling negative claims and two-sided errors (false positives, false negatives) is essential for supporting multiple truths:
  - Negative claims can help detect false attributes
  - Negative claims by high recall sources are usually very accurate, e.g., IMDB
  - Negative claims by low recall sources should not count much, e.g., Netflix
- Thus, LTM Naturally supports multiple true attribute values
- LTM can naturally incorporate prior domain knowledge through Bayesian priors
- An efficient and scalable linear complexity inference algorithm
  - LTM can run in either batch or online streaming modes for incremental truth finding



# The Latent Truth Model

- For each source **k**
  - Generate false positive rate (with **strong** regularization, believing most sources have low FPR): $\phi_k^0 \sim Beta(\alpha_{0,1}, \alpha_{0,0})$
  - Generate its sensitivity (1-FNR) with uniform prior, indicating low FNR is more likely: $\phi_k^1 \sim Beta(\alpha_{1,1}, \alpha_{1,0})$
- For each fact **f**
  - Generate its prior truth prob, uniform prior: $\theta_f \sim Beta(\beta_1, \beta_0)$
  - Generate its truth label: $t_f \sim Bernoulli(\theta_f)$
- For each claim **c** of fact **f,** generate observation of **c**.
  - If **f** is false, use false positive rate of source: $o_c \sim Bernoulli(\phi_{s_c}^0)$
  - If **f** is true, use sensitivity of source: $o_c \sim Bernoulli(\phi_{s_c}^1)$



Graphical Representation

# Inferring Truth

- MAP inference: find truth assignment that maximizes posterior probabilities

$$\hat{\boldsymbol{t}}_{MAP} = \arg\max_{\boldsymbol{t}} \int\int\int p(\boldsymbol{o}, \boldsymbol{s}, \boldsymbol{t}, \boldsymbol{\theta}, \boldsymbol{\phi}^{\mathbf{0}}, \boldsymbol{\phi}^{\mathbf{1}}) \mathrm{d}\boldsymbol{\theta} \mathrm{d}\boldsymbol{\phi}^{\mathbf{0}} \mathrm{d}\boldsymbol{\phi}^{\mathbf{1}}$$

- Collapsed Gibbs sampling (more efficient, only sample truth, other parameters integrated out)

$$p(t_f = i | \boldsymbol{t}_{-f}, \boldsymbol{o}, \boldsymbol{s}) \propto \beta_i \prod_{c \in \mathbf{C}_f} \frac{n^{-f}_{s_c,i,o_c} + \alpha_{i,o_c}}{n^{-f}_{s_c,i,1} + n^{-f}_{s_c,i,0} + \alpha_{i,1} + \alpha_{i,0}}$$

- Prediction of the truth from samples of the latent truth variable.
  - Burn-in: throw away first b samples
  - Thinning: Take every k sample from all the samples
  - Calculate expectation of the taken samples

# Incremental Truth Finding

- Read-off Source Quality Parameters

$$sensitivity(s) = \phi_s^1 = \frac{E[n_{s,1,1}] + \alpha_{1,1}}{E[n_{s,1,0}] + E[n_{s,1,1}] + \alpha_{1,0} + \alpha_{1,1}}$$

$$specificity(s) = 1 - \phi_s^0 = \frac{E[n_{s,0,0}] + \alpha_{0,0}}{E[n_{s,0,0}] + E[n_{s,0,1}] + \alpha_{0,0} + \alpha_{0,1}}$$

- Incremental Prediction (LTMinc)
  - Assuming source quality unchanged, directly utilize source quality to make prediction (very efficient)

$$p(t_f = 1 | \boldsymbol{o}, \boldsymbol{s}) = \frac{\beta_1 \prod_{c \in \mathbf{C}_f} (\phi_s^1)^{o_c} (1 - \phi_s^1)^{1 - o_c}}{\sum_{i=0,1} \beta_i \prod_{c \in \mathbf{C}_f} (\phi_s^i)^{o_c} (1 - \phi_s^i)^{1 - o_c}}$$

  - Can also rerun inference for incremental update by using previous quality counts as Bayesian priors

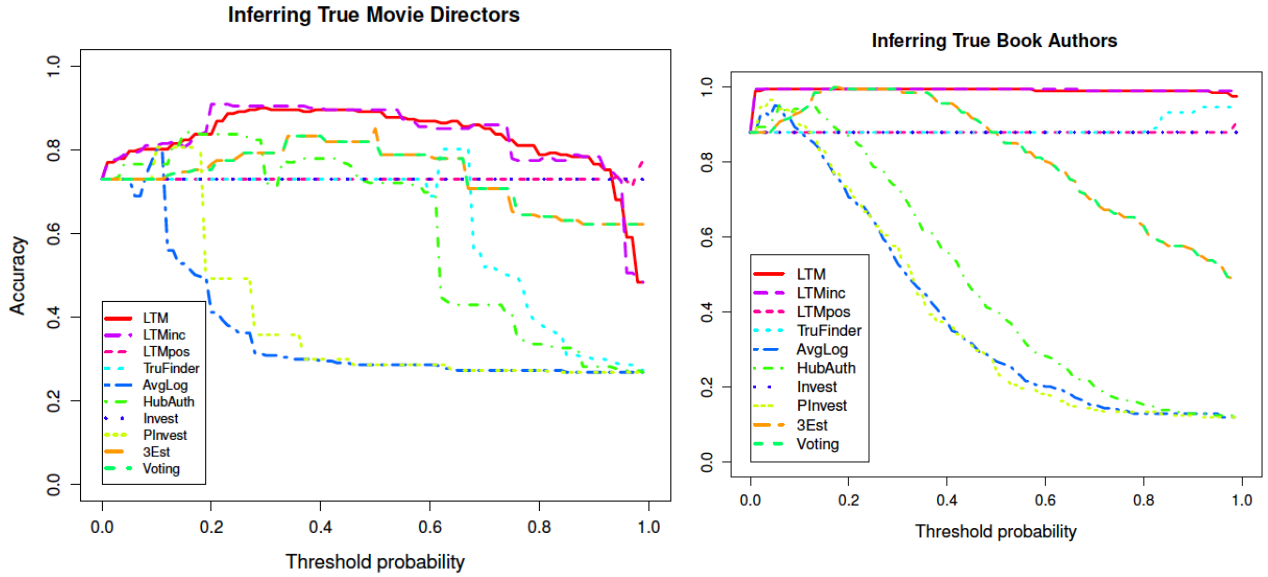
# Experiments (Effectiveness)

- Datasets:
  - Book Authors from abebooks.com (1263 books, 879 sources, 48153 claims, 2420 book-author, 100 labeled)
  - Movie Directors from Bing (15073 movies, 12 sources, 108873 claims, 33526 movie-director, 100 labeled)

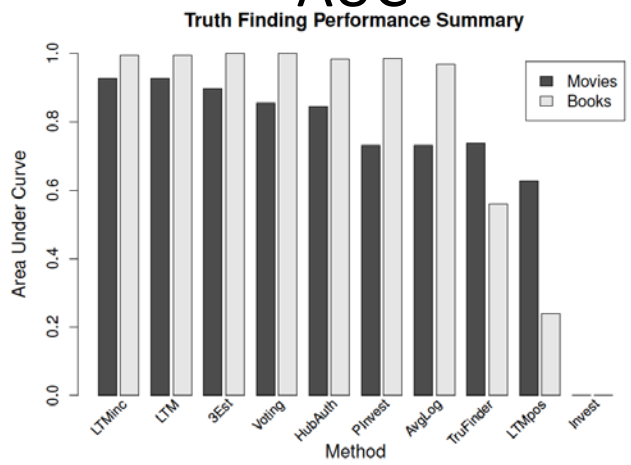
| | *Results on book data* | | | | | *Results on movie data* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *One-sided error* | | | *Two-sided error* | | *One-sided error* | | | *Two-sided error* | |
| | *Precision* | *Recall* | *FPR* | *Accuracy* | *F1* | *Precision* | *Recall* | *FPR* | *Accuracy* | *F1* |
| **LTMinc** | **1.000** | 0.995 | **0.000** | **0.995** | **0.997** | 0.943 | 0.914 | 0.150 | **0.897** | **0.928** |
| **LTM** | **1.000** | 0.995 | **0.000** | **0.995** | **0.997** | 0.943 | 0.908 | 0.150 | 0.892 | 0.925 |
| 3-Estimates | **1.000** | 0.863 | **0.000** | 0.880 | 0.927 | 0.945 | 0.847 | 0.133 | 0.852 | 0.893 |
| Voting | **1.000** | 0.863 | **0.000** | 0.880 | 0.927 | 0.855 | 0.908 | 0.417 | 0.821 | 0.881 |
| TruthFinder | 0.880 | **1.000** | 1.000 | 0.880 | 0.936 | 0.731 | **1.000** | 1.000 | 0.731 | 0.845 |
| Investment | 0.880 | **1.000** | 1.000 | 0.880 | 0.936 | 0.731 | **1.000** | 1.000 | 0.731 | 0.845 |
| HubAuthority | **1.000** | 0.322 | **0.000** | 0.404 | 0.488 | **1.000** | 0.620 | **0.000** | 0.722 | 0.765 |
| AvgLog | **1.000** | 0.169 | **0.000** | 0.270 | 0.290 | **1.000** | 0.025 | **0.000** | 0.287 | 0.048 |
| LTMpos | 0.880 | **1.000** | 1.000 | 0.880 | 0.936 | 0.731 | **1.000** | 1.000 | 0.731 | 0.845 |
| PooledInvestment | **1.000** | 0.142 | **0.000** | 0.245 | 0.249 | **1.000** | 0.025 | **0.000** | 0.287 | 0.048 |

# Experiments (Effectiveness) cont.

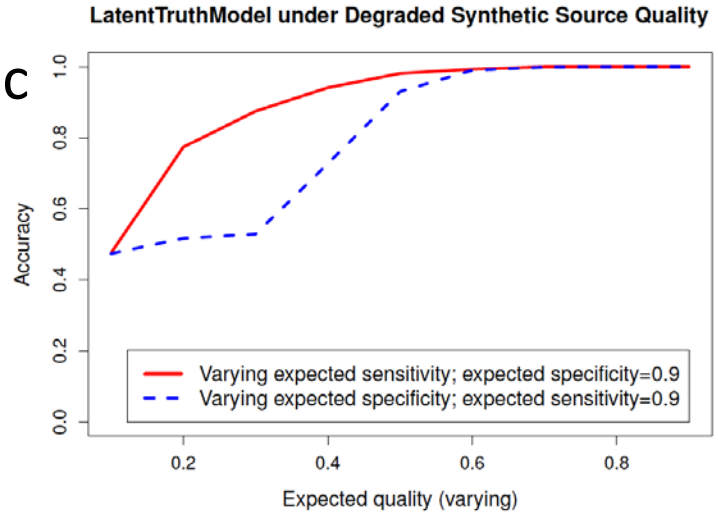
## Varying cutoff threshold (consistently better)




## AUC




## Varying synthetic quality (more tolerant of low sensitivity)

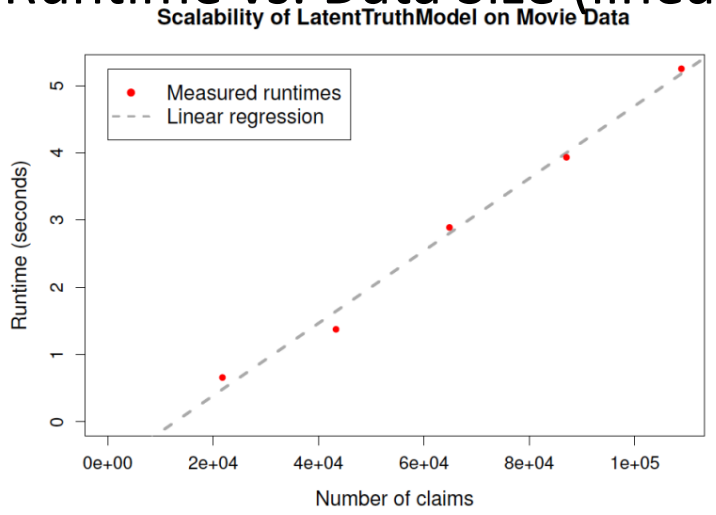



## Case Study of Movie Sources

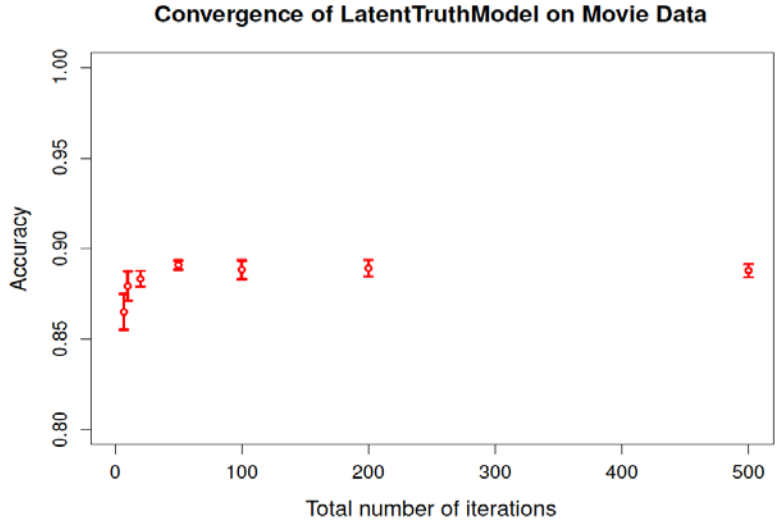
| *Source* | *Sensitivity* | *Specificity* |
|---|---|---|
| imdb | **0.911622836** | 0.898838631 |
| netflix | 0.894019034 | 0.934833904 |
| movietickets | 0.862889367 | 0.978844687 |
| commonsense | 0.809752315 | 0.982347827 |
| cinemasource | 0.794184357 | 0.985847745 |
| amg | 0.776583683 | 0.690600694 |
| yahoomovie | 0.760589896 | 0.897654374 |
| msnmovie | 0.749192861 | 0.987870636 |
| zune | 0.744272491 | 0.973922421 |
| metacritic | 0.678661638 | 0.987957893 |
| flixster | 0.584223615 | 0.911078627 |
| fandango | 0.499623726 | **0.989836274** |

# Experiments (Efficiency)

## Runtime vs. Data Size (linear)




## Convergence Rate (stable at 50)




## Running Time

| | *Runtimes (secs.) vs. #Entities* | | | | |
|---|---|---|---|---|---|
| *#Entities* | 3k | 6k | 9k | 12k | 15k |
| *1 iteration* | | | | | |
| **Voting** | **0.004** | **0.008** | **0.012** | **0.027** | **0.030** |
| LTMinc | **0.004** | **0.008** | **0.012** | 0.037 | 0.048 |
| *100 iterations* | | | | | |
| **AvgLog** | 0.150 | **0.297** | 0.446 | **0.605** | **0.742** |
| **HubAuthority** | **0.149** | **0.297** | **0.445** | 0.606 | 0.743 |
| PooledInvestment | 0.175 | 0.348 | 0.514 | 0.732 | 0.856 |
| TruthFinder | 0.195 | 0.393 | 0.587 | 0.785 | 0.971 |
| Investment | 0.231 | 0.464 | 0.690 | 0.929 | 1.143 |
| 3-Estimates | 0.421 | 0.796 | 1.170 | 1.579 | 1.958 |
| LTM | 0.660 | 1.377 | 2.891 | 3.934 | 5.251 |

*Standard LTM is slightly slower than state-of-the-art due to random sampling*

*LTMinc is as fast as voting!*

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- LTM: Latent Truth Model (Modeling Multi-Valued Truth and Two-sided Errors)
- GTM: A Gaussian Truth Model for Finding Truth among Numerical Data 
- Conclusions and Future Research

# Estimating Real-Valued Truth from Conflicting Sources

- Truth finding from categorical data to numerical data
  - Real valued data could be critical in many applications
- B. Zhao and J. Han, "A Probabilistic Model for Estimating Real-Valued Truth from Conflicting Sources", Proc. of 2012 Int. Workshop on Quality in Databases (QDB'12), Aug. 2012.
- **GTM** (Gaussian Truth Model): A principled probabilistic model
  - Leverage two Gaussian generative processes to simulate the generation of numerical truth and claims
  - Source quality adapts to numerical data
  - Prior on truth and source quality can be easily incorporated as Bayesian priors
  - Efficient inference

# Automatic Finding of True Real Values

- Problem Formulation
  - Input: Claim Table in form of (entity, value, source).
  - Output: Truth Table (entity, true value)

| Entity (city) | Value (pop.) | Source |
|---|---|---|
| NYC | 8,346,794 | Freebase |
| NYC | 8,244,910 | Wikipedia |
| NYC | 8,175,133 | US Census |
| NYC | 7,864,215 | BadSource |
| Urbana | 36,395 | US Census |
| Urbana | 36,395 | Wikipedia |
| Urbana | 34,774 | Freebase |
| Urbana | 1,215 | BadSource |
| … | … | … |

**Input: Claim Table**

| Entity | Value |
|---|---|
| NYC | 8,175,133 |
| Urbana | 36,395 |
| … | … |

**Output: Truth Table**

# Intuition: Normalization vs. Outliers

- Quality varies for different sources
  - US Census > Wikipedia > Freebase > BadSource
- Normalization
  - NYC is more difficult to reach consensus, sources should be punished less for making same amount of error, comparing with Urbana
- Outlier
  - (Urbana, 1215) is an outlier, needs to be recognized

| Entity | Value | Source |
|---|---|---|
| NYC | 8,346,794 | Freebase |
| NYC | 8,244,910 | Wikipedia |
| NYC | 8,175,133 (truth) | US Census |
| NYC | 7,864,215 | BadSource |
| Urbana | 36,395 (truth) | US Census |
| Urbana | 36,395 (truth) | Wikipedia |
| Urbana | 34,774 | Freebase |
| Urbana | 1,215 | BadSource |
| … | … | … |

# Normalization and Outlier Detection

- Leverage truth priors, e.g., median, the most frequent value, or output of any truth-finding algorithms
- Remove outliers by absolute error, relative error, and Gaussian confidence interval (with prior truth as mean, iteratively computed variance)
  - Outliers can significantly shift empirical variance, so update variance after outliers are detected and try to detect outliers based on updated variance
- Normalize all claims to standard Gaussian N(0,1)
  - Prevent biased estimation of source quality

{Outlier Detection}
**for all** $e \in \mathcal{E}$ **do**
  {based on relative error and absolute error}
  **for all** $c \in \mathcal{C}_e$ **do**
    **if** $|v_c - \hat{t}_e|/\hat{t}_e > \delta_0$ or $|v_c - \hat{t}_e| > \delta_1$ **then**
      $outlier[c] \leftarrow True$
  {based on Gaussian confidence intervals}
  $\hat{\sigma}_e \leftarrow calcuate\_standard\_deviation(\mathcal{C}_e)$
  **repeat**
    $new\_outlier \leftarrow False$
    **for all** $c \in \mathcal{C}_e$ **do**
      **if** $|v_c - \hat{t}_e|/\hat{\sigma}_e > \delta_2$ **then**
        $outlier[c] \leftarrow True$
        $new\_outlier \leftarrow True$
    $\hat{\sigma}_e \leftarrow calcuate\_standard\_deviation(\mathcal{C}_e)$
  **until** $new\_outlier = False$
{Normalization}
**for all** $e \in \mathcal{E}$ **do**
  **for all** $c \in \mathcal{C}_e$ **do**
    $o_c \leftarrow (v_c - \hat{t}_e)/\hat{\sigma}_e$

**Preprocessing Routine**

# GTM: Truth Generation Mechanism

- For each source **k**
  - Generate source quality:

$$\sigma_s^2 \sim Inv\text{–}Gamma(\alpha, \beta)$$

$$\sim (\sigma_s^2)^{-\alpha-1} \exp\left(-\frac{\beta}{\sigma_s^2}\right)$$

- For each entity **e**
  - Generate its true value:

(set $\mu_0 = 0$ and $\sigma_0^2 = 1$)

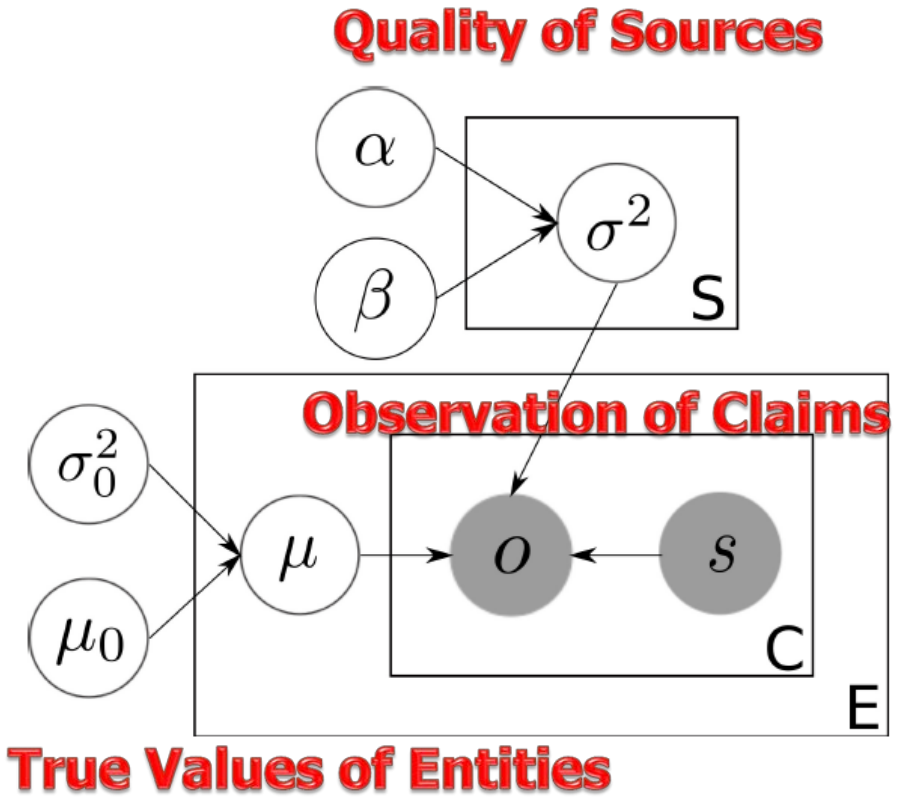
$$\mu_e \sim Gaussian(\mu_0, \sigma_0^2)$$

$$\sim \exp\left(-\frac{(\mu_e - \mu_0)^2}{2\sigma_0^2}\right)$$

- For each claim **c** of entity **e**
  - Generate observation of **c**:

$$o_c \sim Gaussian(\mu_e, \sigma_{s_c}^2)$$

$$\sim \sigma_{s_c}^{-1} \exp\left(-\frac{(o_c - \mu_e)^2}{2\sigma_{s_c}^2}\right)$$



# Inference

- Likelihood:

$$p(\boldsymbol{o}, \boldsymbol{\mu}, \boldsymbol{\sigma}^2 | \mu_0, \sigma_0^2, \alpha, \beta) =$$

$$\prod_{s \in \mathcal{S}} p(\sigma_s^2 | \alpha, \beta) \times \prod_{e \in \mathcal{E}} \left( p(\mu_e | \mu_0, \sigma_0^2) \prod_{c \in \mathcal{C}_e} p(o_c | \mu_e, \sigma_e^2) \right)$$

- MAP Inference of truth:

$$\hat{\boldsymbol{\mu}}_{MAP} = \arg\max_{\boldsymbol{\mu}} \int p(\boldsymbol{o}, \boldsymbol{\mu}, \boldsymbol{\sigma}^2 | \mu_0, \sigma_0^2, \alpha, \beta) \mathrm{d}\boldsymbol{\sigma}^2$$

- Many inference algorithms can be applied, e.g. Gibbs sampling, EM, etc.

- To get actual truth: $\hat{t} + \hat{\mu}_e \hat{\sigma}_e$ , or the closest claimed value

# EM Algorithm

- Given source quality, optimal truth is:

$$\hat{\mu}_e = \frac{\frac{\mu_0}{\sigma_0^2} + \sum_{c \in \mathcal{C}_e} \frac{1}{\sigma_{s_c}^2} \frac{v_c - \hat{t}_e}{\hat{\sigma}_e}}{\frac{1}{\sigma_0^2} + \sum_{c \in \mathcal{C}_e} \frac{1}{\sigma_{s_c}^2}}$$

Regularization

Weighted by source quality

- Given truth, optimal source quality is:

$$\hat{\sigma}_s^2 = \frac{2\beta + \sum_{c \in \mathcal{C}_s} \frac{(v_c - \hat{t}_{e_c} - \hat{\sigma}_{e_c} \mu_{e_c})^2}{\hat{\sigma}_{e_c}^2}}{2(\alpha + 1) + |C_s|}$$

Regularization / smoothing

How close claims are to the truth

# Experiments on Edit History of Wikipedia

- Datasets: Edit history of Wikipedia
  - Population: 2,415 sources; 1,148 city-year; 4,119 claims.
  - Biography: 607,819 sources; 9,924 dates of birth or death; 1,372,066 claims.
- Evaluation: Mean Absolute Error, Root Mean Square Error

| | *Results on the population data* | | *Results on the bio data* | |
|---|---|---|---|---|
| | *MAE* | *RMSE* | *MAE* | *RMSE* |
| **GTM** | **1498.59** | **8339.99** | **228.19** | **4831.53** |
| 3-Estimates | 1640.83 (+9.49%) | 8822.50 (+5.78%) | 237.35 (+4.01%) | 4847.80 (+0.33%) |
| TruthFinder | 1633.60 (+9.00%) | 8824.09 (+5.80%) | 660.66 (+189.51%) | 6959.72 (+44.04%) |
| Investment | 1787.65 (+19.28%) | 9358.80 (+12.21%) | 3858.90 (+1591.04%) | 26237.65 (+443.05%) |
| LTM | 3040.90 (+102.91%) | 12865.52 (+54.26%) | 396.78 (+73.87%) | 5837.66 (+20.82%) |
| Voting | 10327.20 (+589.12%) | 126217.98 (+1413.40%) | 237.35 (+4.01%) | 4847.80 (+0.33%) |
| Median | 10241.81 (+583.42%) | 126198.86 (+1413.17%) | 244.04 (+6.94%) | 4854.90(+0.48%) |
| Average | 10368.54 (+591.88%) | 126199.76 (+1413.18%) | 253.41 (+11.05%) | 4860.28 (+0.59%) |

# Outline

- Motivation: Why Truth Finding?
- TruthFinder:  A Source-Claim-Object Network Framework
- Truth Finding: Variations and Extensions
- LTM: Latent Truth Model (Modeling Multi-Valued Truth and Two-sided Errors)
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- Conclusions and Future Research

# Conclusions

- Truth finding: A critical issue in data cleaning, information integration, and quality of information → Information Trust
- A fundament framework in Truth Finding:
  - A Source-Claim-Object network + iterative enhancement
- LTM (Latent Truth Model): Modeling multi-valued truth and two-sided errors
  - Cares subtlety and demonstrates its power on truth modeling
- GTM: A Gaussian truth model for numerical data
- Integration of methodologies of truth-finding and crowdsourcing
- Still a widely open area: Lots more to be studied!!

# Selected References on Truth Analysis


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