On Robust Truth Discovery in Sparse Social Media Sensing

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***Abstract*—In the big data era, it's important to identify trustworthy information from an influx of noisy data contributed by unvetted sources from online social media (e.g., Twitter, Instagram, Flickr). This task is referred to as *truth discovery* which aims at identifying the reliability of the sources and the truthfulness of claims they make without knowing either of them *a priori*. There are two important challenges that have not been well addressed in current truth discovery solutions. The first one is "misinformation spread" where a majority of sources are contributing to false claims, making the identification of truthful claims difficult. The second challenge is "data sparsity"where sources contribute a small number of claims, providing insufficient evidence to accomplish the truth discovery task. In this paper, we developed a Robust Truth Discovery (RTD) scheme to address the above two challenges. In particular, the RTD scheme explicitly quantifies *different degrees of attitude* that a source may express on a claim and incorporates the *historical contributions of a source* using a principled approach. The evaluation results on two real world datasetsshow that the RTD scheme significantly outperforms the state-of-the-art truth discovery methods.**

***Index Terms*—Big Data, Rumor Robust, Sparse Social Sensing, Truth Discovery, Twitter**

1. Introduction

This paper presents a new robust approach to solve the truth discovery problem in social media sensing applications. Online social media (Twitter, Instagram and Flickr) has emerged as a new paradigm of sensing in the era of big data where humans are used as ubiquitous, versatile and inexpensive sensors to report their observations (often called claims) about the physical world. This paradigm is motivated by the proliferation of portable data collection devices (e.g., smartphones) and the wide adaptation of online social media as the massive information sharing platforms. Examples of social media sensing include obtaining real-time situation awareness in disaster response [23] and intelligent transportation system applications using location based social network services [1] A critical challenge in social media sensing is referred to as *truth discovery* where the goal is to identify the reliability of the sources and the truthfulness of claims they make without prior knowledge on either of them. The truth discovery problem, if appropriately addressed, will directly contribute to addressing the *veracity* challenge of the big data problem.

A rich set of principled solutions have been proposed in data mining, machine learning, and network sensing communities to solve the truth discovery problem [4], [5], [14], [18], [19], [24], [25]. However, two significant challenges have not been well addressed by the state-of-the-art truth discovery solutions in social media sensing. First, existing truth discovery solutions did not fully explore the "misinformation spread" scenario where a large amount of sources are spreading the false information on social media [8], [10], [13], [20], [26]. In such a scenario, the propagated misinformation could easily overshadow the voice of truth and make the truth discovery a challenging task.

Second, existing truth discovery algorithms depend heavily on the correct estimation on the reliability of sources, which often requires a reasonably dense dataset for an accurate estimation [7], [9], [11], [12]. However, "data sparsity" is commonly observed in real world social media sensing applications where the majority of sources only contribute a small number of claims. For example, sources might lack the motivation and incentives to continuously contribute data to a social media sensing application. Alternatively, sources might only be interested in a certain topic or event while neglecting the others.

In this paper, we develop a Robust Truth Discovery (RTD) scheme to address the *misinformation spread* and *data sparsity* challenges in social media sensing applications. To address the misinformation spread challenge, the RTD scheme explicitly considers *different attitudes* that a source may express on a claim (e.g., agree or disagree) as well as the *historical contributions of a source*. Specifically, the fine-grained source attitude enables an effective detection of misinformation, which is based on the observation that the misinformation is more likely to attract opposite opinions and intensive debates. The historical contributions of a source refer to the set of claims made by the source in its data contribution history. It helps track the self-correction behavior of the source, which is related with the reliability of the source. To address the data sparsity challenge, the RTD scheme develops a novel algorithm to calculate claim

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truthfulness based on a function of the source attitude, the source's historical contributions and the source reliability. The estimation is more robust in the sense that it does not merely depend on the source reliability estimation, which is difficult to estimate accurately in a sparse dataset.

We evaluate our RTD scheme in comparison with the state-of-the-art baselines on two real world datasets collected from Twitter during the real world events (Charlie Hebdo Shooting in 2015 and Boston Bombing in 2013). The evaluation results show that our RTD scheme significantly outperforms the compared baselines and accurately identifies the truthful information in the presence of widely spread misinformation and sparse data.

In summary, our contributions are as follows:

- We address two fundamental challenges (misinformation spread and data sparsity) in solving the truth discovery problem in social medial sensing.
- We develop a novel Robust Truth Discovery (RTD) scheme that explicitly considers both the fine-grained source attitudes and a source's historical contributions.
- We evaluate the performance of our scheme and other truth discovery solutions using two large-scale real world datasets and an extensive simulation study. The evaluation results demonstrate the effectiveness and non-trivial performance gains achieved by our RTD scheme.

2. Related Work

The truth discovery problem is first formally formulated by Yin et al. [27], in which a Bayesian based heuristic algorithm, *Truth Finder*, is proposed. It computes the probability of each claim being correct given the estimated source weights and the influences between claims. Pasternack et al. proposed extended models (e.g., *AVGLog, Invest* and *PooledInvest*) to incorporate prior knowledge, such as constraints on truth and background information, into truth discovery solutions [14]. Dong et al. proposed algorithms to handle the source dependency in truth discovery problem [3]. Wang et al. proposed a maximum-likelihood estimation approach that offers a joint estimation on source reliability and claim correctness without knowing either of them a priori [21], [22]. However, there exists a significant knowledge gap of existing truth discovery methods in terms of finding truth among widely spread false information. Finding truth when most people are lying is a challenging task in truth discovery, yet has not been well addressed by existing schemes.

Rumor detection is related to our work. Previous works in rumor detection have found that the crowd could identify and correct rumors which suggests the possibility of building tools to leverage the crowd to identify misinformation [2]. Takahashi et al. implements a document classifier using features like retweet ratio and word distribution to detect rumors on Twitter [16]. Qazvinian et al. build different Bayesian classifiers on various subsets of features including the linguistic features of the tweets, the network structure as well as the URLs to automatically classify rumors [15]. Our work is different from these rumor and malicious activity detection schemes in that our goal is to identify the truthful information with a robust feature against widely spread misinformation including false rumors and spams while the main goal of rumor detection algorithms is to detect potential rumors.

3. Problem Formulation

In this section, we formulate our robust truth discovery problem in sparse social media sensing. In particular, we consider an application scenario where a group of M sources $S = (S_1, S_2, ..., S_M)$ report a set of N claims, namely, $C = (C_1, C_2, ..., C_N)$. In the Twitter example, a source represents a user account and a claim is a statement on an event, topic or object that is derived from his/her tweet. For example, a tweet "Another bomb found in Harvard station... Right next to my school. Sick world we live in." is associated with a claim "another bomb was found in Harvard Station". We assume the social media sensing data is sparse in the sense that the majority of sources only contribute to a small number of claims in an event.

We further let S_u denote the uth source and C_k denote the kth claim. $C_k = T$ and $C_k = F$ represents a claim is true and false respectively. Each claim is also associated with a ground truth label $\{x_k^*\}$ such that $x_k = 1$ when C_k is true and $x_k = 0$ otherwise. The goal of truth discovery is to jointly estimate the truthfulness of each claim and the reliability of each source which are defined as follows:

DEFINITION 1. *Claim Truthfulness D_j for claim C_j: it denotes how trustworthy a claim is. The higher D_j is, the more likely the claim C_j is true.*

DEFINITION 2. *Source Reliability R_i for source S_i: it measures the credibility of the information provided by a source. The higher R_i is, the more likely the source S_i will provide credible information.*

In social media sensing, sources are diversified and can hold different attitudes towards a claim. Moreover, sources may either contribute to an original claim or repeat claims from other sources. To fully capture the reporting behavior of sources, we introduce the concept of *source attitude score* as follows.

DEFINITION 3. *Source Attitude Score A_{ij}: When the ith source reports on jth claim, we use A_{ij} to denote his attitude, which represents how strongly S_i agrees/disagrees with C_j. When S_i agrees with C_j, A_{ij} is positive; otherwise it is negative.*

In this paper, we consider four different source attitudes whose scores are denoted by a_1, a_2, a_3, a_4. The definition of each score is summarized in Table 1.

Our model also explicitly considers the fact that source may report the same claim multiple times. For example, mainstream media accounts on Twitter often keep posting updates on the same topic. Alternatively, a reliable source

Table 1. DEFINITION AND NOTATION

M	Number of sources
N	Number of claims
R_u	The reliability of the uth source
D_j	The truthfulness of the jth claim
t_{ij}^k	The kth attitude score of the ith source on the jth claim
a_1	The attitude score assigned to the attitude that agrees with the claim
a_2	The attitude score assigned to the attitude that agrees with the claim with its content duplicate or copied
a_3	The attitude score assigned to the attitude that disagrees with the claim
a_4	The attitude score assigned to the attitude that disagrees with the claim with its content duplicate or copied
CS_{ij}	The contribution score of source i on claim j
x_i^*	The ground truth of the ith claim.

may proactively correct its previous claims that carry misinformation. To capture such effect, we define a time-series matrix to explicitly model the historical contributions of a source on her/his claims.

Given M sources and N claims, we define a *Time-series Source Claim (TSC)* matrix $TSC_{M\times N}$ where each element $\{t_{ij}^k\}$ represents the historical attitude scores from source S_i on claim C_j at the time instance k.

$$TSC_{ij} = \{t_{ij}^1, t_{ij}^2, \cdots t_{ij}^k\}, t_{ij}^k \in \{a_1, a_2, a_3, a_4\} \tag{1}$$

Using the TSC matrix, we further define the concept of *Contribution Score* to quantify the actual contribution of a source on a claim as follows.

DEFINITION 4. *Contribution Score CS_{ij}: it is defined as the aggregated contribution score from source S_i to claim C_j, which is a function of the source reliability and historical contributions. It will be further explained in Section 4.*

Using the above definitions, we can formally formulate robust truth discovery problem in sparse social media sensing as follows: given only a sparse Time-series Source-Claim Matrix TSC, the objective is to estimate the truthfulness D_j of each claim and the reliability R_i of each source.

4. Solution

In this section, we present the Robust Truth Discovery (RTD) that addresses the misinformation spread and data sparsity challenge we identified in this paper.

4.1. Assumptions

In the RTD scheme, we make the following assumptions:

- Assumption 1: Sources may spread false information by simply copying or forwarding information from others without independent verification (e.g., retweets on Twitter).
- Assumption 2: False claims are often controversial and sources tend to disagree with each other and have intensive debates on those claims.
- Assumption 3: If a source debunks its previous claim, it's very likely the previous claim is false because people are generally more prone to be self-consistent.

4.2. Deriving Contribution Score (CS)

In the RTD scheme, we introduce the concept of *Contribution Score (CS)* of sources to address the data sparsity challenge. The contribution score provides the basis for estimating both the claim truthfulness and source reliability. As discussed in Section 3, contribution score represents a source's contribution to a claim. Previous truth discovery methods usually calculate claim truthfulness solely based on weighed source reliability. In contrast, the proposed contribution score incorporates the source reliability, the weight of source attitude and the historical contributions of the source, which provides a more fine-grained and comprehensive estimation for both source reliability and claim truthfulness.

The contribution score is calculated based on the following rubrics:

- A more reliable source should be assigned a higher contribution score.
- Original reports of a claim should be assigned higher contribution score than simply copying and forwarding reports.
- The self-correction behavior should be honored by increasing the contribution score of the source since the correction represents the reflection ability of the source.
- Spamming behavior (i.e. a source keeps forwarding the same claim) should be punished by decreasing the contribution score.

Based on the above rubrics, we can calculate contribution scores using the input TSC matrix as well as the source reliability. The Contribution Score for S_i on C_j is formally calculated as:

$$CS_{ij} = sgn(t_{ij}^K) \sum_{k=1}^{K} R_i^{K+1-k} |t_{ij}^k| \tag{2}$$

where R_i denotes the reliability of source S_i and t_{ij} denotes the S_i's historical contributions. $sgn(t_{ij}^K)$ represents the sign of t_{ij}^K and K denotes the size of t_{ij}. The equation rewards "self-correction" by increasing the contribution score to the source who debunks her/his own previous claims. It punishes spamming behavior by decreasing the contribution score if a source keeps making the exactly same statement over time.

4.3. RTD Scheme

The RTD scheme jointly estimates the claim truthfulness and source reliability by explicitly considering the contribution score of sources. To calculate the truthfulness for the jth claim, (i.e., D_j), we first sum up all the contribution scores from the set of the sources who contribute to C_j, denoted as TC_j. Then we apply a sigmoid function on the sum as follows.

$$TC_j = \sum_{i \in K(j)} CS_{ij} \tag{3}$$

$$D_j = \frac{1}{1 + exp(-TC_j)} \tag{4}$$

where $K(j)$ is the set of the sources who contribute to the jth claim.

The source reliability can be calculated using the truthfulness of claims contributed by the source as follows.

$$R_i = \frac{\sum_{j \in F(i)} |CS_{ij}|(\chi(CS_{ij})D_j + (1-\chi(CS_{ij}))(1-D_j))}{\sum_{j \in F(i)} |CS_{ij}|}$$

$$\chi(a) = \begin{cases} 1, a > 0 \\ 0, a \le 0 \end{cases} \tag{5}$$

where $F(i)$ is the set of the claims contributed by S_i.

The RTD scheme is an iterative algorithm that iterates between the computation of D_j and R_i. The pseudocode of the RTD scheme is given in Algorithm 1.

Algorithm 1 Robust Truth Discovery (RTD)

```
Initialize R_i = 0.5, ∀i ≤ M, set the values of attitude scores a_1, a_2,
a_3, a_4
while {R_i} and {D_j} do not converge do
    for all i, 1 ≤ i ≤ M do
        for all j, 1 ≤ j ≤ N do
            if TSC_ij exists then
                compute CS_ij based on Equation (3).
            end if
        end for
    end for
    for all j, 1 ≤ j ≤ N do
        compute TC_j based on Equation (4)
        estimate D_j based on Equation (5)
    end for
    for all i, 1 ≤ i ≤ M do
        estimate R_i based on Equation (7)
    end for
end while
for all j, 1 ≤ j ≤ N do
    if D_j ≥ threshold then
        output x̂*_j = 1
    else
        output x̂*_j = 0
    end if
end for
```

5. Evaluation

In this section, we evaluate the RTD scheme in comparison with the state-of-the-art truth discovery schemes on two real-world datasets collected from Twitter in recent events.

5.1. Experimental Setups

5.1.1. Baseline Methods. We chose the following representative truth discovery solutions as the baselines in the evaluation: Sums, AverageLog, Invest, PooledInvest [14], TruthFinder [27], 2-Estimate [6], CATD, ETCIBoot [4], [5]:

Table 2. DATA TRACE STATISTICS

Data Trace	Charlie Hebdo Shooting	Boston Bombing
Start Date	Jan. 1 2015	April 15 2013
Time Duration	3 days	4 days
Location	Paris, France	Boston, USA
Search Keywords	Paris, Shooting, Charlie Hebod	Bombing, Marathon, Attack
# of Tweets	60,559	73,331
# of Users Tweeted	52,380	64,381

We use the same Time-series Source-Claim (TSC) matrix as the input to all compared schemes. For the first 5 baselines (i.e., Sums, AverageLog, Invest, PooledInvest, TruthFinder), their original versions only consider computing the credibility score for a set of mutually exclusive claims on each object. In our model, we consider whether a claim is true or false regarding a object/event. In order to use their models, we “split” one claim into two “virtual” claims: one agrees with the original claim and the other disagrees. Then we apply those baselines and get the credibility scores for the two “virtual” claims and choose the one that has higher credibility scores.

5.2. Experiment on Real World Data

5.2.1. Data Collection. The statistics of the two data traces we use are summarized in Table 2. We noted that both datasets are very sparse. In the Boston dataset, 94.9% of sources only make a single claim and only 1.1% of sources contribute more than two claims. Similarly, in the Charlie Hebdo dataset, 90.8% of sources contribute to a single claim and only 2.3% of sources contribute to more than two claims.

5.2.2. Data Preprocessing. To evaluate our methods in real world settings, we conducted the following data preprocessing steps to prepare the datasets for experiment:

- **Clustering**: We cluster similar tweets into the same cluster using K-means and a commonly used distance metric for micro-blog data clustering (i.e.,Jaccard distance) [17]. We then take each Twitter user as a source and each cluster as a claim in our model described in Section 3.
- **Labeling Source Attitude**: We used a simple heuristic based mainly on the content of the tweet to classify it as “agree” or “disagree” (e.g., whether a tweet contains certain negative words such as “false”, “fake”, “rumor”, “debunked”, “not true”, etc.). After classifying the tweets into two opposite categories, we assign two graders to manually check if the classification labels are correct. To detect the copy or forwarding tweet, we implemented a script to automatically label a tweet as “copying/forwarding” if it is i) a retweet or ii) significantly similar to other tweets that were posted before it.
- **Generating Time-series Source-Claim Matrix**: We generate each element t_{ij} of the TSC matrix as follows: for source S_i, we record all of its tweets

that are related to C_j. Since each tweet has a corresponding source attitude label, the time-series data t_{ij} is represented as a vector of these labels.

- **Labeling Ground Truth**: We manually verified the ground truth of the measured variables using the historical facts about the Boston Bombing and Paris Shooting events.

After the above data pre-processing steps, we find out that our evaluation datasets are imbalanced: there are more true claims than false claims. To handle such imbalance, we choose three classification metrics for imbalanced classification to evaluate the performance of all compared schemes, namely **SPC** (Specificity), **MCC** (Matthews Correlation Coefficient) and **Kappa** (Cohen's Kappa).

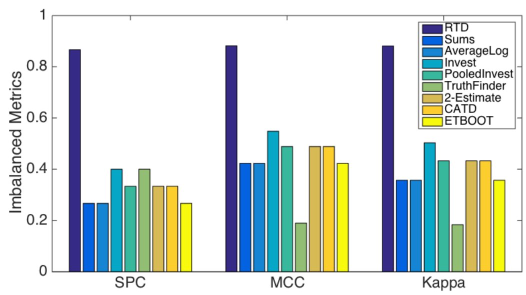

Figure 1. Charlie Hebdo Shooting

5.2.3. Evaluation Results. The evaluation results of Charlie Hebdo Shooting data trace are shown in Figure 1. We can observe that RTD outperforms all the other baselines on all three imbalanced metrics. In particular, the performance gain achieved by RTD compared to Invest (the best performed baseline) on SPC, MCC, and Kappa is 0.46, 0.34 and 0.38 respectively. To further demonstrate the robustness of our scheme in identifying the truth among misinformation spread, we pick the top 10 false claims (ranked by the number of tweets associated with the claims) in the Charlie Hebdo dataset. Then we compare our scheme with other baselines to see which scheme identifies the most number of false claims. Additionally, we also ask 15 individuals to independently label these claims as true or false. We make sure that individuals have no prior knowledge on the truthfulness of these claims. The results are shown in Table 3. RTD successfully identifies 9 out of 10 false claims while the best performed baselines (i.e. TruthFinder) only identifies 5. Interestingly, human labeling identifies 6, which is still worse than the performance of RTD. The results demonstrate the ability of RTD scheme to identify important misinformation in a real world event, which is more accurate than both state-of-the-arts and human labeling.

The results of the Boston Bombing dataset are shown in Figure 2. We observe that the RTD scheme continues to outperform other methods. Compared to the best performed baseline (i.e. TruthFinder), the performance gains achieved by RTD scheme on MCC and Kappa are 0.34 and 0.36.

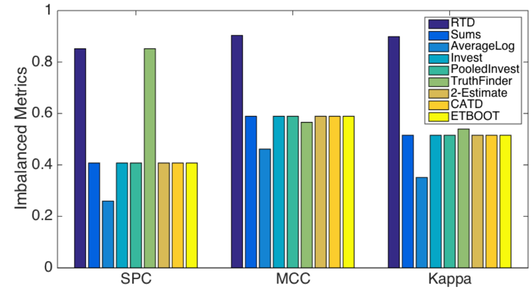

Figure 2. Boston Bombing

6. Conclusion

This paper develops a Robust Truth Discovery (RTD) scheme to solve the data veracity problem in big data social media sensing applications. The framework explicitly incorporates both the different attitudes a source may express on a claim and the source's historical contributions to address the misinformation spread and data sparsity challenges in the truth discovery problem. The evaluation results demonstrate that our solution achieved significant performance gains compared to the state-of-the-art baselines.

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Table 3. TOP10 FALSE CLAIMS

Representative Tweet Text	RTD	AvgLog	Invest	TruthFinder	Human
Charlie Hebdo killers should be called CIA agents! #OpenYourEyes #FalseFlag	√			√	√
All signs point to this attack being a false flag. #CharlieHebdo	√				√
Friday, 9 January 2015 PARIS PSYOP - INSIDE JOB - MOSSAD ATTACKS CHARLIE HEBDO	√		√	√	√
French President Says Illuminati Behind Charlie Hebdo Terrorist Attack in Paris? http://youtu.be/PbXuxemDb40					√
One of the attackers has blue eye #charlie hebdo	√	√	√	√	
@bbcquestiontime the Charlie hebdo video is controversial. Look at it properly. they were firing blanks.	√			√	
lol what next then? jews planned charlie hebdo to increase publication of it to 50 fold and also 2 defame muslims.	√				√
The office of Charlie Hebdo was definitely a Muslim “no-go” zone. Fox is 100% correct.	√				
I donate $1 to UNICEF for each hate-filled tweet I get from http://fb.me/4ggNbJpzo	√	√	√		√
PSG pay respect to the victims of the Charlie Hebdo shooting via Soccer Memes	√	√	√	√	

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