An Effective and Efficient Truth Discovery Framework over Data Streams

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ABSTRACT

Truth discovery, a validity assessment method for conflicting data from various sources, has been widely studied in the conventional database community. However, while existing methods for static scenario involve time-consuming iterative processes, those for streams suffer from much sacrifice on accuracy due to the incremental source weight learning. In this paper, we propose a novel framework to conduct truth discovery over streams, which incorporates various iterative methods to effectively estimate the source weights, and decides the frequency of source weight computation adaptively. Specifically, we first capture the characteristics of source weight evolution, based on which a framework is modeled. Then, we define the conditions of source weight evolution for the situations with relatively small unit and cumulative errors, and construct a probabilistic model that estimates the probability of meeting these conditions. Finally, we propose a novel scheme called adaptive source reliability assessment (ASRA), which converts an estimation problem into an optimization problem. We have conducted extensive experiments over real datasets to prove the high effectiveness and efficiency of our framework.

CCS Concepts

•**Database Management** → **Database Applications;**

Keywords

truth discovery; data streams; source reliability; data quality

1. INTRODUCTION

The current big data era has witnessed various sources providing information on the same set of objects or events [18]. The data inconsistency across multiple sources is an important research issue in many applications. The real world applications like weather situation analysis and health-care require techniques to identify which data sources are more reliable or what information is accurate. For example, when we identify the weather condition of a city, the inconsistent information may be obtained from multiple websites. As another example, different medical records on a patient may be found from different hospitals. Thus, it is highly demanded to automatically identify trustworthy information from conflicting data. For this task, truth discovery has been proposed to model the source quality and derive the truth based on a principle: the information from a reliable source is trustworthy and the source providing trustworthy information is reliable. By leveraging this principle, several mechanisms have been proposed in previous works for both static and dynamic data.

Consider a set of conflicting stock information for Apple Inc. at certain time as shown in Figure 1. As the information on the open price is arriving continuously, the truth on it evolves over time. In addition, the value from Insidestocks is closer to the truth at t_{i-1}, while that from Stocksmart is closer to the truth at t_i. This implies the reliability degrees of these three sources change over time as well. Thus, it is vital to identify the reliability of sources and the truths over continuous data streams, and develop advanced techniques for the truth discovery under dynamic scenario. Existing approaches for truth discovery mainly focus on static data [6, 7, 8, 19, 2, 22, 3, 1, 15, 5, 9, 12, 4, 14, 24], where an iterative process is exploited. The truth discovery process constantly iterates until the source weight converges to an optimal value. Applying the iterative process to the truth discovery at each timestamp over streams, the high accuracy performance can be achieved. However, these approaches suffer from expensive time costs, which is not applicable to high-speed data streams. Recently, some approaches have been proposed to improve the truth discovery efficiency by learning source weights and deriving truths incrementally [11, 23]. However, these methods sacrifice much accuracy,

because they model each source weight as a constant. The reliability of each source estimated by them is converged to a value, while the true source weights in real applications are constantly changing over time [16].

To effectively and efficiently discover truths over streams, we need to well address three issues. First, various iterative methods should be incorporated in a nice way to find the truths and the reliability of sources. This is important, as the optimal truths and source weights at each timestamp can only be derived by iteration strategy. As a result, the accuracy of truth discovery over data streams can be improved. Second, we need to design a set of advanced techniques which adaptively decide the frequency of source weight assessment to minimize the number of iterative operations. As data streams flow in large volume at high speed, it is clearly unacceptable to perform iterations at each timestamp. Finally, we should study the errors caused by not accessing the source weights continually over streams, and control these errors in a certain range.

In this paper, we propose a novel framework for effective and efficient truth discovery over streams. The idea behind it is to incorporate the iterative process in truth discovery for high accuracy and adaptively reduce the frequency of source weight assessment for high efficiency. Specifically, we first define two concepts, *Unit error* and *Cumulative error*, to describe the error caused by not changing the source reliability over data streams. Then, we present the relationship between each of these two concepts and the source reliability change based on theoretical analysis, which guarantees the accuracy of our truth discovery framework. For minimizing the source weight assessment frequency, we turn the problem of source weight assessment into an optimization problem and propose a scheme called ASRA to determine this frequency adaptively over data streams. In summary, we make the following contributions:

- We speculate the condition of the source reliability evolution under the constraints of small errors based on theoretical analysis, which guarantees the accuracy of our method. A probabilistic model is constructed to estimate the probability of meeting these conditions.
- We propose an optimization-based scheme ASRA, that minimizes the source reliability assessment frequency by estimating the maximum value of cumulative error smaller than a given threshold in a certain confidence level of probabilities.
- We propose a framework, which adaptively determines the time of source reliability assessment by combining the incoming data. Our framework incorporates various iterative approaches to estimate the reliability of sources, and balances the efficiency and accuracy by tuning the parameters.
- We validate the proposed framework on real datasets, and the results demonstrate the high performance of our proposed framework in term of effectiveness and efficiency.

The rest of paper is organized as follows. We survey the related work in Section 2, and formulate the research problem in Section 3. Section 4 proves some conclusions of truth discovery over data streams. Section 5 introduces the probability model and proposes our method. Section 6 conducts experiments and analyzes experimental results. Section 7 concludes our paper.

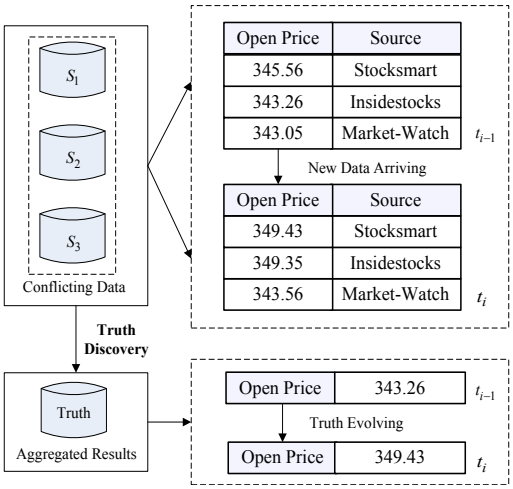


Figure 1: An Example of Truth Discovery over Data Streams

2. RELATED WORK

Truth discovery has been widely recognized in research community, and applied in several domains such as social sensing [17], health communities [13] and wireless sensor networks [20]. Previous works on truth discovery mainly focus on static databases [8, 7, 19, 6, 2, 22, 3, 1, 15, 5, 9, 12, 4, 21, 24]. In [19], Yin et al. propose an algorithm called TruthFinder that identifies truths using an iterative process. In [6], Galland et al. propose three alternative fixpoint algorithms, Consine, 2-Estimates and 3-Estimates, to estimate the truths and the reliability of sources. In [22], Zhao et al. study the truth discovery problem by modeling the two-sided source quality and leveraging Gibbs sampling. In [21], a probabilistic model is designed for the truth discovery over numerical data. In [8], an optimization-based framework is proposed to resolve the conflicts among multiple sources of heterogeneous data types. A confidence aware truth discovery method is proposed to find truths from the conflicting information with long-tails phenomenon [7]. However, none of these approaches can be directly applicable to data streams due to the costly iterative process.

Source correlation analysis has been studied as another topic of truth discovery [2, 3, 1, 15, 5, 9]. In [2], the ACCU model is proposed, which applies Bayesian analysis to decide the dependence between sources. In [3], Dong et al. propose a probabilistic-based approach to decide the copying relationship in a dynamic world. A Hidden Markov Model (HMM) is utilized to decide whether a source is a copier of another source and identify the specific moments at which it copies. In [1], a global model is proposed to identify the co-copying and transitive copying relationships. In [15], Pochampally et al. explore the correlation beyond copying, and propose a Bayesian-based model for addressing the positive and negative relationships in sources. A multilayer probabilistic model is proposed to compute the trustworthiness levels of sources [5]. A set of experiments is conducted to analyze the advantages and limitations of several truth discovery methods [9].

Recently, some attempts have been conducted to solve the truth discovery problem over data streams. In [23], Zhao et al. propose a probabilistic model that handles conflicting values over data streams. However, their method

Table 1: Notations

Notation	Definition	Defined in (Section)
$v_i^{(k,e,m)}$	the observation of the m^{th} property for the e^{th} object by the k^{th} source at t_i	3
V_i	the observations of all the objects on all the properties from all the sources at t_i	3
w_i^k	the weight of the k^{th} source at t_i	3
W_i	the source weight collection at t_i	3
$v_i^{(*,e,m)}$	the truth of the m^{th} property for the e^{th} object at t_i	3
V_i^*	the truths of all the objects on all the properties at t_i	3
λ	the smoothing factor	3.1
Δw_i^k	the source weight evolution on k^{th} source at t_i	3.2
ε	the unit error threshold	4
α	the probability threshold	5.2
E	the cumulative error threshold	5.2

can only work over categorical data. In [11], Li et al. proposed an incremental truth discovery method by transforming their optimization-based solution into a probabilistic model. However, the previous truth discovery work has shown that true source weights change over time [16], and this key point has not been considered in the models proposed in [23] and [11]. The source weight learned by these incremental methods converges to a certain value, which is considered as the corresponding true source weight. Although a smoothing factor has been introduced to capture the source's reliability changes [11], the source weight computed by it also finally converges to a certain value. Thus, these incremental methods suffer from low accuracy compared with optimization-based solutions. To the best of our knowledge, our work is the first attempt ever made to trade off the accuracy and efficiency of truth discovery over streams flexibly by tuning the parameters [10]. Moreover, with our proposed framework, various iterative truth discovery algorithms can be utilized to improve accuracy with neglectable efficiency losses. The notation used in this paper is listed in Table 1 for easy reference.

3. PROBLEM FORMULATION

In this section, we illustrate our proposed framework for truth discovery over data streams. Before proceeding to the problem formalization, we will introduce several important concepts first, *Observation*, *Source Weight*, and *Truth*.

Definition 1. An *observation* is the data that describes an object property of a source at a timestamp. We denote the observation of the m^{th} property on the e^{th} object from the k^{th} source at t_i as $v_i^{(k,e,m)}$, and all observations at t_i as V_i.

Definition 2. A *source weight* is the reliability degree of a source at a timestamp. The source weights at t_i are denoted as $W_i = \{w_i^1, w_i^2, \ldots, w_i^K\}$, where w_i^k is the reliability degree of the k^{th} source at t_i.

Definition 3. A *truth* is an aggregated result derived from truth discovery. We denote the truth of the m^{th} property for the e^{th} object at t_i as $v_i^{(*,e,m)}$. Let $v_{o,i}^{(*,e,m)}$ be the *optimal truth* satisfying the convergence criterion of a given iterative method at t_i, and $Dist$ be a distance function. Given a timestamp t_k for source weight assessment, the truth $v_k^{(*,e,m)}$ is a value that holds the condition: $Dist(v_{o,k}^{(*,e,m)}, v_k^{(*,e,m)}) = 0$. Given a timestamp t_j without source weight assessment, and two thresholds, ε, α, the truth $v_j^{(*,e,m)}$ is a value that is derived by previous source weights W_i $(i < j)$ and holds the condition: the probability of $Dist(v_{o,j}^{(*,e,m)}, v_j^{(*,e,m)}) \leq \varepsilon(j-i)^2$ is no less than α. The truths of all the objects on all the properties at t_i are denoted as V_i^*.

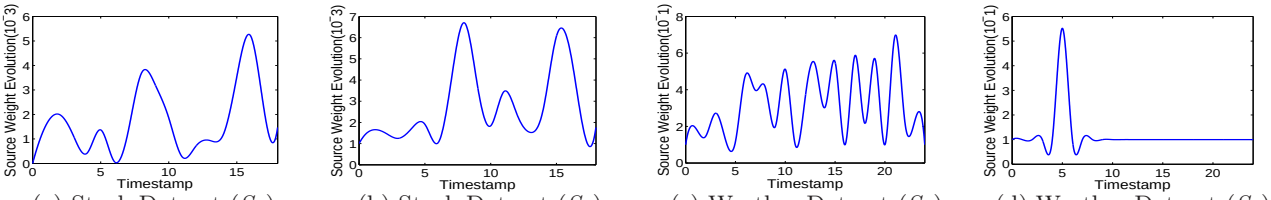
Given a set of observations V_i, truth discovery over data streams is to automatically infer the truths V_i^* and the source weights W_i at each timestamp t_i. In this paper, we propose a novel framework that balances the effectiveness and efficiency of truth discovery over data streams. The idea behind it is to incorporate iterative process in truth discovery for high accuracy and adaptively determine the frequency of source weight assessment for high efficiency. For this task, we first formalize the truth computation and the source weight evolution to analyze the error caused by not assessing source weights continually over data streams. Then, we define two concepts, unit error and cumulative error, and speculate the relationship between the source weight evolution and the two errors based on theoretical analysis, which guarantees the accuracy of our framework. Finally, we propose an optimization-based scheme which minimizes the iterative operations, and then propose our method which adaptively decides the source weight assessment frequency by combining the incoming data. We denote the timestamp that our method updates the source weights as *update point*. Next, we will introduce our basic ideas on truth computation and source weight evolution.

3.1 Truth Computation

Truth computation is to keep the truths close to the claims from reliable sources. Traditional voting or averaging schema assumes all sources are equally reliable, which is generally unreasonable in real applications. To overcome this problem, many truth discovery methods use weighted voting or averaging to obtain the truths [8, 7, 11, 19, 6, 2], which makes the observations from high quality sources more important. In this paper, we infer the truth by exploiting the same weighted averaging strategy considering its advantages:

$$v_i^{(*,e,m)} = \frac{\sum_{k=1}^{K} w_i^k \cdot v_i^{(k,e,m)}}{\sum_{k=1}^{K} w_i^k} \tag{1}$$

According to this weighted combinations, the information from the higher quality sources is more trustworthy, which is consistent with the principle of truth discovery. However, for truth discovery over data streams, the information



(a) Stock Dataset (S_1) (b) Stock Dataset (S_2) (c) Weather Dataset (S_1) (d) Weather Dataset (S_2)

Figure 2: Source Weight Evolution in Real-World Applications

usually evolves smoothly. To capture this characteristic, we add one smooth constraint on the aggregated results. As such, the truth $v_i^{(*,e,m)}$ is computed by:

$$v_i^{(*,e,m)} = \frac{\sum_{k=1}^{K} w_i^k \cdot v_i^{(k,e,m)} + \lambda \cdot v_{i-1}^{(*,e,m)}}{\sum_{k=1}^{K} w_i^k + \lambda} \quad (2)$$

where λ is the smoothing factor [11]. This equation treats the truth $v_{i-1}^{(*,e,m)}$ as the information from a pseudo source and λ as the weight of this source.

Existing iterative truth discovery methods usually assess the truths and source weights by conducting an alternating iterative process [8, 7, 11, 19, 6, 2]. In other words, such methods update truths while fixing source weights and then update source weights while fixing truths until convergence. We aim to design a framework which can embed various iterative truth discovery approaches for the accuracy improvement, and infer the truth by exploiting the weighted combinations strategy (i.e., Formula (1) or (2)). Thus, an iterative truth discovery method can be plugged into our framework only in the case that its truth computation is in the form of weighted combinations.

3.2 Source Weight Evolution

Based on the principle of truth discovery, the source weight reflects the contribution of a source to the results of weighted combinations. Therefore, a relatively smooth evolution of a source weight implies a small variation on the contribution of this source. Under this situation, neglecting the updating of source weights will cause small errors, while decrease the iterative process. Thus the iterative methods can be applied to dynamic scenarios. The *Source Weight Evolution* Δw_i^k on k^{th} source at time t_i is computed by:

$$\Delta w_i^k = \left| w_i^k / \sum_{k=1}^{K} w_i^k - w_{i-1}^k / \sum_{k=1}^{K} w_{i-1}^k \right| \quad (3)$$

To observe the evolution of source weights, we conduct a set of experiments on two real-world datasets: Stock Dataset and Weather Dataset. These datasets have been used in the evaluation of truth discovery solutions [9, 3], and their ground truths are available. For each dataset, we randomly select two sources, S_1 and S_2, for tests. Each source weight is quantified by comparing its observations with the ground truths and measuring the closeness between them. Since data usually contain multiple attributes in real applications, we normalize the deviation from various attribute values. Figure 2 shows the experimental results on source weight evolution over two different real-world datasets. Clearly, the evolution of source weights is quite minor at some moments. Under this scenario, it is natural to utilize previous source weights instead of current ones to obtain truths. For one thing, since the source weight computation is neglected, the iterative process is decreased under dynamic scenario. Thus, the iterative methods are applicable to data streams to improve the accuracy of truth discovery. For another, the deviation between the optimal truth and the approximate one will be small as well. Next, we will analyze this deviation caused by un-assessing source weights.

4. THEORETICAL ANALYSIS

In this section, we prove the condition of the source weight evolution under the constrains of small errors caused by un-assessing source weights. We first define the error in the form of mathematical formula. The unit error Φ_j^i $(i < j)$ is given by:

$$\Phi_j^i = \left(\frac{v_{o,j}^{(*,e,m)} - v_{i/j}^{(*,e,m)}}{v_j^{(\max,e,m)}}\right)^2 \quad (4)$$

where $v_{i/j}^{(*,e,m)}$ $(i < j)$ is the approximate truth computed based on the previous source weight W_i, and $v_j^{(\max,e,m)}$ is the absolute maximum value of $v_j^{(k,e,m)} (1 \le k \le K)$. We use $v_j^{(\max,e,m)}$ to normalize the distance between the optimal truth $v_{o,j}^{(*,e,m)}$ and the approximate one $v_{i/j}^{(*,e,m)}$ at t_j. Here, $v_{i/j}^{(*,e,m)}$ refers to $v_j^{(*,e,m)}$ in Definition 3.3. Specifically, let Φ represent Φ_i^{i-1}. The relationship between the unit error Φ and the source weight evolution is given by Theorem 1.

THEOREM 1. *Given a unit error threshold ε, let K be the size of source collection. If for all k, $1 \le k \le K$, the source weight evolution holds: $\Delta w_i^k \le \sqrt{\varepsilon}/K$, then the unit error $\Phi \le \varepsilon$ is satisfied.*

PROOF. According to Formulas (1) and (4), we derive the following:

$$\sqrt{\Phi} = \left| \frac{\sum_{k=1}^{K} (w_i^k / \sum_{k=1}^{K} w_i^k - w_{i-1}^k / \sum_{k=1}^{K} w_{i-1}^k) \cdot v_i^{(k,e,m)}}{v_i^{(\max,e,m)}} \right|$$

Then, we can infer

$$\sqrt{\Phi} \le \sum_{k=1}^{K} \left| \frac{(w_i^k / \sum_{k=1}^{K} w_i^k - w_{i-1}^k / \sum_{k=1}^{K} w_{i-1}^k) \cdot v_i^{(k,e,m)}}{v_i^{(\max,e,m)}} \right|$$

Since $\left|v_i^{(\max,e,m)}\right| \ge \left|v_i^{(k,e,m)}\right|$ $(1 \le k \le K)$, we have

$$\sqrt{\Phi} \le \sum_{k=1}^{K} \left| w_i^k / \sum_{k=1}^{K} w_i^k - w_{i-1}^k / \sum_{k=1}^{K} w_{i-1}^k \right|$$

Further,

$$\sqrt{\Phi} \le K \cdot \sqrt{\varepsilon}/K = \sqrt{\varepsilon}$$

So far, we prove that $\Phi \le \varepsilon$ holds. □

Theorem 1 demonstrates the relationship between the source weight evolution and the unit error, i.e., the unit error Φ should be no more than ε if the formula (5) is satisfied,

$$\Delta w_i^k \leq \sqrt{\varepsilon}/K \ (1 \leq k \leq K) \tag{5}$$

Under this scenario, we can use W_{i-1} to approximate W_i and ensure that the deviation between the optimal truth and the approximate one will be constrained by a threshold ε. Since we un-assess all sources weights at t_i, the time complexity of truth discovery is linear. For further improving the efficiency, we aim to assess source weights over time as few as possible. Therefore, it is essential to further analyze the relationship between the source weight evolution and the errors cumulated in a time period, i.e., the cumulative error, which is computed by Formula (6),

$$\Psi_j^i = \sum_{h=i+1}^{j} \Phi_h^i \tag{6}$$

Combining with Formula (4), we can see that the cumulative error is defined as the sum of unit errors in a time period. Then, we give the maximum value of the cumulative error under the condition that Formula (5) holds in a time period.

THEOREM 2. *Given a unit error threshold ε, let K be the size of source collection. If for all k, h, $1 \leq k \leq K$, $i < h \leq j$, the source weight evolution holds: $\Delta w_h^k \leq \sqrt{\varepsilon}/K$, then the cumulative error Ψ_j^i meets the condition $\Psi_j^i \leq \Delta T(\Delta T+1)(2\Delta T+1)\varepsilon/6$, where $\Delta T = j - i$.*

PROOF. According to Formulas (1) and (4), we derive the following:

$$\sqrt{\Phi_h^i} = \left| \frac{\sum_{k=1}^{K} (w_h^k / \sum_{k=1}^{K} w_h^k - w_i^k / \sum_{k=1}^{K} w_i^k) \cdot v_h^{(k,e,m)}}{v_h^{(\max,e,m)}} \right|$$

Then similar to Theorem 1, we have

$$\sqrt{\Phi_h^i} \leq \sum_{k=1}^{K} \left| w_h^k / \sum_{k=1}^{K} w_h^k - w_i^k / \sum_{k=1}^{K} w_i^k \right|$$

According to $\Delta w_h^k \leq \sqrt{\varepsilon}/K$, for any h $(i < h \leq j)$, it is easy to derive the following:

$$\sqrt{\Phi_h^i} \leq (h-i) \cdot \sqrt{\varepsilon}$$

Further,

$$\sum_{h=i+1}^{j} \Phi_h^i \leq \sum_{h=i+1}^{j} (h-i)^2 \varepsilon$$

Then,

$$\sum_{h=i+1}^{j} \Phi_h^i \leq (j-i)(j-i+1)(2(j-i)+1)\varepsilon/6$$

Since $\Psi_j^i = \sum_{h=i+1}^{j} \Phi_h^i$, we have

$$\Psi_j^i \leq (j-i)(j-i+1)(2(j-i)+1)\varepsilon/6$$

Let $\Delta T = j - i$, we prove that $\Psi_j^i \leq \Delta T(\Delta T+1)(2\Delta T+1)\varepsilon/6$ holds. □

According to Theorem 2, we can get that the relationship between the unit error and the maximum value of cumulative error under the condition of $\Delta w_h^k \leq \sqrt{\varepsilon}/K$ $(i < h \leq j,\ 1 \leq k \leq K)$:

$$\max(\Psi_j^i) = \Delta T(\Delta T+1)(2\Delta T+1)\varepsilon/6 \tag{7}$$

where $\Delta T = j - i$. Let the size of source collection K be 3 and the unit error threshold ε be 0.03. Suppose that we update the source weights at t_1 and the source weight evolutions satisfy Formula (5) from t_2 to t_5, i.e., $\Delta w_i^k \leq \frac{0.03}{3} = 0.01$ $(1 \leq k \leq 3,\ 1 < i \leq 5)$. The cumulative error Ψ_5^1 will be no more than $4\times(4+1)\times(2\times4+1)\times0.03/6 = 0.9$.

Theorem 2 ensures that, under dynamic scenario, we can incorporate iterative methods to improve the accuracy of truth discovery without scarifying much efficiency. The reason is that we neglect the iterative estimation of source weights W_i when the source weight evolutions Δw_i^k $(1 \leq k \leq K)$ satisfy Formula (5), i.e., the iterative truth discovery methods are utilized over data streams only at certain timestamps. In addition, as the cumulative error is constrained by ε and ΔT, we can ensure the accuracy of truth discovery even if the iterative process is reduced. Although we do not update the source weights at each timestamp, the accuracy of our method is still much higher than the existing incremental methods (as shown in Section 6).

To capture the temporal relations among truths by adding smoothing factor as in Formula (2), we only need to redefine $v_j^{(\max,e,m)}$ in Formula (4) as the absolute maximum value of $v_j^{(1,e,m)}, v_j^{(2,e,m)}, ..., v_j^{(K,e,m)}$, $v_{j-1}^{(*,e,m)}$, and slightly modify Formula (5) by changing K into $K+1$. The reason is that we treat the smoothing factor as the weight of the $(K+1)^{th}$ source and $v_{j-1}^{(*,e,m)}$ as the information from this source. Since we still compute truths by exploiting weighted combinations, the smoothing factor will not affect our conclusions. Moreover, we introduce the smoothing factor for truth computation only when the data changing is smooth, thus it is reasonable to utilize the $v_j^{(\max,e,m)}$ to normalize the unit error.

As shown in Theorems 1 and 2, a relative smooth source weight evolution leads to a lower unit error comparing with a big "jump" (the peaks in Figure 2) of source weight evolution. However, since the evolution of source weight is unknown over data streams, it is hard to make sure whether Formula (5) is satisfied. For solving this issue, we propose a probabilistic model to dynamically estimate the probability of Formula (5) holding over data streams.

5. ASRA-BASED TRUTH DISCOVERY

In this section, we propose an adaptive source reliability assessment scheme (ASRA) for truth discovery over data streams. The basic idea behind this scheme is to dynamically determine the time for source weight assessment. Then the truth with a predetermined accuracy is identified. Specifically, we first derive a probabilistic model to estimate the probability of the source weight evolution which meets the condition in Formula (5). By integrating the conclusions in section 4, we achieve the maximal period of source weight assessment under the condition that the maximum value of cumulative error is smaller than a given threshold in a certain confidence level. This will transform the source weights assessment into an optimization problem. Based on this optimization problem, we then propose our ASRA scheme that adaptively assesses source weights over streams.

5.1 Probability Forecasting Model

As proved in Theorem 1, the source weight evolution has great influence on unit error. If all the source weight evolutions meet the conditions in Formula (5), the unit error will be less than ε. Otherwise, it can not be controlled within the ε constraint. However, in real-world applications, even if

the variation trend of the information from various sources can be obtained, the evolution of each source weight is still not available. Considering this, we propose a probability model based on the Bernoulli distribution to estimate the probability of Formula (5) holding over data streams. Given a timestamp t_i, we can consider $\Delta w_i^k \leq \sqrt{\varepsilon}/K$ $(1 \leq k \leq K)$ as an independent and random event. Here, the probability of the event occurrence is a random variable which follows Bernoulli distribution, i.e., $\xi \sim B(1, p)$. Based on the probability theory, the probability p can be estimated by sampling as explained by Example 1.

EXAMPLE 1. *Given a unit error threshold ε and a source collection, assume that $t_1 \sim t_l$ is the initial period of time. We assess the source weight at each timestamp. Let N be the times of all source weight evolutions satisfying Formula (5) during this period. The total times of counting all source weight evolutions is $M = l - 1$. Thus the probability p can be estimated as N/M.*

As the time increases, both the source weight evolution and the probability p are likely to change. Thus, a dynamic estimation makes the probability p more accurate. This is also the basis of ASRA scheme. We will illustrate the time for the update of probability p while introducing our scheme.

5.2 ASRA Scheme

This section presents our ASRA scheme in details. The ASRA scheme includes two parts: (1) adaptive update point prediction; and (2) ASRA-based truth discovery algorithm. We first transform the update point prediction issue into an optimization problem which minimizes the frequency of source weight assessment. Then, an ASRA-based algorithm is proposed with the support of this optimization strategy. ASRA assesses source weights with changeable frequencies while finding the truth with a certain level of accuracy given by users. Accordingly, we can achieve high efficiency by reducing the frequency of assessing source weights and high accuracy by incorporating the iterative process. Given a current update point t_i, ASRA predicts the next update point t_j by solving the following optimization problem:

$$\begin{gathered} Max \quad j = i + \Delta T \\ s.t. \quad (\Delta T - 1)(\Delta T - 2)(2\Delta T - 3)\varepsilon/6 \leq E \\ p^{\Delta T - 2} \geq \alpha \end{gathered} \tag{8}$$

where ΔT is considered as the maximum period of assessing source weights. There are two constraint functions regarding this optimization problem as listed below:

- $p^{\Delta T-2} \geq \alpha$: This is equivalent to $p(\Delta w_h^k \leq \sqrt{\varepsilon}/K) \geq \alpha$ $(1 \leq k \leq K,\ i+1 < h < j)$, where α is the probability threshold given by users. We do not need to estimate the source weight evolutions at t_{i+1} and t_j. For one thing, we assess the source weights W_i since t_i is an update point. Considering that we should compute the source weight evolutions for dynamically updating p, the source weights W_{i+1} is also assessed to obtain the evolution of all source weights, i.e., $\Delta w_{i+1}^1, \ldots, \Delta w_{i+1}^K$. Then, we utilize W_{i+1} instead of $W_{i+2}, \ldots, W_{j-1}$ to compute the truths at $t_{i+2}, \ldots, t_{j-1}$. For another, we assess the source weights W_j since t_j is also an update point. Thus, it is unnecessary to estimate the probability of $\Delta w_{i+1}^k \leq \sqrt{\varepsilon}/K,\ \Delta w_j^k \leq \sqrt{\varepsilon}/K$ $(1 \leq k \leq K)$.
- $(\Delta T - 1)(\Delta T - 2)(2\Delta T - 3)\varepsilon/6 \leq E$: Based on Theorem 2, when $p(\Delta w_h^k \leq \sqrt{\varepsilon}/K) \geq \alpha$ $(i+1 < h < j)$, the probability of $\max(\Psi_{j-1}^{i+1}) = (\Delta T-1)(\Delta T-2)(2\Delta T-3)\varepsilon/6$ is no smaller than α. Though we expect ΔT to be large for high efficiency, $\max(\Psi_{j-1}^{i+1})$ will become large with ΔT increasing. Thus, we also need to make sure that $\max(\Psi_{j-1}^{i+1})$ is no more than E, where E is the cumulative error threshold given by users. By this way, the cumulative error between any two update points is constrained.

Formula (8) implicates that our ASRA scheme tries to search for the maximum period of assessing source weights. When the unit error threshold ε is fixed, only two tuned parameters, α and E, need to be set. A large α may lead to a small ΔT, while a small E will also result in a small ΔT. However, the performance trend of ε is actually uncertain. We will show in Section 6 that the effects of the probability threshold α, cumulative threshold E and unit error threshold ε in our framework, and the performance of our framework can be flexibly changed by tuning these parameters.

Algorithm 1 presents the whole procedure of ASRA-based truth discovery. Let t_i denote the current timestamp and t_j denote the update point, Algorithm 1 performs in three steps. In the first step (lines 3-4), we update the source weights. Given the update points t_j and t_{j+1} (line 3), we call the existing truth discovery method to assess the source weights W_j, W_{j+1}. In the second step (lines 5-13), we update the probability p of satisfying Formula (5) by re-estimating p according to $\Delta w_{j+1}^k (1 \leq k \leq K)$. In the last step (lines 14-18), we predict the next update point. By utilizing the probability p computed in the second step, we predict the next update point t_j according to Formula (8). If ΔT computed by Formula (8) is less than 2, we set $\Delta T = 2$ (lines 16-17).

In Algorithm 1, line 4 suggests that various methods for source weight computation can be plugged into our scheme only if the truth computation of the plugged method is in the form of weighted combinations. We set a window size M for more accurately estimating the probability p without the influence of out-of-date data. Note that we can introduce the smoothing factor by slightly modifying our algorithm. As mentioned above, we treat the smoothing factor λ as the weight of $(K+1)^{th}$ source and the previous truths as the information from this source. As λ is a constant [11], only the source weight evolution and the size of source collection will be changed when the smoothing factor λ is introduced. Accordingly, for capturing the temporal relationship over streaming data, we only need to change K into $K+1$ in line 6, and change "Formula (1)" into "Formula (2)" in line 21. For the existing truth discovery methods plugged into our scheme (line 4), we also simply change its truth computation from "Formula (1)" into "Formula (2)". Obviously, the complexity of the algorithm is determined by the corresponding iterative truth discovery methods at an update point. Otherwise, its complexity is $O(|V_i|)$ at t_i.

For probability p, there are two points to remark: (1) the cumulative error is usually constrained to a small value in real world applications. According to Formula (8), ΔT will not be a large value. Thus we can assume that p is a constant in a small time window (ΔT); and (2) p is defined as the probability of all the source weight evolutions satisfying Formula (5) at each timestamp, i.e., a small p implies the source weight evolution is generally large over data streams.

Algorithm 1: ASRA-based truth discovery

Input : Observation collection V_i, threshold α, E;
Output: Truth collection V_i^*;

$j \leftarrow 1$, $m \leftarrow 1$, $N[1...M] \leftarrow 0$, $p \leftarrow 0$;
for $i = 1 \rightarrow \infty$ **do**
  if $i == j || i == j + 1$; **then**
    Update V_i^*, W_i according to existing iterative truth discovery methods;
  if $i == j + 1$; **then**
    if *all* Δw_i^k $(1 \leq k \leq K)$ *satisfy Formula (5);* **then**
      $N[m] = 1$;
    if $m <= M$; **then**
      $p = (\sum_{n=1}^{m} N[n])/m$
    else
      Slide the window forward and keep array N always contains M elements;
      $p = (\sum_{n=1}^{M} N[n])/M$;
    $m++$;
    $i = i - 1$;
    Update j by Formula (8);
    if $j - i < 2$; **then**
      $j = i + 2$;
    $i = i + 1$;
  else
    $W_i \leftarrow W_{i-1}$;
    Set V_i^* by Formula (1);
Return V_i^*;

Note that the exact timestamp with a large source weight evolution is still unknown if we do not compute the source weights. Therefore, the algorithm may also neglect source weight computation when the source weight evolution does not satisfy Formula (5). However, according to Formula (8), a small p will lead to more frequent source weight estimation, thus the high performance of our framework can be ensured (as shown in Section 6).

6. EXPERIMENTS

In this section, we experimentally validate the proposed approach for truth discovery over data streams.

6.1 Experimental Setup

We evaluate our framework on three real-world datasets: Sensor Dataset[1], Stock Dataset[2] and Weather Dataset[2]. The Sensor Dataset contains data from 54 sensors deployed in the Intel Berkeley Research lab between Feb. 28, 2004 and Apr. 5, 2004. Each sensor collected the time-stamped topology values once per 30 seconds. The temperature and humidity properties are adopted for evaluation. The Stock Dataset contains data for 1000 stocks that are collected from 55 sources over the weekdays of July 2011. We adopt three properties: change %, change value and last trade price. The ground truths are given. The Weather Dataset contains 18 sources that record weather data for 30 cities of United States from Jan. 28, 2010 to Feb. 4, 2010. We adopt the temperature and humidity properties, and consider the information collected from Accuweather.com as the ground truths.

[1]http://db.csail.mit.edu/labdata/labdata.html
[2]http://lunadong.com/fusionDataSets.htm

Since the ground truths of Stock Dataset and Weather Dataset are known, each source weight can be quantified by measuring the distance between its observations and the ground truths. Accordingly, **the true source weights of Stock Dataset and Weather Dataset are also available.** Moreover, although Stock Dataset and Weather Dataset have been used in [11], the experimental results can be different because we choose various types of properties to conduct the experiments while only one type of property was used in [11].

6.2 Evaluation Methodology

We have conducted extensive experiments to evaluate the effectiveness and efficiency of the proposed method by four steps: (1) validate the effectiveness of the probabilistic model estimateing source weight evolution; (2) analyze the effects of three parameters, probability threshold α, cumulative error threshold E and unit error threshold ε in our framework; (3) evaluate the effectiveness and efficiency of our approach by comparing with state-of-art competitors; and (4) further confirm the accuracy of source weight computation of our proposed approach. Eleven methods, including seven state-of-the-art competitors and four proposed alternatives, are used in the experiments.

Baseline Methods. The following state-of-the-art methods for truth discovery over continuous data are implemented. The parameters of each baseline method are set according to the original paper.

- GTM: Using Bayesian probabilistic model for resolving conflicts on continuous data [21].
- CRH: Working with heterogeneous data by incorporating into various loss functions [8].
- DynaTD: Finding truths over data streams in an incremental way [11].
- DynaTD+smoothing: Adding the smoothing factor based on DynaTD [11].
- DynaTD+decay: Adding the decay factor based on DynaTD [11].
- DynaTD+all: Adding both the smoothing factor and the decay factor based on DynaTD [11].
- Dy-OP: Optimization-based solution of DynaTD [11].

Proposed Alternatives. We plug different existing truth discovery methods into our framework. All these methods iteratively conduct the updates of source weights and truths until convergence. For the truth update, all these methods exploit weighted combinations strategy (i.e., Formula (1) or (2)) [8, 11] and can be plugged into our framework. The details on the source weight update for each method are as follows:

- ASRA(CRH): We incorporate CRH into our framework and choose the normalized squared loss function to measure the deviation from the truths to the observations. The source weight w_i^k is derived as the following formula:

$$w_i^k = -\log(\frac{l_i^k}{\sum_{k'=1}^{K} l_i^{k'}}) \quad (9)$$

where l_i^k refers to the normalized squared loss function of the k^{th} source at t_i [8], i.e.,

$$l_i^k = \sum_{e=1}^{E} \sum_{m=1}^{M} \frac{\left(v_i^{(k,e,m)} - v_i^{(*,e,m)}\right)^2}{std(v_i^{(1,e,m)}, \ldots, v_i^{(K,e,m)})} \quad (10)$$

- ASRA(CRH+smoothing): We further introduce the smoothing factor λ to ASRA(CRH) for capturing the temporal relations over streams. Under this scenario, we consider $v_{i-1}^{(*,e,m)}$ as the information from the $(K+1)^{th}$ source ($v_{i-1}^{(*,e,m)} = v_i^{(K+1,e,m)}$) and λ is the weight of this source. Therefore, only the number of sources in Formula (10) and Formula (9) need to be changed for computing loss functions and source weights.

- ASRA(Dy-OP): We incorporate the basic optimization function of DynaTD [11], denoted as Dy-OP, into our framework. The source weight w_i^k is derived as the following formula:

$$w_i^k = \frac{q_i^k}{\eta \cdot l_i^k} \quad (11)$$

where q_i^k refers to the number of observations provided by the k^{th} source at t_i and η is a trade-off parameter of Dy-OP [11]. In addition, the normalized squared loss functions l_i^k $(1 \leq k \leq K)$ in Formula (11) are computed by Formula (10).

- ASRA(Dy-OP+smoothing): The smoothing factor λ is also introduced to ASRA(Dy-OP) for capturing the temporal relations over streaming data. As mentioned, only the number of sources need to be changed for computing source weights and loss functions.

So far, for each method plugged into our framework, we have presented the formula for its source update step. The details of Formulas (9) and (11) are listed in Appendix. For truth computation, we only need to utilize Formula (2) to capture the temporal relations over streaming data.

Performance Metrics. To evaluate the efficiency of our framework, we report the *running time* of each method. To assess the accuracy of it, we calculate the *Mean of Absolute Error* (MAE) of each method by comparing their outputs with ground truths. For both metrics, lower values indicate better performance. All the algorithms were performed on a PC with Windows OS, Intel Core i7 processor.

6.3 Probabilistic Model Validation

This part validates the effectiveness of the probabilistic model for estimating the source weight evolution over data streams. Obviously, if the probabilistic model can capture the large source weight evolution (Formula (5) cannot be satisfied), our proposed model is effective. Thus, we validate the effectiveness of our probabilistic model by counting all probable scenarios including:

(1) Formula (5) does not hold and our framework updates the source weights at the same time (denoted as TP);

(2) Formula (5) holds and our framework keeps the source weights at the same time (denoted as TN);

(3) Formula (5) does not hold and our framework keeps the source weights at the same time (denoted as FN);

(4) Formula (5) holds and our framework updates the source weights at the same time (denoted as FP).

Table 2: Probabilistic Model Valiadation

(a) Stock Dataset

Parameter Setting		Experimental Results				
ε	α	TP	TN	FN	FP	CR
5×10^{-4}	0.45	0.500	0.278	0.167	0.055	0.778
1×10^{-3}	0.45	0.390	0.333	0.222	0.055	0.723
5×10^{-3}	0.45	0.155	0.500	0.112	0.233	0.655
5×10^{-4}	0.55	0.500	0.278	0.167	0.055	0.778
1×10^{-3}	0.55	0.500	0.389	0.056	0.055	0.889
5×10^{-3}	0.55	0.212	0.444	0.055	0.289	0.656
5×10^{-4}	0.65	0.612	0.278	0.055	0.055	0.890
1×10^{-3}	0.65	0.612	0.333	0	0.055	0.945
5×10^{-3}	0.65	0.389	0.444	0.055	0.112	0.833

(b) Weather Dataset

Parameter Setting		Experimental Results				
ε	α	TP	TN	FN	FP	CR
5×10^{-2}	0.45	0.155	0.540	0	0.305	0.695
1×10^{-1}	0.45	0.058	0.724	0.023	0.195	0.782
5×10^{-1}	0.45	0.034	0.799	0	0.167	0.833
5×10^{-2}	0.55	0.155	0.495	0	0.350	0.650
1×10^{-1}	0.55	0.052	0.695	0.029	0.224	0.747
5×10^{-1}	0.55	0.034	0.776	0	0.190	0.810
5×10^{-2}	0.65	0.255	0.431	0.006	0.308	0.686
1×10^{-1}	0.65	0.063	0.632	0.017	0.288	0.695
5×10^{-1}	0.65	0.035	0.747	0	0.218	0.782

Both scenario (1) and (2) show that our probabilistic model captures the source weight evolution successfully. Thus, the effectiveness of our probabilistic model can be transformed into *Capture Rate* (CR) formulated as:

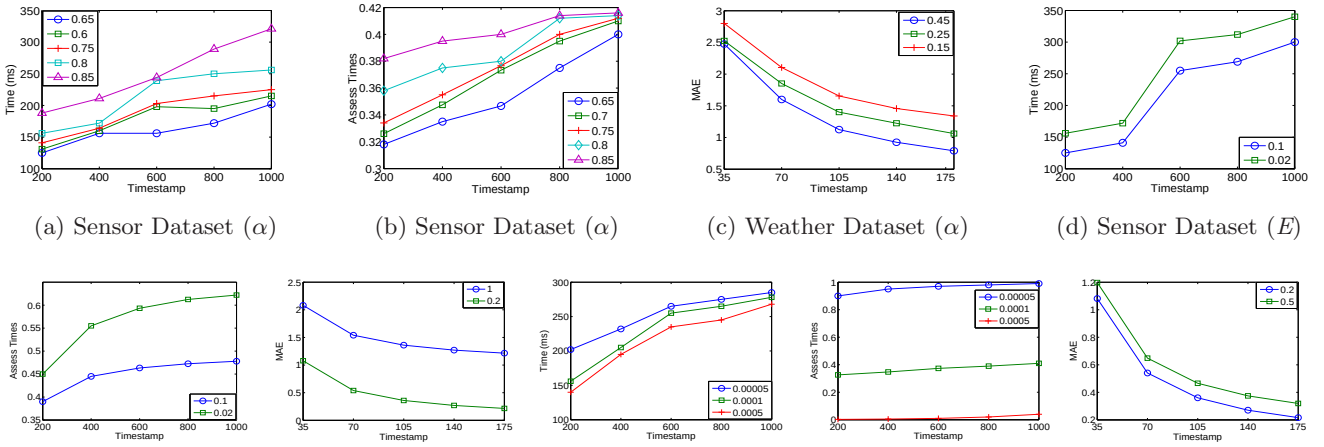
$$CR = TN + TP \quad (12)$$

The experiments are conducted over Stock Dataset and Weather Dataset. We vary two parameters, α and ε, to observe the effectiveness of our probabilistic model with different parameter settings. The cumulative threshold E is given to constrain the maximum of ΔT.

The experimental results are reported in Table 2. As we can see, CR is always more than 0.6 on both two datasets and can achieve more than 0.9 at some cases. Note that our framework assigns the first two timestamps to update points, which may lead to a higher FP and a lower CR. Therefore, our probabilistic model can capture the source weight evolution in most situations, which further proves the effectiveness of our framework.

6.4 Evaluation on Parameters

To analyze the effects of the probability threshold α, cumulative error threshold E and unit error threshold ε in our framework, we test the performance of our method over the Sensor Dataset and Weather Dataset by changing the value of one parameter while fixing the others. To discover truths, we incorporate Dy-OP into our framework, i.e., ASRA(Dy-OP). Three metrics, running time, MAE and assess times, are used to observe the influence of three parameters to our framework. Here, *assess times* is defined as the average times of assessing source weight over streaming data. Ob-



(a) Sensor Dataset (α) (b) Sensor Dataset (α) (c) Weather Dataset (α) (d) Sensor Dataset (E)

(e) Sensor Dataset (E) (f) Weather Dataset (E) (g) SensorDataset (ε) (h) Sensor Dataset (ε) (i) Weather Dataset (ε)

Figure 3: Evaluation on Parameters

viously, lower assess times indicates higher efficiency and lower accuracy.

6.4.1 *Effect of* α

In this test, we evaluate the effect of the probability threshold α on the accuracy and efficiency of our framework. For Sensor Dataset, we fix ε to 10^{-5} and E to 1, and vary the value of α from 0.65 to 0.85. For Weather Dataset, we fix ε to 0.1 and E to 1, and vary the value of α from 0.15 to 0.45. The results are shown in Figures 3(a)-(c).

As we can see, with the increasing of α, running time and assess times increase while MAE decreases. This result is caused by the following reason. The probability threshold α controls the holding probability of Formula (5) during the period of keeping source weights. Therefore, a relatively large α means Formula (5) should be more likely hold, and a smaller α will relax this constraint while leading to a relatively large ΔT. In other words, a lager α achieves a higher accuracy while suffering from much sacrifice on efficiency.

6.4.2 *Effect of* E

In this test, we evaluate the effect of the cumulative error threshold E on the performance of our framework. For Sensor Dataset, we set E to 0.02 and 0.1 respectively, and fix ε to 10^{-5} and α to 0.75. For Weather Dataset, we set E to 0.2 and 1 respectively, and fix ε to 0.1 and α to 0.2. The results are shown in Figures 3(d)-(f).

Obviously, with the decreasing of cumulative threshold E, running time and assess times increase while MAE decreases. According to Formula (8), a relatively large E means our framework is allowed to make more errors between any two update points. Therefore, a large E will lead to a large period of assessing source weights and improve the efficiency. However, it suffers from much sacrifice on accuracy.

6.4.3 *Effect of* ε

We test the effect of the unit error threshold, ε, on three metrics. For Sensor Dataset, we fix α to 0.6 and E to 0.01, and set ε to 5×10^{-5}, 10^{-4} and 5×10^{-4} respectively. For Weather Dataset, we fix α to 0.95 and E to 1, and set ε to 0.2 and 0.5 respectively. The results are shown in Figures 3(g)-(i).

As we can observe, with the increasing of ε, running time and assess times decrease while MAE increases. However, the performance trend of unit error threshold is actually uncertain. Based on the first constraint function of Formula (8), a relatively small ε may result in a larger ΔT. At the same time, the second constraint of Formula (8) implicates that a relatively small ε can also result in a smaller ΔT. Since we set a relatively large cumulative error threshold E ($E = 1$) in our experiments, the optimal ΔT is mainly restricted by the second constraint function of Formula (8). Thus a larger ε achieves a better efficiency and suffers from much sacrifice on accuracy.

For the same parameter setting, with the time increasing, MAE decreases while both running time and assess time increase over two datasets. This is because the source weight evolutions of these two datasets become large as the time increases. Thus our framework automatically improve the frequency of assessing source weights and achieve the high accuracy of the truth discovery.

To summarize, all the experimental results (Figures 3(a)-(i)) show that these three parameters of our framework can tune the performance of truth discovery flexibly.

6.5 Evaluation on Performance

We first compare our proposed approach with the state-of-the-art competitors in terms of effectiveness and efficiency. Then, we further study the effectiveness of our approach under the optimal efficiency, and its efficiency under the best accuracy.

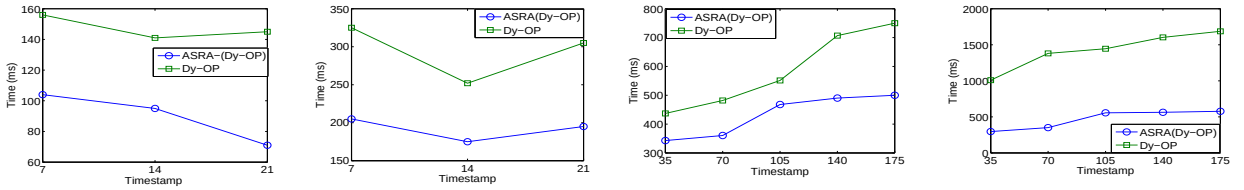
6.5.1 *Comparison with Existing Approaches*

In this test, we evaluate our proposed approach by comparing with the existing competitors: DynaTD, DynaTD+smoothing, DynaTD+decay, DynaTD+all, Dy-OP, CRH and GTM. For Stock Dataset, we set ε to 10^{-3}, α to 0.75 and E to 1. For Weather Dataset, we set ε to 0.1, α to 0.8 and E to 1. For Sensor Dataset, we set ε to 5×10^{-6}, α to 0.85 and E to 0.01. Table 3 shows the experimental results for all the methods on the three datasets. Since the ground truths of Sensor Dataset are unknown, we only report the accuracy (MAE) on two datasets with ground truths, i.e., Stock Dataset and Weather Dataset.

Efficiency. In terms of efficiency, the proposed method performs nearly as well as DynaTD, DynaTD+smoothing,

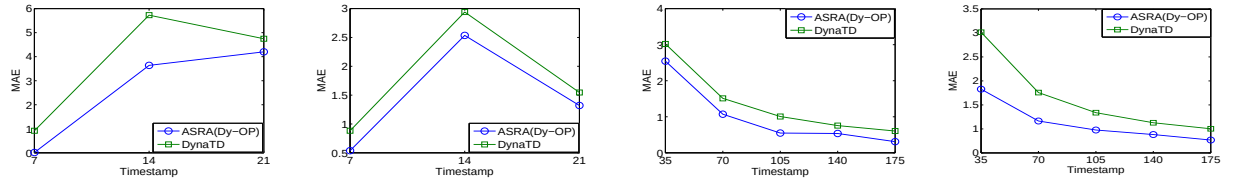
Table 3: Comparison with Existing Approaches

Method	Stock Dataset		Weather Dataset		Sensor Dataset
	MAE	Time(ms)	MAE	Time(ms)	Time(ms)
ASRA(Dy-OP)	1.3941	99	0.4974	419	658
ASRA(CRH)	1.4007	104	0.5029	424	674
ASRA(Dy-OP+smoothing)	1.0142	103	0.4474	417	638
ASRA(CRH+smoothing)	1.0781	117	0.5076	427	676
DynaTD	1.5462	99	1.0593	316	549
DynaTD+smoothing	1.5064	98	0.9261	306	595
DynaTD+decay	1.4956	98	0.9300	310	552
DynaTD+all	1.4455	93	0.9205	307	570
Dy-OP	1.3328	305	0.4425	1680	2041
CRH	1.3994	325	0.5028	1782	2092
GTM	1.4112	430	0.6011	1718	2133



(a) Stock Dataset (Sin) (b) Stock Dataset (Mul) (c) Weather Dataset (Sin) (d) Weather Dataset (Mul)

Figure 4: Efficiency Study



(a) Stock Dataset (Sin) (b) Stock Dataset (Mul) (c) Weather Dataset (Sin) (d) Weather Dataset (Mul)

Figure 5: Accuracy Study

DynaTD +decay and DynaTD+all. As all these methods work in an incremental way, they can be viewed as the low bound of the iterative methods. Therefore, the results shown in Table 3 implicate our proposed framework can achieve high efficiency. Meanwhile, ASRA(Dy-OP) can run as fast as DynaTD on Stock Dataset. The reason is that the proposed framework only performs iterations at certain timestamps. Moreover, our proposed framework is more efficient compared with other iteration-based truth discovery methods. Specifically, our framework outperforms the iterative method GTM in terms of both accuracy and efficiency. The reason is that the basic methods plugged into our framework (CRH, Dy-OP) achieve better performance than GTM.

Accuracy. In terms of effectiveness, the proposed method is better than existing competitors, DynaTD, DynaTD+smoothing, DynaTD+decay and DynaTD+all. The reason is that these competitors exploit incremental computation, updating the source weights according to the new arrival data until each source weight converges to a certain value. However, the true source weights in real applications are constantly changing. Thus, the source weights computed by the incremental methods deviate from the true ones, leading to big errors. In addition, CRH and Dy-OP are more accurate than our methods (ASRA(CRH), ASRA(Dy-OP)), as they solve the truth discovery task by an iterative process that iteratively computes the truths and source weights at each timestamp. In this way, each source weight converges to its optimal one. However, without computing the source weights at each timestamp, the accuracy of ASRA(Dy-OP) and that of ASRA(CRH) are still similar to the corresponding basic methods Dy-OP and CRH. The reason is that our proposed framework updates the source weights frequently when the source weight evolutions are generally large. Based on Theorems 1 and 2, we can constrain the cumulative error and ensure the accuracy of our framework. When a smoothing factor is introduced, our methods, ASRA(Dy-OP+smoothing) and ASRA(CRH+smoothing), achieve the best accuracy among all the methods on Stock Dataset. It can also be observed that ASRA(Dy-OP) achieves better accuracy than ASRA(CRH), while Dy-OP performs better than CRH on both two datasets. Obviously, the accuracy of our framework is consistent with the basic method plugged into it.

In conclusion, from the performance comparison results, it can be seen that our framework always outperforms the iterative methods with respect to efficiency and performs better than the incremental methods in terms of accuracy.

Since our framework can contain different plugged truth discovery methods, it also outperforms some baselines in terms of both accuracy and efficiency (such as GTM).

6.5.2 Further Study

To further confirm the performance of our framework, we evaluate its efficiency while achieving the optimal accuracy, and its accuracy while the efficiency is optimal. In this test, we conduct experiments on Stock Dataset and Weather Dataset. Since our framework can flexibly tune the efficiency and accuracy of truth discovery over streaming data, both accuracy and efficiency can be optimized by tuning the parameters. Also, we change the number of properties in this part, and denote the experiments conducted on a single property as Single-Property ("Sin" in Figures (4)-(5)), and the ones on multiple properties as Multiple-Property ("Mul" in Figures (4)-(5)). For evaluation on Single-Property, we choose the last trade price property for Stock Dataset, and the humidity property for Weather Dataset.

Efficiency. From Table 3, we can see that Dy-OP achieves the best accuracy comparing with all the baselines. Thus, the accuracy of Dy-OP can be considered as the optimal accuracy. We achieve the same accuracy with Dy-OP by tuning the parameters ($\varepsilon = 10^{-3},\ \alpha = 0.85,\ E = 0.1$ for Stock Dataset and $\varepsilon = 10^{-3},\ \alpha = 0.85,\ E = 1$ for Weather Dataset). Under this scenario, we evaluate the efficiency of our framework by comparing with Dy-OP.

From Figures 4(a)-(d), we can see that our framework achieves much higher efficiency performance than Dy-OP for both Single-Property and Multi-Property. The reason is that our framework does not assess the source weights continually. In addition, the gap between our framework and Dy-OP on Multiple-Property is larger than the one on Single-Property, which illustrates our method is more suitable for addressing different types of properties.

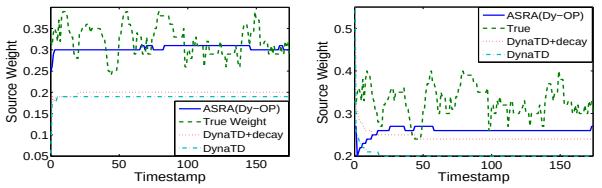
Accuracy. To the best of our knowledge, DynaTD is the most effective incremental truth discovery method for continuous data, and also the basis of DynaTD+smoothing, DynaTD+decay, DynaTD+all [11]. Thus, we consider the efficiency of DynaTD as the optimal efficiency. Then we achieve the same efficiency with DynaTD by tuning the parameters ($\varepsilon = 10^{-3},\ \alpha = 0.75,\ E = 1$ for Stock Dataset and $\varepsilon = 0.1,\ \alpha = 0.65,\ E = 1$ for Weather Dataset). Under this scenario, we evaluate the accuracy of our framework by comparing with DynaTD.

Figures 5(a)-(d) show that, for both Single-Property and Multi-Property, the accuracy of our proposed framework is much higher than the incremental method. For one thing, we use the iterative method to assess source weights, which makes source weights converge to the optimal values at each timestamp. For another, both Theorems 1 and 2 ensure the accuracy of our framework. Although we do not assess the source weights continually, our framework achieves much higher accuracy comparing with the existing incremental methods. Moreover, Figure 5(a) shows that, at the initial time, the truths computed by our framework is nearly equal to the ground truths, which also implicates the high accuracy of our framework.

To summarize, by tuning the parameters of our framework, we can balance the efficiency and accuracy of the truth discovery task, and achieve better performance than the state-of-the-art competitors as well.

6.6 Evaluation on Source Weight

As aforementioned, the estimation of source weights plays a vital role in the truth discovery task. Thus, we design a set of experiments to evaluate the accuracy of source weight computation using our proposed framework. In this test, we choose Weather Dataset as the experimental dataset. We randomly select two sources (denoted as S_1, S_2 respectively) for experiments. Dy-OP method is plugged into our framework, i.e., ASRA(Dy-OP). For comparison purpose, we also compute the source weights using the existing incremental methods, DynaTD and DynaTD+decay. Moreover, for controlling the source weights in a same range, we utilize L^1-norm to regularize the source weights computed by all the methods.



(a) Weather Dataset (S_1) (b) Weather Dataset (S_2)

Figure 6: Evaluation on Source Weight

Figures 6(a)-(b) show the experimental results. Clearly, each true source weight changes constantly over time, and the source weights computed by our framework are usually more closer to the true values. Conversely, a source weight computed by DynaTD and DynaTD+decay can converge to a certain value quickly, which is inconsistent with the real source weight change. In conclusion, these results prove the accuracy of our approach in terms of source weight computation.

7. CONCLUSION

In this paper, we study the truth discovery problem over data streams. We propose a framework for truth discovery which adaptively determines the frequency of assessing source weights for high efficiency and incorporates various iterative truth discovery methods for high accuracy. We first define and study the unit error and the cumulative error of truth discovery. Then we transform the prediction of the cumulative error into an optimization problem, and propose our ASRA scheme. Tuning parameters of our framework supports a trade-off between accuracy and efficiency in truth discovery. Moreover, by a series of theoretical analysis, the accuracy of our framework is guaranteed while the iterative processes are reduced. Extensive experiments on real-world datasets have been conducted to evaluate the effectiveness and efficiency of our approach, and the experimental results have proved the high performance of our truth discovery framework.

8. ACKNOWLEDGMENTS

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9. REFERENCES

[1] X. L. Dong, L. BertiEquille, Y. Hu, and D. Srivastava. Global detection of complex copying relationships between sources. *PVLDB*, 3(12):1358–1369, 2010.

[2] X. L. Dong, L. BertiEquille, and D. Srivastava. Integrating conflicting data: the role of source dependence. *PVLDB*, 2(1):550–561, 2009.
[3] X. L. Dong, L. BertiEquille, and D. Srivastava. Truth discovery and copying detection in a dynamic world. *PVLDB*, 2(1):562–573, 2009.
[4] X. L. Dong, E. Gabrilovich, G. Heitz, W. Horn, , N. Lao, K. Murphy, T. Strohmann, S. Sun, and W. Zhang. Knowledge vault: A web-scale approach to probabilistic knowledge fusion. In *SIGKDD Conference Proceedings*, pages 601–610, 2014.
[5] X. L. Dong, E. Gabrilovich, K. Murphy, and V. Dang. Knowledge-based trust: Estimating the trustworthiness of web sources. *PVLDB*, 8(9):938–949, 2015.
[6] A. Galland, S. Abiteboul, A. Marian, and P. Senellart. Corroborating information from disagreeing views. In *WSDM Conference Proceedings*, pages 131–140, 2010.
[7] Q. Li, Y. Li, J. Gao, M. Demirbas, B. Zhao, L. Su, W. Fan, and J. Han. A confidence-aware approach for truth discovery on longtail data. *PVLDB*, 8(4):425–436, 2014.
[8] Q. Li, Y. Li, J. Gao, B. Zhao, W. Fan, and J. Han. Resolving conflicts in heterogeneous data by truth discovery and source reliability estimation. In *SIGMOD Conference Proceedings*, pages 1187–1198, 2014.
[9] 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.
[10] Y. Li, J. Gao, C. Meng, Q. Li, L. Su, B. Zhao, W. Fan, , and J. Han. A survey on truth discovery. *SIGKDD Explorations*, 17(2):1–16, 2015.
[11] Y. Li, Q. Li, J. Gao, L. Su, W. Fan, and J. Han. On the discovery of evolving truth. In *SIGKDD Conference Proceedings*, pages 675–684, 2015.
[12] F. Ma, Y. Li, Q. Li, M. Qiu, J. Gao, S. Zhi, L. Su, B. Zhao, H. Ji, and J. Han. Faitcrowd: Fine grained truth discovery for crowdsourced data aggregation. In *SIGKDD Conference Proceedings*, pages 745–754, 2015.
[13] S. Mukherjee, G. Weikum, and C. Danescu-Niculescu-Mizil. People on drugs: Credibility of user statements in health communities. In *SIGKDD Conference Proceedings*, pages 65–74, 2014.
[14] J. Pasternack and D. Roth. Latent credibility analysis. In *WWW Conference Proceedings*, pages 1009–1020, 2013.
[15] R. Pochampally, A. D. Sarma, X. L. Dong, A. Meliou, and D. Srivastava. Fusing data with correlations. In *SIGMOD Conference Proceedings*, pages 433–444, 2014.
[16] T. Rekatsinas, X. L. Dong, and D. Srivastava. Characterizing and selecting fresh data sources. In *SIGMOD Conference Proceedings*, pages 919–930, 2014.
[17] D. Wang, L. Kaplan, H. Le, and T. Abdelzaher. On truth discovery in social sensing: A maximum likelihood estimation approach. In *ISPN Conference Proceedings*, pages 233–244, 2012.
[18] X. Wu, X. Zhu, G.-Q. Wu, and W. Ding. Data mining with big data. *IEEE Trans. Knowl. Data Eng.*, 26(1):97–107, 2014.
[19] X. Yin, J. Han, and P. S. Yu. Truth discovery with multiple conflicting information providers on the web. *IEEE Trans. Knowl. Data Eng.*, 20(6):796–808, 2007.
[20] L. Yu, J. Li, S. Cheng, S. Xiong, and H. Shen. Secure continuous aggregation in wireless sensor networks. *IEEE Trans. Parallel Distrib. Syst.*, 25(3):762–774, 2014.
[21] B. Zhao and J. Han. A probabilistic model for estimating real-valued truth from conflicting sources. In *QDB Conference Proceedings*, 2012.
[22] B. Zhao, B. I. P. Rubinstein, J. Gemmell, and J. Han. A bayesian approach to discovering truth from conflicting sources for data integration. *PVLDB*, 5(6):550–561, 2012.
[23] Z. Zhao, J. Cheng, and W. NG. Truth discovery in data streams: A single-pass probabilistic approach. In *CIKM Conference Proceedings*, pages 1589–1598, 2014.
[24] S. Zhi, B. Zhao, W. Tong, J. Gao, D. Yux, H. Jix, and J. Han. Modeling truth existence in truth discovery. In *SIGKDD Conference Proceedings*, pages 1543–1552, 2015.

APPENDIX

A. PROOF OF FORMULA (9)

PROOF. According to [8], for each timestamp t_i, the source weights W_i are conducted as the following:

$$W_i \leftarrow \arg\min_{W_i} \sum_{k=1}^{K} w_i^k l_i^k \quad s.t. \quad \sum_{k=1}^{K} \exp(-w_i^k) = 1 \tag{13}$$

Then the derivation of Formula (9) is the same as the derivation of source weights in [8].

□

B. PROOF OF FORMULA (11)

PROOF. According to [11], as we model that each source weight changes over time, the source weights W_i can be conducted as the following:

$$W_i \leftarrow \arg\min_{W_i} \eta \sum_{k=1}^{K} w_i^k l_i^k - \sum_{k=1}^{K} q_i^k \log(w_i^k) \tag{14}$$

where q_i^k denotes the number of observations provided by k^{th} source at t_i, and η is given to support the trade-off between the two terms in Formula (14) [11]. Moreover, the initial loss function in [11] is un-normalized. However, in this paper, we choose the normalized squared loss function for addressing different types of attributes (Formula (10)). Since the standard deviation of the observations at each timestamp can be considered as a constant, the conclusions will not be affected. We take the partial derivative of W_i in Formula (14) with respect to w_i^k, and set the partial derivative equal to zero. Then we obtain the source weight expression as shown in Formula (11).

□