Exploiting Source-Object Network to Resolve Object Conflicts in Linked Data

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Abstract. Considerable effort has been made to increase the scale of Linked Data. However, an inevitable problem when dealing with data integration from multiple sources is that multiple different sources often provide conflicting objects for a certain predicate of the same real-world entity, so-called object conflicts problem. Currently, the object conflicts problem has not received sufficient attention in the Linked Data community. In this paper, we first formalize the object conflicts resolution problem as computing the joint distribution of variables on a heterogeneous information network called the Source-Object Network, which successfully captures the all correlations from objects and Linked Data sources. Then, we introduce a novel approach based on network effects called ObResolution (Object Resolution), to identify a true object from multiple conflicting objects. ObResolution adopts a pairwise Markov Random Field (pMRF) to model all evidences under a unified framework. Extensive experimental results on six real-world datasets show that our method exhibits higher accuracy than existing approaches and it is robust and consistent in various domains.

Keywords: Linked Data, Object Conflicts, Linked Data Quality, Truth Discovery

1 Introduction

Considerable effort has been made to increase the sale of Linked Data, especially the bootstrapping of Linked Open Data (LOD) project\(^1\). As of August 2014, the scale of the Linked Data has reached more than 31 billion triples with more than 504 million links, and the number of available Linked Data sources also increased from 12 in 2007 to 1,014 [1]. The resource in Linked Data is encoded in the form of \((\text{Subject, Predicate, Object})\) triples through RDF (Resource Description Framework) format. Subject denotes the resource, and the predicate is used to express relationships between the subject and the object. Given that many Linked Data sources on the web have been created from semi-structured datasets (e.g., Wikipedia) and unstructured ones [2] though automatic or semi-automatic algorithm, errors inevitably are made during the creation process. As a result,

\(^1\) http://lod-cloud.net/
conflicting objects of a certain predicate for the same real-world entity occur when dealing with data integration from multiple sources. For example, the object of the `dbp:height` for Statue of Liberty in Freebase\(^2\) and Yago\(^3\) is “93” and “46.0248” respectively as shown in Table 1. This problem is surprising prevalent according to a recent research reported in [3]: approximately 45% of predicates have conflicting objects, and the average number of conflicting objects is 11. So it would extremely helpful for Linked Data integration if an effective method can automatically distinguish between true and false object.

A straightforward method to resolve object conflicts is to conduct the majority voting, which regrading the object with the highest number of occurrences as the correct object. The drawback of this method is that it assumes all Linked Data sources are equally reliable [3]. But in reality, some Linked Data sources are more trustable than others and thus may result in inaccuracy results in scenarios when there are some Linked Data sources provide untrustable objects. In order to overcome the limitation of majority voting, many truth discovery methods have been proposed to estimate source reliability [4–6, 3] in recent years. The basic principle of these methods is that a source which provides trustworthy objects more often is more reliable, and an object from a reliable source is more trustworthy. Therefore, the truth discovery problem in these methods is formulated as an iterative problem, which star by assigning the same trustworthiness to all Linked Data sources, and iterate by computing the trust value of each object and propagating back to the Linked Data source.

However, there is a major problem with the above approaches. The iterative procedure in these methods is performed by simple weighted voting, and this can result in that the rich will get richer over iterations [7]. Especially in Linked Data, data sharing between different Linked Data source are common in reality. So errors can easily propagate and lead to error objects can often appear in many sources. As such, these methods based on an iterative procedure easily get a wrong conclusion. The situation is ever worse for many predicates are time sensitive, which the corresponding object tends to change over time (e.g., `dbo:populationTotal`), since many out-of-date object often exists in more Linked Data source than up-to-date object. The experimental results of [3] also shows

\(^2\) https://www.freebase.com/m/072p8
\(^3\) http://yago-knowledge.org/resource/Statue_of_Liberty
the same conclusion, which method based on an iterative procedure achieves lowest accuracy in reasons of out-of-date.

To address this we just discussed, we capitalize our prior work [3] to propose a new method, called ObResolution (Object Resolution), that utilize the Source-Object network to infer the true object. The Source-Object network successfully captures the all correlations from objects and Linked Data sources, e.g. an object from a reliable source is more trustworthy and a source which provides trustworthy objects more often is more reliable. As such, we build a message propagation-based method that exploits the network structure to infer the trust values of all objects and then the object with the maximum trust score is regarded as the true object. In our evaluation, we show our method outperforms the previously-proposed TruthDiscover framework and several other truth discovery methods because these methods either model all clues by iterative procedure, or didn’t take the sharing between Linked Data sources into consideration. We summarize the main contributions of our work as follows.

- We first formalize the object conflicts resolution problem as computing the joint distribution of variables on a heterogeneous information network called the Source-Object Network, which successfully captures the all correlations from objects and Linked Data sources.

- We proposed a novel truth discovery approach, ObResolution, to identify the truth in Linked Data. This approach leverages pairwise Markov Random Field (pMRF) to model the interdependencies from objects and source, and a message propagation-based method is utilized that exploits the Source-Object Network structure to infer the trust values of all objects.

- We conducted extensive experiments on six real-world Linked Data datasets to validate the effectiveness of our approach. Experimental results show that our method exhibits higher accuracy than several baseline methods.

The remainder of this paper is organized as follows. Related work is discussed in Section 2. Section 3 presents the formulation of this problem and the detail of our method are discussed in Section 4. The evaluation of our method is reported in Section 5. Section 6 presents the conclusions and future work.

2 Related Work

Resolving object conflicts is a key step for Linked Data integration and consuming Linked Data. However, to be best of our knowledge, research on resolving object conflicts has elicited less attention in the Linked Data community. Accordingly, existing methods to resolve object conflicts in Linked Data can be grouped into three major categories of conflict handling strategies: conflict-ignoring, conflict-avoiding and conflict-resolution strategies.

Conflict-ignoring strategy ignores the object conflicts when consuming the Linked Data and defer conflict resolution to user. For instance, Wang et al.[8]
presented an effective framework to fuse knowledge cars from various search engines. In this framework, knowledge cards fusion task involves card disambiguation and property aligning. As for the value conflicts, this framework just adopted a method to deduplicate the values and group these values into clusters.

Conflict-avoiding strategy acknowledge the existence of object conflicts, but do not resolve this conflicts. Instead, they apply a unique decision to all data, such as manual rules. For instance, Mendes et al. [9] presented a Linked Data quality assessment framework called Sieve. In this framework, the strategy Trust Your Friends preferring the data from specific data source was adopted to avoid the conflict.

Conflict-resolution strategy focus on how to solve a conflict regarding the characteristics of all data and metadata. For example, Michelfeit et al. [10] presented an assessment model that leverages the quality of the source, data conflicts, and confirmation of values to decide which values should be the true value. Recently, Liu et al.[3, 11] found that the number of conflicting objects provided by multiple Linked Data sources typically follows the approximate power law, and proposed a method called TruthDiscover based on an iterative procedure to identify the truth in Linked Data with a scale-free property.

Previous work enlightens us on resolve object conflicts. In this study, we proposed a novel method that exploits the heterogeneous information network effect among source and object. Our approach is different in two aspects. First, we formalize the object conflicts resolution problem though a heterogeneous information network, which successfully captures the all correlations from objects and Linked Data sources. Second, we adapt a message propagation-based method that exploits the network structure to infer the trust values of all objects. Our method has several advantages: (1) it avoids the problem of the rich will get richer over iterations, (2) it works in an unsupervised circumstance.

3 Preliminaries

3.1 Basic Definitions

Before defining the object conflicts problem in Linked Data, several important notations utilized in this study are introduced in this subsection.

**Definition 1 (RDF Triple)** [12]. We let \( I \) denotes the set of IRIs (Internationalized Resource Identifier), \( B \) denotes the set of blank nodes, and \( L \) denotes the set of literals (denoted by quoted strings, e.g., "Beijing City"). An RDF triple can be represented by \( (s, p, o) \in (I \cup B) \times I \times (I \cup B \cup L) \), where \( s \) is a subject, \( p \) is a predicate, and \( o \) is an object.

**Definition 2 (Trustworthiness of Sources)** [6]. The trustworthiness of a source \( \omega_j \) is the expected confidence of the objects provided by \( \omega_j \), denoted by \( t(\omega_j) \).

**Definition 3 (Trust Values of Objects)** [6]. The trust value of an object \( o_i \) is the probability of being correct, denoted by \( \tau(o_i) \).
3.2 Problem Formulation

**Definition 4 (Object Conflicts Problem).** Given two triples \( t_i = (s_i, p_i, o_i) \) and \( t_j = (s_j, p_j, o_j) \), \( o_i \) and \( o_j \) are object conflict when \( s_i \) and \( s_j \) denote the same-world entity, \( p_i \) and \( p_j \) present the same predicate, and the similarity \( S(o_i, o_j) \) between \( o_i \) and \( o_j \) is less than preset threshold \( \alpha \).

**Definition 5 (Object Conflicts Resolution).** We let \( O = \{ o_i \}_m \) denotes a set of conflicting objects for a certain predicate of a real-world entity. The process of object conflicts resolution in Linked Data is formally defined as follows: given a set of conflicting objects \( O \), ObResolution will assign a trust score which lies on between 0 and 1 to each object. A score of object close to 1 indicates that we have very confident this object is true. Therefore, the truth can be represented by \( o^* = \arg \max_{o_i \in O} \tau(o_i) \).

3.3 Problem Analysis

Through the observation and analysis of the object conflicts in our sample Linked Data, we found three helpful correlations from Linked Data source and objects for effective distinguishing the true and false objects.

- **Correlations among Linked Data Sources and Objects:** If an object comes from a reliable source, it will be assigned a high trust value; thus if a source which provide trustworthy objects more often has big change to be selected as a reliable source. For example, the object provided by DBpedia\(^5\) is more reliable than supported by many small sources because DBpedia is created from Wikipedia. This also serves as a basic principle for many truth discovery methods \([4, 13, 5, 14–17]\).

- **Correlations among Objects:** If two objects are similar, they should have similar trust values, which indicates similar object appears to mutual support. For example, suppose one source claims the \( \text{dbp:height of Statue of Liberty} \) is “46.0248” and another says it is “47”. If one of these has a high trust value, the other should have a high trust value as well. Meanwhile, if two objects are mutually excluded, they cannot be both true. If one of them has a high trust value, the other should have a low trust value. For instance, if two different sources claim the \( \text{dbp:height of Statue of Liberty} \) are “93” and “46.0248” respectively. If the true object is “46.0248”, the “93” should be a wrong object.

- **Correlations among Linked Data Sources:** In many truth discovery methods, the trustworthiness of a source is formulated as the probability of the object provided by this source being truth. Therefore, the more same objects two different sources provide, the more similar the trustworthiness

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\(^4\) In this work, we use \( \alpha=0.01 \)

\(^5\) http://wiki.dbpedia.org/
of the two source are. Consider an extreme case when two sources provide same objects for each predicate, the trustworthiness of these two sources are same.

As discussed above, there are three principles that can be used to infer the trust value of objects. A key problem for object resolution is how to model these principles under a unified framework. In this paper, we proposed a method based on the heterogeneous information network to model these three correlations from source and object. The detail of our method will be introduced in the next Section.

4 ObResolution Method

In this section, we will formally introduce our proposed method, called ObResolution for discovering the most reliable objects from the set of conflicting objects. We first formulate the object conflicts resolution problem as the Source-Object network analysis problem, which successfully captures the all correlations from objects and Linked Data sources. Then, a message propagation-based method that exploits the Source-Object network structure is introduced to solve this problem, and finally several important issues that make this method practical are discussed.

4.1 Model Details

In this paper, we only consider the case wherein a certain predicate of a real-world entity has only one truth. Therefore, for each predicate of a same world-entity, ObResolution aims at identifying the most reliable objects from the set of conflicting objects.

In general, the input to our problem includes three parts: i) objects, these objects are the values of a certain predicates for the same real-world entity, e.g., the “93” and “46.0248” are the values of dbp:height for Statue of Liberty, ii) Linked Data sources, which provide these objects, e.g., Freebase, iii) mappings between objects and Linked Data sources, e.g., which Linked Data sources provide which objects for the certain predicate of the same real-world entity. As such, a set of objects and sources can be presented as a bipartite network. In this bipartite network, the source node is connected to object node, in which the links represent the “provider” relationships. For ease of illustration, we give an example network of six sources and four conflicting objects as shown in Figure 1(a). According to the first principle, which is an object from a reliable source is more trustworthy, and thus a source which provides trustworthy objects more often is more reliable, the “provided” relationships between the source and objects also indicates the interdependent relationships between trust values of objects and trustworthiness of Sources. Besides the “provider” relationships between the source and objects, among objects and among Linked Data sources also have correlations, for instance, because source $\omega_1, \omega_3, \omega_5$ provide the same object $o_1$ in
Figure 1(a), therefore, they have a correlation for any two of these three sources. Therefore, the bipartite network in Figure 1(a) can be converted to a heterogeneous information network called the Source-Object Network as shown in Figure 1(b).

The Source-Object Network \( G = (V, E) \) contains \( n \) Linked Data Sources nodes \( \Omega = \{\omega_1, ..., \omega_n\} \) and \( m \) conflicting object nodes \( O = \{o_1, ..., o_m\} \), \( V = \Omega \cup O \), connected with edges \( E \). Because of three types of correlations from objects and Linked Data sources, the Source-Object Network \( G \) have three types of edges \( E = E_\Omega \cup E_O \cup E_{\Omega \rightarrow O} \), where \( E_\Omega \subseteq \Omega \times \Omega \) represents the correlations between sources, \( E_O \subseteq O \times O \) indicates the correlations among objects and \( E_{\Omega \rightarrow O} \) represents the "provided" relationships between the source and objects.

Given a Source-Object Network, which successfully captures all correlations from objects and Linked Data sources, the task is to estimate sources reliability and trust values of all conflicting objects. Each node in \( G \) is a random variable, which can represent the trust values of objects and trustworthiness of sources. However, we find the trust values of objects and trustworthiness of sources are assumed to be dependent on its neighbors and independent of all the other nodes in this network. This condition motivated us to select a method based on pairwise Markov Random Fields (pMRF), which is a powerful formalism used to model real-world events based on the Markov chain and knowledge of soft constraints. Therefore, Source-Object Network is represented by pMRF in this study. As we all know, pMRF is mainly composed of three components: an unobserved field of random variables, an observable set of random variables, and the neighborhoods between each pair of variables. We let the all nodes \( V = \Omega \cup O \) in \( G \) are observation variables. As such, the unobserved variables \( Y = Y_\Omega \cup Y_O \) have two types of labels. For each unobserved variable \( y_i \in Y_\Omega \) indicates whether corresponding object is a truth, which follows the Bernoulli distribution defined as follows.

\[
P(y_i) = \begin{cases} 
\tau(o_i) & \text{if } o_i \text{ is true, } y_i = 1, \\
1 - \tau(o_i) & \text{if } o_i \text{ is false, } y_i = 0.
\end{cases} \tag{1}
\]

Meanwhile, the unobserved variable \( y_j \in Y_O \) represents whether corresponding source is reliable source and also follows the Bernoulli distribution.

\[
P(y_j) = \begin{cases} 
t(\omega_j) & \text{if } \omega_j \text{ is a reliable source, } y_j = 1, \\
1 - t(\omega_j) & \text{if } \omega_j \text{ is a unreliable source, } y_j = 0.
\end{cases} \tag{2}
\]
The problem of inferring the trust values of conflicting objects and trustworthiness of sources can be converted to compute the joint distribution of variables in pMRF, which is factorized as follows:

\[
P(y_1, ..., y_m, ..., y_{m+n}) = \frac{1}{Z} \prod_{c \in C} \psi_c(X_c),
\]

\[
Z = \sum_{X_c \in X} \prod_{c \in C} \psi_c(X_c),
\]

where \( Z \) is a constant selected to ensure that the distribution is normalized, \( C \) denotes the set of all maximal cliques, the set of variables of a maximal clique is represented by \( X_c, c \in C \) and \( \psi_c(X_c) \) is a potential function in pMRF.

### 4.2 Inference Algorithms

In general, exact inference joint distribution of variables in pMRF is known to be an NP-hard problem [18]. Loopy Belief Propagation (LBP) is an approximate inference algorithm, which has been shown to perform extremely well for various of applications in the real world. In belief propagation, estimating the joint distribution of variables is a process of minimizing the graph energy. The key steps of the propagation process can be concisely expressed as follows.

- **Spreading the Belief Message.** The message from variable \( y_i \) to \( y_j \) is represented by \( m_{i \rightarrow j}(y_j), y_j \in \{0, 1\} \), which is defined as follows:

\[
m_{i \rightarrow j}(y_j) = \sum_{y_i \in \{0, 1\}} U(y_i, y_j) \psi(y_i) \prod_{y_k \in N(y_i) \cap Y \setminus \{y_j\}} m_{k \rightarrow i}(y_i).
\]

where \( N(y_i) \) indicates the set of neighbors of node \( y_i \); \( \psi(y_i) \) denotes the prior belief of \( P(y_i) \), and \( U(y_i, y_j) \) is a unary energy function.

- **Belief Assignment.** The marginal probability \( P(y_i) \) of unobserved variable \( y_i \) is updated according to its neighbors, and is defined as follows:

\[
P(y_i) = \psi_i(y_i) \prod_{y_j \in N(y_i) \cap Y} m_{j \rightarrow i}(y_i).
\]

The algorithm updates all messages in parallel and assigns the label until the message stabilize, i.e. convergence. Although convergence is not theoretically guaranteed, the LBP has been shown to converge to beliefs within a small threshold fairly quickly with accurate results[18]. After they stabilize, we compute the marginal probability \( P(y_i) \). As such, we can get the trust value of objects trustworthiness of sources. Given only one truth for a certain predicate of a real-world entity, the true object is \( o_i \) when \( \tau(o_i) \) is the maximum. Until now, we have described the main steps of LBP. But, there are two problems with this algorithm, which are discussed below.
Energy Function. The energy function $U(y_i, y_j)$ denotes the likelihood of a node with label $y_i$ to be connected to a node with label $y_j$ through an edge. There are three types of energy functions depended on different types of edges:

| Source       | Object | Source |
|--------------|--------|--------|
|             | True   | False  |
| Reliable     | $\beta$ | $1-\beta$ | $\epsilon$ | $1-\epsilon$ |
| Unreliable   | $1-\delta$ | $\delta$ | $1-\epsilon$ | $\epsilon$ |

- The energy function between sources and objects. As we all know, a basic principle between sources and objects is the reliable source tend to provide true object and unreliable sources to false object. However, with same probability reliable sources may also provide false objects as unreliable sources to true object. In this study, we let $\beta$ denotes the likelihood between reliable source and true object, whereas $\delta$ denotes the likelihood between unreliable source and false object. Therefore, the energy function between sources and objects is shown in the first three columns of Table 2.

- The energy function among Objects. The more similar two objects are, the more probability they appears to have same trust values. Therefore, there was a positive correlation between energy function and the similarity $S(o_i, o_j)$ between object $o_i$ and $o_j$ as shown in Table 3.

- The energy function among sources. We assume the more same objects two different sources provide, the more similar the trustworthiness of two sources are. The coefficient $\epsilon = |F(\omega_i) \cap F(\omega_j)|/\max(|F(\omega_i)|, |F(\omega_j)|)$ are used to denote the likelihood between sources $\omega_i$ and $\omega_j$, where $F(\omega)$ is the set of objects provided by source $\omega_i$ as shown in the last two columns of Table 2.

Prior Belief. To completely define the LBP method, we need to estimate the prior belief value $\psi_i(y_i)$ of nodes. In this study, we adopt the BeliefRank algorithm described in our previous work [3] to estimate the prior belief of sources. The non-uniform priori beliefs of all sources are computed by leveraging the topological properties of the Source Belief Graph. The priori trust value of object $o_i$ can be computed as as the average priori beliefs of the sources, which provide object $o_i$. The pseudo code of this method is shown in Algorithm I.

4.3 Practical Issues

Here we discuss several important issues to make this method work practical including similarity functions, missing values.

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6 Sensitivity analysis in Section 5 found that $\beta, \delta \in [0.7, 1]$ yields desirable and comparable results. In this work we use different $\beta, \delta$ for different datasets in order to make our method perform best.
Algorithm 1: ObResolution

Input: a set of conflicting objects \( O = \{o_1, \ldots, o_m\} \), a set of sources \( \Omega = \{\omega_1, \ldots, \omega_n\} \) and the mapping relations between source and object

Output: the trust value \( \tau(o_i), o_i \in O \); the trustworthiness of sources \( t(\omega_j), \omega_j \in \Omega \)

1. Initialize the prior belief of all nodes \( \psi_i(y_i) \) through BeliefRank
2. \( \forall o_i, o_j \in O \): Calculating their similarity \( S(o_i, o_k) \);
3. \( \forall y_i, y_j \in Y \): \( m_{i\rightarrow j}(y_i) = 1 \); // Initialize the message
4. repeat
   // Perform message propagation
   for \( j \leftarrow 1 \) to \( m + n \) do
     for \( i \leftarrow 1 \) to \( m + n \) do
       \( m_{i\rightarrow j}(y_j) = \sum_{y_i \in \{0, 1\}} U(y_i, y_j) \psi_i(y_i) \prod_{y_k \in N(y_i) \cap Y \setminus \{y_j\}} m_{k\rightarrow i}(y_k) \).
     end
   end
   until the convergence criterion is satisfied;
5. for \( i \leftarrow 1 \) to \( m + n \) do
   // Belief Assignment
   \( P(y_i) = \psi_i(y_i) \prod_{y_j \in N(y_i) \cup Y} m_{j\rightarrow i}(y_j) \).
end
6. return \( \tau(o_i), \forall o_i \in O \); \( t(\omega_j), \omega_j \in \Omega \)

Similarity functions. The energy function between objects depends on the similarity function. We respect the characteristic of each data type and adopts different similarity function to describe the similar degree. Below we discuss two similarity functions for numerical and categorical data, two most common data types including.

For numerical data, the most commonly used similarity function is defined as:

\[
S(o_i, o_k) = \frac{1}{1 + d(o_i, o_k)}, \quad (6)
\]

\[
d(o_i, o_k) = \frac{|o_i - o_k|}{\max(|o_i|, |o_k|)}. \quad (7)
\]

For string data, the Levenshtein distance [19] is adopted to describe the similarities of objects. The similarity function is defined as follows:

\[
S(o_i, o_k) = 1 - \frac{ld(o_i, o_k)}{\max(len(o_i), len(o_k))}, \quad (8)
\]

where \( ld(o_i, o_k) \) denotes the Levenshtein distance between objects \( o_i \) and \( o_k \); \( len(o_i) \) and \( len(o_k) \) are the length of \( o_i \) and \( o_k \) respectively.

Besides these two most common data types, our method can take any similarity function that is selected based on data types. Some other examples include KL divergence or semantic similarity for text data, Mahalanobis distance.
for continuous data. In order to deal with complex data types in Linked Data, ObResolution takes the ensemble of multiple similarity functions, which defined on the raw data.

**Missing Values.** As we all know, Linked Data is built on the Open World Assumption (OWA), which assumes that what is not known to be true is simply unknown. Therefore, for the sake of simplicity in this study, we assume that all missing values is not known to be true.

5 Evaluation

In this section, our proposed method, ObResolution was evaluated in term of accuracy by performing experiments on six real Linked Data datasets

5.1 The Datasets

Six Linked Data datasets were used in our experiments. The first three datasets persons, locations, organizations are constructed based on the OAEI2011 New York Times dataset\(^7\), which is a well-known and carefully created dataset of Linked Data. In order to draw more robust conclusions, three other domains, including films, book and song are constructed through SPARQL queries over DBpedia. Because object conflict in this study is built on the problem of subject conflict and schema conflict have been solved, the construction process of datasets mainly involves the three necessary steps. First, we adopt a well-known tool, sameas.org\(^8\) to identify subjects for the same real-world entities in these six dataset. Then we crawl the data of every subject from BTC2014 \(^9\), which is a comparatively complete LOD cloud, and consist of 4 billion triples. Finally, we constructed a manual schema mapping rule, which a strict process was established to ensure the quality of the annotation to resolve the problem of schema conflict. The statistics of the six datasets are shown in Table 4. The row “#Subjects” indicates the total number of subjects returned by sameas.org and the row “#Conflicting Predicates” represents the total number of predicates that have conflicting objects and.

One truth was selected from multiple conflicting objects for experimental verification. A strict process was established to ensure the quality of the annotation. This process mainly involved the following steps:

(i) The annotators were provided annotated examples and annotation guidelines.

(ii) Every two annotators were asked to label the same predicate on the same entity independently.

(iii) The annotation results from two annotators were measured by using Cohen’s kappa coefficient [21]. The agreement coefficient of the six datasets was set to be at least 0.75. When an agreement could not be reached, a third annotator was asked to break the tie.

\(^7\) http://data.nytimes.com/#

\(^8\) http://sameas.org/

\(^9\) http://data.nytimes.com/
Table 4: Statistics of the six datasets.

| Datasets  | # Entities | # Subjects | # Conflicting Predicates | # Triples  |
|-----------|------------|------------|--------------------------|------------|
| Person    | 4,978      | 21,340     | 69,706                   | 141,937    |
| Locations | 1,910      | 21,324     | 38,200                   | 558,773    |
| Organizations | 2,000 | 4,529 | 14,000 | 15,928 |
| Films     | 2,000      | 4,935      | 8,000                    | 20,692     |
| Books     | 9,081      | 15,644     | 45,405                   | 71,532     |
| Song      | 2,000      | 2,872      | 10,000                   | 7,170      |

The manually labeled results were regarded as the ground truth used in the evaluation.

5.2 Baselines and Metrics

We compared our method with five well-known state-of-the-art truth discovery methods as baseline, which were modified, if necessary.

- **Majority Voting**: This method regards the object with the maximum number of occurrences as truth. Moreover, voting is a straightforward method.

- **Sums (Hubs and Authorities) [22]**: This method regards the object which supported by the maximum number of reliable sources as true. In this study, a source is recognized as a reliable source if its trustworthiness score exceeds 0.5.

- **TruthFinder [6]**: It’s a seminal work that used to resolve conflicts based on source reliability estimation. It adopts Bayesian analysis to infer the trustworthiness of sources and the probabilities of a value being true.

- **F-Quality Assessment [10]**: This method is a popular algorithm used to resolve conflicts in Linked Data. Three factors, namely, the quality of the source, data conflicts, and confirmation of values from multiple sources, are leveraged to decide which value should be true value.

- **TruthDiscovery [3]**: This work is the latest research on the object conflict of Linked Data. This method leverages the topological properties of the Source Belief Graph and the interdependencies between objects to infer the trustworthiness of sources and the trust values of objects.

In the experiments, accuracy as a unified measure is adopted in the experiments for all methods, and can be measured by computing the percentage of matched values between the output of each method and ground truths.

The parameters of the baseline methods were set according to the authors’ suggestions. We implemented all algorithms using Eclipse (Java) platform\(^9\) by a single thread and conducted experiments on a windows sever computer with Intel Core E7-4820 CPU 2 GHz with 32 GB main memory, and Microsoft Windows 7 professional operating system.

\(^9\) [https://www.eclipse.org/](https://www.eclipse.org/)
5.3 Results

Comparison of Baselines. The Figure 2 shows the performance of different algorithms on the six datasets in terms of accuracy. It can be seen from Figure 2 that our method consistently achieve the best accuracy among all the baselines. Majority Voting achieves lowest accuracy (ranging from 0.3 to 0.45) on the six datasets among all the baselines. There are two reasons why majority voting performs poorly in Linked Data. Firstly, approximately 50% of predicates has no dominant object [3]. In this case, majority voting can only randomly select one object in order to break the tie. Secondly, majority voting assumes all sources are equally reliable and does not distinguish them, which is not applicable to Linked Data as discussed in Section 1. Although source reliable estimation was taken into consideration in Sums, this method still achieves relatively low accuracy in all dataset due to that it just considers the correlation between sources and object, and ignores the correlation between objects, and the correlation between sources. TruthFinder, F-Quality Assessment and TruthDiscovery model all the clues by the iterative procedure, which easily leads to the problem of the rich will get richer over iterations. In this study, our proposed method utilizes the Source-Object network successfully capturing the all correlations from objects and Linked Data sources in a unified framework to infer the true object which, which can explain why our method consistently achieve the best accuracy among all the baselines.

Fig. 2: Performance comparison in six datasets.

Sensitive Analysis. We also studied the impact of the parameter $\beta, \delta$ to our methods. As discussed in Section 3, $\beta$ indicates the likelihood between reliable source and true object, whereas $\delta$ denotes the likelihood between unreliable source and false object. The Figure 3 shows that the accuracy of ObResolution varies in different value of $\beta, \delta$ in the same dataset, and ObResolution achieve best accuracy on six datasets with different values of $\beta, \delta$ ($\beta=0.9, \delta=0.7$ for
Fig. 3: Sensitive analysis in six Linked Data datasets.

Person, in Books $\beta=0.7, \delta=0.9$). Therefore, the parameter $\beta, \delta$ is sensitive to the different datasets due to different Linked Data datasets have different quality [23]. ObResolution use different $\beta, \delta$ for different datasets in order to make our method perform best.

6 Conclusion and Future Work

To obtain insightful knowledge from a large number of Linked Data sources generated by numerous industries, it’s crucial to solve the problem of object conflict. However, Existing object conflicts works either just considers the partial correlations from source an object, or models all clues by iterative procedure. Therefore, we propose a novel method called ObResolution, to model all the clues from sources and objects by a heterogeneous information network called the Source-Object Network in a unified. In this method, Source-Object Network is represented by pMRF because the trust values of all the nodes in this network are dependent on its neighbors and independent of all the other nodes in this network. Therefore, The problem of inferring the trust values of conflicting objects and trustworthiness of sources is defined as computing the joint distribution of variables. As such, we build a message propagation-based method that exploits the network structure to infer the trust values of all objects and
then the object with the maximum trust score is regarded as the true object. We conducted experiments on six datasets collected from multiple platforms. Results demonstrated that ObResolution exhibits higher accuracy than several baseline methods. A potential direction[1] for future research is to focus on more complicated conflict resolution scenarios, such as the situation involving copying relations of different sources and multiple true objects.

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