Comparative Analysis of Privacy Preserving Techniques in Distributed Database

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Abstract: In recent years, isolation takes an imperative role to secure the data from various probable attackers. For public advantage data need to be shared as required for Health care and researches, individual privacy is major concern with respect to sensitive information. For that anonymization of data with K-anonymity and L-diversity are studied. Existing system is depends on providers and is used generalization technique for anonymization. This will increase in data loss to avoid this slicing techniques are used. Data publishing is done in such a way that privacy of data should be preserved. While publishing collaborative data to multiple data provider’s two types of problem occurs, first is outsider attack and second is insider attack. Outsider attack is by the people who are not data providers and insider attack is by colluding data provider who may use their own data records to understand the data records shared by other data providers. The paper focuses on insider attack, and makes some contributions. This problem can be overcome by combining slicing techniques with m-privacy techniques and addition of protocols as secure multiparty computation and trusted third party will increase the privacy of system effectively.

Keywords: Anonymization, Bucketization, Distributed database, Privacy, Security

1. Introduction

In distributed databases there is increasing need of sharing data that contain personal information. In healthcare domain, focus is to develop Information Network for distributing data among providers with privacy protection. Privacy preserving data publishing have established consideration in recent years as promising approaches are used for sharing data while preserving individual privacy.

Major goal is to distribute an anonymized view of combined data, T, which will be immune to attacks (figure 1). Attacker can be single or group of internal and external entities that want to break privacy of data using background knowledge. Collaborative data publishing is carried out successfully with the help of trusted third party (TTP), which guarantees that information or data about particular individual is not disclosed anywhere, that means it maintains privacy. A more desirable approach for collaborative data publishing is, first aggregate then anonymize data into T* (figure1).

In health care all information related to patient is present in central network which includes disease details, corresponding treatment and test details. By using anonymization technique the data is anonymized and then released to the public. This process is called as the privacy preservation data publishing. The attributes are classified into three types as Key attribute, quasi identifier and sensitive attribute. Key attribute represents unique identification such as names, SSN (Social Security Number). Quasi-identifiers are segments of information that are not unique identifiers but well correlated with an entity; they can be combined with other quasi-identifier to create a unique identifier. Example birth date, gender, which can be used link unionized dataset with other data. Sensitive attributes contain sensitive value such diseases, policy detail, and salary etc. A data recipient may have access to some background knowledge which represents any publicly available information about released data, e.g., Census datasets. By m-privacy techniques, the information of the employee can be protected such as sensitive attribute (SA) e.g. disease of patient, identifier (ID) e.g. name and quasi identifier (QI) i.e. age or zip code etc. But these methods have some limitation such as membership disclosure and data loss.
2. Generalization

It is the process of generalizing attribute separately. Using generalization the correlation between attribute is lost.

3. Suppression

Suppression is used to prevent the membership disclosure in the k-anonymity thus it be an assignment technique of placing * for the attribute values instead of their original values. This suppression technique is used in the quasi identifier fields to preserve the individual data.

4. Bucketization

In Bucketization SAs are separated from the QIs by doing the random permutation on the SA values in each bucket. The anonymized data is collection of buckets, those bucket undergo the permutation on sensitive attribute values. Bucketization does not prevent membership disclosure. Bucketization requires the clear separation of SA and QI attributes and it breaks the attribute correlation between them.

5. Slicing

Slicing is a technique in which data is divided into vertical partition and horizontal partition. Vertical partition is a group of attributes in column based on correlation among attribute. Horizontal partition is a group of tuples into buckets. In each bucket, each column consists of randomly permitted value.

6. Literature Survey

This section highlights the different methods which are previously used for anonymization. Also discuss some advantages and limitation of these systems. Privacy preserving data analysis and collaborative data publishing has received considerable attention in current years as promising approaches for sharing data while preserving individual privacy.


In this paper [1] author has developed new anonymization technique that is that is effective in generalization in privacy protection but it able to retain significantly more as micro data. ANGEL(Anatomy and Generalization on Multiple Sensitive) is relevant to any monotonic principles . Author shows that ANGEL provides itself sophisticatedly to the hard problem of bordering publication. In generalization can issue only restricted marginal, ANGELM method can be used to publish any marginal with strong privacy guarantees.

To develop this approach they have use k-anonymity, data distribution, E-M generalization, anonymization principle and monotonicity. They also establish the privacy guaranty with generalization and anonymization algorithms.

Definition 1 (k-anonymity): E satisfies k-anonymity if every Equivalence Class in E comprises at least k tuples.

Definition 2 (SA-distribution): Given a multiset S of sensitive values, the SA-distribution in S is considered by a pdf

Definition 3 (E-M Generalization modeling): A generalization of a microdata table T can be effectively represented as a pair of E and M, denoted by (E,M).
Definition 4 (Anonymization principle): An anonymization principle is a constraint on an SA-distribution. A generalization (E,M) satisfies the principle if the SAdistribution of every EC in E satisfies the constraint.

Definition 5 (Monotonicity): An anonymization principle is monotonic if the following is true: given any two multisets of sensitive values S1 and S2 whose SA-distributions obey the principle, the SA-distribution of the union S1 U S2 also obeys the principle.


This paper [2] presents a new technique slicing which undergoes horizontal and vertical partitions of the data. Paper shows that slicing provide better data utility than generalization. Slicing can work efficiently on high-dimensional data and it can also be used for attribute disclosure protection. Slicing partitions attributes into columns which undergoes generalization, and divide tuples into buckets.


This system [3] is develop without knowing John and Harish content of tuple and database, inserted tuple is checked for K-anonymity. Author has proposed two protocols based on suppression and generalization. These protocol based on cryptographic assumption. This paper provides theoretical analyses to proof and experimental results to show their efficiency. This paper has data anonymization techniques to address the problem of privacy.


In this system they have develop a new generalization principle that effectively limits the risk of Multiple Sensitive Attributes privacy disclosure in re-publication. The results show that algorithm has higher degree of privacy protection and lower hiding rate. This approach the below definitions for execution

Definition 1(Identifier) Identifier can uniquely identify a single individual attribute such as name, id etc.

Definition 2(Quasi-identifier) Quasi-identifier can connection with external data sources which can identify individual attribute such as age, sex etc.

Definition 3(Sensitive Attribute) Sensitive Attribute contains the properties of private dataset, such as disease doctor’s salaries.

Definition 4(Generalization) Generalization is a popular methodology of privacy preservation. It divides the tuple into QI-group, and then transforms the QI values in every group to a uniform format.

Definition 5(QI group) For a micro data table T(j), a QI-group is a subset of the tuples in T(j), which have the same generalized value for each non-sensitive attribute.

Definition 6(Signature) Let QI* be a QI group in T*(j) for any j. The signature of QI* is the set of distinct sensitive values in QI*.

Definition 7(Candidate Update Set) Suppose a is an element in the domain of attribute A, its candidate update set is the union of same elements in dom(A), such that a has non-zero update probability to it.


This paper [5] has given suppression slicing is done by suppressing any one of the attribute value in the tuples and then perform the slicing. Thus utility is maintained with minimum loss by suppressing only very few values and privacy is maintained by random permutation. The next model is Mondrian slicing in this the random permutation is done with all the buckets not within the single bucket. Thus same utility of the original dataset is maintained. This approach use slicing, data publication, bucketization and generalization in the database.

7. Comparative Studies

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<td>ANGEL [1]</td>
<td>The last experiment on this approach gives comparison results when p(Anonymization principle) is 10-diversity (0.2-closeness). In all cases, releasing marginal always reduces reconstruction error. The improvement becomes more obvious when a marginal has a lower dimensionality.</td>
<td>This paper proposes angelization as a new anonymization technique for privacy preserving publication, which is applicable to any monotonic anonymization principle.</td>
</tr>
<tr>
<td>Slicing [2]</td>
<td>Workload experiments shows that slicing preserves data more accurately than Generalization. Slicing is better than Bucketization in workload consist of sensitive attribute. Experiment shows better performance with Slicing technique. Drawback of Bucketization is overcome by slicing.</td>
<td>A Slicing is a privacy-preserving technique for data publishing. Drawbacks of Bucketization and Generalization are overcome by Slicing. Slicing protects against privacy threat. Data characteristics is analyzed before anonymization of data.</td>
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Volume 4 Issue 1, January 2015

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privacy-preserving for anonymous and confidential databases [3]

Some observations are done:
1: If none of the tuples in the chunk matches the user tuple, then the loader reads another chunk of tuples from the k-anonynous DB. Note the communication between the prototype and User is mediated by an anonymizer (like Crowds) and that all the tuples are encrypted.
2: The experiments confirm the fact that the time spent by both protocols in testing whether the tuple can be safely inserted in the anonymized database decreases as the value of k increases. Intuitively, this is partly due to the fact that the larger the k is, the smaller the witness set. Fewer are the partitions in which table T is divided. Consequently, fewer protocol runs are needed to check whether the update can be made. Further, we report that the experiments confirm the fact that the execution times of functions varies with k.

8. Conclusion

This paper presents two enhanced techniques to preserve the privacy in data publishing. These techniques are based on the Mondrian and suppression slicing. These techniques will satisfy privacy requirements of l-diversity. Basically slicing is the important technique with all available methodologies like data publication, bucketization and generalization in the database.

9. Acknowledgement

I would like to thank my guide Dr. A. N. Banubakode and Dr. P. K. Deshmukh for their help and guidance throughout this project and the semester, without him this would not have been possible.

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Volume 4 Issue 1, January 2015

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