



2 level K Anonymization Approach for Privacy Preserving in Data Mining

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Abstract— Privacy-preserving preserving in data mining, area for a research work. Till now randomization, k -anonymization model, l diversity, t closeness, cryptography and many more techniques have been used to preserve the privacy of an individual. But each and every technique have their own demerits i.e. Information Loss, Privacy breached, Low Data Utility. After studying about all of these techniques and methods. It seems that the k anonymization approach one of the broadly used anonymization based approach. However, this approach suffers from the issue of information loss. so, it is challenging task for data miner to mine data. To decrease information loss new proposed approached introduced in this paper. 2 level k anonymization approach will decrease information loss and also preserve privacy as compared to the traditional approach. The main aim of this approach is to decrease data loss and no compromise with privacy.

Keywords—privacy preserving; anonymization; generalization; suppression; information loss

I. INTRODUCTION

Privacy-Preserving after heard this word first thought comes to mind is that what kind of privacy will be preserved. Privacy preservation is required when some organization gives their user's data to another organization for a specific purpose. For example, Canatics is a company in Canada. It works is to find fraud from insurance claimers for that canatics have to collect all the data of insurance companies for fraud detection but because of it some private or sensitive information of insurance holders will be released in front of canatics. As a result, protecting the private information of an individual becomes a prime research issue in privacy preserving data

mining [2]. Here k -Anonymization will help. k -Anonymization Approach is The concept of k -anonymity was first introduced by Latanya_Sweeney and Pierangela Samarati in a paper published a publication of information is supposed to have the[k -anonymity possessions if the info for each individual contained in the publication cannot be eminent from at least $k-1$ persons whose info also appear in the publication.

II. APPROACH AND FORMULAS

A. K -Anonymization Approach

This approach is better in cost, time complexity as compared to other approaches of privacy-preserving but, Information Loss and data utility this both are major issues of this approach. Mainly data set attributes classified in three types of attributes identifiers attributes (name, ssid number), quasi identifier attributes QI (age, zip code, gender), sensitive attributes SA (disease, salary). It can be further classified in numerical and categorical attributes. After classification generalization and suppression process will be applied on dataset [6]. Generalization as per name it will replace general value of that attribute in place of original value for example have quasi attribute Age and values are 31, 32, 33, 34, 35 and 36, then they can be represented as (31-36). In other hand suppression hides unique digits of the k records with same example 31, 32, 33, 34, 35 and 36, then they can be represented as 3*. Here data loss is higher in suppression than generalization.

To Explain information loss because of generalization and suppression is described by example of medical dataset this medical organization wants to share their patient's data with research institute for research and mining reasons. Medical dataset is given in Table I

After applied Generalization and Suppression information get loss for example in table II original value of age replaced with range of age values, in attribute gender 'M' or 'F' values replaced with 'P' because of generalization and in zip code last digits by which patient record can be identified those digits are also hide by star so ultimately privacy is preserved but information got loss so, authors Pawan Baladhare and Devesh Jinwala[1] discussed this information loss problem and also introduced a novel approach which decrease a IL at some extent.

TABLE I SUBDATABASE FROM HOSPITAL'S ORIGINAL DATASET

Identifiers	Quasi-identifier			Sensitive
NAME	AGE	GENDER	ZIP CODE	DISEASE
AVS	22	M	132011	FLU
FVD	21	F	132150	HIV
RZG	15	F	132012	CANCER
TAH	20	M	132012	DIABETES
YDK	30	F	132150	CANCER
EDT	19	M	132011	HIGH BP
RNE	17	M	132050	DIABETES
WGE	41	F	132012	CANCER
GDA	27	M	132012	HIV
BEA	45	M	132150	CANCER
CKL	49	F	132011	FLU
XHI	43	M	133150	HIV
BFX	49	M	133012	CANCER
BSN	50	F	132012	DIABETES
JSM	45	M	132153	CANCER
OAE	42	F	132453	HIGH BP

B. Formulas to Calculate Information Loss

Let dataset D consists of a set of r tuples with n numeric and c categorical quasi identifier attribute. Let $\gamma = \{\sigma_1, \sigma_2, \sigma_3, \dots, \sigma_p\}$ be a dividing of γ , where σ characterize a cluster Let ζ be the taxonomy tree as shown in Figs. 1 and 2 with respect to Table II. The taxonomy tree is used to generalize the value of each categorical and numerical attribute. The info loss (ILn) for the n numerical attributes of a dataset D via generalization and suppression is calculated as follows: Let Ri_{max} , Ri_{min} be the maximum and minimum value of the tuples in a cluster σ . Let Ti_{max} , Ti_{min} be the maximum and minimum value of the tuples in a dataset D .

$$IL_n = |\gamma| \sum_{i=1}^n \frac{Ri_{max} - Ri_{min}}{Ti_{max} - Ti_{min}} \quad (1)$$

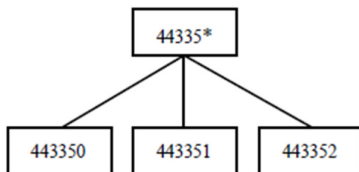


Fig.1. Taxonomy tree of zip code.

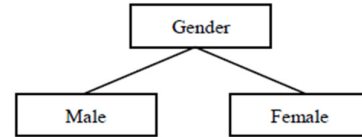


Fig.1. Taxonomy tree of gender.

Similarly, the information loss (IL_c) for the c categorical attribute is calculated as follows: Let c_j (where $j = 1, 2, \dots, c$) be a set of categorical attributes.

$$IL_c = |\gamma| \sum_{j=1}^c \frac{H(\Delta(c_j))}{H(\zeta c_j)} \quad (2)$$

Systematic clustering approach [11] from this approach they got motivation and research on information loss problem of k -anonymization introduced these approaches Approach-1: Unequal Group of QI and SA; and Approach-2: Equal Group of QI and SA and they had two objectives first was decrease information loss and second was to reserve the privacy by presenting the least number of attributes in the anonymized dataset.

- In paper [1] two approaches give minimum information loss but after that some Information loss is still there so our main goal is to decrease information loss as much as possible by 2- Level Anonymization approach in this approach anonymize only that cluster which have more information loss.
- This approach is improved version of novel approaches for privacy preserving data mining in k -anonymity model which is invented by authors Pawan Baladhare and Devesh Jinwala [1]
- Let's see how this improved version of this approach will give minimum information loss by same hospital dataset example.

III. COMPARISION OF THREE APPROACHES

1. Traditional K-Anonymized Approach [2]
2. Novel Approach Equal group of QI and SA [1]
3. 2-Level K-Anonymization Approach

1. Traditional K-Anonymized Approach version of above hospital's dataset shown in Table II

TABLE II SUBDATABASE FROM HOSPITAL'S ANONYMIZED DATASET

ID	AGE	GENDER	ZIP CODE	DISEASE
3	[15-30]	P	132***	CANCER
7	[15-30]	P	132***	DIABETES
6	[15-30]	P	132***	HIGH BP



ID	ZIP CODE		DISEASE	
1	13201*		FLU	
6	13201*		HIGH BP	
11	13201*		FLU	
3	13201*		CANCER	
4	13201*		DIABETES	
8	13201*		CANCER	
9	13201*		HIV	
14	13201*		DIABETES	
7	13****		DIABETES	
2	13****		HIV	
5	13****		CANCER	
10	13****		CANCER	
15	13****		CANCER	
16	13****		HIGH BP	
13	13****		CANCER	
12	13****		HIV	
4	[15-30]	P	132***	DIABETES

ID	GENDER	DISEASE
2	P	HIV
3	P	CANCER
5	P	CANCER
8	P	CANCER
11	P	FLU
14	P	DIABETES
16	P	HIGH BP
1	P	FLU
4	M	DIABETES
6	M	HIGH BP
7	M	DIABETES
9	M	HIV
10	M	CANCER
12	M	HIV
13	M	CANCER
15	M	CANCER
5	[15-30]	CANCER
8	[41-50]	CANCER
16	[41-50]	CANCER
12	[41-50]	HIV
10	[41-50]	CANCER
15	[41-50]	CANCER
11	[41-50]	FLU
13	[41-50]	CANCER
14	[41-50]	HIGH BP

2	[15-30]	P	132***	HIV
1	[15-30]	P	132***	FLU
9	[15-30]	P	132***	HIV
5	[15-30]	P	132***	CANCER
8	[41-50]	P	13****	CANCER
16	[41-50]	P	13****	HIGH BP
12	[41-50]	P	13****	HIV
10	[41-50]	P	13****	CANCER
15	[41-50]	P	13****	CANCER
11	[41-50]	P	13****	FLU
13	[41-50]	P	13****	CANCER
14	[41-50]	P	13****	DIABETES

Information Loss Calculation of Traditional K-Anonymization

ID	GENDER	DISEASE
2	F	HIV
3	F	CANCER
5	F	CANCER
8	F	CANCER
11	P	FLU
14	P	DIABETES
16	P	HIGH BP
1	P	FLU
4	M	DIABETES
6	M	HIGH BP
7	M	DIABETES
9	M	HIV
10	M	CANCER
12	M	HIV
13	M	CANCER
15	M	CANCER

Approach for table II

$$IL = IL_n + IL_c = 8 \times \left[\left(\frac{30-15}{50-15} \right) + \left(\frac{50-41}{50-15} \right) + (1+1) + (3+4) \right] \approx 77.50$$

2. Novel Approach Equal group of QI and SA

TABLE III K-ANONYMIZATION APPROACH EQUAL GROUP OF QA,SA(AGE,DISEASE)

TABLE IV K-ANONYMIZATION APPROACH EQUAL GROUP OF QA,SA(GENDER,DISEASE)

TABLE V K-ANONYMIZATION APPROACH EQUAL GROUP OF QA,SA(ZIP CODE,DISEASE)

Information Loss Calculation of Novel Approach for table III, IV, V

$$IL = IL_n + IL_{c1} + IL_{c2} = 8 \times \left[\left(\frac{30-15}{50-15} \right) + \left(\frac{50-41}{50-15} \right) + (1+0) + (1+4) \right] \approx 53.50$$

3. 2-level K-Anonymization Approach

TABLE VI 2-LEVEL K-ANONYMIZATION APPROACH EQUAL GROUP OF QA,SA(AGE,DISEASE)

ID	AGE	DISEASE
3	[15-20]	CANCER
7	[15-20]	DIABETES
6	[15-20]	HIGH BP
4	[15-20]	DIABETES
2	[21-30]	HIV
1	[21-30]	FLU
9	[21-30]	HIV
5	[21-30]	CANCER
8	[41-50]	CANCER
16	[41-50]	CANCER
12	[41-50]	HIV
10	[41-50]	CANCER
15	[41-50]	CANCER
11	[41-50]	FLU
13	[41-50]	CANCER
14	[41-50]	HIGH BP

TABLE VII 2-LEVEL K-ANONYMIZATION APPROACH EQUAL GROUP OF QA,SA(GENDER,DISEASE)

TABLE VIII 2-LEVEL K-ANONYMIZATION APPROACH EQUAL GROUP OF QA,SA(ZIP CODE,DISEASE)

Information Loss Calculation of 2-Level K-Anonymization for table VI, VII, VIII

$$IL = IL_n + IL_{c1} + IL_{c2}$$

$$= \left[4 \times \left(\frac{20-15}{50-15} \right) + 4 \times \left(\frac{30-21}{50-15} \right) + 8 \times \left(\frac{50-41}{50-15} \right) \right] +$$

$$[4 \times (0 + 1) + 8 \times (0)] + [4 \times (1 + 0 + 0 + 4)] \approx 27.65$$

TABLE IX COMPARISON OF ALL THREE APPROACHES

No	Approach	Information Loss
1	Traditional K-Anonymization Approach [2]	77.50
2	Novel Approach K Anonymization of equal combination of QA, SA [1]	53.50
3	2-level K-Anonymization Approach of equal combination of QA, SA	27.65

2-level K-Anonymization Approach have lowest Information Loss that is approx. 27.65

IV. 2-LEVEL K-ANONYMIZATION APPROACH

In table II anonymized table gives high rated information loss but in novel approach of equal group of QA and SA gives less information loss as we can see in table IV in attribute gender only 8 records get generalization instead of all and in table V in attribute zip code values got lesser suppression as compared to traditional approach. Now by comparing this approach to 2-level anonymization approach in table VII in attribute gender only 4 records generalizations, it saves 4 more to get generalized and table VIII in attribute zip code values less suppressed than both traditional and in novel approach of equal group of QA and SA approaches.

Algorithm:

Input: Dataset D which has r tuples

Output: $\gamma = \{\sigma_1, \sigma_2, \sigma_3, \dots, \sigma_p\}$ be a subdividing of r

// D is main database

// r is the amount of tuples in the dataset

// γ is a subdividing of r tuples

// σ is a clusters

// k is no of tuples for anonymization

Begin

1. Recognize the attributes such as identifier, quasi-identifier (QI) (numeric and non-numerical means categorical) and sensitive attribute (SA)
2. Eliminate the identifier attribute and exchange it with ID

3. Sort all tuples by their quasi-identifiers attributes.
4. Recognize the amount of equivalence classes and groups
5. Create an Equal/Unequal grouping of QI and SA to generate the sub-database

ID	ZIP CODE	DISEASE
1	13201*	FLU
6	13201*	HIGH BP
11	13201*	FLU
3	13201*	CANCER
4	132012	DIABETES
8	132012	CANCER
9	132012	HIV
14	132012	DIABETES
7	132050	DIABETES
2	132150	HIV
5	132150	CANCER
10	132150	CANCER
15	13****	CANCER
16	13****	HIGH BP
13	13****	CANCER
12	13****	HIV

6. Make a divider of all tuples into k tuples groups
7. Select a tuple r_i arbitrarily from the initial block of k tuples
8. Likewise select next tuples r_j from the other block of k tuples
9. Do generalization and Suppression.
10. Do further clustering only that cluster which have more information loss
 $K = k/2$
11. Do generalization and Suppression.
12. Compute info loss

$$IL(\gamma) = \sum_{i=1}^p IL(\sigma_i)$$

13. Transfer the tuples in a group with lowest information loss
14. Search additional element in a group those who surpass the k size
15. Add further element in a group whose info loss is lowermost

End

This algorithm steps taken from novel approach of equal/unequal group of QA and SA and step 10 and 11 are added by us to minimize information loss purpose. Conferring to the algorithm we initial identify and categorize the attributes such as *identifier*, *quasi-identifier* and *sensitive* attributes in a dataset (step 1). Next, we eliminate the *identifier* attribute from the dataset and sort all tuples using the *quasi-identifiers* (steps 2 and 3). Then, we find out the number of groups and clusters such that $\sigma = \frac{r}{k}$, where r is the number of tuples in a database and k is the anonymization factor (step 4). Later recognizing the groups and clusters in an original



dataset, we generate a sub-dataset using a grouping of QI and SA (step 5). In Approach, we create an equal/unequal grouping of QI, SA. From each generated sub-dataset, we make a partition of all tuples into k groups (step 6). Next, we used Systematic clustering algorithm in demand to generate the clusters [11]. Conferring to the Systematic clustering algorithm [11], we arbitrarily select a tuple from the first cluster for the formation of the first cluster (step 7). Likewise, we make the remaining cluster by arbitrarily selecting the tuples from the outstanding groups (step 8). Generalization and suppression applied (step 9) after that do further clustering of only that clusters which have more information loss (step 10) and again generalization and suppression. Next, we compute the information loss of each cluster (step 11). Now, we select other tuples from the initial group and add tuples in a cluster whose info loss is the lowermost (step 12). In the similar way, we select and add other tuples in a cluster whose information loss is the lowermost. Throughout the clustering process if nearly cluster has exceeded to the k size, the extra record should be added in a cluster whose info loss is the lowest (step 13 and step 14).

V. DATASET AND SOFTWARE SETUP

We practice the ADULT dataset from the UCI Machine Learning Repository [18] for testing. The ADULT dataset holds 32561 records and 15 attributes. Out of them, we recollect only attributes Age, Gender, fnlwt, Occupation, Marital-status, Race. The attributes Age and fnlwt are numeric attributes, and Race, Gender, Marital-status and Occupation are the categorical attributes. The attribute Occupation is reserved as a sensitive attribute in the dataset. The research will be executed in Java with JDK 1.6 in a system constructed with Intel core i3 processor, 4 GB RAM and 500GB hard disk.

CONCLUSION

In conclusion after research in privacy preserving main goal is to preserve a privacy but to preserve privacy in other hand Information getting loss so, as per our concern information loss is main important issue for this anonymization so, for that 2-level anonymization approach introduced for in case of $k=8$ and 4. $K=4$ has less information loss as compared to $k=8$ and higher data utility but by comparing privacy parameter of this both case $k=8$ have higher privacy than $k=4$ by this 2-level anonymization is approach which gives benefits of both first privacy parameter from $k=8$ and second less information loss from $k=4$.

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