A Noise Addition Scheme in Decision Tree for Privacy Preserving Data Mining

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Abstract—Data mining deals with automatic extraction of previously unknown patterns from large amounts of data. Organizations all over the world handle large amounts of data and are dependent on mining gigantic data sets for expansion of their enterprises. These data sets typically contain sensitive individual information, which consequently get exposed to the other parties. Though we cannot deny the benefits of knowledge discovery that comes through data mining, we should also ensure that data privacy is maintained in the event of data mining. Privacy preserving data mining is a specialized activity in which the data privacy is ensured during data mining. Data privacy is as important as the extracted knowledge and efforts that guarantee data privacy during data mining are encouraged. In this paper we propose a strategy that protects the data privacy during decision tree analysis of data mining process. We propose to add specific noise to the numeric attributes after exploring the decision tree of the original data. The obfuscated data then is presented to the second party for decision tree analysis. The decision tree obtained on the original data and the obfuscated data are similar but by using our method the data proper is not revealed to the second party during the mining process and hence the privacy will be preserved.

Index Terms—Privacy preserving data mining, Data perturbation, Decision Tree.

1 INTRODUCTION

Organizations in the modern business world collect lots of data and they are data rich. On top of data they place a layer of data mining algorithms which help extract patterns/classes/associations in the data without any apriori hypothesis. This process of knowledge discovery has multifold benefits to the organizations and organizations continue to plunder the data by using various mining techniques. It is imperative that once the organizations start sharing the data during the mining process the data proper gets exposed and privacy of individual records is breached. It is important there fore to mine the data without revealing the data proper to other parties. Privacy preserving data mining is such a specialized set of data mining activity where techniques are evolved to protect the privacy of the data and at the same time the knowledge discovery process is carried out without ban or bash. It is a matter of history now that Privacy Preserving Data Mining (PPDM) techniques have bailed out the Data Mining (DM) technology from a total ban .PPDM is an active field of research in knowledge engineering. In this paper we propose a novel method that ensures the data privacy in the event of decision tree analysis on the data. It is basically a noise addition framework specifically tailored toward classification task in data mining. The method also preserves averages and few other statistical parameters thus making the modified data set useful for both statistical and data mining purposes. Let D be the original data set and T be its decision tree. Our effort will be to modify D to D’ and get the corresponding decision tree T’ such that T and T’ are similar. This way we can suggest to expose D’ instead of D for mining purposes where by one can avoid revealing the data proper and still be assured of unaffected data mining results (specifically decision tree).

2 PREVIOUS WORK

For the past few years, several approaches have been proposed in the context of privacy preserving data mining. These techniques can be classified based on the different protection methods used, such as Data modification methods, Cryptographic methods with distributed privacy and Query auditing. Fig-1 shows the classification.

Data modification techniques modify the data before releasing it to the users. Data is modified in such a way that the privacy is preserved in the released data set. Several data modification techniques are proposed including noise addition[1][5][23], data swapping[24][25], aggregation[26][27], suppression[28][29] and signal transformation[30][31].

Cryptographic methods[22] encrypt the data with encryption schemes while still allowing the data mining tasks. These methods use certain set of protocols such as secured multiparty computation(SMC).SMC techniques are not supposed to disclose any new information other than the final result of the computation to a participating party. SMC techniques are applied to distributed data sets.
As an extension, SMC protocol is applied to centralized data sets by partitioning the data sets either vertically or horizontally. Cryptographic methods bring in the overhead of encryption decryption and are less efficient for larger data set and where data utility is of concern. Query auditing methods preserve privacy by modifying or restricting the results of a query. In these methods too many denials to a query leads to less utility of the data set. Lesser denial though increases the utility but sacrifices privacy. However no method is complete and satisfactory. Each method suffers from one or the other kind of bias. If we consider the data mining tasks and classify the privacy preserving methods then another set of interesting classification can be seen such as (i) Methods that preserve statistical parameters. (ii) Methods that preserve classification results. (iii) Methods that preserve clustering results. (iv) Methods that preserve association rules. (iv) Methods that preserve more than one data mining features.

3 OVERVIEW OF DECISION TREE

Decision Tree algorithm uses a splitting criterion based on the information gain in the attribute. The attribute with highest information gain will form the root of the tree and algorithm iteratively continues splitting the data to form a decision tree. It essentially finds the best splitting attribute and the best splitting point of the numeric continuous attributes. It was first proposed by Quinlan in 1986 and later improved to be known as C4.5 and C5.0 algorithm. The formulas of information gain and gain ratio are as follows.

\[
\text{Info}(S) = -\sum_{i=1}^{n} \left( \frac{\text{freq}(C_i, S)}{|S|} \right) \times \log_2 \left( \frac{\text{freq}(C_i, S)}{|S|} \right)
\]

\[
\text{Info}_{\text{Test}(A)}(S) = \sum_{i=1}^{n} \left( \frac{|S_i|}{|S|} \times \text{Info}(S_i) \right)
\]

\[
\text{gain}(\text{Test}_A) = \text{Info}(S) - \text{Info}_{\text{Test}(A)}(S)
\]

\[
\text{splitInfo}(\text{Test}_A) = -\sum_{i=1}^{n} \left( \frac{|S_i|}{|S|} \times \log_2 \left( \frac{|S_i|}{|S|} \right) \right)
\]

\[
\text{gainRatio}(\text{Test}_A) = \frac{\text{gain}(\text{Test}_A)}{\text{splitInfo}(\text{Test}_A)}
\]

With respect to the following table-1 we show how the

![Fig-1: Classification of Privacy Preserving Data Mining Techniques.](https://sites.google.com/site/journalofcomputing/)
Information gain terms are calculated in the decision tree formation. Fig-1 shows the typical decision tree obtained for the sample table taken in table-2.

**TABLE-1**

| Liver Size | Patient’s Weight | Eats Pizza | Diagnostic Class |
|------------|------------------|-----------|------------------|
| NORMAL     | 70               | YES       | CLASS1           |
| NORMAL     | 90               | YES       | CLASS2           |
| NORMAL     | 85               | NO        | CLASS2           |
| NORMAL     | 95               | NO        | CLASS2           |
| ENLARGED   | 70               | NO        | CLASS1           |
| ENLARGED   | 90               | YES       | CLASS1           |
| ENLARGED   | 78               | NO        | CLASS1           |
| ENLARGED   | 65               | YES       | CLASS1           |
| ENLARGED   | 75               | NO        | CLASS1           |
| SHRINKED   | 80               | YES       | CLASS2           |
| SHRINKED   | 70               | YES       | CLASS2           |
| SHRINKED   | 80               | NO        | CLASS1           |
| SHRINKED   | 80               | NO        | CLASS1           |
| SHRINKED   | 96               | NO        | CLASS1           |

In the dataset in table-1 nine samples belong to CLASS1 and five samples belong to CLASS2. Let $Test_a$ is the LiverSize attribute, the entropy before splitting is

$$Info_{Test_a}(S) = \frac{5}{14} \left( - \frac{2}{5} \log_2 \left( \frac{2}{5} \right) - \frac{3}{5} \log_2 \left( \frac{3}{5} \right) \right)$$

$$+ \frac{4}{14} \left( - \frac{4}{4} \log_2 \left( \frac{4}{4} \right) - \frac{0}{4} \log_2 \left( \frac{0}{4} \right) \right)$$

$$+ \frac{5}{14} \left( - \frac{3}{5} \log_2 \left( \frac{3}{5} \right) - \frac{2}{5} \log_2 \left( \frac{2}{5} \right) \right)$$

$$= 0.940$$ bits

$$Info_{Test_a}(S) = \frac{5}{14} \left( - \frac{2}{5} \log_2 \left( \frac{2}{5} \right) - \frac{3}{5} \log_2 \left( \frac{3}{5} \right) \right)$$

$$+ \frac{4}{14} \left( - \frac{4}{4} \log_2 \left( \frac{4}{4} \right) - \frac{0}{4} \log_2 \left( \frac{0}{4} \right) \right)$$

$$+ \frac{5}{14} \left( - \frac{3}{5} \log_2 \left( \frac{3}{5} \right) - \frac{2}{5} \log_2 \left( \frac{2}{5} \right) \right)$$

$$= 0.694$$ bits

$$Gain(Test_a) = 0.940 - 0.694 = 0.246$$

The algorithm is applied recursively to each child node until all samples at a node are of one class. Every path to the leaf in decision tree represents a classification rule. Attribute selection is based on minimizing an information entropy measure applied to the example at a node.

### 4 OUR APPROACH

We use Quinlan's [17] C5.0 decision tree builder on the selected data set [18] and obtain the decision tree of the original data set. We then approach a unique method of listing the nodes (attributes) that we touch in the path from the root of the tree to the leaf. We then use a noise addition strategy for each of the attributes.

### 4.1 Terminology

In any decision tree we have some leaves and some internal nodes. The path that leads from the root to the leaf is called Leaf Reaching Path (LRP) and nodes that form LRPs are listed as Leaf Reaching Path Attributes (LRPAs). For example in the tree in Fig-3, for LEAF1 the LRPA is percentage low income earners, Av rooms per dwelling, pupil-teacher ratio. The path that doesn’t lead to a leaf is called Leaf Wrong Path (LWP). There may be many Wrong Paths to a leaf. set of attributes that don’t form LRP are grouped as Leaf Wrong Path Attributes (LWPA). The LWPA for LEAF1 is nitric oxides ppm. Each leaf in the tree has a set of LRPAs and LWPAs. Each LRPA attribute or LWPA attribute may be numerical or categorical. If the attribute is categorical (either in LRPA list or LWPA list), we are using a CAPT, (Categorical Attribute Perturbation Technique) for perturbing it. For numerical attributes of LRPA & LWPA we will use specific noise addition techniques (PTLRPA & PTLWPA) explained in the sections that follow.
PTLRPA is the perturbation technique used to perturb numeric attributes of LRPA and PTLWPA is the perturbation technique used for perturbing numeric attributes of LWPA.

We use a wrapping function V_WRAP to wrap the numeric values if, after addition of noise values exceed their respective attribute domain. Domain of the attribute is the range of values for that attribute. Example, for an attribute such as age the domain would be [1..100].

![Fig-3 Decision Tree from BHP Dataset used for explaining terminology of our approach.](image)

Fig-3: Decision Tree from BHP Dataset used for explaining terminology of our approach.

### 4.2 CAPT

Categorical Attribute Perturbation Technique basically shuffles/changes the attribute values with certain probability. Depending upon the type of the leaf in the tree. The leaf can be a heterogeneous leaf or a homogeneous leaf. Heterogeneous leaf is the one that contains more than one class type and homogeneous leaf is the one that contains only one class type. Heterogeneous leaf will have some majority records and zero or more minority records. Majority records are those whose occurrence is maximum times than the other records with respect to the class identified. In Fig-4, L1 is a heterogeneous leaf and L2 is a homogeneous leaf. In L1 A is the majority class and S is the minority class.

Let p be the user defined probability, then CAPT shuffles the class values of the leaf with probability (1-p).

![Fig.4 : Heterogeneous and homogeneous leaves.](image)

Fig.4: Heterogeneous and homogeneous leaves.

### 4.3 CAPT Algorithm

BEGIN CAPT

Scan the records one by one.

For each record

DO

Identify the leaf to which the record belongs.

IF (the leaf has no siblings)

DO

IF (leaf is heterogeneous)

Assign,

\[ m = \text{the number of majority records.} \]
\[ n_i = \text{the number of records having minority } i \text{th class.} \]
\[ t = \text{Number of different minority classes.} \]
\[ k = \sum_{i=1}^{t} n_i; \]
\[ q = \frac{m}{m+k}; \]
\[ l = \frac{n_i}{n_i+k}; \]

BEGIN shuffling the records

FOR (the majority class records)

assign \((1-p)\times q\) probability,

FOR (minority class records)

assign \((1-p)\times l\) probability.

END shuffling the records

END IF

ELSE

IF (Leaf has siblings)

Identify the majority class in the leaf.

Assign,

New_class_of_the_record = majority_class_of_the_leaf.

END IF

END ELSE

END DO

END CAPT.
4.4 PTLRPA Algorithm

Perturbation Technique for Leaf Reaching Path Attributes. In this technique first we obtain the attributes that are tested in reaching the leaf. If the attribute is categorical, we use CAPT otherwise we use the following PTLRPA algorithm to add noise to the numerical attributes of LRP.

BEGIN PTLRPA
    Find normal distributions of all numeric attributes of Decision Tree.
    For each record of the dataset,
        Do
            Determine the leaf L to which it belongs.
            Identify the LRPAs.
            Identify Domains of each numeric attribute of LRP.
            Add a small noise drawn from respective distributions of attributes, having certain mean and variance.
            IF (attribute value + Noise) > Domain Value
                Call a wrapper function (V_WRAP) to wrap around the value.
            ENDIF
        END DO
    END PTLRPA.

4.5 PTLWPA Algorithm

Perturbation Technique for Leaf Wrong Path Attributes. In this technique first we obtain the attributes that are not tested in reaching the leaf. If the attribute is categorical, we use CAPT, otherwise we use the following PTLWPA algorithm to add noise to the numerical attributes of LWP.

BEGIN PTLWPA
    Find the distributions of all numeric attributes of Decision Tree.
    For each record of the dataset,
        Do
            Determine the leaf L to which it belongs.
            Identify the LWPA.
            Identify Domains of each attribute of LWPA.
            Add a small noise drawn from respective distributions of attributes, having certain mean and variance.
            IF after addition, the attribute value exceeds its domain value,
                THEN
                    call a wrapper function (V_WRAP) to wrap around the value.
                ENDIF
        END DO
    END PTLWPA

4.6 V_WRAP Algorithm

This function is called by PTLRPA or PTLWPA algorithms when after addition of noise the attribute value exceeds its domain value.

BEGIN V_WRAP
    Record the Domain limits [a, (a+D)] of the attribute.
    Get the input value P, for Wrapping.
    Compare P with max domain limit.
    IF (P > (a+D))
        d=P-(a+D)
    ELSEIF (P < a )
        d=P-a
    ENDIF
    P=a+d-1
    RETURN(P)
END IF
END V_WRAP.

5 Data Sets

In our experiments we have used the following data sets from UCI machine learning repository [38].

5.1 The BHP data set

The Boston Housing Price (BHP) data set has altogether 12 attributes, out of which one is the categorical attribute with domain size 2 top 20%, bottom 80%. The non-class attributes are crime rate, proportion large lots, proportion industrial, nitric oxide ppm, Av rooms per dwelling, proportion pre-1940, distance to employment centers, accessibility to radial highways, property tax rate 10,000 dollars, pupil-teacher ratio and percentage low income earners. All non-class attributes are continuous. Other two non-class attributes "CHAS" and "B" are ignored throughout our experiments.

5.2 Census Income Data Set

This data set has fourteen attributes, six continuous and eight nominal. It altogether has 48842 instances and 16281 testing data instances. This data set can be downloadable from University of California Irvine repository.

5.3 Car Evaluation Data Set

This data set is derived from a hierarchical decision model, and was first used in [21]. This data set has mainly six categorical attributes and 1728 instances. Associated task is classification.
6 Experiments and Results

We initially conducted our experiments on the sample dataset of table-1 and later the other data sets were tested. We added the random noise drawn from the distributions to the Patient’s Weight attribute and the perturbed table was obtained (table-2). The random noise was chosen from the distribution shown in Fig-5. The decision tree obtained for these two tables, table-1 and table-2 were same (Fig-6).

Fig-5. Normal distribution of sample data set (LiverDataSet) of table-1.

We then selected the datasets from UCI machine learning repository. We built a classifier from the perturbed tree and applied the classifier on the training and testing data sets separately. We also built a classifier from the original tree and applied on the training and testing data sets. We then compared their accuracies. (Tabl-3).

![Fig-6 Experimental setup with C5.0 node.](image)

DGN-Diagnosis.
Two instances of DGN node are shown in Fig-6. The DGN node after Derive1 and generated nodes is receiving perturbed data as input.

![Fig-7 The Decision tree for the sample dataset (LiverDataSet) and its perturbed instance](image)

### Table-2

| Liver Size   | Patient’s Weight (original) | Patient’s Weight (perturbed) | Eats Pizza | Diagnostic Class |
|--------------|------------------------------|------------------------------|------------|------------------|
| NORMAL       | 70                           | 65.74                        | YES        | CLASS1           |
| NORMAL       | 90                           | 85.74                        | YES        | CLASS2           |
| NORMAL       | 85                           | 80.74                        | NO         | CLASS2           |
| NORMAL       | 95                           | 90.74                        | NO         | CLASS2           |
| NORMAL       | 70                           | 65.74                        | NO         | CLASS1           |
| ENLARGED     | 90                           | 85.74                        | YES        | CLASS1           |
| ENLARGED     | 78                           | 73.74                        | NO         | CLASS1           |
| ENLARGED     | 65                           | 60.74                        | YES        | CLASS1           |
| ENLARGED     | 75                           | 70.74                        | NO         | CLASS1           |
| SHRINKED     | 80                           | 75.74                        | YES        | CLASS2           |
| SHRINKED     | 70                           | 65.74                        | YES        | CLASS2           |
| SHRINKED     | 80                           | 75.74                        | NO         | CLASS1           |
| SHRINKED     | 96                           | 91.74                        | NO         | CLASS1           |
Ideally, the accuracy of a perturbed classifier should be as good as the accuracy of the original classifier. We observe that the comparative results are tending to fulfill this requirement. The data quality of the perturbed data set is considered to be high when the perturbed data set is similar to the original data set in terms of decision tree and the classifier accuracies.

7 CONCLUSION

The approach taken in this paper integrates both categorical and numeric data types and focuses on privacy preserving during classification, particularly in decision tree analysis. The noise addition methods used are effective in preserving the privacy of the data proper and producing prediction accuracies on par with the original dataset. Crucial properties of a noise addition technique are the ability to maintain good data quality and ensure individual privacy. More experiments are to be conducted on data quality and security level measurements. In the context of various data mining tasks, as our approach deals only with the classification task, we conclude that our approach is addressing the issue of PPDM partially. Future research however may incorporate the approach taken in this paper to evolve a unified privacy preserving framework that addresses as many data mining tasks as possible.

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