An Approximate Microaggregation Approach for Microdata Protection

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Abstract

Microdata protection is a hot topic in the field of Statistical Disclosure Control, which has gained special interest after the disclosure of 658000 queries by the America Online (AOL) search engine in August 2006. Many algorithms, methods and properties have been proposed to deal with microdata disclosure. One of the emerging concepts in microdata protection is k-anonymity, introduced by Samarati and Sweeney. k-anonymity provides a simple and efficient approach to protect private individual information and is gaining increasing popularity. k-anonymity requires that every record in the microdata table released be indistinguishably related to no fewer than k respondents.

In this paper, we apply the concept of entropy to propose a distance metric to evaluate the amount of mutual information among records in microdata, and propose a method of constructing dependency tree to find the key attributes, which we then use to process approximate microaggregation. Further, we adopt this new microaggregation technique to study k-anonymity problem, and an efficient algorithm is developed. Experimental results show that the proposed microaggregation technique is efficient and effective in the terms of running time and information loss.

1 Introduction

British politicians gasped with astonishment when they were told on November 20th, 2007, that two computer disks full of personal data of 25m British individuals had gone missing [24]. The fate of the disks is unknown and the privacy of the individuals, whose personal data are lost, is in danger. Unfortunately, this is the latest in a series of similar incidences. In October, HM's Revenue and Customs (HMRC) lost another disk containing pension records of 15,000 people, and it also lost a laptop containing personal data on 400 people in September [7]. Data on 26.5m people were stolen from the home of an employee of the Department of Veterans Affairs in America in 2006, and 658000 queries were disclosed by the AOL search engine in August of the same year [15]. These pitfalls are not new. Due to the great advances in the information and communication technologies, it is very easy to gather large amounts of personal data, and mistakes such as those described are magnified.

There are many real-life situations in which personal data is stored: For example: (i) Electronic commerce results in the automated collection of large amounts of consumer data. These data, which are gathered by many companies, are shared with subsidiaries and partners. (ii) Health care is a very sensitive sector with strict regulations. In the U.S., the Privacy Rule of the Health Insurance Portability and Accountability Act (HIPAA [16]) requires the strict regulation of protected health information for use in medical research. In most western countries, the situation is similar, (see e.g. [2]). (iii) Cell phones have become ubiquitous and services related to the current position of the user are growing fast. If the queries that a user submits to a location-based server are not securely managed, it could be possible to infer the consumer habits of the user [33]. (iv) The massive deployment of the Radio Frequency IDentification (RFID) technology is a reality. On the one hand, this technology will increase the efficiency of supply chains and will eventually replace bar codes. On the other hand, the existence of RFID tags in almost every object could be seen as a privacy problem [34].

In addition to these real-life situations, most countries have legislation which compels national statistical agencies to guarantee statistical confidentiality when they release data collected from citizens or companies; see [23] for regulations in the European Union, [26] for regulations in Canada, [27] for regulations in the U.S, and [28] for regulations in Australia. Thus, protecting individual privacy is a key issue for many institutions, especially statistical

agencies, Internet companies, manufacturers, etc; and many efforts have been devoted to develop techniques guaranteeing some degree of personal privacy.

In order to protect privacy, Samarati and Sweeney [31, 38, 29, 30] proposed the k-anonymity model, where some of the quasi-identifier fields are suppressed or generalized so that, for each record in the modified table, there are at least $k-1$ other records in the modified table that are identical to it with respect to the quasi-identifier attributes. The general approach adopted in the literatures to achieve k-anonymity is suppression/generalization, so that minimizing information loss translates to reducing the number and/or the magnitude of suppressions and generalizations [1, 29, 38, 35, 37, 39, 20, 19, 21].

Another method to achieve anonymity is through microaggregation [12, 11, 32]. Microaggregation is a Statistical Disclosure Control (SDC) technique consisting in the aggregation of individual data. It can be considered as an SDC sub-discipline devoted to the protection of microdata. Microaggregation can be seen as a clustering problem with constraints on the size of the clusters. It is somehow related to other clustering problems (e.g., dimension reduction or minimum squares design of clusters). However, unlike clustering, microaggregation is not considered with the number of clusters or the number of dimensions, but only the minimum number of elements that are grouped in each cluster.

1.1 Motivation

As stated in [9, 10, 11], the result and execution time of miroaggregation depends on the number of the variables used in the microaggregation process. Microaggregation using fewer variables sometimes offer the best solution. The question of interest is: Do we have to use all the dimension resources (attributes) in the microaggregation, or can we use only a small number of the attributes in the microaggregation process and obtain better solutions?

This paper is highly motivated by this. To answer the question, we introduce the concept of *entropy*, an important concept in information theory, and propose a distance metric to evaluate the amount of the mutual information among records in the microdata, and propose the method of constructing dependency tree to find the key attributes, which we can use to process approximate microaggregation. Further, we apply this new microaggregation technique to solve k-anonymity problem, and an efficient algorithm is developed. Finally, experimental

3

results show that the proposed microaggregation technique is efficient and effective in terms of running time and information loss.

Our Contributions:

• We propose a novel metric to measure the mutual information between attributes in the microdata based on the concept of entropy, which captures the expected uncertainty in the attribute pairs and the mutual information between them. We also discuss the properties of this metric.

• Based on this mutual information measure, we develop a simple, yet efficient algorithm to find the best dependency tree from the given microdata, and we also discuss how to select key attributes from the best dependency tree, and how to use it for the approximate microaggregation.

• We apply our technique to k-anonymity problem, and develop an efficient algorithm for it. Experimental results show that the proposed microaggregation technique is effective and efficient compared with the previous microaggregation method.

Running Example

ID	A_1	A_2	A_3	A_4	A_5	A_6
r_1	0	0	0	1	1	1
r_2	0	1	1	0	1	0
r_3	1	1	0	1	0	0
r_4	0	0	1	1	1	1
r_5	0	1	1	1	0	0
r_6	0	0	1	0	0	1
r_7	1	1	1	0	0	1
r_8	0	1	1	0	0	0
r_9	1	1	1	0	1	1
r_{10}	0	1	1	1	0	1
r_{11}	0	1	1	1	0	0
r_{12}	1	1	1	1	1	1

Table 1: Sample data

For the simplicity of illustration, we use the data shown in Table 1 as our running example. There are 12 records $\{r_1, r_2, \cdots, r_{12}\}$ in the sample data and each record contains 6 attributes $\{A_1, \cdots, A_6\}$. For each attribute A_i ($1 \leq i \leq 6$), we define the probability $P(A_i = x)$ as the fraction of rows whose projection onto A_i is equal to x, where $x \in \{0, 1\}$. For instance, $P(A_1 = 1) = 1/3$, $P(A_3 = 0) = 1/6$ and $P(A_1 = 1, A_3 = 0) = 1/12$.

2 Background

Many techniques have been proposed to deal with the anonymity problem. In this section, we introduce some basic concepts regarding this. First, we take a look at some fundamental concepts of microaggregation and k-anonymity. Then, we show how to achieve k-anonymity through microaggregation.

2.1 Microaggregation

Statistical Disclosure Control (SDC) seeks to transform data in such a way that the data can be publicly released whilst preserving utility and privacy, where the latter means avoiding disclosure of information that can be linked to specific individual or corporate respondent entities. Microaggregation is an SDC technique consisting in the aggregation of individual data. It can be considered as an SDC sub-discipline devoted to the protection of the micro-data. Microaggregation can be seen as a clustering problem with constraints on the size of the clusters. It is somehow related to other clustering problems (e.g., dimension reduction or minimum squares design of clusters). However, the main difference of the microaggregation problem is that it does not consider the number of clusters to generate or the number of dimensions to reduce, but only the minimum number of elements that are grouped in the same cluster.

Microaggregation has been used for several years in different countries. It started at Eurostat [8] in the early nineties, and has since then been used in Germany [25] and several other countries [13]. Microaggregation is relevant not only with SDC, but also in artificial intelligence [10]. In the latter field, the application is to increase the knowledge of a system for decision making and domain representation. Microaggregation techniques may also be

Gender	Age	Postcode	Problem
male	middle	4350	stress
male	middle	4350	obesity
male	young	**4351**	stress
female	young	**4352**	obesity
female	old	4353	stress
female	old	4353	obesity

Table 2: A raw microdata

Gender	Age	Postcode	Problem
male	middle	4350	stress
male	middle	4350	obesity
*	young	**435***	stress
*	young	**435***	obesity
female	old	4353	stress
female	old	4353	obesity

Table 3: A 2-anonymous microdata
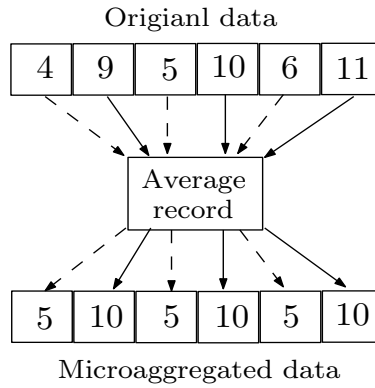
Figure 1: Example of microaggregation

used in data mining in order to scale down or even compress the data set while minimizing the information loss.

When we microaggregate data we have to keep two goals in mind: (i) *Preserving data utility.* To do this, we should introduce as little noise as possible into the data; i.e., we should aggregate similar elements instead of different ones. In the example in Figure 1, groups of three elements are built and aggregated. Note that elements in the same aggregation group are similar. (ii) *Protecting the privacy of the individuals.* Data have to be sufficiently modified to make re-identification difficult; i.e., by increasing the number of aggregated elements, we increase data privacy. In the example in Figure 1, after aggregating the chosen elements, it is impossible to distinguish them, so that the probability of linking any individual is inversely proportional to the number of aggregated elements.

In order to determine whether two elements are similar, a similarity function such as the Euclidean distance, Minkowski distance or Chebyshev distance can be used. A common

measure is the Sum of Squared Errors (SSE). The SSE is the sum of squared distances from the centroid of each group to every record in the group, and is defined as:

$$SSE = \sum_{i=1}^{s} \sum_{j=1}^{n_i} (x_{ij} - \bar{x}_i)'(x_{ij} - \bar{x}_i) \tag{1}$$

where s is the number of groups, n_i is the number of records in the ith group, x_{ij} is the jth record in the ith group and $\bar{x}_i$ is the average record of the ith group. Optimal multivariate microaggregation, that is, with minimum SSE, was shown to be NP-hard in [22]. The only practical microaggregation methods are heuristic.

2.2 K-Anonymity

k-anonymity, suggested by Samarati and Sweeney [31, 38, 29, 30], is an interesting approach to reduce the conflict between information loss and privacy protection. To define of k-anonymity, we need to enumerate the various types of attributes that can appear in a microdata set T:

- *Identifier attributes* that can be used to identify a record, such as Name and Medicare card. Since our objective is to prevent sensitive information from being linked to specific respondents, we will assume in what follows that *identifier attributes* in the microdata have been removed or encrypted in a pre-processing step.

- *Quasi-identifier (QI) attributes* are those, such as Postcode and Age, that in combination, can be linked with external information to re-identify (some of) the respondents to whom (some of) the records in the microdata belong. Unlike *identifier attributes*, *QI attributes* can not be removed from the microdata, because any attribute is potentially a *QI attribute*.

- *Sensitive attributes* that are assumed to be unknown to an intruder and need to be protected, such as Disease or ICD-9 Code[1].

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[1]International Statistical Classification of Diseases and Related Health Problems: ICD-9, which provides multiple external links for looking up ICD codes. Available `http://icd9cm.chrisendres.com/`.

Definition 1 (*k*-anonymity). *A protected microdata set is said to satisfy k-anonymity, if, for each combination of QI attributes, at least k records exist in the microdata sharing that combination*

Note that, if a protected microdata T' satisfies k-anonymity, an intruder trying to link T' with an external non-anonymous data source will find at least k records in T' that match any value of the QI attributes the intruder use for linkage. Thus re-identification, i.e., mapping a record in T' to a non-anonymous record in the external data source, is not possible. For example, Table 3 is a 2 anonymous view of Table 2 if QI attributes are {Gender, Age, Postcode}.

If for a given k, k-anonymity is assumed to be enough protection for respondents, one can concentrate on minimizing information loss with the only constraint that k-anonymity should be satisfied. This is a clean way of solving the tension between data protection and data utility. The general approach adopted in the literature to achieve k-anonymity is suppression/generalization, so that minimizing information loss translates to reducing the number and/or the magnitude of suppressions and generalizations [29, 38, 35]. Generalization consists in substituting the values of a given attribute with more general values. We use $*$ to denote the more general value. For instance, in Table 3, Postcode 4351 and 4352 are generalized to $435*$. Suppression refers to removing the part or entire value of attributes from the microdata. Note that suppressing an attribute to reach k-anonymity can equivalently be modeled via a generalization of all the attribute values to $*$.

The drawbacks of partially suppressed and coarsened data for analysis were highlighted in [12]:

1. Satisfying k-anonymity with minimum data modification using generalization (recoding) and local suppression was shown to be NP-hard by Meyerson and Williams [21], Aggarwal et al. [1] and Sun et al. [36];

2. Using global recoding for generalization causes too much information loss, and using local recoding complicates data analysis by causing old and new categories to co-exist in the recoded data;

3. There is no standard way of using local suppression and analyzing partially suppressed data usually requires specific software;

4. Last but not least, when numerical attributes are generalized, they become non-numerical.

Joint multivariate microaggregation of all QI attributes with minimum group size k was proposed in [12] as an alternative to achieve k-anonymity. Besides being simpler, this alternative has the advantage of yielding complete data without any coarsening (nor categorization in the case of numerical data). Other proposals [18, 35, 36, 37] generalize ordinal numerical data, replacing numerical data by intervals. In the case of the k-anonymity application, micro-aggregation is performed on the projection of records on QI attributes.

The first algorithm, known as Maximum Distance to Average Vector (MDAV), to achieve microaggregation through k-anonymity was proposed in [11]. The MDAV algorithm works as follows: First, it computes the centroid (average record) of records in the data set, and find the most distant record r from the centroid and the most distant record s from r. Second, it forms two groups around r and s: the first group contains r and the $k - 1$ records closest to r; the other group contains s and the $k - 1$ records closest to s. Finally, the two group are microaggregated and removed from the original dataset. The steps are repeated until there are no records in the original dataset. Although MDAV generates groups of fixed size k, it lacks flexibility for adapting the group size to the distribution of the records in the data set, which may result in poor homogeneity in a group. Variable-size MDAV (V-MDAV) was proposed to overcome this limitation by computing a variable-size group, and a detailed analysis can be found in [32].

In the next section, we will propose our approximate microaggregation technique, and show how to apply it to solve k-anonymity in order to overcome most of the problems of generalization/suppression listed above.

3   Approximate Microaggregation

The work presented in this paper is based on information theory, and is related to the application of dependency tree of information theory in data mining and databases. In this section,

we first introduce the concept of entropy, and the mutual information measure, which captures the mutual dependency between attributes. Then we introduce our microaggreation technique by constructing the dependency tree, and finally, we apply this microaggregation technique to k-anonymity problem, and an efficient algorithm is proposed.

3.1 Mutual Information Measure

We are more surprised when an unlikely outcome happens than a likely one occurs. A useful measure of the surprise of an event with probability p is $-\log_2 p$. The main concept of information theory is that of entropy, which measures the expected uncertainty or the amount of information provided by a certain event. The entropy of X is defined by:

$$H(X) = -\sum_x P(X = x)\log_2 P(X = x)$$

with $0\log_2 0 = 0$ by convention. It can be shown that $0 \leq H(X) \leq \log_2 |X|$, with $H(X) = \log_2 |X|$ only for the uniform distribution, $P(X = x) = 1/|x|$ for all $x \in X$. For instance, in the given running example, $H(A_1) = -(8/12)\log_2(8/12) - (4/12)\log_2(4/12) = 0.9183$, $H(A_2) = 0.8113$ and $H(A_1, A_2) = 1.5546$.

The conditional entropy $H(Y|X)$ of a random variable Y given X is then defined as:

$$H(Y|X) = -\sum_{x,y} p(x,y)\log_2 p(y|x)$$

where $p(x, y)$ is the joint distribution of variables X and Y. The conditional entropy has the following properties:

Proposition 1: *Let $H(Y|X)$ be the conditional entropy for Y given X, then,*

(1) $0 \leq H(Y|X) \leq H(Y)$;

(2) $H(X, Y) = H(X) + H(Y|X) = H(Y) + H(X|Y)$;

(3) $H(X, Y) \leq H(X) + H(Y)$

The proof of **Proposition 1** is given in [40]. According to the proposition, the conditional entropy $H(Y|X)$ can be rewritten as: $H(Y|X) = H(X,Y) - H(X)$, which provides an alternative and easy way to compute the conditional entropy $H(Y|X)$. For instance, in our running example, $H(A_1|A_2) = H(A_1, A_2) - H(A_1) = 1.5546 - 0.9183 = 0.6363$ and $H(A_2|A_1) = 0.7433$.

We adopt the conditional entropy to measure the mutual information, which is a distance metric.

Definition 2 (Mutual Information Measure). *The mutual information measure with regard to two random variables A and B is defined as:*

$$MI(A, B) = H(A|B) + H(B|A) \qquad (2)$$

Mutual information measure is a measure of how independent are the two random variables when the value of each random variable is known. Two events A and B are independent if and only if their mutual information measure achieves the maximum $H(A) + H(B)$. Therefore, the less the value of the mutual information measure is, the more dependent the two random variables are. According to this measure, A is said to be more dependent on B than C, if $MI(A, B) \leq MI(A, C)$.

Theorem 1: *The mutual information measure $MI(A, B)$ satisfies the following properties:*

(1) $MI(A, B) \geq 0$;

(2) $MI(A, B) = MI(B, A)$;

(3) $MI(A, B) + MI(B, C) \geq MI(A, C)$

Proof: The first two are easy to be verified. Here, we give the detail for the third one. Note that,

11

$$\begin{array}{rrl}
H(A|C) & \leq & H(A,B|C) \hfill (3) \\
& \leq & H(B|C) + H(A|B,C) - H(C) \hfill (4) \\
& \leq & H(B|C) + H(A|B) + H(C) - H(C) \hfill (5) \\
& = & H(B|C) + H(A|B) \hfill (6)
\end{array}$$

The inequalities (3) and (4) hold because of Proposition 1(1) and (2). (5) holds due to Proposition 1(3) and (6) holds because of Proposition 1(2). Then,

$$\begin{array}{rrl}
& & MI(A,B) + MI(B,C) \hfill (7) \\
& = & H(A|B) + H(B|A) + H(B|C) + H(C|B) \hfill (8) \\
& = & (H(A|B) + H(B|C)) + (H(C|B) + H(B|A)) \\
& \geq & H(A|C) + H(C|A) \hfill (9) \\
& = & MI(A,C) \hfill (10)
\end{array}$$

The equality (8) holds because of the definition of mutual information measure and the inequality (9) holds because of (6). ∎

It is easy to verify that $MI(A,B) = 0$ if and only if there is a one-to-one function mapping between A and B. Since when $H(B|A) = 0$, B is a function of A, then when $MI(A,B) = 0$ if and only if $H(B|A) = 0$ and $H(A|B) = 0$; i.e, there is a one-to-one function mapping between A and B. In this sense, the mutual information measure $MI(A,B)$ we defined is a distance metric.

3.2 Dependency Tree

Dependency tree was introduced by Chow and Liu [4], in which they introduced an algorithm for fitting a multivariate distribution with a tree (i.e., a density model that assumes that there are only pairwise dependency between variables). In the maximum likelihood sense, the

12

dependency tree is the best tree to fit the dataset, and it uses mutual information measure to estimate the dependency of two random variables.

The dependency tree has been used in finding dependency structure in the features which improve the classification accuracy of the Bayes network classifiers [14]. [5] uses the dependency tree to represent a set of frequent patterns, which can be used to summarize patterns into few profiles. [17] presents a large node dependency tree, in which the nodes are subsets of variables of dataset. The large node dependency tree is applied to density estimation and classification.

Definition 3 (Dependency Matrix). *Given microdata T with n records $\{r_1, r_2, \cdots, r_n\}$, where each record contains m attributes $\{A_1, A_2, \cdots, A_m\}$, the dependency matrix D_T is defined as:*

$$D_T = (MI(i,j))_{m \times m}$$

where $MI(i,j)$ is the mutual information measure, $i, j \in \{A_1, A_2, \cdots, A_m\}$.

For instance, the dependency matrix in our running example is as follows:

$$\begin{pmatrix} 0 & 1.3796 & 1.5339 & 1.8777 & 1.8777 & 1.8126 \\ 1.3796 & 0 & 1.3753 & 1.7772 & 1.6681 & 1.3180 \\ 1.5339 & 1.3753 & 0 & 1.3368 & 1.6217 & 1.6217 \\ 1.8777 & 1.7772 & 1.3368 & 0 & 1.9586 & 1.9586 \\ 1.8777 & 1.6681 & 1.6217 & 1.9586 & 0 & 1.7510 \\ 1.8126 & 1.3180 & 1.6217 & 1.9586 & 1.7510 & 0 \end{pmatrix}$$

With the dependency matrix, we could construct a fully connected weighted graph $G = (V, E, \omega)$, where $V = \{v_1, v_2, \cdots, v_m\}$ is the set of vertices, which corresponds to the attributes in T, and for each pair of vertices (v_i, v_j) there is an edge e_{ij} connecting them, and $\omega(e_{ij})$ refers to the weight of each e_{ij} between v_i and v_j, which can be obtained from the dependency matrix. An example of such a fully connected graph is shown in Figure 2(Left).

We observe that $\omega(e_{ij})$ represents to what extent vertex v_i (or attribute A_i) is dependent on v_j (or A_j). Although, in the worst case, any pair of attributes can be dependent, however, as stated in [4], we could simplify by using an approximation which ignores the conditions on
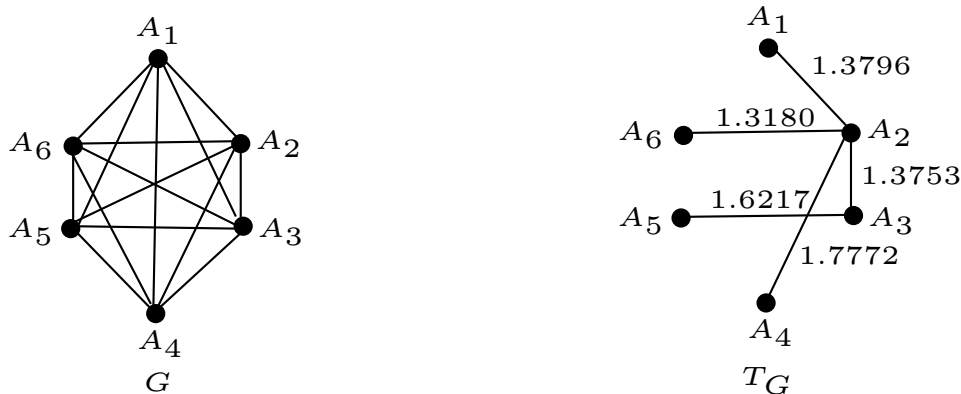
Figure 2: Left: Fully connected graph G; Right: Its minimum spanning tree T_G (Right)
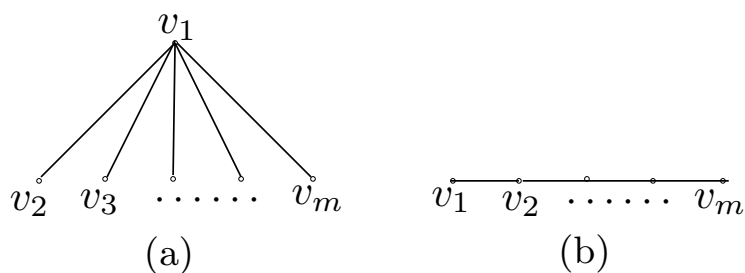

Figure 3: Proof of **Theorem** 2

multiple attributes, and retaining only dependency in at most a single attribute at a time, which results in a tree-like structure. It is easy to see that in the fully connected weighted graph G, there are a large number of trees, each of which represents a unique approximation dependency structure. Here, in order to reduce the uncertainty in the dataset and maximize the mutual information among the attributes simultaneously, we find the minimum spanning tree as our best dependency tree from the fully connected graph G based on our proposed mutual information measure. Here, we use the Kruskal algorithm [6], which is essentially a greedy algorithm. The candidate edges are sorted in increasing order of their weights (i.e. mutual information measure). Then, starting with an empty set E_0, the algorithm examines one edge at a time (in the order resulting from the sort operation), checks if it forms a cycle with the edges already in E_0 and, if not, adds it to E_0. The algorithm ends when $m-1$ edges have been added to E_0, where m refers to the number of vertices in G.

14

> **Algorithm 1: Finding best dependency tree**
> ---
> 1. Compute the mutual information measure between each pair of attributes in T and construct the dependency matrix D_T. There are $m(m-1)/2$ weight need to be calculated, since T has m attributes.
>
> 2. Construct a fully connected graph, where the nodes correspond to the attributes in T. The weight of each edge refers to their mutual information measure.
>
> 3. Find the best dependency tree by the the minimum spanning tree algorithm.

The algorithm of finding best dependency tree is briefly described in Algorithm 1 and an example of the found out best dependency tree is shown in Figure 2(Right).

After finding out the best dependency tree, we need to set out rules to select the key attributes from the dependency tree to process approximate microaggregation.

Definition 4 (Degree of The Vertex). *Let $G = (V, E)$ be a graph, where $V = \{v_1, v_2, \cdots, v_m\}$. Then, the degree of the node v_i is the number of edges incident to the nodes, denoted by $deg(v_i)$.*

For example, in Figure 2(Right), $deg(A_2) = 4$, and $deg(A_3) = 2$. Let T_G be the best dependency tree found in G. We then compute the degree of each vertex in T_G and sort them in decreasing order. Without loss of generality, we assume that $deg(v_1) \geq deg(v_2) \geq \cdots \geq deg(v_m)$ after they are sorted in decreasing order. Then, the principle of choosing the key attributes is as follows:

Definition 5 (Choosing Key Attributes). *Suppose $deg(v_1) \geq deg(v_2) \geq \cdots \geq deg(v_m)$ after they are sorted. Then, the vertices $v_1, v_2, \cdots v_k$ are chosen as the key attributes if the following two requirements are satisfied at the same time:*

$$\sum_{i=1}^{k-1} deg(v_i) < m \tag{11}$$

$$\sum_{i=1}^{k} deg(v_i) \geq m \tag{12}$$

For example, for the minimum spanning tree T_G in Figure 2, we choose attributes A_2 and A_3 as the key attributes, since according to the principle described above, $deg(A_2) < 6$ and $deg(A_2) + deg(A_3) = 6$.

Theorem 2: *Let T_G be the best dependency tree of G, with $V = \{v_1, v_2, \cdots, v_m\}$, and N be the number of selected key attributes. Then, $2 \leq N \leq m/2$.*

Proof: Since in a tree-like structure, the maximum degree of a vertex is $m-1$ [6], and without loss of generality, we assume that $deg(v_1) = m - 1$, and in this case, the best dependency tree found has the form as shown in Figure 3(a), and then according to Definition 5, only two vertices will be selected as key attributes, say v_1 and v_2. This is the situation when the number of the selected key attributes reaches the minimality. On the other hand, when the number of the selected key attributes reaches the maximality, the structure of the best dependency tree has the form as shown in Figure 3(b), and in this case, at most $m/2$ key attributes will be selected. So, $2 \leq N \leq m/2$. ∎

Theorem 2 assures that at most half the amount of dimension resources are needed in the microaggregation process with our technique, which could significantly reduce the execution time. In the next section, we discuss in detail how to apply this technique to k-anonymity problem.

3.3 Application to K-Anonymity

Our aim is to obtain k-anonymous microdata without coarsened nor partially suppressed data. This makes their analysis and exploitation easier, with the additional advantage that numerical continuous attributes are not categorized. In this section, we adopt the approximate microaggregation technique to solve k-anonymity problem.

Our algorithm receives as input a microdata set T consisting of n records having m attributes each. The result of the algorithm is a k-partition used to microaggregate the original microdata set and to generate a microaggregated data set T' that fulfils the k-anonymity property. Instead of taking all the attributes into the microaggregation process, we only use the selected key attributes, which captures the dependency between attributes, to microaggregate the data. The novelty and difference from the previous microaggregation methods exist here. Our proposed approach is effective and efficient in terms of running time and information loss.

The first two steps of the algorithm builds the initial dataset for microaggregation. It selects the key attributes from the best dependency tree and returns a projected dataset, which has the same number of records as T, but each record only contains the value of key

attributes. Once the average record is computed, the algorithm looks for other records which are distant to it and adds records to it until it reaches a minimum cardinality k (Step 3-4). After repeating this process several times, a set of groups satisfying the k-anonymity property is obtained. However, a number of records can remain unassigned, and they must be distributed amongst the previously created groups (Step 5-7). Finally, the algorithm further microaggregates the original microdata T by replacing each record in T by the centroid of the group to which it belongs (Step 8). The algorithm is outlined in Algorithm 2.

In this section, we discuss in detail how to apply our microaggregation technique to solve k-anonymity in order to overcome most of the problems of generalization/suppression listed in Section 2 in the following aspects:

- Approximate microaggregation is a unified approach, unlike the dual method combining generalization and suppression.

- It does not complicate data analysis by adding new categories to the original scale, unlike generalization/suppression.

- It does not result in suppressed data, which makes analysis of k-anonymous data easy.

- It is suitable to protect continuous data without removing their numerical semantics.

4   Experimental Results

4.1   Data set

We employ a real-life CENSUS data set downloadable at `http://www.ipums.org` in the experimental study. The CENSUS data set contains the personal information of 500K American adults. The data set has 9 discrete attributes summarized in Table 4. From CENSUS, we create two sets of micro tables, in order to examine the influence of dimensionality and the impact of cardinality. The first set has 6 tables, denoted as CENSUS-20%, $\cdots$, CENSUS-100%, respectively. Specifically, CENSUS-t% ($20 \leq t \leq 100$) indicates the data set consisting of t% records randomly sampled from the whole CENSUS data set, and each record has 9

Attribute	Number of distinct values
Age	78
Gender	2
Education	17
Marital	6
Race	9
Work-class	8
Country	83
Occupation	50
Salary-class	50

Table 4: Summary of attributes in CENSUS

attributes shown in Table 4. The second set contains 5 tables, denoted as 5-CENSUS, $\cdots$, 9-CENSUS, respectively, where n-CENSUS ($3 \leq n \leq 9$) represents the data set with the first n attributes selected from Table 4, and each data set has the same number of records as the whole CENSUS data set.

4.2 Experiment setup

Our aim is to test the efficiency and effectiveness of the proposed approximate microaggregation algorithm for k-anonymity. We denote our proposed algorithm as MA, and we compare it with the previous MDAV-based algorithm [11], denoted as MA. We first evaluate the execution time of our approach by varying the cardinality of the data sets, the number of attributes and the value of k. In order to compare the effectiveness, for each data set, we adopt two measurements. One is to measure the information loss in terms of SSE/SST, where SSE is the sum of square errors as defined in equation (1), and SST refers to the sum of square errors applied over the whole dataset. The other metric is to compare the number of key attributes projected in the microaggregation.

4.3 Results

Efficiency: Figures 4(a)-(c) show the comparison of execution time of two microaggregation methods. In this set of experiments, we fixed $k = 20$ and vary the data percentage. Figure
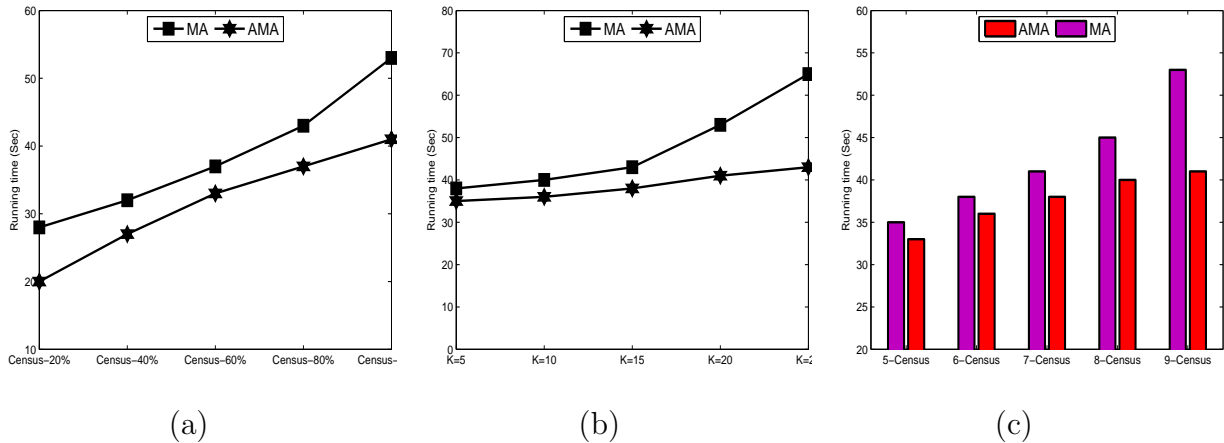
Figure 4: Running time comparison between different methods

4(a) plots the result by varying the data percentage of the whole Census data set from 20% to 100%. As we can see, the AMA incurs less computation time than MA method. This is expected since in the AMA process, less attributes are used in the microaggregation. We can see the difference of the computation cost is getting larger with the increased data cardinality. Figure 4(b) describes the running time comparison when varying the privacy parameter k. The computation cost of both MA and AMA algorithms is increasing with k, but AMA consistently outperforms MA method. Figure 4(c) shows the computation overhead differences by altering the number of attributes. The computation overhead of both methods is increasing when enlarging the number of attributes. The result is expected since the overhead is increased with the more dimensions. The AMA method performs better than MA algorithm since we use a part of the attributes instead of the whole dimensional resources, which is significantly reduce the amount of computation.

Effectiveness: Having verified the efficiency of our technique, we proceed to test its effectiveness. We measure the utility in terms of SSE/SST, where SSE is the sum of square errors as defined in equation (1), and SST refers to the sum of square errors applied over the whole data set. Figure 5 shows the number of key attributes used in MA and AMA approaches. As we can see, the number remains the same for MA method, since it projects all the attributes into the microaggregation process. On the contrary, the number of key attributes used in
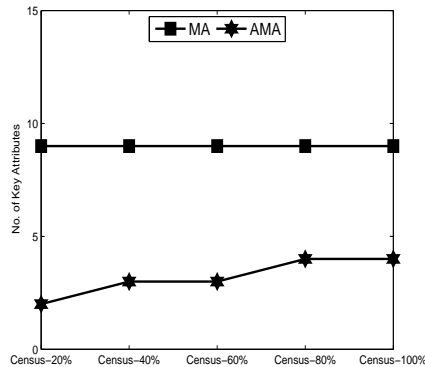
Figure 5: No. of key attributes comparison

AMA is less than half of that used by MA approaches, which verifies the results in Theorem 2.

Figures 6(a) and (b) show the information loss by applying MA and AMA algorithms. Figure 6(a) is plotted by changing the percentage of data set. Although the result indicates that AMA generates a little bit more information loss than MA, the difference is not enlarged when the data cardinality is increased. Similar tread is obtained in Figure 6(b) by varying the value k. The information loss is increased with k, since larger k demands more strict privacy requirement, which reduces the utility of the data.

Summary: Overall, the AMA outperforms MA in terms of efficiency, and the difference is getting larger when the volume and dimension of data are increasing. Although AMA generates a little bit more information loss than MA, it is still practical since AMA only uses at most half of the attributes in the microaggregation process.

5   Related Work

Privacy preservation is an important issue in the release of data for mining purpose. The k-anonymity model, which was introduced for protecting individual identification by Samarati and Sweeney [29, 31], has been extensively investigated for its simplicity and effectiveness [1, 29, 38, 35, 37, 39, 20, 19, 21]. k-anonymity requires that each record in the anonymous table
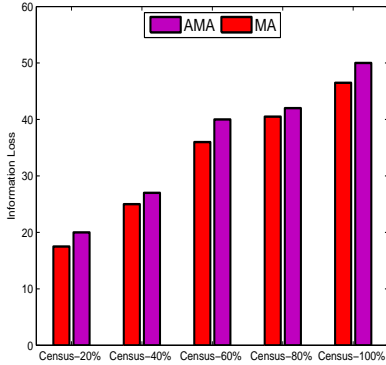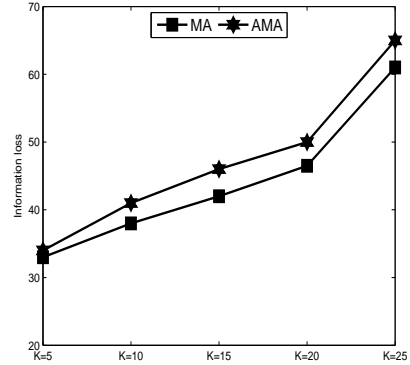
Figure 6: Information loss comparison between different methods

be indistinguishable with at least $k-1$ other records within the dataset with respect to a set of quasi-identifier attributes. In this case, individuals cannot be uniquely identified by adversary, so the individuals' privacy can be preserved. Started from [29, 31, 30], the general approach adopted in the literature to achieve k-anonymity is based on generalization/suppression, which has some defects on efficiency, information loss and implementation. Our work in this paper is related to the microaggregation technique, which has been introduced to implement k-anonymous data set recently and remedies most of defects of generalization and suppression [12, 10, 11, 22, 9].

In the previous research, all the dimensional resources (attributes) are required in the microaggregation process. However, as mentioned in [10, 11, 9], the result and execution time of the microaggregation highly depends on the number of the variables used in the microaggregation process, since few variables sometimes offers the better solutions. Different from previous microaggregation methods, in this paper, we propose a new approach to select only a small number of dimensional resources that captures the maximal dependency relationship among resources and as experiments show that the new technique achieves better microaggregation results. Specifically, our microaggregation method is effective and efficient in terms of information loss and running time. In the case of k-anonymity problem, the microaggregation approach presented in this paper could overcome most of the problems of

22

generalization/suppression. (1) Our method is a unified approach, unlike the dual method combining generalization and suppression. (2) It does not complicate data analysis by adding new categories to the original scale, unlike generalization/suppression. (3) It does not result in suppressed data, which makes analysis of k-anonymous data easy. (4) It is suitable to protect continuous data without removing their numerical semantics. From a different perspective, the microaggregation technique discussed in this paper produces better solutions compared with previous ones.

Our work is also related to the application of dependency tree of information theory in data mining and databases. The dependency tree has been used in finding dependency structure in the features which improve the classification accuracy of the Bayes network classifiers [14]. [5] uses the dependency tree to represent a set of frequent patterns, which can be used to summarize patterns into few profiles. [17] presents large node dependency tree, in which the nodes are subsets of variables of data set. The large node dependency tree is applied to density estimation and classification. As far as its application to privacy preserving data mining, fewer results are obtained. In this paper, we introduce the concept of entropy and propose the mutual information measure to evaluate the mutual dependency between attributes, and the method to construct the dependency tree. We also discuss how to select key attributes from the constructed dependency tree, and how to use them in the approximate microaggregation. We prove theoretically that at most half the amount of resources are needed with our approach.

6   Conclusion and Future Work

k-anonymity is a property that, when satisfied by the microdata, can help increase the privacy of the respondents whose data is being used. Previous approaches to obtain microdata sets fulfilling the k-anonymity property were mainly based on suppression and generalization. In this article, we have shown how to achieve the same property by means of approximate microaggregation, which, different from the previous microaggregation method, uses a part of the dimensional resources. It works by selecting key attributes from the best dependency tree, which is constructed based on a new mutual information measure based on information theory,

23

which captures the dependency between attributes in the microdata. The experimental results show that the proposed technique is efficient and effective in the terms of running time and information loss.

A number of other sophistication of k-anonymity for protecting against attribute disclosure have recently been proposed, such as (p^+, α)-sensitive k-anonymity [37], l-diversity [20], (α, k)-anonymity [39], t-closeness [19]. All of them rely on generalizations, so the microaggregation approach proposed in this paper would be a novelty in all of them. The technique proposed in this paper restricted its focus on numerical attributes, and it is interesting to investigate the extension to other types of attributes.

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