

# New Multi-dimensional Sorting Based K-Anonymity Microaggregation for Statistical Disclosure Control

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**Abstract.** In recent years, there has been an alarming increase of online identity theft and attacks using personally identifiable information. The goal of privacy preservation is to de-associate individuals from sensitive or *microdata* information. Microaggregation techniques seeks to protect microdata in such a way that can be published and mined without providing any private information that can be linked to specific individuals. Microaggregation works by partitioning the microdata into groups of at least  $k$  records and then replacing the records in each group with the centroid of the group. An optimal microaggregation method must minimize the information loss resulting from this replacement process. The challenge is how to minimize the information loss during the microaggregation process. This paper presents a new microaggregation technique for Statistical Disclosure Control (SDC). It consists of two stages. In the first stage, the algorithm sorts all the records in the data set in a particular way to ensure that during microaggregation very dissimilar observations are never entered into the same cluster. In the second stage an optimal microaggregation method is used to create  $k$ -anonymous clusters while minimizing the information loss. It works by taking the sorted data and simultaneously creating two distant clusters using the two extreme sorted values as seeds for the clusters. The performance of the proposed technique is compared against the most recent microaggregation methods. Experimental results using benchmark datasets show that the proposed algorithm has the lowest information loss compared with a basket of techniques in the literature.

**Keywords:** Privacy, Microaggregation, Microdata protection,  $k$ -anonymity, Disclosure control.

## 1 Introduction

In recent years, the phenomenal advance of technological developments in information technology enable government agencies and corporations to accumulate

an enormous amount of personal data for analytical purposes. These agencies and organizations often need to release individual records (microdata) for research and other public benefit purposes. This propagation has to be in accordance with laws and regulations to avoid the propagation of confidential information. In other words, microdata should be published in such a way that preserve the privacy of the individuals. Microdata protection in statistical databases has recently become a major societal concern and has been intensively studied in recent years. Microaggregation for Statistical Disclosure Control (SDC) is a family of methods to protect microdata from individual identification. SDC seeks to protect microdata in such a way that can be published and mined without providing any private information that can be linked to specific individuals. SDC is often applied to statistical databases before they are released for public use.

To protect personal data from individual identification, SDC is often applied before the data are released for analysis [2,26]. The purpose of microdata SDC is to alter the original microdata in such a way that the statistical analysis from the original data and the modified data are similar and the disclosure risk of identification is low. As SDC requires suppressing or altering the original data, the quality of data and the analysis results can be damaged. Hence, SDC methods must find a balance between data utility and personal confidentiality.

Various methods for Microaggregation has been proposed in the literature for protecting microdata [3,4,7,8,11,12,20,23]. The basic idea of microaggregation is to partition a dataset into mutually exclusive groups of at least  $k$  records prior to publication, and then publish the centroid over each group instead of individual records. The resulting anonymized dataset satisfies  $k$ -anonymity [18], requiring each record in a dataset to be identical to at least  $(k - 1)$  other records in the same dataset. As releasing microdata about individuals poses privacy threat due to the privacy-related attributes, called quasi-identifiers, both  $k$ -anonymity and microaggregation only consider the quasi-identifiers. Microaggregation is traditionally restricted to numeric attributes in order to calculate the centroid of records, but also has been extended to handle categorical and ordinal attributes [4,8,19]. In this paper we propose a microaggregated method that is also applicable to numeric attributes.

The effectiveness of a microaggregation method is measured by calculating its information loss. A lower information loss implies that the anonymized dataset is less distorted from the original dataset, and thus provides better data quality for analysis.  $k$ -anonymity [17,18,21] provides sufficient protection of personal confidentiality of microdata, while ensuring the quality of the anonymized dataset, an effective microaggregation method should incur as little information loss as possible. In order to be useful in practice, the dataset should keep as much informative as possible. Hence, it is necessary to seriously consider the tradeoff between privacy and information loss. To minimize the information loss due to microaggregation, all records are partitioned into several groups such that each group contains at least  $k$  similar records, and then the records in each group are replaced by their corresponding mean such that the values of each variable are the same. Such similar groups are known as clusters. In the context of data

mining, clustering is a useful technique that partitions records into groups such that records within a group are similar to each other, while records in different groups are most distinct from one another. Thus, microaggregation can be seen as a clustering problem with constraints on the size of the clusters.

Many microaggregation methods derive from traditional clustering algorithms. For example, Domingo-Ferrer and Mateo-Sanz [3] proposed univariate and multivariate  $k$ -Ward algorithms that extend the agglomerative hierarchical clustering method of Ward et al. [24]. Domingo-Ferrer and Torra [6,7] proposed a microaggregation method based on the fuzzy  $c$ -means algorithm [1], and Laszlo and Mukherjee [13] extended the standard minimum spanning tree partitioning algorithm for microaggregation [27]. All of these microaggregation methods build all clusters gradually but simultaneously. There are some other methods for microaggregation that have been proposed in the literature that build one/two cluster(s) at a time. Notable examples include Maximum Distance [15], Diameter-based Fixed-Size microaggregation and centroid-based Fixed-size microaggregation [13], Maximum Distance to Average Vector (MDAV) [8], MHM [9] and the Two Fixed Reference Points method [28]. Most recently, Lin *et al.* [29] proposed a density-based microaggregation method that forms clusters by the descending order of their densities, and then fine-tunes these clusters in reverse order.

The remainder of this paper is organized as follows. We introduce the problem of microaggregation in Section 2. Section 3 introduces the basic concept of microaggregation. Section 4 reviews previous microaggregation methods. We present a brief description of our proposed microaggregation method in Section 5. Section 6 shows experimental results of the proposed method. Finally, concluding remarks are included in Section 7.

## 2 Problem Statement

The algorithms for microaggregation works by partitioning the microdata into groups, where within groups the records are homogeneous but between groups the records are heterogeneous so that information loss is low. The similar groups are also called clusters. The level of privacy required is controlled by a security parameter  $k$ , the minimum number of records in a cluster. In essence, the parameter  $k$  specifies the maximum acceptable disclosure risk. Once a value for  $k$  has been selected by the data protector, the only job left is to maximize data utility. Maximizing utility can be achieved by microaggregating optimally, i.e. with minimum within-groups variability loss. So the main challenge in microaggregation is how to minimize the information loss during the clustering process. Although plenty of work has been done, to maximize the data utility by forming the clusters, this is not yet sufficient in terms of information loss. So more research needs to be done to form the clusters such that the information loss is as low as possible. This paper analyses the problem with a new multi-dimensional sorting algorithm such that the information loss is minimal.

Observing this challenge, this work presents a new clustering-based method for microaggregation, where a new multi-dimensional sorting algorithm is used in the

first stage. In the second stage two distant clusters are made simultaneously in a systematic way. According to the second stage, sort all records in ascending order by using a sorting algorithm in the first stage explained in Section 5) so that the first record and the last record are most distant to each other. Form a cluster with the first record and its  $(k - 1)$  nearest records and another cluster with the last record and its  $(k - 1)$  nearest records. Sort the remaining records  $((n - 2k)$ , if dataset contains  $n$  records) by using the same sorting algorithm and continue to build pair clusters at the same time by using the first and the last record as seeds until some specified records remain. Finally form one/two cluster(s) depending on the remaining records. Thus all clusters produced in this way contain  $k$  records except the last cluster that may contain at the most  $(2k - 1)$  records. Performance of the proposed method is compared against the most recent widely used microaggregation methods. The experimental results show that the proposed microaggregation method outperforms the recent methods in the literature.

### 3 Background

Microdata protection through microaggregation has been intensively studied in recent years. Many techniques and methods have been proposed to deal with this problem. In this section we describe some fundamental concepts of microaggregation.

When we microaggregate data we should keep in mind two goals: data utility and preserving privacy of individuals. For preserving the data utility we should introduce as little noise as possible into the data and preserving privacy data should be sufficiently modified in such a way that it is difficult for an adversary to reidentify the corresponding individuals. Figure 1 shows an example of microaggregated data where the individuals in each cluster are replaced by the corresponding cluster mean. The figure shows that after aggregating the chosen elements, it is impossible to distinguish them, so that the probability of linking any respondent is inversely proportional to the number of aggregated elements.

Consider a microdata set  $T$  with  $p$  numeric attributes and  $n$  records, where each record is represented as a vector in a  $p$ -dimensional space. For a given positive integer  $k \leq n$ , a microaggregation method partitions  $T$  into  $g$  clusters, where each cluster contains at least  $k$  records (to satisfy  $k$ -anonymity), and then replaces the records in each cluster with the centroid of the cluster. Let  $n_i$  denote the number of records in the  $i$ th cluster, and  $x_{ij}$ ,  $1 \leq j \leq n_i$ , denote the  $j$ th record in the  $i$ th cluster. Then,  $n_i \geq k$  for  $i = 1$  to  $g$ , and  $\sum_{i=1}^g n_i = n$ . The centroid of the  $i$ th cluster, denoted by  $\bar{x}_i$  is calculated as the average vector of all the records in the  $i$ th cluster.

In the same way, the centroid of  $T$ , denoted by  $\bar{x}$ , is the average vector of all the records in  $T$ . Information loss is used to quantify the amount of information of a dataset that is lost after applying a microaggregation method. In this paper we use the most common definition of information loss by Domingo-Ferrer and Mateo-Sanz [3] as follows:

$$IL = \frac{SSE}{SST} \quad (1)$$

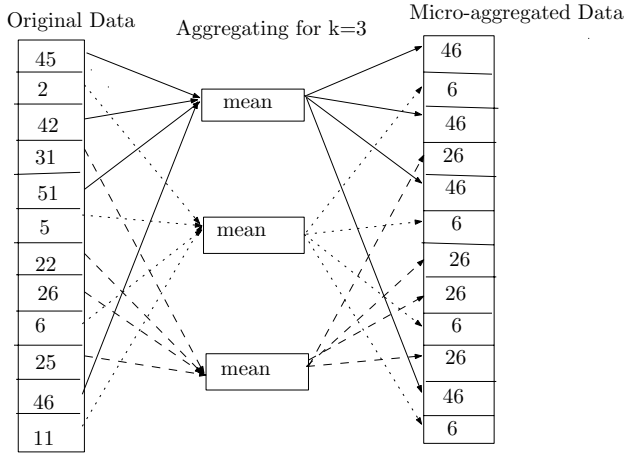


Fig. 1. Example of Microaggregation using mean

where  $SSE$  is the within-cluster squared error, calculated by summing the Euclidean distance of each record  $x_{ij}$  to the average value  $\bar{x}_i$  as follows:

$$SSE = \sum_{i=1}^g \sum_{j=1}^{n_i} (x_{ij} - \bar{x}_i)' (x_{ij} - \bar{x}_i) \tag{2}$$

and  $SST$  is the sum of squared error within the entire dataset  $T$ , calculated by summing the Euclidean distance of each record  $x_{ij}$  to the average value  $\bar{x}$  as follows:

$$SST = \sum_{i=1}^g \sum_{j=1}^{n_i} (x_{ij} - \bar{x})' (x_{ij} - \bar{x}) \tag{3}$$

For a given dataset  $T$ ,  $SST$  is fixed regardless of how  $T$  is partitioned. On the other hand,  $SSE$  varies of a dataset depending on the partition of the dataset. In essence,  $SSE$  measures the similarity of the records in a cluster. The lower the  $SSE$ , the higher the within-cluster homogeneity and the higher the  $SSE$ , the lower the within cluster homogeneity. If all the records in a cluster are the same, then the  $SSE$  is zero indicating no information is lost. On the other hand, if all the records in a cluster are more diverse,  $SSE$  is large indicating more information is lost. In this paper, we used  $SSE$  as a measure of similarity indicating a record will be included in a particular cluster if it causes least  $SSE$  among all other records in the dataset. Therefore, the microaggregation problem can be enumerated as a constraint optimization problem as follows:

**Definition 1 (Microaggregation Problem).** Given a dataset  $T$  of  $n$  elements and a positive integer  $k$ , find a partitioning  $G = \{G_1, G_2, \dots, G_g\}$  of  $T$  such that

1.  $G_i \cap G_j = \Phi$ , for all  $i \neq j = 1, 2, \dots, p$ ,
2.  $\cup_{i=1}^p G_i = T$ ,
3.  $SSE$  is minimized,
4. for all  $G_i \in T$ ,  $|G_i| \geq k$  for any  $G_i \in \mathbf{G}$ .

The microaggregation problem stated above can be solved in polynomial time for a univariate dataset [12] but has been shown to be NP hard for multivariate dataset [14]. It is a natural expectation that  $SSE$  is low if the number of clusters is large. Thus the number of records in each cluster should be kept close to  $k$ . Domingo-Ferrer and Mateo-Sanz [3] showed that no cluster should contain more than  $(2k - 1)$  records since such clusters can always be partitioned to further reduce information loss.

## 4 Previous Microaggregation Methods

Previous microaggregation methods have been roughly divided into two categories, namely fixed-size and data-oriented microaggregation [3,9]. For fixed-size microaggregation, the partition is done by dividing a dataset into clusters that have size  $k$ , except perhaps one cluster which has a size between  $k$  and  $(2k - 1)$ , depending on the total number of records  $n$  and the anonymity parameter  $k$ . For the data-oriented microaggregation, the partition is done by allowing all clusters with sizes between  $k$  and  $(2k - 1)$ . Intuitively, fixed-size methods reduce the search space, and thus are more computationally efficient than data-oriented methods [29]. However, data-oriented methods can adapt to different values of  $k$  and various data distributions and thus may achieve lower information loss than fixed-size methods.

Domingo-Ferrer and Mateo-Sanz [3] proposed a multivariate fixed-size microaggregation method, later called the Maximum Distance (MD) method [15]. The MD method repeatedly locates the two records that are most distant to each other, and forms two clusters with their respective  $(k - 1)$  nearest records until fewer than  $2k$  records remain. If at least  $k$  records remain, it then forms a new cluster with all remaining records. Finally when there are fewer than  $k$  records not assigned to any cluster yet, this algorithm then individually assigns these records to their closest clusters. This method has a time complexity of  $O(n^3)$  and works well for most datasets. Laszlo and Mukherjee [13] modified the last step of the MD method such that each remaining record is added to its own nearest cluster and proposed Diameter-based Fixed-size microaggregation. This method is however not a fixed size method because it allows more than one cluster to have more than  $k$  records.

The MDAV method is the most widely used microaggregation method [15]. MDAV is the same as MD except in the first step. MDAV finds the record  $r$  that is furthest from the current centroid of the dataset and the record  $s$  that is furthest from  $r$  instead of finding the two records that are most distant to each other, as is done in MD. Then form a cluster with  $r$  and its  $(k - 1)$  nearest records and form another cluster with  $s$  and its  $(k - 1)$  nearest records. For

the remaining records, repeat this process until fewer than  $2k$  records remain. If between  $k$  and  $(2k - 1)$  records remain, MDAV simply forms a new group with all of the remaining records. On the other hand, if the number of the remaining records is below  $k$ , it adds all of the remaining records to their nearest clusters. So MDAV is a fixed size method. Lin *et al.* [29] proposed a modified MDAV, called MDAV-1. The MDAV-1 is similar to MDAV except when the number of the remaining records is between  $k$  and  $(2k - 1)$ , a new cluster is formed with the record that is the furthest from the centroid of the remaining records, and its  $(k - 1)$  nearest records. Any remaining records are then added to their respective nearest clusters. Experimental results indicate that MDAV-1 incurs slightly less information loss than MDAV [29]. Another variant of the MDAV method, called MDAV-generic, is proposed by Domingo-Ferrer and Torra [8], where by the threshold  $2k$  is altered to  $3k$ . If between  $2k$  and  $(3k - 1)$  records remain, then find the record  $r$  that is furthest from the centroid of the remaining records and form a cluster with  $r$  and its  $(k - 1)$  nearest records and another cluster with the remaining records. Finally when fewer than  $2k$  records remain, this algorithm then forms a new cluster with all the remaining records. Laszlo and Mukherjee [13] proposed another method, called Centroid-based Fixed-size microaggregation that is also based on a centroid but builds only one cluster during each iteration. This algorithm first find a record  $r$  that is furthest from the current centroid of the dataset and then find a cluster with  $r$  and its  $(k - 1)$  nearest records. For the remaining records repeat the same process until fewer than  $k$  records remain. Finally add each remaining record to its nearest clusters. This method is not a fixed-size method as more than one cluster has more than  $k$  records. Solanas *et al.* [16] proposed a variable-size variant of MDAV, called V-MDAV. V-MDAV first builds a new cluster of  $k$  records and then tries to extend this to up to  $(2k - 1)$  records based on some criteria. V-MDAV adopts a user-defined parameter to control the threshold of adding more records to a cluster. Chang *et al.* [28] proposed the Two Fixed Reference Points (TFRP) method to accelerate the clustering process of  $k$ -anonymization. During the first phase, TFRP selects two extreme points calculated from the dataset. Let  $N_{min}$  and  $N_{max}$  be the minimum and maximum values over all attributes in the datasets, respectively, then one reference point  $G_1$  has  $N_{min}$  as its value for all attributes, and another reference point  $G_2$  has  $N_{max}$  as its value for all attributes. A cluster of  $k$  records is then formed with the record  $r$  that is the furthest from  $G_1$  and the  $(k - 1)$  nearest records to  $r$ . Similarly another cluster of  $k$  records is formed with the record  $s$  that is the furthest from  $G_2$  and  $(k - 1)$  nearest records to  $s$ . These two steps are repeated until fewer than  $k$  records remain. Finally, these remaining records are assigned to their respective nearest clusters. This method is quite efficient as  $G_1$  and  $G_2$  are fixed throughout the iterations. When all clusters are generated, TFRP applies an enhancement step to determine whether a cluster should be retained or decomposed and added to other clusters.

Lin *et al.* [29] proposed a density-based algorithm (DBA) for microaggregation. The DBA has two different scenarios. The first state of DBA (DBA-1) repeatedly builds a new cluster using the  $k$ -neighborhood of the record with the

highest  $k$ -density among all records that are not yet assigned to any cluster until fewer than  $k$  unassigned records remain. These remaining records are then assigned to their respective nearest clusters. The DBA-1 partitions the dataset into some clusters, where each cluster contains no fewer than  $k$  records. The second state of DBA (DBA-2) attempts to fine-tune all clusters by checking whether to decompose a cluster and merge its content with other clusters. Notably, all clusters are checked during the DBA-2 by the reverse of the order that they were added to clusters in the DBA-1. After several clusters are removed and their records are added to their nearest clusters in the DBA-2, some clusters may contain more than  $(2k - 1)$  records. At the end of the DBA-2, the MDAV-1 algorithm is applied to each cluster with size above  $(2k - 1)$  to reduce the information loss. This state is finally called MDAV-2. Experimental results show that the DBA attains a reasonable dominance over the latest microaggregation methods.

All of the microaggregation methods described above repeatedly choose one/two records according to various heuristics and form one/two cluster(s) with the chosen records and their respective  $(k - 1)$  other records. However there are other microaggregation methods that build all clusters simultaneously and work by initially forming multiple clusters of records in the form of trees, where each tree represent a cluster. The multivariate  $k$ -Ward algorithm [3] first finds the two records that are furthest from each other in the dataset and build two clusters from these two records and their respective  $(k - 1)$  nearest records. Each of the remaining record then forms its own cluster. These clusters are repeatedly merged until all clusters have at least  $k$  records. Finally the algorithm is recursively applied to each cluster containing  $2k$  or more records. Domingo-Ferrer *et al.* [10] proposed a multivariate microaggregation method called  $\mu$ -Approx. This method first builds a forest and then decomposes the trees in the forest such that all trees have sizes between  $k$  and  $\max(2k - 1, 3k - 5)$ . Finally, for any tree with size greater than  $(2k - 1)$ , find the node in the tree that is furthest from the centroid of the tree. Form a cluster with this node and its  $(k - 1)$  nearest records in the tree and form another cluster with the remaining records in the tree.

Hansen and Mukherjee [12] proposed a microaggregation method for univariate datasets called HM. After that Domingo-Ferrer *et al.* [9] proposed a multivariate version of the HM method, called MHM. This method first uses various heuristics, such as nearest point next (NPN), maximum distance (MD) or MDAV to order the multivariate records. Steps similar to the HM method are then applied to generate clusters based on this ordering. Domingo-Ferrer *et al.* [7] proposed a microaggregation method based on fuzzy  $c$ -means algorithm (FCM) [1]. This method repeatedly runs FCM to adjust the two parameters of FCM (one is the number of clusters  $c$  and another is the exponent for the partition matrix  $m$ ) until each cluster contains at least  $k$  records. The value of  $c$  is initially large (and  $m$  is small) and is gradually reduced (increased) during the repeated FCM runs to reduce the size of each cluster. The same process is then recursively applied to those clusters with  $2k$  or more records.



## 5 The Proposed Approach

This section presents the proposed sorting algorithm and pairwise systematic algorithm for microaggregation that minimizes the information loss and satisfies the  $k$ -anonymity requirement.

It has been observed that the reason many of the existing techniques has high information loss is due to some clusters containing very *different* observations which increases the information of a cluster. Therefore, the initial choice of cluster(s) is often difficult since these observations are not known in advance. The proposed technique solves this problem by applying a multi-dimensional sorting on the dataset in a particular way so that the different observations are at opposite ends of the sorted dataset. This process is explained in Section 5.1. Next, a pairwise systematic method takes this sorted dataset to create two clusters repeatedly by minimizing information loss and observing  $k$ -anonymity. The algorithm is described in Section 5.2.

### 5.1 Sorting Technique

Before describing the sorting technique, first we consider a simple example. Consider Table 1 which consists of two variables  $V_1$  and  $V_2$ . Rank/Index each of the variables in ascending order individually and create a table where the columns indicates the **position** of the value in the original data (Table 1). For example, the first rank (3) of column 1 in Table 2A indicates the position of smallest value of the first variable (1) in Table 1. Similarly, the second (4) and third (2) ranks indicate the positions of second smallest (2) and third lowest (3) values respectively. The second column is also created in the same way. Now sum the positions of each rank. For example, in Table 2B rank 1 comes from the positions of 5<sup>th</sup> row of first column and 4<sup>th</sup> row of second column, rank 2 comes from the positions of third row of first column and fifth row of second column and so on, i.e., 1(9), 2(8), 3(4), 4(3), 5(6), where first number is the rank and the number in bracket is the sum of the respective positions. The last column is the rank of the sum-values in bracket of the previous column. For example, 4(3) is ranked 1, since 3 is the smallest sum in 9, 8, 4, 3, 6. Thus according to this sorting algorithm, the first record in the sorted table (see Table 3) should be the 4<sup>th</sup> row, the second record should be third row of original table in Table 1 and so on. The sorted table is presented in Table 3. The algorithm of this sorting technique is presented in Table 4.

Using the algorithm in Table 5, it is expected that the first record and the last record are more distant and there is zero probability that the first record and the last recorded will be included in the same cluster.

### 5.2 Pairwise-Systematic Microaggregation Algorithm

The Pairwise-Systematic (P-S) microaggregation proposed by Kabir *et al.* [22] is a practical microaggregation algorithm that creates two distant clusters in a systematic way. Based on the information loss measure in equation (1), the

**Table 1.** Original variable

$V_1$	$V_2$
5	6
3	10
1	3
2	1
4	2

**Table 2.** A.Rank of sorted values B.Sum of Ranks and final positions

$R_1$	$R_2$
3	4
4	5
2	3
5	1
1	2

Rank Sum	$R$
$1(5+4)=1(9)$	5
$2(3+5)=2(8)$	4
$3(1+3)=3(4)$	2
$4(2+1)=4(3)$	1
$5(4+2)=5(6)$	3

**Table 3.** Sorted variables

$V_1$	$V_2$
2	1
1	3
4	2
3	10
5	6

sorting algorithm in Table 5 and the definition of the microaggregation problem, the Pairwise-Systematic (P-S) microaggregation algorithm is as follows. Please refer to Kabir *et al.* [22] for detailed of the algorithm.

According to this method, first sort all records of  $n$  in the dataset  $T$  in ascending order by using the algorithm in Table 5. Thus in the sorting dataset, the first record and the last record are the most distant to each other among all other pair records in the dataset  $T$ . The algorithm (see Table 5) repeatedly builds pair clusters using the first record and the last record in the sorting dataset and their corresponding  $(k - 1)$  nearest records until fewer than  $3k$  records remain (see steps 2-6 of Table 5). The nearest records in a cluster are chosen in such a way that the inclusion of these records causes less SSE than the other records in the dataset. If between  $2k$  and  $(3k - 1)$  records remain, then sort these records in ascending order by using the same sorting algorithm in Table 5 and find the first record  $f$ . Form a cluster with  $f$  and its  $(k - 1)$  nearest records, and another cluster with the remaining records (see step 7 of Table 5). Moreover, if fewer than  $2k$  records remain, then form a new cluster with all remaining records (see step 9 of Table 5).

The proposed algorithms stated above endeavours to repeatedly build two clusters simultaneously in a systematic way. As the records in the dataset  $T$  are

**Table 4.** Multi-dimensional Sorting Algorithm

```

function [C, IX]= MultiDSort(X)

Input: X is a d-dimensional matrix with m rows or instances
Output: C is a d-dimensional matrix, IX is index of the sorted matrix

For n = 1 to d
Y = Sortn(X) along dimension n
Create an index array IA such that the value at IA(i) = j represents X(i)'s
position/index in the sorted array Y(j)(n)
End For

For p = 1 to m
  For n = 1 to d
    Let z be an m dimensional array containing indeces of the
    multidimensional sorted matrix, then
    Z(p) = Z(p) + Y(p)(n)
  End For
End For

End function

```

arranged in ascending order and the first record and the last record are most distant to each other, building clusters in this systematic way, the algorithm easily captures if there are any extreme values in the dataset.

**Definition 2 (Systematic clustering-based microaggregation decision problem).** In a given dataset  $T$  of  $n$  records, there is a clustering scheme  $G = \{G_1, G_2, \dots, G_g\}$  such that

1.  $|G_i| \geq k, 1 < k \leq n$ : the size of each cluster is greater than or equal to a positive integer  $k$ , and
2.  $\sum_{i=1}^g IL(G_i) < c, c > 0$ : the total information loss of the clustering scheme is less than a positive integer  $c$ .

where each cluster  $G_i (i = 1, 2, \dots, p)$  contains the records that are more similar to each other such that the cluster means are close to the values of the clusters and thus cause the least information loss.

## 6 Experimental Results

This section presents the experimental results and compares the results with several existing techniques. The objective of this experiment is to investigate the

**Table 5.** P-S microaggregation algorithm

Input: a dataset  $T$  of  $n$  records and a positive integer  $k$

Output: a partitioning  $\mathbf{G} = \{G_1, G_2, \dots, G_g\}$  of  $T$ , where  $g = |\mathbf{G}|$  and  $G_i \geq k$  for  $i = 1$  to  $g$ .

1. Let  $\mathbf{G} = \Phi$ , and  $T' = T$ ;
2. Sort all records in  $T'$  in ascending order by using the algorithm in Table 5;
3. Find the first  $f \in T'$  and the last record  $l \in T'$ ;
4. Form a cluster  $G_1$  containing first record  $f$  and its  $(k - 1)$  nearest records in  $T'$ ;  
and another cluster  $G_2$  containing last record  $l$  and its  $(k - 1)$  nearest records in  $T'$ ;
5. Set  $\mathbf{G} = \mathbf{G} \cup G_1 \cup G_2$  and  $T' = T' - G_1 - G_2$ ;
6. Repeat steps 2-4 until  $|T'| < 3k$ ;
7. If  $2k \leq |T'| \leq (3k - 1)$ ;
- (i) Go to step 2;
- (ii) Form a cluster containing the first record  $f \in T'$ ;  
and its  $(k-1)$  nearest records in  $T'$ ;
- (iii) Form another cluster with remaining records in  $T'$ ;
8. else;
9. If  $|T'| < 2k$ ;
- (i) Form a new cluster with all the remaining records in  $T'$ .

effectiveness of the proposed algorithm in terms of measured information loss of represented cluster data. The following three datasets [9], which have been used as benchmarks in previous studies to evaluate various microaggregation methods, were adopted in the experiments.

1. The “Tarragona” dataset contains 834 records with 13 numerical attributes.
2. The “Census” dataset contains 1,080 records with 13 numerical attributes.
3. The “EIA” dataset contains 4,092 records with 11 numeric attributes (plus two additional categorical attributes not used here).

To accurately evaluate our approach, the performance of the proposed algorithm is compared in this section with various microaggregation methods. Tables 6-8 show the information losses of these microaggregation methods. The lowest information loss for each dataset and each  $k$  value is shown in bold face. The information losses of methods DBA-1, DBA-2, MDAV-1 and MDAV-2 are quoted from [29]; the information losses of methods MDAV-MHM, MD-MHM, CBFS-MHM, NPN-MHM and M-d (for  $k = 3, 5, 10$ ) are quoted from [9]; the information losses of methods  $\mu$ -Approx and M-d (for  $k = 4$ ) are quoted from [10], and the information losses of methods TFRP-1 and TFRP-2 are quoted from [28]. TFRP is a two-stage method and its two stages are denoted as TRFP-1

**Table 6.** Information loss comparison using Tarragona dataset

Method	$k = 3$	$k = 4$	$k = 5$	$k = 10$
MDAV-MHM	16.9326		22.4617	33.1923
MD-MHM	16.9829		22.5269	33.1834
CBFS-MHM	16.9714		22.8227	33.2188
NPN-MHM	17.3949		27.0213	40.1831
M-d	16.6300	19.66	24.5000	38.5800
$\mu$ -Approx	17.10	20.51	26.04	38.80
TFRP-1	17.228	19.396	22.110	33.186
TFRP-2	16.881	19.181	21.847	33.088
MDAV-1	16.93258762	19.54578612	22.46128236	33.19235838
MDAV-2	16.38261429	19.01314997	22.07965363	33.17932950
DBA-1	20.69948803	23.82761456	26.00129826	35.39295837
DBA-2	16.15265063	22.67107728	25.45039236	34.80675148
Multi-DSort	<b>9.8572</b>	<b>11.9989</b>	<b>18.17</b>	<b>32.1338</b>

**Table 7.** Information loss comparison using Census dataset

Method	$k = 3$	$k = 4$	$k = 5$	$k = 10$
MDAV-MHM	5.6523		9.0870	14.2239
MD-MHM	5.69724		8.98594	14.3965
CBFS-MHM	5.6734		8.8942	13.8925
NPN-MHM	6.3498		11.3443	18.7335
M-d	6.1100	8.24	10.3000	17.1700
$\mu$ -Approx	6.25	8.47	10.78	17.01
TFRP-1	5.931	7.880	9.357	14.442
TFRP-2	5.803	7.638	8.980	13.959
MDAV-1	5.692186279	7.494699833	9.088435498	14.15593043
MDAV-2	5.656049371	7.409645342	9.012389597	13.94411775
DBA-1	6.144855154	9.127883805	10.84218735	15.78549732
DBA-2	5.581605762	7.591307664	9.046162117	13.52140518
Multi-DSort	<b>2.0954</b>	<b>3.6254</b>	<b>3.4595</b>	<b>6.8497</b>

**Table 8.** Information loss comparison using EIA dataset

Method	$k = 3$	$k = 4$	$k = 5$	$k = 10$
MDAV-MHM	0.4081		1.2563	3.7725
MD-MHM	0.4422		1.2627	3.6374
NPN-MHM	0.5525		0.9602	2.3188
$\mu$ -Approx	0.43	0.59	0.83	2.26
TFRP-1	0.530	0.661	1.651	3.242
TFRP-2	0.428	0.599	0.910	2.590
MDAV-1	0.482938725	0.671345141	1.666657361	3.83966422
MDAV-2	0.411101515	0.587381756	0.946263963	3.16085577
DBA-1	1.090194828	0.84346907	1.895536919	4.265801303
DBA-2	0.421048322	0.559755523	0.81849828	2.080980825
Multi-DSort	<b>0.4048</b>	<b>0.5299</b>	<b>0.7956</b>	<b>1.7709</b>

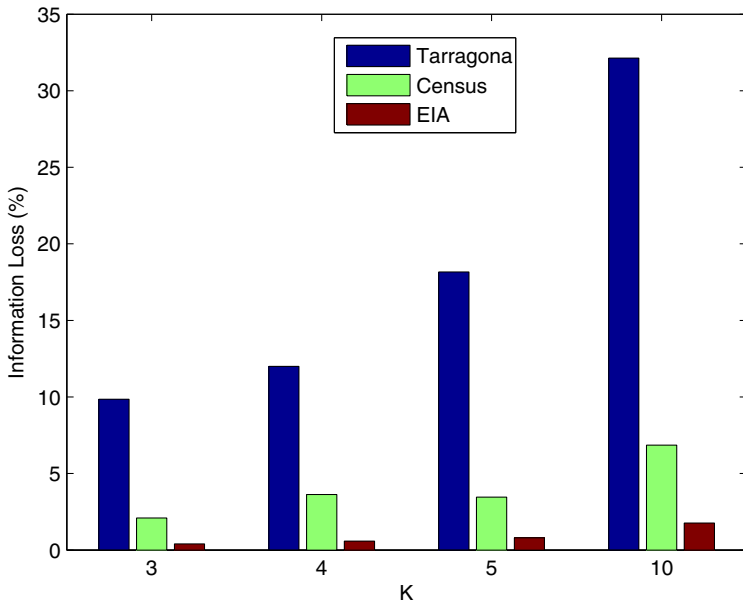


Fig. 2. Information Loss vs  $k$  for Tarragona, Census, and EIA datasets

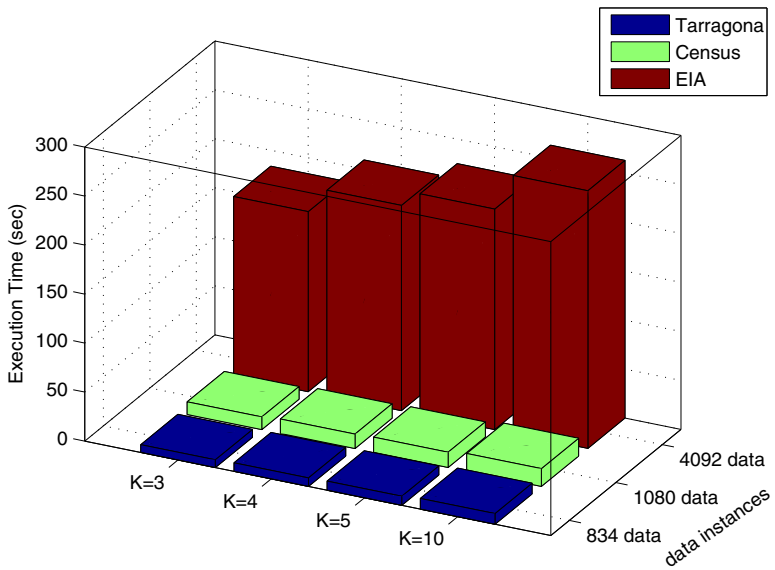


Fig. 3. Execution time vs  $k$

and TRFP-2 respectively. The TFRP-2 is similar to the DBA-2 but disallows merging a record to a group of size over  $(4k - 1)$ .

Tables 6-8 show the information loss for several values of  $k$  and the Tarragona, Census and for the EIA datasets respectively. The information loss is compared with the proposed algorithm among the latest microaggregation methods listed above. Information loss is measured as  $\frac{SSE}{SST} \times 100$ , where SST is the total sum of the squares of the dataset. Note that the within-groups sum of squares SSE is never greater than SST so that the reported information loss measure takes values in the range  $[0,100]$ . Tables 6-8 illustrate that in all of the test situations, the proposed algorithm causes significantly less information loss than any of the microaggregation methods listed in the table. This shows the utility and the effectiveness of the proposed algorithm.

*Analysis:* Figure 2 shows how the information loss values changes with  $k$  for each dataset. Results indicate that information loss increases with  $k$ . This is obvious since the higher number of records in each cluster results in higher sum-of-squared-error (SSE) values due to the fact that each cluster now has more observations and possibly larger variance. Interestingly, there is little correlation between overall information loss of a dataset and its size as evident from the fact that the information loss for CIA dataset (containing 4092 instances) is much lower than the information loss for Tarragona dataset (containing 1082 instances). This may be due to the lower variance in EIA dataset resulting in clusters with lower SSE, hence lower information loss.

Figure 3 shows the how the execution time varies with  $k$  and different file sizes. Again, results show that the execution time depends on the value of  $k$ . It shows that the execution time increases slightly due to the increased number of permutations that need to be calculated for each cluster for the higher  $k$ . Furthermore, as expected the execution is also related to the file size. As shown in Figure 3 it takes the longest time to find  $k$ -anonymous clusters for the EIA dataset (4092 instances) and quickest time for the census dataset (834 instances).

## 7 Conclusion

Microaggregation is an effective method in SDC for protecting privacy in microdata and has been extensively used world-wide. The level of privacy required is controlled by a parameter  $k$ , often called the anonymity parameter. For  $k$ -anonymization,  $k$  is basically the minimum number of records in a cluster. Once the value of  $k$  has been chosen, the data protector and the data users are interested in minimizing the information loss. This work has presented a new multidimensional sorting technique for numerical attributes. The new method consists of two stages. In the first stage it sorts all the records in the dataset so that the first and the last record are very different, and in the second stage it describes a pairwise systematic clustering algorithm that builds clusters with minimum information loss. A comparison has been made of the proposed algorithm with the most widely used microaggregation methods using the three most popular benchmark datasets (Tarragona, Census and the EIA). The experimental results

show that the proposed algorithm outperforms all the tested microaggregation methods with respect to information loss. Thus the proposed method is very effective in preserving the privacy microdata sets and can be used as an effective privacy preserving  $k$ -anonymization method for Statistical Disclosure Control.

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