Privacy Preserving Sensitive Data Publishing using (k,n,m) Anonymity Approach

Nancy Victor and Daphne Lopez

Abstract—**Open Science movement has enabled extensive knowledge sharing by making research publications, software, data and samples available to the society and researchers. The demand for data sharing is increasing day by day due to the tremendous knowledge hidden in the digital data that is generated by humans and machines. However, data cannot be published as such due to the information leaks that can occur by linking the published data with other publically available datasets or with the help of some background knowledge. Various anonymization techniques have been proposed by researchers for privacy preserving sensitive data publishing. This paper proposes a (k,n,m) anonymity approach for sensitive data publishing by making use of the traditional k-anonymity technique. The selection of quasi identifiers is automated in this approach using graph theoretic algorithms and is further enhanced by choosing similar quasi identifiers based on the derived and composite attributes. The usual method of choosing a single value of 'k' is modified in this technique by selecting different values of 'k' for the same dataset based on the risk of exposure and sensitivity rank of the sensitive attributes. The proposed anonymity approach can be used for sensitive big data publishing after applying few extension mechanisms. Experimental results show that the proposed technique is practical and can be implemented efficiently on a plethora of datasets.**

Index Terms— **anonymization, data publishing, k anonymity, privacy, quasi identifier.**

I. INTRODUCTION

Data sharing benefits research community by deriving value out of the data; thereby facilitating new findings within the domain. As the amount of digital data generated rises rapidly, efficient mechanisms are needed for collecting, processing and sharing data. Data sharing is identified to be very useful in almost all the domains including the medical domain [1], as the data shared across the globe can be used for collaborative research and free exchange of test reports among doctors, patients and data publishers. Clinical data sharing is advantageous in many aspects such as: (i) providing effective treatment by reviewing similar patient history (ii) finding new research prospects (iii) avoiding medication errors and (iv) reducing the need for duplicate testing [2]. However, sharing data often leads to a variety of challenges including the privacy concerns that can arise when linking the published data with other publically available information.

Privacy preserving data publishing deals with developing methods to publish practically useful data, while preserving individual's privacy [3]. Generally, any data item can be categorized into either (i) Explicit identifiers (ii) Quasi-identifiers (iii) sensitive attributes or (iv) non-sensitive attributes. Explicit identifiers and sensitive attributes are relatively easy to choose based on the type of data that is published. Choosing quasi-identifiers (QI) is an important task, as information leakage mainly occurs in published data by linking quasi-identifiers with some external knowledge. Yan Y, Wang W, Hao X, and Zhang L. [4] proposed a method for identification of quasi-identifiers by initially generating an attribute graph using the publishing data, published data and external knowledge, and then by making use of the cut vertex method. This method is further improved in this paper by identifying new set of quasi-identifiers from the derived and composite attributes, so as to generate better attribute graphs with more quasi-identifier values.

A variety of anonymization techniques have been proposed by various researchers for publishing the data without questioning individual's privacy in any manner. k-anonymity approach was the first step in this direction, where the dataset was anonymized in such a way that at least 'k' records should have the same value for all the quasi-identifiers. However, a single value of 'k' was chosen for the entire dataset, without considering the sensitivity levels of the sensitive attribute. For records with higher sensitivity, a higher value of 'k' is required for satisfying privacy constraints. The use of multiple values of 'k' for a single dataset is addressed in the proposed anonymity approach in this paper. A sensitivity rank is therefore assigned to each record by considering the class labels in the sensitive attribute. These are in turn grouped into various data splits based on the sensitivity rank. Based on this, an optimal value of 'k' is chosen for the data split by employing the elbow method.

The paper thus aims in proposing a (k,n,m) anonymity approach for privacy preserving sensitive data publishing. The main contributions of the research are listed below:
1. Extending the traditional k-anonymity approach by including a sensitivity rank for each class in the sensitive

attribute. This sensitivity rank is used for choosing different values of 'k'.

2. Identify the optimum value of 'k' for each class by making use of the sensitivity ranks assigned. Elbow method is employed here to choose the value of 'k'.

3. Automated selection of quasi-identifiers using graph theoretic algorithms and choosing other similar quasi-identifier attributes with the help of derived and composite attributes.

The rest of the paper is organized as follows. Section II gives an overview of the research works related to data anonymization and publishing and the selection of attributes in a dataset. Section III discusses about the preliminaries and section IV elaborates on the proposed (k,n,m) anonymity approach. Section V shows the experimental results and section VI concludes the findings in this paper.

II. RELATED WORK

A. Data Anonymization

As the amount of digital data that is generated increases at a rapid rate, valuable insights can be generated out of it, if the data is made available for analysis. However, data cannot be published as such due to the sensitive personal information that may be associated with it. Data anonymization is the technique of removing or modifying personally identifiable information (PII) from data in order to publish the same without questioning individual's privacy in any manner. The synthetic data with similar statistical properties as that of the original data aids in data analysis, without any sensitive information from getting disclosed.

However, Brickell and Shmatikov compared privacy gain with utility gain after data anonymization, and argued that "even modest privacy gains require almost complete destruction of the data-mining utility" [5]. The fundamental characteristics of privacy and utility was studied by Li, T., & Li, N. [6] and proved that it is inappropriate to directly compare privacy with utility. One of the major reasons is that privacy is actually an individual concept, whereas utility is aggregate. Privacy gain cannot be considered as equal to utility gain even if the adversary and the researcher learn exactly the same information. Direct comparison of privacy and utility was proved to be infeasible by evaluating the trade-off between privacy and utility. An empirical investigation on the parameters that could be fine-tuned for achieving acceptable level of data privacy and utility was studied by Mivule, K., & Turner, C [7].

Various methods of data anonymization, for structured and unstructured data have been studied by researchers worldwide.

The basic models for privacy preserving relational data publishing are listed below.

1) k-anonymity: For satisfying k-anonymity, an equivalence class should contain at least 'k' rows. Equivalence class can be well defined as the set of records that have identical value for QIs [9].

2) l-diversity: There should be at least 'l' well represented values for each sensitive attribute in a dataset for it to satisfy l-diversity principle [10].

3) t-closeness: t-closeness suggests that the distance between the distribution of a sensitive attribute in the class and the distribution of the attribute in the whole table is no more than a threshold 't' [11].

4) Differential privacy: Adding mathematical noise to the original data values [12].

Table I presents the widely used techniques for data anonymization [8]:

TABLE I
TECHNIQUES FOR DATA ANONYMIZATION

Anonymization Technique	Description
Attribute Suppression	Deletion of an entire attribute or column in a dataset.
Record Suppression	Deletion of an entire record or row in a dataset.
Character Masking	Modifying the characters in a data value, usually by using symbols.
Pseudonymization	Replacing original data with made up data values. Also known as coding.
Generalization	Reducing the precision of data values by removing a part of the data or by providing a more general value. Also referred to as recoding.
Swapping	Rearranging the data values in such a way that even though the individual values are present in the dataset, it doesn't correspond to the original record. Also known as shuffling or permutation.
Data Perturbation	Data values are modified to a slightly different one.
Synthetic data generation	To generate fake or artificial data directly, instead of modifying the original data values in the dataset.
Data aggregation	Uses summarized values such as total or average instead of the original data values.

These basic privacy models were further modified by data publishers and researchers for developing enhanced privacy models. A personalized anonymity scheme was proposed by Liu X et al. [13] by dividing the sensitive attributes into various groups according to its sensitivities and a frequency threshold was then assigned to each group. The sensitive values could then be changed with respect to the guardian node. A scalable k-anonymization (SKA) technique using MapReduce was proposed by Mehta et al. [14]. KC-Slice method was proposed by Onashoga, S. A. et al. [15] for dynamically anonymizing multiple sensitive attributes. A model for data anonymization that preserves utility was proposed by Lee, Hyukki et al. [16]. Wang, Zhibo et al. [17] put forward a distributed agent-based framework for privacy preservation, the DADP, which uses a novel allocation mechanism for budget in a distributed manner. An agent-based dynamic grouping mechanism is also proposed in the paper.

A privacy-preserving framework for social network data publishing called PrivRank was proposed by Yang, Dingqi et al. [18]. Generation of synthetic datasets with similar statistical properties was studied both theoretically and experimentally by Bindschaedler, Vincent et al. [19]. A technique for social network sensitive data publishing based on BIRCH was proposed by Zhang, Jinquan et al. [20]. Maximum Delay Anonymous Clustering Feature (MDACF) tree data publishing algorithm was studied by the authors. A scalable k-anonymization scheme using MapReduce was proposed by Mehta, Brijesh B., and Udai Pratap Rao [21]. Piao, Chunhui et al. [22] proposed a differential privacy based

framework for governmental data publishing based on fog computing.

Fung et al. surveyed the various techniques for privacy preserving relational data publishing; whereas privacy models for big data has been surveyed by Victor N, Lopez D, and Abawajy JH [23]. Various challenges with respect to privacy preserving data publishing also have been studied by Victor. N and Lopez. D [24]. Google uses the techniques of data generalization and noise addition for anonymizing the data [25].

B. Selection of Attributes in the Dataset

One of the primary concerns of any data publisher lies in the appropriate and efficient classification of attributes in a dataset as explicit identifier, quasi-identifier, sensitive or non-sensitive attribute. Explicit or direct identifiers help in identifying an individual uniquely whereas quasi-identifiers help in the unique identification of an individual by linking the same with some external information. Sensitive attributes contain person specific sensitive information, which is to be released by the data publisher. Non-sensitive attributes are those that don't belong to the other three categories. Explicit identifiers, sensitive and non-sensitive attributes are relatively easy to identify in a dataset, but the main problem lies in the selection of quasi identifier attributes as these are the attributes which are in turn linked with external information for the unique identification of the individual.

HIPAA privacy rule provides two standards for health data de-identification [26]: Expert determination by applying statistical or scientific principles and Safe harbor de-identification method by removing 18 different types of identifiers. Most of the existing methods of de-identification use empirical understanding in order to choose the quasi identifiers for privacy protection. However, few studies have been conducted so far which aims in the automatic identification of quasi identifiers. A method for quantifying quasi identifiers using distinct ratio and separation ratio was presented by Motwani R and Xu Y. [27], but the method just focused on publishing data and not on the data connection risks. Yan Y, Wang W, Hao X, and Zhang L. [4] proposed a method for QI identification by initially generating an attribute graph using the publishing data, published data and external knowledge, and then by making use of cut vertex method. This method can be used for attribute graphs with single and multiple sensitive attributes. Another method proposed in the US patent application US20160342636A1 [28] uses an indexing mechanism for each dataset and an indicator for each attribute value in each record for identifying a unique record for the attribute combination.

III. PRELIMINARIES

Definition 1 (Attributes): Let $T(A_1,…,A_n)$ be a table with 'n' tuples. The finite set of attributes of T are $\{A_1,…,A_n\}$.

Example 1: The finite set of attributes in Table II corresponds to the hospital number, name, age, gender, job, discharge status and diagnosis. These attributes are in turn classified as either explicit identifiers, quasi-identifiers, sensitive attributes or non-sensitive attributes. Hospital number and name can be used for identifying an individual explicitly; and these columns should be removed completely before data release. As this is a medical dataset, the attribute "diagnosis" is taken as the sensitive attribute. The selection of quasi-identifiers is discussed in the following sub section.

TABLE II
ORIGINAL DATASET (SAMPLE)

Sl No	H. No	Name	Age	Gender	Job	Dis Status	Diagnosis
1	10	Sarah	23	F	Dancer	Y	Hepatitis
2	11	Jacob	36	M	Singer	Y	Malaria
3	12	Julie	24	F	Singer	Y	Influenza
4	13	Luke	31	M	Singer	N	HIV
5	14	Anna	27	F	Dancer	Y	Malaria
6	15	Isaac	44	M	Doctor	N	H1N1
7	16	Andrew	46	M	Lawyer	Y	Malaria
8	17	Dania	29	F	Keyboardist	Y	Hepatitis
9	18	Mark	33	M	Dancer	N	H1N1
10	19	Samuel	49	M	Engineer	Y	Influenza
11	20	John	38	M	Keyboardist	Y	Hepatitis
12	21	Mathew	41	M	Engineer	N	HIV

Definition 2 (Quasi-identifier): A set of attributes $\{A_1,…A_n\}$ in a table T is said to be a quasi- identifier(QI) set if $\forall x_i \epsilon T$, a specific individual x_i can be re-identified with a high probability 'p' by linking these attribute combination of values with some external information.

Example 2: Age, gender and job attributes are easy to be obtained from a census database or voter's list. If this publically available information is linked with the data in Table II, the probability of identifying the person correctly increases many fold. Background knowledge also plays a major role in the unique identification of a particular individual [29]; hence discharge status can also be considered as a quasi-identifier. Quasi-identifiers are chosen empirically in most of the cases using the experience of the data publisher or with certain assumptions. Thus, it becomes a necessity to choose quasi-identifiers with the help of mathematical approaches.

Definition 3 (Sensitivity rank): Let $\{A_1…A_n\}$ be the set of attributes in a table T, S be the sensitive attribute, where $S \epsilon \{A_1,..A_n\}$ and $\{c_1…c_j\}$ be the different class labels in the sensitive attribute S. A sensitivity rank $m_i \epsilon \{m_1,…m_j\}$ refers to the severity or level of sensitivity of each class c_i in the sensitive attribute S, obtained by referring to an attribute $A_k \epsilon \{A_1,..A_n\}$ if there is a dependency from A_k->S, else by linking with external knowledge.

Example 3: The sensitive attribute in Table II is the attribute "diagnosis" and it includes five different class labels such as

Hepatitis, Influenza, Malaria, HIV and H1N1. The severity of this attribute can be either found out by using the dependency attribute "discharge status" or by making use of publically available information. An attribute A is said to be a dependent attribute of B, if the value of attribute 'A' depends on the attribute 'B'. Here, the discharge status solely depends on the diagnosis of the individual. Based on this information, the severity of the disease can be predicted. Another way of finding the severity of a disease is by using the mortality rate associated with a particular disease, and this information can be obtained from public health centers.

Definition 4 (Risk of re-identification): Let $\{A_1 \ldots A_n\}$ be the set of attributes in a table T, S be the sensitive attribute, where $S \epsilon \{A_1, ..A_n\}$ and $\{c_1 \ldots c_j\}$ be the different class labels in the sensitive attribute S. A value $r_i \epsilon \{r_1, ..., r_j\}$ refers to the risk of exposure of each class c_i in the sensitive attribute S, if the data is published as such.

Example 4: The measures such as journalist risk, prosecutor risk and marketer risk can be used for evaluating the re-identification risk. Based on these measures, the probability of correctly identifying the disease can be found out, if the data is published as such.

Definition 5 (k-anonymity): Let $T(A_1, ..., A_n)$ be a table and QI_T be the quasi-identifier associated with it. T is said to satisfy k-anonymity if and only if each sequence of values in $T[QI_T]$ appears with at least k occurrences in $T[QI_T]$.

Example 5: In order to satisfy the k-anonymity principle where k = 2, an equivalence class should have at least two rows. Equivalence class can be defined as the set of rows that have identical values for quasi identifiers. k-anonymization technique is applied only after applying generalization operations. The dataset after applying k-anonymization technique is given in Table III. The rows 1 and 2 belong to the same equivalence class as it contains identical value for all the quasi-identifiers. Likewise, this table contains six equivalence classes.

IV. PROPOSED (k,n,m) ANONYMITY APPROACH

The goal of this section is to provide a formal description about the (k,n,m) anonymity model for constructing and evaluating data publishing systems that release sensitive information without comprising individual's privacy in any manner.

Definition 6 ((k,n,m) anonymity): Let $T(A_1, \ldots A_n)$ be a table with n tuples, QI_T be the set of quasi identifiers associated with it, $\{m_1 \ldots m_i\}$ be the sensitivity rank of each label in the sensitive attribute, $\{r_1, \ldots r_i\}$ be the risk of re-identification of each label in the sensitive attribute, $\{k_1, \ldots k_i\}$ be the number of tuples to be generalized based on the sensitivity rank. T is said to satisfy (k,n,m) anonymity if and only if each sequence of values in $T[QI_T]$ with sensitive rank m_j appears with at least k_j occurrences in $T[QI_T]$.

TABLE III
K-ANONYMIZED DATASET WITH K=2

Sl No.	Age	Gender	Job	Dis Status	Diagnosis
1	20-25	F	Artist	Y	Hepatitis
2	20-25	F	Artist	Y	Influenza
3	25-30	F	Artist	Y	Malaria
4	25-30	F	Artist	Y	Hepatitis
5	30-35	M	Artist	N	HIV
6	30-35	M	Artist	N	H1N1
7	35-40	M	Artist	Y	Malaria
8	35-40	M	Artist	Y	Hepatitis
9	40-45	M	Professional	N	H1N1
10	40-45	M	Professional	N	HIV
11	45-50	M	Professional	Y	Malaria
12	45-50	M	Professional	Y	Influenza

Example 6: The sensitive attribute in the original table corresponds to the attribute "diagnosis", with five different classes such as Hepatitis, Influenza, Malaria, HIV and H1N1. Sensitive values m1, m2, m3, m4 and m5 are found out using the dependent attribute of "diagnosis", the "discharge status". If the discharge status is "Y", the disease can be considered less sensitive. But, this alone cannot be considered as a deciding criterion for setting the sensitivity values of each class. Hence, publically available information regarding the severity of disease can be used for setting up the sensitivity values. Based on the sensitivity rank, a value of 'k' for each class is found out. The number of distinct sensitive values in each equivalence class should be equal to at least 'c/2', where 'c' corresponds to the class label of sensitive attribute.

Fig. 1 depicts the series of operations to be applied for achieving (k,n,m) anonymity principle. Each step is detailed in the following section.

A. Classification of Attributes

The aim of this step is to classify the attributes in a dataset into one of the four categories: explicit identifiers, quasi-identifiers, sensitive attributes and non-sensitive attributes. As detailed in the related work section of this paper, classification of attributes into explicit identifiers, sensitive attributes and non-sensitive attributes is relatively easy with the help of standards such as HIPAA. Choosing quasi-identifiers (QI) is an important task, as information leakage mainly occurs in published data by linking quasi-identifiers with some external knowledge. Graph theoretic approaches as suggested by Yan Y, Wang W, Hao X, and Zhang L[4] can be employed for the optimal selection of quasi-identifiers in a dataset. Attribute graphs are generated in this approach by making attributes as the nodes and relationship between them as the edges. Fig. 2 consists of three blocks, where the first, second and third blocks represent the set of identifier attributes, quasi-identifiers and sensitive attributes respectively. The set of quasi-identifiers are determined by finding out cut-vertex on the paths from identifier attribute to sensitive attribute.
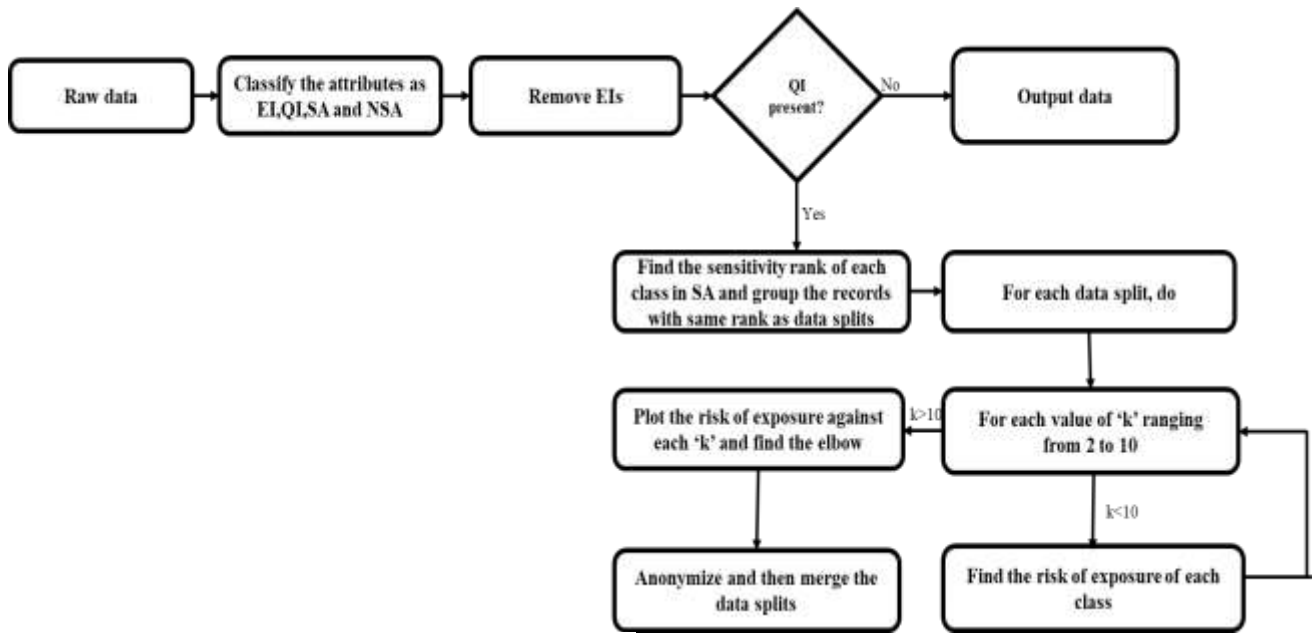
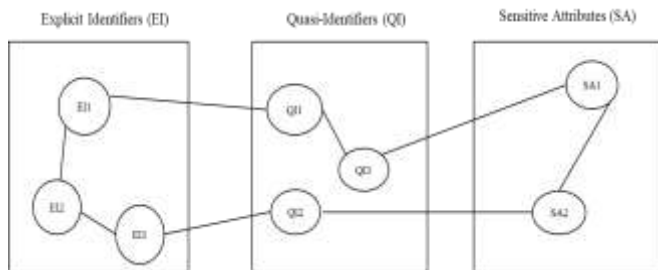Fig.1. Flowchart for (k,n,m) anonymity

Fig. 2. Attribute graph

An extension to the proposed approach is done by categorizing the QI attribute into atomic, derived or composite attribute as shown in Fig. 3.
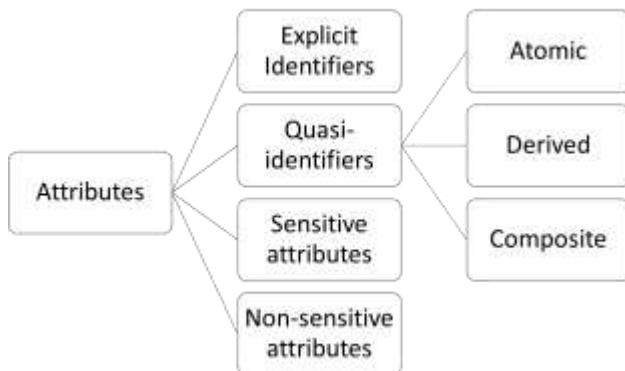

Fig. 3. General classification of attributes

Any attribute that can't be divided further can be termed as an atomic attribute. A derived attribute can be defined as an attribute which is derived from other attributes. Even if the derived attribute is not physically present in the dataset, the same can be found out easily. For example, if the "date of birth" attribute is present in a dataset, "age" of the person can be found out using the current date. Hence, the attribute "age" can be considered as a derived attribute of "date of birth". If the base attribute is a QI, then the derived attribute should also be considered as a QI. A composite attribute is any attribute which is composed of more than one simple attribute. The attribute "address" can be further divided into simple attributes such as "locality" and "zip code". If any composite attribute is a QI, each of its simple attribute is also considered as a QI. Figures 4. a) and 4. b) depict a derived attribute and composite attribute respectively.
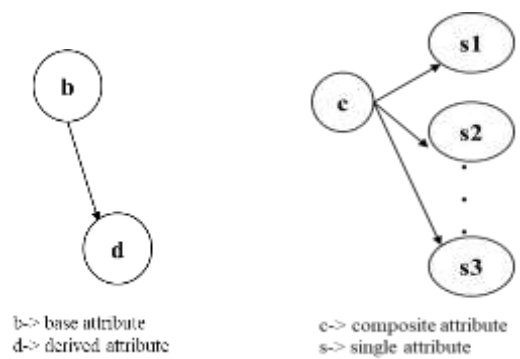
Fig. 4. (a) derived attribute   (b) composite attribute

Consider QI1 in Fig. 2 as a derived attribute and QI2, a composite attribute. The attribute graphs after replacing the base attribute with derived attribute and composite attribute with one of the simple attributes is shown in Fig 5. Each attribute graph generated using this approach can be further used for choosing QIs. One drawback of this approach is that the composite attribute can't be replaced with all the simple attributes because doing so will result in the graph being connected even after applying the cut vertex method.
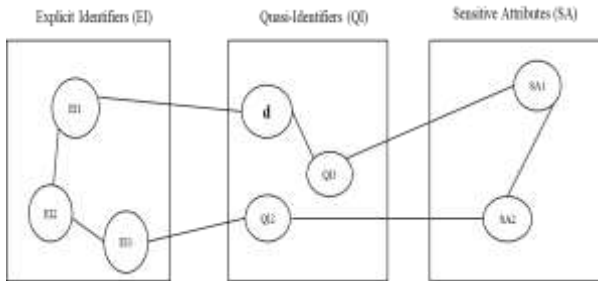
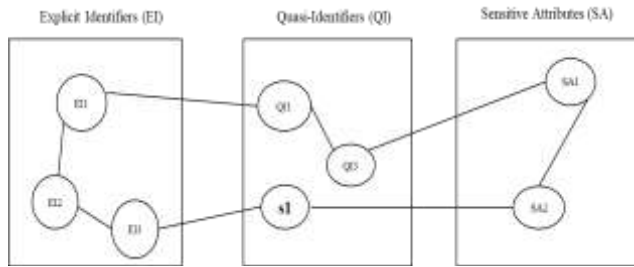Fig. 5. a) replacing base attribute with derived attribute

Fig. 5. b) replacing composite attribute with a simple attribute

B. Choosing the Class Labels (c_i)

The class labels in a sensitive attribute correspond to the unique values present in the attribute. For example, the sensitive attribute in Table II is the attribute "diagnosis" and it includes five unique values such as Hepatitis, Influenza, Malaria, HIV and H1N1, which are considered as the class labels for the given dataset to be published.

C. Finding the Sensitivity Rank of each Class Label (m_i):

Sensitivity rank refers to the level of severity of each class label in the sensitive attribute. Severity level can be thought of as a scale which ranges from "highly sensitive" to "least sensitive", and can be identified with the help of two approaches: (i) by using a dependent attribute (ii) by making use of external information. In the case of a medical dataset, the information which is publically available with health centers about the severity of a disease can be used for deciding the sensitivity rank. If "salary" is considered as a sensitive attribute in a particular dataset, the sensitivity of each value in the attribute can be identified using a dependent attribute like "occupation". The method for choosing the sensitivity rank lies solely on the decision of the data publisher. Table IV shows the various severity levels and their ranks.

TABLE IV
SENSITIVITY RANK

Severity level	Sensitivity rank
Critical	1
Major	2
Medium	3
Low	4

D. Finding the Value of 'k_i':

The elbow method for finding the optimal number of 'k' in the clustering approach [30] can be extended for finding the value of 'k' in (k,n,m) anonymity approach. Here, different values of 'k' are to be found out based on the sensitivity rank of the class in the sensitive attribute. The various steps for finding the value of 'k' are given below.

1. For each class c_i in the sensitive attribute, find the sensitivity rank $m_i \in \{1,2,3,4\}$.
2. Group the tuples with the same sensitivity rank into appropriate bins, say b1 to b4.
3. for i=1 to 4,
   begin
   Apply elbow method for determining 'k' for each b_i.
   end for.

Elbow method for anonymity:
1. Compute k-anonymity for different values of 'k' ranging from 2 to 20.
2. For each k, calculate the re-identification risk.
3. Plot the curve based on the value of 'k' and the re-identification risk.
4. Find the point in the curve where an elbow, a deep change is observed and choose the corresponding value in the axis as the optimal value of 'k'.

If the value of 'k' is large, lot of tuples are replaced with generalized values for ensuring anonymity. On the other hand, if the value of 'k' is small, there is a risk of re-identification. Hence, an optimal selection of 'k' is required in the (k,n,m) anonymity approach because the tuples are grouped based on the sensitivity rank of the sensitive attribute. A sensitivity rank value of 1 represents the tuple with high sensitivity and a value of 4 corresponds to a tuple with less sensitivity. Therefore, the value of 'k' also should be varied based on the sensitivity rank.

E. Calculating the Re-identification Risk:

Risk of exposure of a particular class in a sensitive attribute corresponds to the probability of correctly identifying the dependent variable in a dataset, given a tuple, i.e. the probability with which an attacker can find the identity of a single record or a set of records [31]. 'θ_i' refers to the probability of a record 'i' being correctly re-identified in a dataset, where 'i' ranges from 1 to n, the total number of records. 'J' refers to the set of tuples with same values; say an equivalence class, in the disclosed dataset and |J| denotes the total number of equivalence classes present. Basically, three criteria are considered for calculating the risk of re-identification pertaining to a dataset. The first criterion considers the number of records with a probability of re-identification greater than a threshold 'τ'. It is calculated using the equation:

$$R_1 = \frac{1}{n} \sum_{j \in J} f_j \times I(\theta_j > \tau) \tag{1}$$

where I(.) is the indicator function which returns either a one or zero based on whether the parameters are true or not, f_j refers to the size of the jth equivalence class in the database and 'τ' refers to the uppermost permissible probability of accurately re-identifying a single record.

Another criterion considers the equivalence class with uppermost probability of re-identification risk. This represents the entire dataset and is given by the equation:

$$R_2 = max_{j \in J}(\theta_j) \qquad (2)$$

The third criterion considers the average re-identification probability of all tuples in the dataset, and is represented using the equation given below:

$$R_3 = \frac{1}{n}\sum_{j \in J} f_j \theta_j \qquad (3)$$

Three different metrics have been devised mainly for assessing the re-identification risks, which consists of the prosecutor model, journalist model and the marketer model:

Prosecutor model: In this model, it is assumed that the attacker has prior knowledge that the target is present in the database. Target refers to the individual that is being re-identified. Generally, the probability with which the target can be correctly identified is given by the equation:

$$p\theta_j = \frac{1}{f_j} \qquad (4)$$

where 'f_j' refers to the size of the matching equivalence class in the de-identified file.

The re-identification risk with respect to the prosecutor model can be calculated using the three criteria mentioned above:

$$pR_1 = \frac{1}{n}\sum_{j \in J} f_j \times I(\frac{1}{f_j} > \tau) \qquad (5)$$

$$pR_2 = \frac{1}{\min_{j \in J}(f_j)} \qquad (6)$$

$$pR_3 = \frac{|J|}{n} \qquad (7)$$

Here, 'p' denotes the prosecutor risk, 1, 2 and 3 denotes the three criteria, and f_i refers to the size of equivalence class in the de-identified dataset. If the de-identified file is same like the population considered, then $f_j = F_J$, where F_J represents the size of the equivalence class in the population.

Journalist model: No background knowledge regarding the presence of a particular record in the database is known to the attacker. The presence of the target in the de-identified file is not known to the attacker in this scenario, and the attacker could be a journalist who tries to question a data custodian, as he knows that all the people in the de-identified file exists in a public data base. In the journalist scenario, the anonymized data is a subset of a larger public database. The re-identification risk is calculated as follows:

$$jR_1 = \frac{1}{n}\sum_{j \in J} f_j \times I(\frac{1}{F_j} > \tau) \qquad (8)$$

$$jR_2 = \frac{1}{\min_{j \in J}(F_j)} \qquad (9)$$

$$jR_3 = max\left(\frac{|J|}{\sum_{j \in J}F_j}, \frac{1}{n}\sum_{j \in J}\frac{f_j}{F_j}\right) \qquad (10)$$

Marketer model: This model can be considered as a derived metric which aims at re-identifying a larger number of individuals, instead of focusing on a particular individual. In this scenario, it gives a measure of the average number of records that would be correctly re-identified when the intruder tries to match all the records in the de-identified file. The marketer is less concerned if some of the records are misidentified. Here the risk pertains to everyone in the dataset, as the marketer is less concerned about certain records being wrongly re-identified since the focus is not on any particular individual. The re-identification risk can be identified based on whether the identifying dataset has exactly the same set of records and data subjects as the de-identified file. The equations are given below:

$$mR_1 = \frac{|J|}{N}, when\ n = N \qquad (11)$$

$$mR_2 = \frac{1}{n}\sum_{j \in J}\frac{f_j}{F_j}, when\ n < N \qquad (12)$$

Since the data publisher always try to safeguard the published data from prosecutor or journalist risks, by default the data is protected against the marketer risk too. The relationship between the three risks can be expressed as follows:

Prosecutor risk ≥ Journalist risk ≥ Marketer risk

V. EVALUATION

The aim of this section is to evaluate the performance of (k,n,m) anonymity approach for anonymizing sensitive data.

A. Experimental set up

ARX, a health data de-identification tool, is integrated with our proposed method for evaluating its performance [32]. Extensive experimental evaluation has been done on three different datasets [33] [34]. Table V presents the various datasets used and the attributes considered for evaluation. This gives an overview of the number of quasi-identifier attributes and the number of levels (class labels) in the sensitive attribute.

TABLE V
DATASETS

Dataset	Number of QI attributes	Number of levels in the sensitive attribute
Adult dataset	8	2
Toy dataset	4	2
Disease dataset	4	5

The "Adult" dataset consists of 30162 records after pre-processing. Out of the 14 attributes, 8 have been taken as the QI attributes. This includes age, gender, race, marital status, educational qualification, native country, work class and occupation. The attribute "salary" is taken as the sensitive attribute. There are two levels in the sensitive attribute, which

corresponds to <=50K and >50K. Hence, the dataset is split into two, and appropriate anonymization strategy is performed. The toy dataset consists of just 7053 records with a total of 7 attributes. The dataset "disease" consists of approximately 18000 records with a total of 9 attributes. The quasi-identifiers and sensitive attributes were chosen according to the dataset under consideration.

B. Experimental Results

Each attribute should be first categorized as either identifying, quasi-identifying, sensitive or non-sensitive attributes. All the identifying attributes will be removed from the dataset whereas the quasi-identifying attributes will be transformed. Sensitive attributes will be kept as such, but are protected using privacy models such as t-closeness. Non-sensitive attributes won't be modified and kept as such in the original dataset. Transformation methods such as generalization can be used for transforming the quasi-identifiers, by specifying the minimum and maximum levels in the generalization hierarchy. As the attribute 'age' is common for all datasets considered for evaluation, it is explained in detail with respect to the generalization schemes used. Fig. 6. a) shows the generalization hierarchy for the attribute 'age'. Figures 6. b) and 6. c) represent the frequency distribution of age values in the dataset before and after applying generalization hierarchy schemes respectively.

Level-0	Level-1	Level-2	Level-3	Level-4
1	[1, 5]	[1, 10]	[1, 20]	*
2	[1, 5]	[1, 10]	[1, 20]	*
3	[1, 5]	[1, 10]	[1, 20]	*
4	[1, 5]	[1, 10]	[1, 20]	*
5	[1, 5]	[1, 10]	[1, 20]	*
6	[6, 10]	[1, 10]	[1, 20]	*
7	[6, 10]	[1, 10]	[1, 20]	*
8	[6, 10]	[1, 10]	[1, 20]	*
9	[6, 10]	[1, 10]	[1, 20]	*

Fig. 6. a) Generalization hierarchy of the attribute 'age'
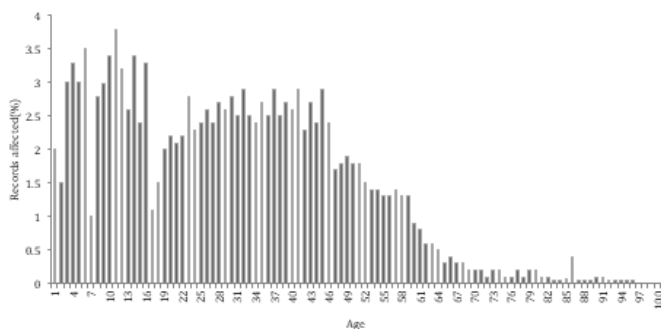
Fig. 6. b) Distribution of age values in the original dataset

As the generalization technique yielded an unequal histogram due to the use of equal spaced bins, the technique is further modified by using a simple equalization technique by dividing the values into intervals that produce approximately equal number of samples. The distribution of values after equalization is presented in Fig. 6. d).
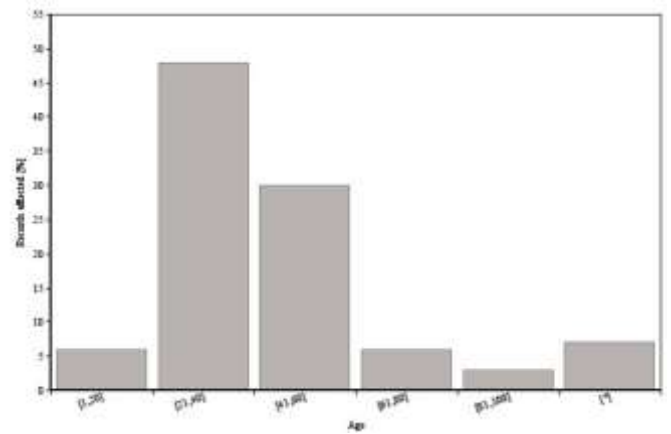

Fig. 6. c) Distribution of age values after applying generalization
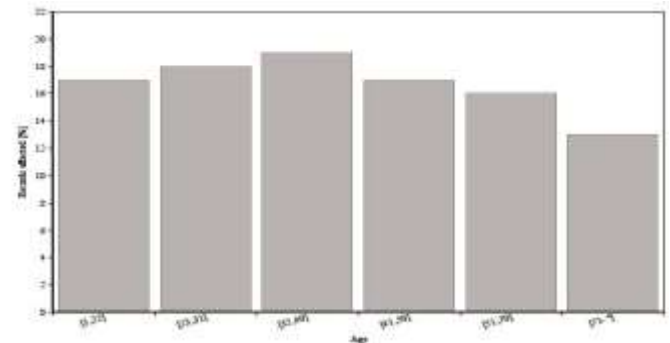

Fig. 6. d) Distribution of age values after equalization

Once the generalization scheme is set for all quasi-identifiers, the next step is to identify the number of sensitivity ranks and hence the severity levels in the sensitive attribute based on either the number of distinct values or using publicly available data repositories. Fig. 7 shows the sensitivity ranks of the sensitive attribute 'disease' used for evaluation [35].

Fig. 7. Sensitivity rank of various diseases

Based on the severity level, the original dataset is divided into various small datasets, say, data splits, and each one is treated separately for applying anonymization techniques. An optimal search strategy is implemented in the proposed method so that it accurately finds the transformation resulting in the utmost possible quality of resultant data. Based on the dataset under consideration, a global or local transformation mechanism can be used. Figures 8. a) and 8. b) show the contingency table with respect to the attributes 'age' and 'sex' before and after applying transformations, which depicts the

multivariate frequency distribution of the selected attributes. '*' in Fig. 8. b) refers to the generalized gender value. i.e. without disclosing whether the person is a male or female. Here, the generalized values before equalization are taken into account.
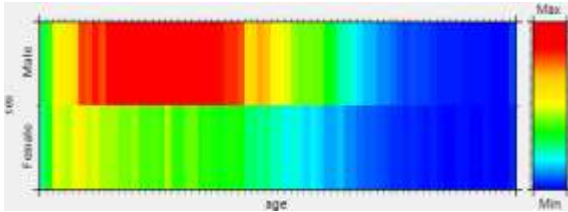

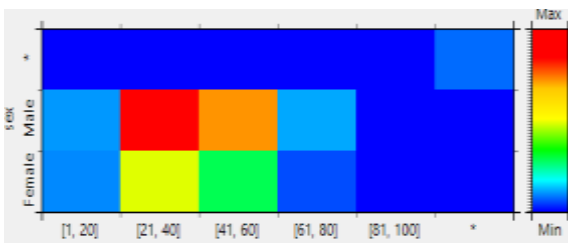Fig. 8. a) Contingency table before applying transformation

Fig. 8. b) Contingency table after applying transformation

The next step is to find the appropriate value of 'k' for the dataset splits by considering the severity level. A higher value of 'k' is recommended for dataset splits with higher severity levels when compared to the data splits with lesser severity levels. Fig. 9 represents the risk associated with the original dataset with different values of 'k' for anonymization.
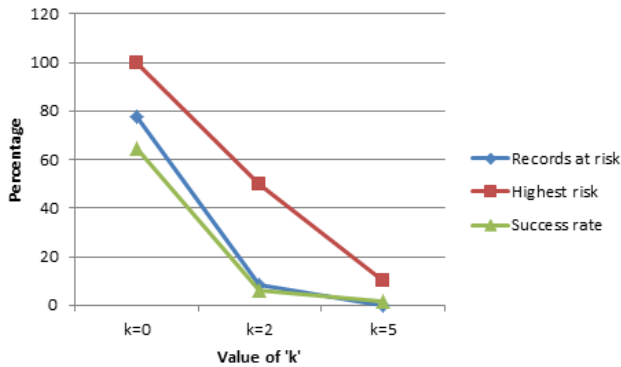
Fig. 9. Risk associated with the dataset

An optimal value of 'k' is chosen for each data split based on the "elbow method" used for the selection of 'k' in the clustering approaches. For anonymization, the value of 'k' is plotted against the risk associated with it and the optimal value is chosen based on the "bend" in the plot obtained. As an example, here the adult dataset is considered and different values of 'k' ranging from 2 to 10 is chosen and risk associated is measured after applying anonymization techniques.

Table VI presents the different values based on the risk of re-identification when applying different values of 'k'.

TABLE VI
RISK OF RE-IDENTIFICATION

VALUE OF 'K'	RECORDS AT RISK (%)	HIGHEST RISK (%)	SUCCESS RATE (%)
2	8.61	50	5.95
3	4.29	33.33	3.99
4	1.46	25	2.5
5	0	20	2.18
6	0	16.67	1.97
7	0	14.29	1.78
8	0	12.5	1.6
9	0	11.11	1.51
10	0	10	1.45

Fig. 10 represents the values of risk of exposure such as the highest risk, records at risk and success rate for different values of 'k' ranging from 2 to 10.
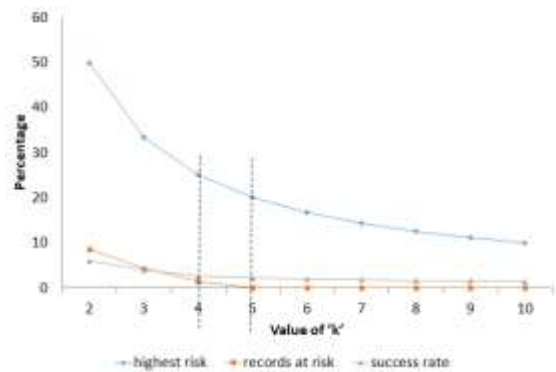

Fig. 10. Choosing optimal value of 'k' based on elbow method

The value of 'k' for which the bend occurs is chosen as the optimal value of 'k' for the data split. In Fig. 10, there can be two choices for the bend, where the values of 'k' are 4 and 5. After that the risk of exposure decreases very slowly. A better option is to choose the value of 'k' as 5 as records at risk falls to 0% after that. Similarly the optimal value of 'k' is chosen for all the data splits and anonymization is applied. Based on this, the values of 'k' and risk measures for each data split is found out and appropriate anonymization strategy is applied. Finally, all the data splits are combined to produce the resultant anonymized dataset, which has different set of equivalence classes for records with different sensitivity ranks.

The attribute-level quality and data level quality with different values of 'k' for anonymization is shown in Fig. 11. a), b), c) and d). Attribute level quality refers to the quality estimates pertaining to the individual QIs, whereas data level quality refers to the quality estimates pertaining to the entire set of QIs.

Fig. 11. a) Attribute level quality after applying anonymization with the value of k=2

Fig. 11. b) Data level quality after applying anonymization with the value of k=2

Fig. 11. c) Attribute level quality after applying anonymization with the value of k=10
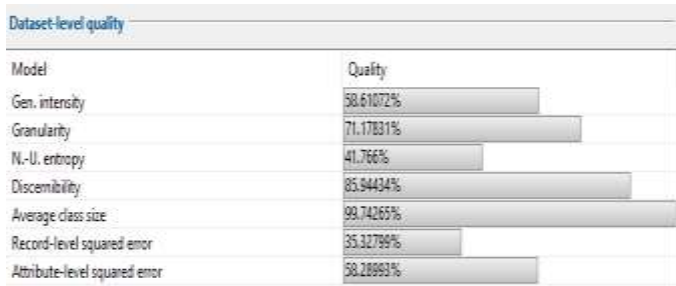

Fig. 11.d) Data level quality after applying anonymization with the value of k=2

VI. CONCLUSION

This paper aims at developing an anonymization technique named as (k,n,m) anonymity based on the severity levels of the values in the sensitive attribute, and thereby finding an optimal value of 'k' for different records in the same dataset. The well-known elbow method used for choosing 'k' in the clustering approach is used for the selection of 'k' in (k,n,m) anonymity technique by comparing the re-identification risk associated with it. As the dataset is further divided into various data splits based on the sensitivity ranks, a higher value of 'k' can be chosen for records with higher sensitivity ranks when compared to the records with lesser sensitivity ranks. One of the major applications of (k,n,m) anonymity lies in the publishing of sensitive data such as medical records from different hospitals, as the dataset does not rely on a single value of 'k' for anonymization. The work can be further extended by choosing 'k' based on other approaches and also by integrating unstructured data into the model.

REFERENCES

[1] Ross, M. K., Wei, W., & Ohno-Machado, L., "Big data" and the electronic health record. Yearbook of medical informatics, 23(01), 2014, pp. 97-104. DOI: 10.15265/IY-2014-0003

[2] Stanley Huff M.D, "Open data sharing will improve care, lower costs", 2017, [online] Available: https://www.athenahealth.com/insight/open-data-sharing-will-improve-care-lower-costs

[3] Benjamin CM, Fung M, Wang K, Chen R, Yu PS. Privacy-preserving data publishing: A survey of recent developments. ACM Computing Surveys., 42(4): pp 1-53, 2010. DOI: 10.1145/1749603.1749605

[4] Yan Y, Wang W, Hao X, Zhang L. Finding Quasi-identifiers for K-Anonymity Model by the Set of Cut-vertex. Engineering Letters., 1;26(1), 2018.

[5] Brickell, J., & Shmatikov, V. (2008, August). The cost of privacy: destruction of data-mining utility in anonymized data publishing. In Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 70-78). DOI:10.1145/1401890.1401904

[6] Li, T., & Li, N. (2009, June). On the tradeoff between privacy and utility in data publishing. In Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 517-526). DOI:10.1145/1557019.1557079

[7] Mivule, K., & Turner, C. (2013). A comparative analysis of data privacy and utility parameter adjustment, using machine learning classification as a gauge. Procedia computer science, 20, 414-419. DOI: 10.1016/j.procs.2013.09.295

[8] Guide to basic data anonymisation techniques, 2018, [online] Available: https://www.pdpc.gov.sg/-/media/Files/PDPC/PDF-Files/Other-Guides/Guide-to-Anonymisation_v1-(250118).pdf

[9] Sweeney, Latanya. "k-anonymity: A model for protecting privacy." International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems 10, no. 05, 2002, pp: 557-570. DOI: 10.1142/S0218488502001648

[10] Machanavajjhala A, Gehrke J, Kifer D, Venkitasubramaniam M. "l-diversity: Privacy beyond k-anonymity". in 22nd International Conference on Data Engineering (ICDE'06), IEEE, 2006 Apr 3, pp. 24-24. DOI: 10.1109/ICDE.2006.1

[11] Li N, Li T, Venkatasubramanian S. t-closeness: Privacy beyond k-anonymity and l-diversity. in 2007 IEEE 23rd International Conference on Data Engineering, IEEE, 2007 Apr 15, pp. 106-115. DOI: 10.1109/ICDE.2007.367856

[12] Dwork C. Differential privacy. Encyclopedia of Cryptography and Security. 2011: pp 338-40. DOI:10.1007/978-1-4419-5906-5_752

[13] Liu, Xiangwen, Qingqing Xie, and Liangmin Wang. "Personalized extended (α, k)-anonymity model for privacy-preserving data publishing." Concurrency and Computation: Practice and Experience 29, no. 6 (2017): e3886. DOI: 10.1002/cpe.3886

[14] Mehta, Brijesh B., and Udai Pratap Rao. "Privacy preserving big data publishing: a scalable k-anonymization approach using MapReduce." Iet Software 11, no. 5 (2017): 271-276. DOI: 10.1049/iet-sen.2016.0264

[15] Onashoga, S. A., B. A. Bamiro, A. T. Akinwale, and J. A. Oguntuase. "KC-Slice: A dynamic privacy-preserving data publishing technique for multisensitive attributes." Information Security Journal: A Global Perspective 26, no. 3 (2017): 121-135. DOI: 10.1080/19393555.2017.1319522

[16] Lee, Hyukki, Soohyung Kim, Jong Wook Kim, and Yon Dohn Chung. "Utility-preserving anonymization for health data publishing." BMC medical informatics and decision making 17, no. 1 (2017): 104. DOI: 10.1186/s12911-017-0499-0

[17] Wang, Zhibo, Xiaoyi Pang, Yahong Chen, Huajie Shao, Qian Wang, Libing Wu, Honglong Chen, and Hairong Qi. "Privacy-preserving crowd-sourced statistical data publishing with an untrusted server." IEEE Transactions on Mobile Computing 18, no. 6 (2018): 1356-1367. DOI: 10.1109/TMC.2018.2861765

[18] Yang, Dingqi, Bingqing Qu, and Philippe Cudré-Mauroux. "Privacy-preserving social media data publishing for personalized ranking-based recommendation." IEEE Transactions on Knowledge and Data Engineering 31, no. 3 (2018): 507-520. DOI: 10.1109/TKDE.2018.2840974

[19] Bindschaedler, Vincent, Reza Shokri, and Carl A. Gunter. "Plausible deniability for privacy-preserving data synthesis." arXiv preprint arXiv:1708.07975 (2017). DOI: 10.14778/3055540.3055542

[20] Zhang, Jinquan, Bowen Zhao, Guochao Song, Lina Ni, and Jiguo Yu. "Maximum delay anonymous clustering feature tree based privacy-

preserving data publishing in social networks." Procedia Computer Science 147 (2019): 643-646. DOI: 10.1016/j.procs.2019.01.190

[21] Mehta, Brijesh B., and Udai Pratap Rao. "Improved l-Diversity: Scalable Anonymization Approach for Privacy Preserving Big Data Publishing." Journal of King Saud University-Computer and Information Sciences (2019). DOI: 10.1016/j.jksuci.2019.08.006

[22] Piao, Chunhui, Yajuan Shi, Jiaqi Yan, Changyou Zhang, and Liping Liu. "Privacy-preserving governmental data publishing: A fog-computing-based differential privacy approach." Future Generation Computer Systems 90 (2019): 158-174. DOI: 10.1016/j.future.2018.07.038

[23] Victor N, Lopez D, Abawajy JH. Privacy models for big data: a survey. International Journal of Big Data Intelligence. 3(1), 2016, pp 61-75. DOI: 10.1504/IJBDI.2016.073904

[24] Victor N, Lopez D. "Privacy Preserving Big Data Publishing: Challenges, Techniques, and Architectures". in HCI Challenges and Privacy Preservation in Big Data Security, IGI Global. 2018, pp. 47-70. DOI: 10.4018/978-1-5225-2863-0.ch003

[25] How Google anonymizes data, [online]. Available: https://policies.google.com/te chnologies/anonymization?hl=en-US

[26] Office for Civil Rights (OCR). Guidance regarding methods for de-identification of protected health information in accordance with the Health Insurance Portability and Accountability Act (HIPAA) Privacy Rule.

[27] Motwani R, Xu Y. Efficient algorithms for masking and finding quasi-identifiers. In Proceedings of the Conference on Very Large Data Bases (VLDB), pp. 83-93, 2007.

[28] Detecting quasi-identifiers in datasets, by International Business Machines Corporation, Armonk, NY (US), (2015, May 22), Patent US20160342636A1

[29] Han J, Yu H, Yu J. An improved l-diversity model for numerical sensitive attributes. in 2008 Third International Conference on Communications and Networking in China pp. 938-943, 2008. DOI: 10.1109/CHINACOM.2008.4685178

[30] Kodinariya TM, Makwana PR. Review on determining number of Cluster in K-Means Clustering. International Journal. (6):90-5, 2013.

[31] El Emam K. Guide to the de-identification of personal health information. Auerbach Publications; 2013.

[32] Prasser, F., & Kohlmayer, F. (2015). Putting statistical disclosure control into practice: The ARX data anonymization tool. In Medical Data Privacy Handbook (pp. 111-148). Springer, Cham. DOI: 10.1007/978-3-319-23633-9_6

[33] Prasser, F., Kohlmayer, F., & Kuhn, K. A. (2014, May). A benchmark of globally-optimal anonymization methods for biomedical data. In 2014 IEEE 27th International Symposium on Computer-Based Medical Systems (pp. 66-71). IEEE. DOI: 10.1109/CBMS.2014.85

[34] Ron Kohavi, "Scaling Up the Accuracy of Naive-Bayes Classifiers: a Decision-Tree Hybrid", Proceedings of the Second International Conference on Knowledge Discovery and Data Mining, 1996

[35] Leading causes of death and numbers of deaths, by sex, race, and Hispanic origin: United States, 1980 and 2016 [online] https://www.cdc.gov/nchs/hus/contents2017.htm#019.

Nancy Victor is currently working as an Assistant Professor at Vellore Institute of Technology, Vellore, Tamilnadu India. She received her M.Tech in Computer and Information Technology from Manonmaniam Sundaramar University with first rank and gold medal. She completed her B.Tech from Kerala University. She is a member of LITD 27, Bureau of Indian Standards. She is an active researcher in the field of big data privacy. Her research interests include privacy preserving data publishing, data anonymisation, big data privacy, etc.

Daphne Lopez is a Professor in the School of Information Technology and Engineering, Vellore Institute of Technology University. Her research spans the fields of grid and cloud computing, spatial and temporal data mining and big data. She has a vast experience in teaching and industry. Prior to this, she has worked in the software industry as a consultant in data warehouse and business intelligence.