Approximation algorithms for \( k \)-anonymity and privacy preservation in query logs

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NATO Advanced Study Institute on Mining Massive Data Sets for Security

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Villa Cagnola, Gazzada, Italy
- privacy preservation
- $k$-anonymization
  - models, metrics, trade-offs, algorithms
- privacy preservation of query logs
Many organizations collect and hold large volumes of data
  - credit card companies
  - real estate companies
  - hospitals
  - search engines

Would like to publish the data for the purposes of data mining
At the same time data contain a lot of sensitive information
Would like to preserve the privacy of the individuals represented in the data
How to preserve privacy?

- **Manipulate** data in order to hide sensitive information
  - remove data records
  - perturb values (e.g., add random noise)
  - generalize entries (e.g., Barcelona ⇒ Catalunya)

- **Trade-off** between data manipulation and utility
A successful paradigm for privacy preservation in data-mining and algorithms community


Main idea: ensure that in the released data each data record is indistinguishable from \( k - 1 \) other records
### $k$-anonymity — motivating example

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Still not perfect privacy ensured; \(-\)diversity
**k-anonymity**

- **Quasi-identifier**: a set of attributes in the public database that can be linked with external information (e.g., Name, Age, Edu, Job, PostCode)

- **k-anonymity property**
  Let $D$ be a database and $Q_D$ quasi-identifier attributes. We say that $D$ is $k$-anonymized iff each set of values in $D(Q_D)$ appears in at least $k$ records of $D$

- **k-anonymization problem**
  Given a database table (public part)
  - hide minimum amount of information, and
  - ensure $k$-anonymity
$k$-anonymity issues

- What kind of operations are allowed to modify the data?
- How to measure information loss?
- Complexity of the problem and algorithms
Suppression
a data entry is always replaced by *

Generalization
a data entry is replaced by a more general value
e.g., 08003 $\Rightarrow$ 0800*, or MS $\Rightarrow$ PostGraduate
Domain generalization hierarchy (DGH) generalize along a hierarchy (usually provided by the user)

Natural domain generalization hierarchy (NDGH) [Nergiz and Clifton, 2006] generalize along arbitrary lattices (not restricted to trees)

Unrestricted generalization as NDGH
How to apply the generalization operation?

- **Single-dimension generalization (SDG)**
  a value is mapped always to the same generalized value e.g.,
  \[ 08003 \rightarrow 0800^* \] (always)

- **Multiple-dimension generalization (MDG)**
  a set of values is mapped always to the same generalized set of values, e.g.,
  \[
  \{ 08003, \text{high-school} \} \rightarrow \{ 0800^*, \text{elem/high} \} \] (always)
  \[
  \{ 08003, \text{BS} \} \rightarrow \{ 080^{**}, \text{uni} \} \] (always)

- **Cell-based generalization (CBG)**
  the same value in different data records can be mapped to different generalized values

\[
\text{SDG} \subseteq \text{MDG} \subseteq \text{CBG}
\]
In the next of the talk we focus on CBG
Some notation

Dataset: $D$ $n$ records, $m$ attributes

$i$-th row: $D_i$ $i = 1 \ldots n$

$j$-th value of $i$-th row: $D_i(j)$ $j = 1 \ldots m$

Values of the $j$-th attribute: $A_j$ $j = 1 \ldots m$
Generalization:

- a mapping $g : A_j \rightarrow \overline{A}_j \subseteq \mathcal{P}(A_j)$
- natural assumption $A_j \subseteq \overline{A}_j$
- suppression: $\overline{A}_j = A_j \cup \{\ast\}$
- hierarchical: $\overline{A}_j$ forms a hierarchy under $\subseteq$
- unrestricted: $\overline{A}_j = \mathcal{P}(A_j)$

Generalization of a dataset $D$:

- $g_i : A_1 \times \cdots \times A_n \rightarrow \overline{A}_1 \times \cdots \times \overline{A}_n$ generalization operators
- $\overline{D}_i := g_i(D_i)$, $1 \leq i \leq n$
- $g(D) := \{\overline{D}_1, \ldots, \overline{D}_n\}$ generalization of $D$
Measures of information loss

**Recall:** $k$-anonymization problem

Given a database table
- hide minimum amount of information, and
- ensure $k$-anonymity

**Measures of information loss**
- **Suppressions:** number of *'s [Meyerson and Williams, 2004]
- **Generalization by hierarchies** [Aggarwal et al., 2005a]

![Diagram](image)

Cost: $\sum \frac{l_{ij}}{h_j}$
Measures of information loss

Unrestricted generalizations

- **LM measure:**

  \[
  \text{LM}(g(D)) = \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{|D_i(j)| - 1}{|A_j| - 1}
  \]

- **DM measure:**

  \[
  \text{DM}(g(D)) = \sum_{i=1}^{n} |I_{g(D)}(D_i)|,
  \]

  where \(I_{g(D)}(t)\) the set of records indistinguishable from \(t\)

- and more: **CM measure, AM measure**

(Recall, \(D = \{D_1, \ldots, D_n\}\) generalizes to \(g(D) = \{\overline{D}_1, \ldots, \overline{D}_n\}\))
Entropy-based measures of information-loss

[Gionis and Tassa, 2007]
{Male, Female} → * loses 1 bit
Age → * loses many bits

\[ P[X_j = a] = \frac{\#\{1 \leq i \leq n : D_i(j) = a\}}{n} \]

\[ H(X_j) = - \sum_{a \in A_j} P[X_j = a] \log_2 P[X_j = a] \]

\[ H(X_j | B_j) = - \sum_{b \in B_j} P[X_j = b | X_j \in B_j] \log_2 P[X_j = b | X_j \in B_j] \]

Then, find the mapping \( g_i : D_i(j) \rightarrow \overline{A}_j \) to minimize

\[ I(g(D)) = \sum_{i=1}^{n} \sum_{j=1}^{m} H(A_j | g_i(D_i(j))) \]
Example – how accurate is the entropy measure

Inter-dependencies among columns not taken into account
Inter-dependencies among rows not taken into account

\[ D = \begin{bmatrix}
1 \\
2 \\
3 \\
3 \\
\end{bmatrix}, \quad g(D) = \begin{bmatrix}
* \\
* \\
3 \\
3 \\
\end{bmatrix}, \quad p_1 = \frac{1}{4}, \quad p_2 = \frac{1}{4}, \quad p_3 = \frac{1}{2} \]

\[ H(A|\ast) = 1.5, \text{ implying } I(g(D)) = 1.5 + 1.5 + 0 + 0 = 3 \]

However, the actual information loss is 2 bits

Entropy measure overestimates the actual information loss
Non monotonicity

- Consider $A_j = \{1, 2, 3\}$ with probabilities $(1 - 2\epsilon, \epsilon, \epsilon)$
- Replacing 2 and 3 by $\{2, 3\}$ loses 1 bit
- Replacing 2 and 3 by $\ast$ loses $O(\epsilon)$ bits
- **Non monotonicity:** generalizing to a larger set gives smaller amount of information loss
- Does not seem natural to have non-monotone measure
- But we can design $\overline{A}_j$ so that entropy is monotone
Rectification of non monotonicity

- Recall

\[ I(g(D)) = \sum_{i=1}^{n} \sum_{j=1}^{m} H(A_j|\overline{D_i}(j)) \]

1. We can design \( \overline{A}_j \) so that entropy is monotone
   e.g., use a bottom-up algorithm that merges pairs of sets
   in which monotonicity is violated

2. Monotone entropy measure:

\[ I'(g(D)) = \sum_{i=1}^{n} \sum_{j=1}^{m} P(\overline{D_i}(j)) H(A_j|\overline{D_i}(j)) \]
[Meyerson and Williams, 2004]

- Only suppressions (*)
- $k$-anonymization problem is NP-hard, for $k \geq 3$ and large alphabet,
  (where alphabet is the domain of each attribute)
- $O(k \log k)$-approximation algorithm
  algorithm based on set cover
  running time $O(n^{2k})$
- $O(k \log n)$-approximation algorithm
  strongly polynomial
Hardness results and approximation algorithms

[Aggarwal et al., 2005b, Aggarwal et al., 2005a]

- Extended to generalization by suppressions
- NP-hardness for ternary alphabets and $k \geq 2$
- $O(k)$-approximation algorithm for any $k$
  - 1.5 approximation algorithm for $k = 2$
  - 2 approximation algorithm for $k = 3$
- $\Omega(k)$ lower bound on the approximation ratio, if graph representation is used
The forest algorithm

[Aggarwal et al., 2005b, Aggarwal et al., 2005a]

- Based on the graph representation
- Provides $O(k)$-approximation for the $k$-anonymization problem
- Consider a graph $G = (V, E)$, in which $V$ is the set of rows in the database and the cost of an edge $(u, v) \in E$ denotes the minimum generalization cost paid for $u$ and $v$ to become identical

Outline:

- Find a forest of $G$ with total cost at most $\text{OPT}$ and such that all trees have size at least $k$
- Split large trees, so that all trees have size at most $L = O(k)$
- Approximation ratio is $L$
New results and the entropy measures

[Gionis and Tassa, 2007]

- NP-hardness for the entropy measure and the monotone entropy measure
- $O(\log k)$-approximation algorithm for both of the entropy measures, as well as the previous measures
- Running time is $O(n^{2k})$
- Adapt the Forest algorithm to obtain $O(k)$-approximation algorithm for the entropy measures in time polynomial in both $n$ and $k$
In a $k$-anonymity solution, let a cluster be a set of identical rows (after the information hiding process).

**Observation 1**: All clusters in an optimal $k$-anonymity solution have between $k$ and $2k - 1$ rows.

**Observation 2**: Given a set of rows $X$ to be clustered together, we can compute the optimal information loss $I(X)$ required for the rows to become identical.
Generate all subsets of rows of sizes between $k$ and $2k - 1$ ($O(n^{2k})$ such sets)

for each such set $X$ compute its cost $I(X)$

Solve set cover on those subsets

/* find a minimum-cost collection of the sets that cover all rows can be approximated within factor $O(\log k)$ */

Convert cover to clustering

/* check each pair of overlapping sets and eliminate overlaps * need to assume that collection $\overline{A}_j$ is proper */
Entropy-based measures for $k$-anonymity
- $O(\log k)$ approximation algorithm for the entropy measure and other previous measures (non-strongly polynomial)
- $O(k)$ approximation algorithm for the entropy measures (strongly polynomial)
- $O(k)$ ratio has been shown to be optimal for the graph representation case
Privacy preservation in query logs

- Search engines collect a large amount of query logs
- Contain a lot of interesting information that can be used for:
  - analyzing users’ behavior
  - creating user profiles
  - personalization
  - creating knowledge bases and folksonomies
  - finding similar concepts
  - building systems for query suggestions and recommendations
  - using statistics for improving systems’ performance
  - etc.
Privacy preservation in query logs

- Users’ online behavior is sensitive
- People would not like to have their web searches revealed
- Some searches are more sensitive than others
- On the other hand, releasing query logs can be beneficial for analysis, research, improving systems’ performance and functionality
Trade-off between utility and privacy

- Release of a query log can be possible after sufficient obfuscation of the data.
- Trade-off between utility of released information and privacy.
- The more complex the data mining task needed to be performed, the more the amount of privacy that needs to be taken away from the users.
  - For example, for building a model for query inter-arrival times, can release a query log with no private information.
  - For building a model for predicting the salary of a user on their queries, it is not so clear...
American Online (AOL) query log released in August 2006
Objective was to contribute to IR research
Query log rough statistics
- 20 million queries
- 650 K users
- from over 3 months
Social security numbers, credit card numbers, driver license numbers, etc.
Possible to uniquely identify many users by combining information from queries and yellow pages
Big media scandal, big damage to AOL and the privacy of its users
A typical query log

Entries of the format

<cookie, query, rank, clickURL, timeStamp, IP, country,...>
Anonymizing query logs

[Adar, 2007]

- Argue that anonymization is potentially possible
- Two main techniques:
  1. Eliminate infrequent queries
  2. Splitting personalities
- Additionally:
  3. Eliminate identifying information (SSN, credit card numbers, etc.)
Anonymizing query logs

Eliminate infrequent queries

- Keep only queries generated by a large number of users
- Computationally possible using counters
- How to do it on-the-fly?
Online elimination of infrequent queries

- **Background:** How to split a secret among $n$ people so that every coalition of $k$ persons can access the secret?

- **Answer:**
  Let the secret be the coefficients of a $(k - 1)$-degree polynomial
  \[ f(x) = a_{k-1}x^{k-1} + \ldots + a_1x + a_0 \]

  For the $i$-th person, select a number $x_i$, and give to the person the pair $(x_i, f(x_i))$

  Any $k$ persons can cooperate and recover the polynomial, while no $k - 1$ persons can recover it.
Online elimination of infrequent queries

- Straightforward application in eliminating infrequent queries
- A query $q$ is decoded as a $(k - 1)$-degree polynomial $f_q$
- For a person $u; \text{ who makes the query } q$, print
  $$(u; \, f_q(u;))$$
- If $k$ or more people type the query $q$, it is possible to decrypt $q$!
Split personality

- Split the queries of the same user into sessions
- E.g., queries about food recipes, sport results, buying books, music, etc.
- Assign each of those sessions to a different virtual user
- Released query log can be still useful for many applications
- More difficult to identify users by combining queries
- Finding similar queries and finding query sessions is quite hard problem
Anonymization via **token-based hashing**: The query is split into terms and each term is hashed to a token.

**Co-occurrence analysis** and **frequency analysis** can be used to reveal the query terms.

Assume access to an unencrypted query log.

Query term statistics remain constant across different query logs.

Provide practical graph-matching algorithms and analysis of real query logs.
Releasing data so that privacy is preserved is an important research area.

Studied $k$-anonymity, new notions, algorithms.

Privacy preservation in query logs — a lot of care is needed.
User 4XXXXX9: Anonymizing Query Logs.
In WWW.

Approximation algorithms for $k$-anonymity.
*Journal of Privacy Technology.*

Approximation algorithms for $k$-anonymity.
In *ICDT.*

Data privacy through optimal $k$-anonymization.
In *ICDE.*

$k$-anonymization with minimal loss of information.


Protecting respondent’s privacy in microdata release.
*IEEE Transactions on Knowledge and Data Engineering, 13*:1010–1027.

Generalizing data to provide anonymity when disclosing information (abstract).
In *PODS*.

$k$-anonymity: A model for protecting privacy.