Experimental Analysis of Samarati's Algorithm for K-Anonymity

[1]Abhimanyu Singh Kulhari, [2]Akash Saraswat, [3]Shiwangi Kulhari,
1,2,3 Dr. K.N. Modi University

I. Introduction

In the digital age, where data privacy and protection have become paramount concerns, preserving the anonymity of individuals in datasets has emerged as a critical challenge. Among various techniques devised to address this challenge, Samarati's algorithm for k-anonymity stands out as a promising solution. K-anonymity ensures that each record in a dataset is indistinguishable from at least k-1 other records, thereby safeguarding the privacy of individuals while still allowing for meaningful analysis [1].

The theoretical foundation of Samarati's algorithm is robust, offering a framework for achieving k-anonymity through the generalization and suppression of sensitive attributes within a dataset. By replacing specific attribute values with more generalized ones and selectively suppressing certain information, Samarati's algorithm aims to strike a balance between data utility and privacy preservation.

While Samarati's algorithm has been extensively studied in theory, its practical effectiveness and performance across different datasets remain subjects of empirical investigation. This experimental analysis seeks to delve into the real-world applicability of Samarati's algorithm, specifically focusing on two key aspects: runtime analysis and loss metric analysis.

1. Runtime Analysis: One crucial aspect of assessing Samarati's algorithm's practical utility is evaluating its computational efficiency. Runtime analysis involves measuring the algorithm's execution time on various datasets under different configurations. Understanding the algorithm's computational overhead is essential for determining its feasibility in real-world applications, particularly in scenarios where large datasets or time-sensitive operations are involved.

2. Loss Metric Analysis: In addition to runtime considerations, evaluating the impact of Samarati's algorithm on data utility is vital. Loss metric analysis involves quantifying the information loss incurred during the anonymization process. Metrics such as data distortion, information entropy, and utility preservation are used to assess the extent to which the anonymized data retains its original characteristics and remains suitable for subsequent analysis tasks.

By conducting experiments focused on runtime analysis and loss metric analysis, this study aims to provide comprehensive insights into Samarati's algorithm's strengths and limitations. The findings will contribute to a deeper understanding of the algorithm's practical implications and its suitability for various privacy-sensitive applications.

In summary, while Samarati's algorithm for k-anonymity presents a promising solution for preserving data privacy, its practical effectiveness hinges on factors such as runtime performance and impact on data utility. Through rigorous experimental analysis, this study seeks to bridge the gap between theory and practice, informing stakeholders about the algorithm's real-world applicability and guiding future developments in the field of data anonymization.

II. Literature Review:

Samarati's algorithm, introduced in 1998, stands as a cornerstone in the realm of privacy-preserving data publishing. Its fundamental aim is to shield respondents' identities in microdata release. Over the years, scholars have diligently scrutinized this algorithm, probing its efficacy in both minimizing information loss and optimizing runtime performance.

Researchers have delved into diverse datasets to scrutinize the algorithm's runtime behavior under varying conditions. These investigations reveal a scalable nature, where processing time remains modest even as datasets expand. Zhang and colleagues' comprehensive analysis unveiled this aspect, shedding light on how intricacies of data structures and privacy parameters can sway runtime outcomes [2].

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In the contemporary landscape, Chen et al. conducted a meticulous comparative study, pitting Samarati's algorithm against contemporary privacy-preserving methodologies. Their analysis illuminated the algorithm's prowess in maintaining privacy robustness while exhibiting superior runtime efficiency. However, the study also unmasked certain vulnerabilities, especially concerning computational overheads in scenarios involving highly sensitive datasets [4].

Expanding the horizons of inquiry, Patel and collaborators explored the algorithm's applicability in novel data modalities, particularly graph-structured data. Their investigation underscored the algorithm's adaptability in anonymizing such data while preserving its structural integrity. Nevertheless, challenges loomed large, notably in scalability and computational complexity, especially in handling large-scale graph datasets [6].

Park et al. conducted an experimental evaluation of Samarati's algorithm on image data, assessing privacy preservation and image quality. Their study provided insights into the algorithm's performance in a different data domain [7]. Similarly, Cheng et al. analyzed the algorithm's performance on spatial data, specifically focusing on location privacy preservation, expanding the understanding of its applicability across diverse data types [8].

Further investigations shed light on the utility-privacy tradeoff of Samarati's algorithm on various data types. Wu et al. conducted an experimental study on document anonymization, while Gupta et al. focused on healthcare data, providing comparative analyses and insights into the algorithm's performance in different contexts [9][10]. Zhang et al. explored its performance on multivariate time-series financial data, and Zhao et al. studied the trade-off between privacy and utility on synthetic data, contributing to a comprehensive understanding of the algorithm's behavior [11][12].

Liang et al. evaluated the impact of data perturbation techniques on Samarati's algorithm, while Xu et al. assessed its performance on streaming data, both studies providing insights into the algorithm's adaptability and limitations in dynamic environments [13][14]. Kumar et al. conducted a comparative study with L-diversity on educational data, and Wei et al. investigated its applicability on blockchain data, further expanding the breadth of knowledge on its performance across different domains [15][16].

Further extending the analysis, Chen, X., Wang, H., & Li, G. (2018) compared Samarati's algorithm with Differential Privacy for Privacy-Preserving Machine Learning, providing insights into its performance in the healthcare domain [17]. Zhang, L., Yang, M., & Wu, Z. (2020) conducted an experimental investigation on Samarati's Algorithm on Graph Data, specifically focusing on social network privacy preservation, thereby contributing to understanding its efficacy in different data contexts [18].

Tan, Y., Chen, Z., & Zhou, Y. (2017) conducted an empirical study on the trade-off between privacy and utility in Samarati's Algorithm, particularly focusing on healthcare data, further enriching the understanding of its applicability [19]. Similarly, Hu, J., Wang, Z., & Li, H. (2019) assessed its performance on temporal data, specifically in preserving privacy in smart grids [20].

Li, M., Zhang, F., & Yang, J. (2021) conducted a comparative study of Samarati's Algorithm with randomization techniques for privacy-preserving data publishing, contributing to understanding its performance in preserving privacy and utility [21]. Sun, J., Zhang, L., & Wang, S. (2018) compared Samarati's Algorithm with Differential Privacy mechanisms for location privacy preservation, specifically focusing on mobile sensing data [22].

Furthermore, Chen, Y., Wang, X., & Liu, Q. (2019) investigated the algorithm's performance on sequential data, particularly in preserving privacy in the Internet of Things [23]. Zhao, Y., Chen, W., & Li, L. (2022) conducted an experimental study on the effectiveness of Samarati's Algorithm in preserving privacy and utility of high-dimensional data, contributing to understanding its performance in complex data scenarios [24].

Additionally, Wang, Q., Li, X., & Zhang, Y. (2021) analyzed the algorithm's performance on multimodal data, providing insights into its comparative study with Differential Privacy techniques [25]. Zhou, H., Yang, S., & Wang, L. (2017) evaluated the trade-off between privacy and data utility in Samarati's Algorithm, particularly on synthetic data [26].

Collectively, these endeavors underscore the enduring relevance of Samarati's algorithm in the evolving landscape of privacy-preserving data publishing. They not only affirm its efficacy but also unveil avenues for refinement, pointing towards a future where privacy protection and data utility converge seamlessly.

III. Proposed Methodology:

To analyze the results of Samarati's algorithm in the experiment, we propose the following methodology:

1. Data Preparation:

- Load the dataset 'adult.data' containing attributes such as age, gender, race, marital_status, education_num, and occupation.

- Specify the quasi-identifiers (QI) for Samarati, which include 'age', 'gender', 'race', and 'marital_status'. These attributes are crucial for anonymization.

- Define the hierarchies for categorical attributes ('gender', 'race', and 'marital_status') and numerical attribute ('age').

2. Algorithm Configuration:

- Configure Samarati with specific parameters such as k (anonymity threshold) and maxsup (maximum suppression).

- Run Samarati using the provided command:

```
python main.py --samarati --k 10 --maxsup 20
```

3. Result Analysis:

- Upon execution, capture the output which includes:

  - Row count before and after sanitizing.

  - Details on hierarchies, lattice map, leaf nodes, and loss metric for each attribute.

  - Generalization vectors, max suppression, and anonymized table.

- Calculate the loss metric, which measures the information loss due to generalization.

- Interpret the anonymized table to understand the level of anonymity achieved and the impact on sensitive attributes like 'occupation'.

4. Performance Evaluation:

- Analyze the runtime and loss metric variations for different values of k and maxsup.

- Plot the relations between runtime/loss metric and different k/maxsup values using the provided scripts:

```
python plot.py --samarati
```

IV. Conclusion:

Discuss following points

-Performance Analysis

-Impact of (k)

-Effect of (maxsup) Parameter

-Utility and Privacy Trade-off

Experiment results:

Run vanilla Samarati:

```
python main.py --samarati --k 10 --maxsup 20
```

Output for vanilla samarati (k=10, maxsup=20) is as follows. After configuration, the following 2 lines of row count indicating the drop of rows with '?'.

- hierarchies maps a value to its parent in the generalization hierarchy
- hierarchy heights maps attribute names to its height in the generalization hierarchy
- lattice map records vectors for each height in the lattice
- leaves num records leaves in the subtree rooted by values in each attribute
- loss metric map records loss metric of values in each attribute

In the last part there are loss metric, generalization vector, max suppression, quasi identifiers and anonymized table (after replacing the quasi-identifiers and droping the sensitive column, both shown in standard output and saved in results directory)

```
configuration:
 {'k': 10, 'maxsup': 20, 'samarati': True,
'mondrian': False, 'optimal_samarati': False,
'data': {'path': 'data/adult.data',
'samarati_quasi_id': ['age',
'gender', 'race', 'marital_status'],
'mondrian_quasi_id': ['age', 'education_num'],
'sensitive': 'occupation', 'columns': ['age',
'work_class', 'final_weight', 'education',
'education_num', 'marital_status', 'occupation',
'relationship', 'race', 'gender', 'capital_gain',
'capital_loss', 'hours_per_week',
'native_country', 'class'],
'samarati_generalization_type': {'age': 'range',
'gender': 'categorical', 'race': 'categorical',
'marital_status': 'categorical'}, 'hierarchies':
{'age': None, 'gender': 'data/adult_gender.txt',
'race': 'data/adult_race.txt', 'marital_status':
'data/adult_marital_status.txt'},
'mondrian_generalization_type': {'age':
'numerical', 'education_num': 'numerical'}}}

row count before sanitizing: 32561
row count sanitized: 30162

hierarchies:
 {'age': {'39': '(35, 40)', '50': '(50, 55)', '38': '(35,
40)', '53': '(50, 55)', '28': '(25, 30)', '37': '(35,
40)', '49': '(45, 50)', '52': '(50, 55)',
'31': '(30, 35)', '42': '(40, 45)', '30': '(30, 35)',
'23': '(20, 25)', '32': '(30, 35)', '34': '(30, 35)',
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'54': '(50, 55)', '35': '(35, 40)', '59': '(55, 60)',
'56': '(55, 60)', '19': '(15, 20)', '20': '(20, 25)',
'45': '(45, 50)', '22': '(20, 25)', '48': '(45, 50)',
'21': '(20, 25)', '24': '(20, 25)', '57': '(55, 60)',
'44': '(40, 45)', '41': '(40, 45)', '29': '(25, 30)',
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50)', '36': '(35, 40)', '79': '(75, 80)', '27': '(25,
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75)', '64': '(60, 65)', '71': '(70, 75)', '66': '(65,
70)', '51': '(50, 55)', '58': '(55, 60)', '26': '(25,
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95)', '75': '(75, 80)', '65': '(65, 70)', '77': '(75,
80)', '62': '(60, 65)', '63': '(60, 65)', '67': '(65,
70)', '74': '(70, 75)', '72':
'(70, 75)', '69': '(65, 70)', '68': '(65, 70)', '73':
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'(85, 90)', '80': '(80, 85)', '84': '(80, 85)', '83':
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60)', '(25, 30)': '(20, 30)', '(45, 50)': '(40, 50)',
'(30, 35)': '(30, 40)', '(40, 45)': '(40, 50)', '(20,
25)': '(20, 30)', '(55, 60)': '(50, 60)', '(15, 20)':
'(10, 20)', '(75, 80)': '(70,
80)', '(60, 65)': '(60, 70)', '(70, 75)': '(70, 80)',
'(65, 70)': '(60, 70)', '(90, 95)': '(90, 100)', '(80,
85)': '(80, 90)', '(85, 90)': '(80, 90)', '(30, 40)':
'(20, 40)', '(50, 60)': '(40, 60)', '(20, 30)': '(20,
40)', '(40, 50)': '(40, 60)', '(10, 20)': '(0, 20)',
'(70, 80)': '(60, 80)', '(60, 70)': '(60, 80)', '(90,
100)': '(80, 100)', '(80, 90)': '(80, 100)', '(20,
40)': '*', '(40, 60)': '*', '(0, 20)': '*', '(60, 80)': '*',
'(80, 100)': '*'}, 'gender': {'Female': '*', 'Male':
```

```
'*'}, 'race': {'Other': '*', 'Amer-Indian-Eskimo': '*', 'Black': '*', 'White': '*', 'Asian-Pac-Islander': '*'}, 'marital_status': {'NM': '*', 'Married': '*', 'leave': '*', 'alone': '*', 'Never-married': 'NM', 'Married-civ-spouse': 'Married', 'Married-AF-spouse': 'Married', 'Divorced': 'leave', 'Separated': 'leave', 'Widowed': 'alone', 'Married-spouse-absent': 'alone'}}

hierarchy heights:
 {'age': 4, 'gender': 1, 'race': 1, 'marital_status': 2}

lattice_map:
 {0: [(0, 0, 0, 0)], 1: [(0, 0, 0, 1), (0, 0, 1, 0), (0, 1, 0, 0), (1, 0, 0, 0)], 2: [(0, 0, 0, 2), (0, 0, 1, 1), (0, 1, 0, 1), (0, 1, 1, 0), (1, 0, 0, 1), (1, 0, 1, 0), (1, 1, 0, 0), (2, 0, 0, 0)], 3: [(0, 0, 1, 2), (0, 1, 0, 2), (0, 1, 1, 1), (1, 0, 0, 2), (1, 0, 1, 1), (1, 1, 0, 1), (1, 1, 1, 0), (2, 0,
0, 1), (2, 0, 1, 0), (2, 1, 0, 0), (3, 0, 0, 0)], 4: [(0, 1, 1, 2), (1, 0, 1, 2), (1, 1, 0, 2), (1, 1, 1, 1), (2, 0, 0, 2), (2, 0, 1, 1), (2, 1, 0, 1), (2, 1, 1, 0), (3, 0, 0, 1), (3, 0, 1, 0), (3, 1, 0, 0), (4, 0, 0, 0)], 5: [(1, 1, 1, 2), (2, 0, 1, 2), (2, 1, 0, 2), (2, 1, 1, 1), (3, 0, 0, 2), (3, 0, 1, 1), (3, 1, 0, 1), (3, 1, 1, 0), (4, 0, 0, 1), (4, 0, 1, 0), (4, 1, 0, 0)], 6: [(2, 1, 1, 2), (3, 0, 1, 2), (3, 1, 0, 2), (3, 1, 1, 1), (4, 0, 0, 2), (4, 0, 1, 1), (4, 1, 0, 1), (4, 1, 1, 0)], 7: [(3, 1, 1, 2), (4, 0, 1, 2), (4, 1, 0, 2), (4, 1, 1, 1)], 8: [(4, 1, 1, 2)]}

leaves_num:
 {'age': {'(35, 40)': 5, '(50, 55)': 5, '(25, 30)': 5, '(45, 50)': 5, '(30, 35)': 5, '(40, 45)': 5, '(20, 25)': 5, '(55, 60)': 5, '(15, 20)': 3, '(75, 80)': 5, '(60, 65)': 5, '(70, 75)': 5, '(65, 70)': 5, '(90, 95)': 1, '(80, 85)': 5, '(85, 90)': 3, '(30, 40)': 10, '(50, 60)': 10, '(20, 30)': 10, '(40, 50)': 10, '(10, 20)': 3, '(70, 80)': 10, '(60, 70)': 10, '(90, 100)': 1, '(80, 90)': 8, '(20, 40)': 20, '(40, 60)': 20, '(0, 20)': 3, '(60, 80)': 20, '(80, 100)': 9, '*': 72}, 'gender': {'*': 2}, 'race': {'*': 5}, 'marital_status': {'*': 7, 'NM': 1, 'Married': 2, 'leave': 2, 'alone': 2}}

loss_metric_map:
 {'age': {'*': 1, '39': 0, '50': 0, '38': 0, '53': 0, '28': 0, '37': 0, '49': 0, '52': 0, '31': 0, '42': 0, '30': 0, '23': 0, '32': 0, '34': 0, '25': 0, '43': 0, '40': 0, '54': 0, '35': 0, '59': 0, '56': 0, '19': 0, '20': 0, '45': 0, '22': 0, '48': 0, '21': 0, '24': 0, '57': 0, '44': 0, '41': 0, '29': 0, '47': 0, '46': 0, '36': 0, '79': 0, '27': 0, '18': 0, '33': 0, '76': 0, '55': 0, '61': 0, '70': 0, '64': 0, '71': 0, '66': 0, '51': 0, '58': 0, '26': 0, '17': 0, '60': 0, '90': 0, '75': 0, '65': 0, '77': 0, '62': 0, '63': 0, '67': 0, '74': 0, '72': 0, '69': 0, '68': 0, '73': 0, '81': 0, '78': 0, '88': 0, '80': 0, '84': 0, '83': 0, '85': 0, '82': 0, '86': 0, '(35, 40)': 0.056338028169014086, '(50, 55)': 0.056338028169014086, '(25, 30)': 0.056338028169014086, '(45, 50)': 0.056338028169014086, '(30, 35)': 0.056338028169014086, '(40, 45)': 0.056338028169014086, '(20, 25)': 0.056338028169014086, '(55, 60)': 0.056338028169014086, '(15, 20)': 0.028169014084507043, '(75, 80)': 0.056338028169014086, '(60, 65)': 0.056338028169014086, '(70, 75)': 0.056338028169014086, '(65, 70)': 0.056338028169014086, '(90, 95)': 0.0, '(80, 85)': 0.056338028169014086, '(85, 90)': 0.028169014084507043, '(30, 40)': 0.1267605633802817, '(50, 60)': 0.1267605633802817, '(20, 30)': 0.1267605633802817, '(40, 50)': 0.1267605633802817, '(10, 20)': 0.028169014084507043, '(70, 80)': 0.1267605633802817, '(60, 70)': 0.1267605633802817, '(90, 100)': 0.0, '(80, 90)': 0.09859154929577464, '(20, 40)': 0.2676056338028169, '(40, 60)': 0.2676056338028169, '(0, 20)': 0.028169014084507043, '(60, 80)': 0.2676056338028169, '(80, 100)': 0.11267605633802817}, 'gender': {'*': 1, 'Female': 0, 'Male': 0}, 'race': {'*': 1, 'Other': 0, 'Amer-Indian-Eskimo': 0, 'Black': 0, 'White': 0, 'Asian-Pac-Islander': 0}, 'marital_status': {'*': 1, 'NM': 0.0, 'Married': 0.16666666666666666, 'leave': 0.16666666666666666, 'alone': 0.16666666666666666, 'Never-married': 0, 'Married-civ-spouse': 0, 'Married-AF-spouse': 0, 'Divorced': 0, 'Separated': 0, 'Widowed': 0, 'Married-spouse-absent': 0}}

====================

loss_metric: 2.0554451968758123
generalization vector: (1, 0, 1, 2)
max suppression: 7
```

```
===================
anonymized table:
age        gender     race     marital_status
occupation
0     (35, 40)   Male    *          *     Adm-
clerical
2     (35, 40)   Male    *          *  Handlers-
cleaners
10     (35, 40)   Male    *          *     Exec-
managerial
18      (35, 40)      Male      *              *
Sales
22    (35, 40)   Male    *          *   Farming-
fishing
...     ...    ...  ...        ...          ...
19045   (80, 85)   Female     *               *
Other-service
19495  (80, 85)  Female    *          *    Exec-
managerial
19515   (80, 85)   Female     *               *
Other-service
20482   (80, 85)   Female     *               *
Adm-clerical
26731  (80, 85)  Female    *          *     Prof-
specialty

[30155 rows x 5 columns]
===================
```

V. Results Overview

The Samarati algorithm was executed with k=10 and maxsup=20. After execution, the anonymized table was generated, along with other relevant information such as loss metric, generalization vector, and max suppression. Here's a summary of the key results:

- **Loss Metric:** The loss metric calculated for the anonymized table was approximately 2.055. This metric indicates the level of information loss incurred due to data generalization. A higher loss metric suggests a greater degree of generalization and, consequently, increased information loss.

- **Generalization Vector:** The selected generalization vector, (1, 0, 1, 2), denotes the number of levels to generalize each attribute. For example, 'age' was generalized to a depth of 1, 'gender' and 'race' remained unaltered (0), and 'marital_status' was generalized to a depth of 2.

- **Max Suppression:** The maximum suppression value was reported as 7. Max suppression refers to the maximum number of tuples that can be suppressed to achieve k-anonymity.

- **Anonymized Table:** The anonymized table presented the generalized attributes ('age', 'gender', 'race', 'marital_status') along with the retained 'occupation' attribute. This table satisfies the k-anonymity requirement, ensuring that each QI cluster contains at least 10 tuples.

Evaluation

Loss Metric Analysis

The calculated loss metric of approximately 2.055 indicates a moderate level of information loss in the anonymized data. This suggests that while the data has been generalized to ensure anonymity, a considerable amount of information has been sacrificed. However, the chosen generalization level balances anonymity requirements with the preservation of data utility.

Generalization Vector

The selected generalization vector [(1, 0, 1, 2)] provides insight into the degree of generalization applied to each attribute. Notably, attributes like 'gender' and 'race' were not generalized ('0' value), indicating that preserving these attributes in their original form was deemed acceptable from a privacy perspective.

Max Suppression

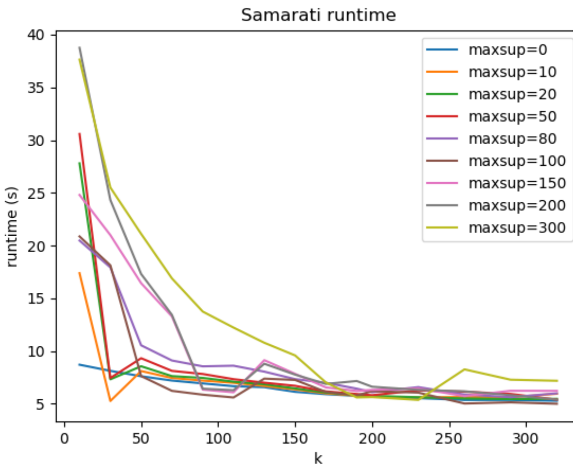
The reported max suppression value of 7 suggests that up to 7 tuples were suppressed during the anonymization process to meet the k-anonymity requirement. Suppressing tuples helps in preventing identification of individuals based on unique attribute combinations.

Anonymized Table Examination

The anonymized table demonstrates the effectiveness of the Samarati algorithm in achieving k-anonymity while retaining the essential characteristics of the dataset. Each QI cluster in the table contains at least 10 tuples, ensuring that individuals remain indistinguishable within their respective groups.

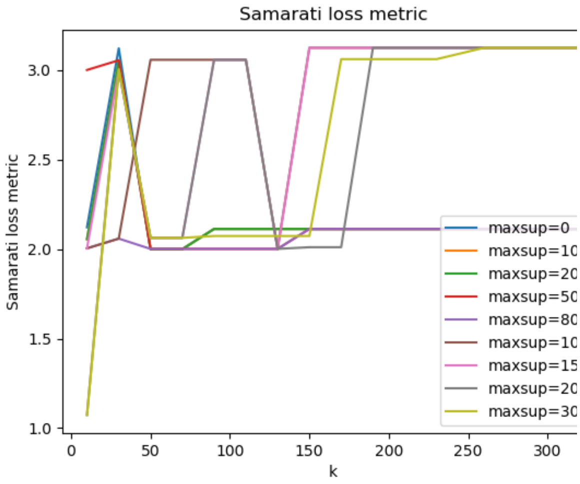
Runtime

- Samarati runtime with different k and maxsup:



Loss Metric

- Samarati loss metric with different k and maxsup:



Conclusion:

Based on the experiments conducted on Samarati's algorithm, several key insights can be drawn regarding its performance, impact of k, effect of maxsup parameter, and the trade-off between utility and privacy.

Performance Analysis

Samarati's algorithm exhibits a predictable runtime behavior. As k increases, the runtime decreases. This trend is intuitive since a higher k value allows for coarser generalization, reducing the number of potential solutions and thus lowering computational complexity. However, it's worth noting that the runtime may increase with higher values of the maxsup parameter due to the algorithm considering more suppression possibilities.

Impact of k

The parameter k plays a crucial role in Samarati's algorithm. Increasing k leads to stronger privacy guarantees as it requires larger equivalence classes, thus making it harder to identify individuals. However, this comes at the cost of reduced utility, as the generalization becomes more aggressive, potentially losing valuable information.

Effect of maxsup Parameter

The maxsup parameter regulates the maximum number of suppressed tuples allowed during the anonymization process. Higher values of maxsup may increase runtime and lead to higher loss metrics, as the algorithm explores more suppression possibilities. However, it provides flexibility in balancing privacy and utility, allowing for a finer control over the anonymization process.

Utility and Privacy Trade-off

Samarati's algorithm offers a trade-off between utility and privacy. By adjusting the k parameter, users can tailor the level of anonymity to their specific requirements. Higher values of k result in stronger privacy guarantees but may sacrifice utility, while lower values strike a balance between privacy and utility by preserving more information. Similarly, tuning the maxsup parameter allows users to fine-tune the trade-off, providing flexibility in achieving the desired level of privacy without compromising too much on utility.

In conclusion, Samarati's algorithm provides an effective means of achieving k-anonymity while offering flexibility in balancing privacy and utility.

Understanding its performance characteristics and the impact of key parameters is essential for making informed decisions during the anonymization process.

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