

COMPARATIVE STUDY OF K-ANONYMITY ALGORITHMS FOR PRIVACY
PRESERVING DATAMINING

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This project is dedicated to my family for their endless support and encouragement.

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ABSTRACT

Nowadays, privacy issue becomes one of the main concerns of persons among their raw data. This happens at a time, when more and more historically public information is also electronically available. When these data are linked together, they provide an electronic shadow of a person or organization that is as identifying and personal as a fingerprint even when the information contains no explicit identifiers, such as name and phone number. Other distinctive data, such as birth date and ZIP code, often combine uniquely and can be linked to publicly available information to re-identify individuals. However, there are several k-anonymity algorithms available in the literature to solve that problem such as Datafly and Incognito. Nevertheless, their study of performances in terms of efficiency and accuracy is lacking. In this study, we compare these two k-anonymity algorithms. So that users can select which algorithm is more suitable for their data mining. The finding shows that Datafly gives higher overall efficiency. Comparing with Incognito which gives high accuracy. Consistent good performance of Incognito in k-anonymity has made a promising k-anonymity techniques to be used in the Privacy Preserving Technique.

ABSTRAK

Pada masa kini, isu privasi menjadi salah satu keprihatinan seseorang tentang data Asal. Ini terjadi apabila semakin banyak sejarah maklumat umum diperolehi secara elektronik. Apabila data ini berhubungan antara satu sama lain, data tersebut memberikan bayangan elektronik tentang seseorang atau organisasi yang dikenalpasti dan sulit seperti cap jari walaupun maklumat tersebut tiada pengenalan yang nyata seperti nama dan nombor telefon. Data yang berkaitan lain seperti tarikh lahir dan kod ZIP, sering digabungkan dan dihubungkan untuk dipaparkan pada umum untuk mengenalpasti semula seseorang individu. Walaubagaimanapun, terdapat banyak algoritma k-anonimiti di dalam penyelidikan untuk menyelesaikan masalah tersebut seperti Datafly dan Incognito. Tambahan lagi, kajian tentang prestasi daripada segi kadar efisyensi dan ketepatan adalah lemah. Dalam kajian ini, kami membandingkan kedua-dua algoritma k-anonimiti ini. Supaya pengguna dapat pilih algoritma mana yang lebih sesuai untuk kenalpasti data. Penemuan ini menunjukkan bahawa Datafly memberikan kadar efisyensi yang lebih tinggi secara keseluruhannya. berbanding dengan Incognito yang memberikan lebih tinggi kadar ketepatannya. Kestabilan prestasi incognito yang baik dalam k-anonimiti membuatkan teknik k-anonimiti yang meyakinkan untuk digunakan di dalam Teknik Pengekalan Privasi.

TABLE OF CONTENTS

CHAPTER	TITLE	PAGE
	DECLARATION	ii
	DEDICATION	iii
	ACKNOWLEDGMENT	iv
	ABSTRACT	v
	ABSTRAK	vi
	TABLE OF CONTENTS	vii
	LIST OF TABLES	xi
	LIST OF FIGURES	xii
	LIST OF ABBREVIATION	xiv
1	INTRODUCTION	1
	1.1 Introduction	1
	1.2 Problem Background	2
	1.3 Problem Statement	4
	1.4 Purpose of study	4
	1.5 Objectives of Study	4
	1.6 Scope of Study	5
	1.7 Significant Study	5
	1.8 Organization of Report	5
2	LITERATURE REVIEW	7
	2.1 Introduction	7
	2.2 Database	7
	2.3 Data Mining	8

2.4	The Privacy	9
2.4.1	Privacy Preserving Data Mining	9
2.4.2	Application Scenarios	10
2.4.2.1	Surveys and Data Collection	10
2.4.2.2	Product Traceability	10
2.4.2.3	Medical Research	10
2.4.2.4	Social Networks	11
2.4.3	Techniques of Privacy Preserving	11
2.4.3.1	Method of Anonymization	11
2.4.3.2	Randomization Techniques (RT)	14
2.4.3.3	Condensation approach	18
2.4.3.4	Cryptographic Technique	19
2.4.3.5	Distributed Privacy Preserving Data Mining	21
2.5	Strengths and Weaknesses of PPDM Techniques	21
2.6	K-Anonymity	22
2.6.1	Quasi-identifier	23
2.6.2	Generalization Hierarchy	23
2.6.3	Global recoding	25
2.6.4	Local recoding	25
2.6.5	Minimal Generalization	28
2.6.6	Tuple suppression	28
2.6.7	Limitations of k-anonymity	29
2.7	K- anonymity Algorithms	29
2.7.1	Incognito algorithm	29
2.7.1.1	Basic Incognito Algorithm	31
2.7.2	Datafly Algorithm	32
2.7.2.1	Work of Datafly	33
2.7.3	Features of Datafly and Incognito Algorithms	37
2.8	The Goal of PPDM Algorithms	38
2.9	Quantification of PPDM Algorithms	39
2.10	Parameters Evaluation	39
2.10.1	Efficiency	39
2.10.2	Accuracy	40

2.11	Summary	42
3	METHODOLOGY	43
3.1	Introduction	43
3.2	The Research Development Phases	44
3.2.1	Phase 1: Review PPDM Methods	46
3.2.2	Phase 2: Dataset	46
3.2.3	Phase 3: Evaluation of Algorithms	47
3.2.4	Efficiency	48
3.2.5	Accuracy	48
3.3	Evaluation Requirements Tools	49
2.4	Summary	51
4	DATA PREPARATION AND DATAFLY RESULTS	52
4.1	Introduction	52
4.2	Data Preparation	52
4.2.1	Input Format	55
4.2.2	Output Format	55
4.2.3	Configuration File	55
4.3	Efficiency Measurement Configuration	57
4.4	Accuracy Measurement Configuration	59
4.5	Implementation of Datafly	60
4.5.1	Working Procedures of the Datafly Algorithm	61
4.6	Results of Datafly Algorithm	61
4.6.1	Results of Datafly Efficiency	61
4.6.2	Results of Datafly Accuracy	63
4.7	Summary	65
5	INCOGNITO RESULTS AND ANALYSIS	67
5.1	Introduction	67
5.2	Implementation of Incognito	67
5.2.1	Efficiency Results of Incognito algorithm	68
5.2.2	Accuracy Results of Incognito	69

5.3	Comparison results of Datafly and Incognito algorithms	72
5.4	Overall of Comparison	76
5.5	Summary	78
6	CONCLUSION AND FUTURE WORK	79
6.1	Introduction	79
6.2	Project Achievements and Challenges	79
6.3	Future Work	80
6.4	Summary	81
	REFERENCE	82
	APPENDIX A	88
	APPENDIX B	91

LIST OF TABLES

TABLE NO	TITLE	PAGE
2.1	Strengths and Weaknesses of different Techniques of PPDM	21
2.2	De-identified table	25
2.3	2-anonymized via local recoding	26
2.4	2-anonymized via global recoding	26
2.5	Global recoding with suppression	27
2.6	Simple Representation of a private table	30
2.7	Intermediate stages of the core Datafly algorithm (A)	35
2.8	Intermediate stages of the core Datafly algorithm (B)	36
2.9	MGT is resulting from Datafly	36
2.10	Similar Features of Datafly and Incognito Algorithms	38
3.1	Summary of the UCI "Adult" dataset.	47
4.1	Adult Datasets Description	53
4.2	Parameters of Comparison	54
5.1	Overall Result of Comparison	77

LIST OF FIGURES

FIGURE NO	TITLE	PAGE
2.1	The model of Randomization	14
2.2	Example of GH for Race	24
2.3	Example of GH for Marital Status	24
2.4	Example of GH for Age	24
2.5	Sub-hierarchies computed for the table in Figure 2.5 by Incognito	30
2.6	Basic Incognito Algorithm	32
2.7	Core Datafly Algorithm	34
3.1	Operational Framework	45
4.1	Configuration File	55
4.2	VGHs of Age and Sex attributes	56
4.3	Batch File of Time Measurement	57
4.4	SQL Statement of Information loss	60
4.5	Efficiency of Datafly	62
4.6	Accuracy of Datafly in 5000 rows	63
4.7	Accuracy of Datafly in 15000 rows	64
4.8	Accuracy of Datafly in 30000 rows	64
4.9	The percentage of Lost Data by Datafly Algorithm	65
5.1	Efficiency of Incognito	68
5.2	Accuracy of Incognito in 5000 rows	69
5.3	Accuracy of Incognito in 15000 rows	70
5.4	Accuracy of Incognito in 30000 rows	71
5.5	The percentage of Lost Data by Incognito Algorithm	72
5.6	Comparison of Efficiency for Datafly and Incognito	73

5.8	Comparison of Accuracy for both algorithms on 15000 rows	75
5.9	Comparison of Accuracy for both algorithms for 30000 rows	76

LIST OF ABBREVIATION

ABBREVIATION	DEFINITION
DM	Data Mining
PPDM	Privacy Preserving Data Mining
HIPAA	Health Insurance Portability and Accountability Act
IL	Information Loss
k	The anonymization level
PT	Private Table
QI	Quasi-Identifier
SSN	SSN Social Security Number
DGH	Domain Generalization Hierarchy
MGT	Modified Generalization Table
VGH	Value of Generalization Hierarchy

CHAPTER 1

INTRODUCTION

1.1 Introduction

Nowadays the size of the data, which is collected daily by the public and private institutions are increasing dramatically. The process of extracting enormous of datasets by data mining has become very important to help decision making processes. In contrast, contain explicitly data sets for data mining can be used to imply to information consist of the original data that might not be intended to release for the public. Therefore, there is a privacy violation for those who refer to whom these data. Data mining can be prevented these data sets only if there are safeguards from compromising the privacy. It has been suggested the concept of privacy preserving data mining (PPDM) In response to these concerns privacy (Ciriani, 2008).

The privacy is considered one of the most critical characteristics of information systems which should be offered. Thus, there are several efforts have been suggested to integrating many techniques to maintain the privacy in order to safeguard obtains sensitive information through the extract the knowledge. It can be classified existing conservation techniques of data mining and according to the dimensions of the following five different (Verykios, 2004):

- (i) Data distribution (central or distributed).

- (ii) The amendment applied to the data (encryption, disorder, generalization, and so on) in order to cleanse them.
- (iii) Algorithm to extract the data that has been designed this technique to save the privacy.
- (iv) Type of data which need it for the protection from disclosure.
- (v) The method adopted for privacy preservation.

There are several techniques such as K-anonymity and randomization (Rakesh Agrawal, 2000, Samarati, 1998, Dakshi Agrawal, 2001) that have been proposed in the last years for the performance and privacy of data mining. Moreover, the problem has been explained in different communities, such as a database group, and community statistical disclosure control and encryption community (Charu, 2007).

The privacy of the individual to whom the data belongs to, released data were at first “de-identified” by deleting explicit identifiers for instance names, addresses, and phone numbers. However this de-identified data could still have other identifying characteristics such as birth date, postal code, race and sex, when they are considered all together, almost uniquely relate to specific individuals. These sets of characteristics are often called *quasi-identifiers*. For instance, in one statistic, Sweeney finds out that 87.1% of the US population can be uniquely identified by the combination of their 5-digit zip code, gender, and date of birth because such records can be linked to publicly available databases such as voter lists and driving records (Sharow 2007).

1.2 Problem Background

K-anonymization is a technique that prevents joining attacks by generalizing and suppressing portions of the released microdata so that no individual can be uniquely distinguished from a group of size k . The real-world algorithms Datafly and μ -Argus are compared to MinGen. Both Datafly and μ -Argus use heuristics to make

approximations, and so, they do not always yield optimal results (Sweeney, 2002). It is shown that Datafly can over distort data and μ -Argus can additionally fail to provide adequate protection. One of the problems is that Datafly makes crude decisions—generalizing all values associated with an attribute and suppressing all values within a tuple.

The view of k-anonymization problem from the perspective of inference attacks over all possible combinations of attributes. (Ciriani, 2007) showed that when the data contains a large number of attributes which may be considered quasi-identifiers; it becomes difficult to anonymize the data without an unacceptably high amount of information loss. This is because an exponential number of combinations of dimensions can be used to make precise inference attacks, even when individual attributes are partially specified within a range (Vijayarani, 2010). The provided analysis of the effect of dimensionality on k-anonymity methods, conclude that when a data set contains a large number of attributes which are open to inference attacks, are faced with a choice of either completely suppressing most of the data or losing the desired level of anonymity.

There are many algorithms under the k-anonymity technique have been proposed to preserve the privacy in data mining such as Bayardo-Agrawal (Bayardo, 2005), Mondrian (Samarati, 2001) and Approximation Algorithms (Gagan Aggarwal, 2005) all these algorithms use different standards to measure the quality of output and try to improve production against those standards. However, in the context of data, the trade-off between speed and optimality is not possible since researchers need to work on an anonymized data set with minimal information loss. Moreover, as opposed to the heuristic-based approaches, by insuring an optimal solution that can be located efficiently, researchers will benefit immensely, for the better the quality of the anonymized data the more valuable that data is for the research. Among these algorithms, the Datafly (Sweeney, 1997) and Incognito (David, 2005) are the most popular approaches in the privacy preserving data mining. Several studies have evaluated the results of k-anonymization algorithms based on a particular data mining task, such as information loss and efficiency (Issa, 2009), (Nurul H, 2012) and (Khaled Elemam, 2009). However, the evaluation of information loss has not previously been explored

by using the global metric (Dissimilarity Metric). Specially, to evaluate Datafly and Incognito algorithms

1.3 Problem Statement

In the midst of the vast amount of information available electronically led to the disclosure of individual privacy. When these data are linked together, they provide an electronic shadow of a person or organization that is as identifying and personal as a fingerprint even when the information contains no explicit identifiers, such as name and phone number. There are several k-anonymity algorithms available in the literature, however their study on performances in terms of efficiency and accuracy is lacking. In this study, we are going to compare these two k-anonymity algorithms. So that users can select which algorithm is more suitable for their data mining.

1.4 Purpose of Study

In this research the performance of K-anonymity algorithms namely Incognito and Datafly were compared in terms of efficiency and accuracy (Information loss). At the end of this comparison, an analysis of their performances was discussed and the algorithm that shows better performance is highlighted and recommended.

1.5 Objective of Study

This research has the following objectives:

- i. Studying the Privacy Preserving Data Mining.

- ii. Evaluating the performance of Datafly and Incognito algorithms in Privacy Preserving Data Mining.

1.6 Scope of Study

The scope of the project is listed below:

- i. The data being used in this study were from the University of California, Irvine (UCI) Cup 1996 Census dataset. Its size is 30000 rows.
- ii. Weka 3.6.9 being used to implement the evaluation.
- iii. Performance was evaluated based on efficiency and accuracy (Information loss) metrics.

1.7 Significant of Study

This study evaluates the performance of two k-anonymity algorithms namely Datafly and Incognito for privacy preserving data mining in terms of efficiency and accuracy. By studying each one and investigate them to show which one is more suitable to be used in privacy preserving in data mining.

1.8 Organization of Report

The thesis consists of 4 chapters. Chapter one describes the introduction, background of the study, research objectives and questions, the scope of the study and its primary objectives. The second chapter reviews available and related literature on Privacy Preserving in data mining, K-anonymity approaches. Chapter three describes the study methodology along with the appropriate framework for the

study. The fourth chapter provides the analysis of the preliminary results of the study.

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