CS-523 Advanced topics on Privacy Enhancing Technologies

Privacy-preserving Data Publishing I
Live exercises

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Key	Gender	Zipcode	Age	Disease
Eric	M	1007	25	Cancer
Justine	F	1012	25	Heart Disease
Emma	F	1012	25	Flu
Helen	F	1012	*	Flu
Paul	M	1007	25	Cancer
Philip	M	1012	35	Herpes
Michel	M	1012	35	Cancer
Mory	M	1007	25	Cancer
Adrien	M	1007	25	Heart Disease
Mallory	M	1012	35	Flu
Camille	F	1012	25	Herpes
Samuel	M	1012	35	Cancer
Marco	M	1007	*	Cancer
Damien	M	1012	35	Flu

Consider only the *Gender, Zipcode, Age* attributes.

Which statement is TRUE?

(A) The database achieves k-anonymity with k = 4.

(B) The database does not achieve k-anonymity for any k.

(C) The database achieves k-anonymity with k = 1.

(D) The database achieves k-anonymity with k = 2.

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Emma	F	1012	25	Flu
Helen	F	1012	*	Flu
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Michel	M	1012	35	Cancer
Mory	M	1007	25	Cancer
Adrien	M	1007	25	Heart Disease
Mallory	M	1012	35	Flu
Camille	F	1012	25	Herpes
Samuel	M	1012	35	Cancer
Marco	M	1007	*	Cancer
Damien	M	1012	35	Flu

Consider *Gender, Zipcode, Age* *as quasi-identifying* attributes.

Which statement is TRUE?

(A) The database achieves k-anonymity with k = 4.

(B) The database does not achieve k-anonymity for any k.

(C) The database achieves k-anonymity with k = 1.

(D) The database achieves k-anonymity with k = 2.

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Marco	M	1007	*	Cancer
Damien	M	1012	35	Flu

Consider the *Disease* attribute to be sensitive.

Which statement is TRUE?

(A) The database achieves 3-diversity.

(B) The database is differentially private.

(C) The database achieves 5-diversity.

(D) None of the above

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Damien	M	1012	35	Flu

Consider the *disease* attribute to be sensitive.

Which statement is TRUE?

(A) The database achieves 3-diversity.

(B) The database is differentially private.

(C) The database achieves 5-diversity.

(D) None of the above

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Consider *Age as quasi-identifying and Disease* as the sensitive attribute.

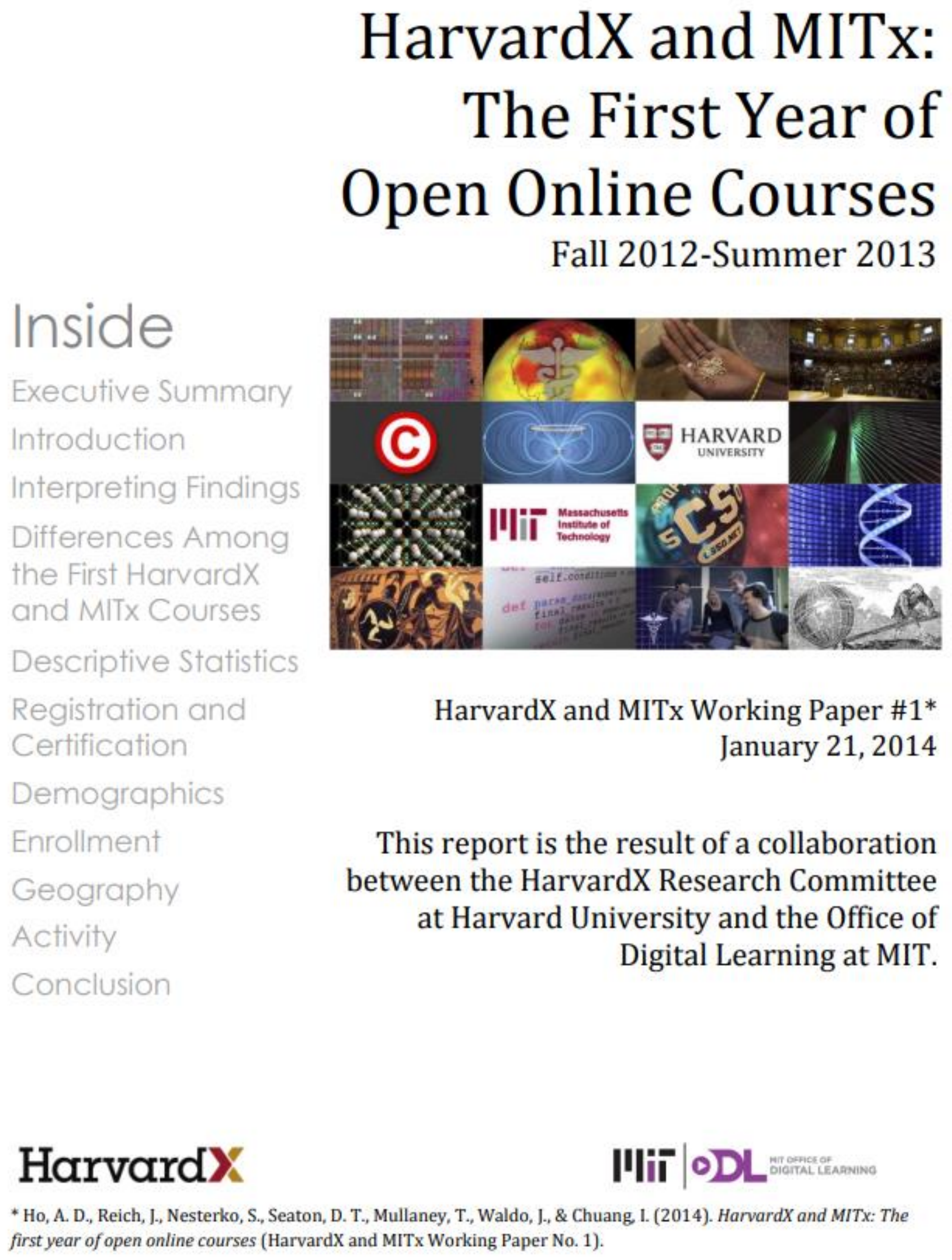
Which statement is TRUE?

(A) The database achieves 3-diversity.

(B) The database is differentially private.

(C) The database achieves 5-diversity.

(D) None of the above



HarvardX and MITx: The First Year of Open Online Courses

Fall 2012-Summer 2013

Inside

HarvardX and MITx Working Paper #1*
January 21, 2014

This report is the result of a collaboration between the HarvardX Research Committee at Harvard University and the Office of Digital Learning at MIT.

HarvardX MIT ODL MIT OFFICE OF DIGITAL LEARNING

* Ho, A. D., Reich, J., Nesterko, S., Seaton, D. T., Mullaney, T., Waldo, J., & Chuang, I. (2014). *HarvardX and MITx: The first year of open online courses* (HarvardX and MITx Working Paper No. 1).

- 597,692 individuals registered for 17 online courses offered by Harvard and MIT through the EdX platform

- Data collected: students' demographics, engagement with course content, and final course grade

- "To meet these privacy specifications, the HarvardX and MITx research team (guided by the general counsel, for the two institutions) opted for a k-anonymization framework" [3]. A value of k = 5 "was chosen to allow legal sharing of the data" in accordance with FERPA. Ultimately, EdX published the 5-anonymized dataset with 476,532 students' records"

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- Published data **Xed**:
    - Basic demographics: self-reported level of education, gender, and year of birth, country (inferred from the student's IP address)
    - Activities and Results in 16 out of 17 courses
        - Results: enrolled, grade, certification status
        - Activities: e.g., number of posts in course
- K-anonymized (Generalization and supression) with respect to:
    - $Q*$ = {enrolled in course 1, . . . , enrolled in course 16}
    - Qi = {gender, year of birth, country, enrolled in course i, number of forum posts in course i}

- If you were a student of one of these courses: what would be the privacy concerns? What adversaries would you worry about?

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- If you were a student of one of these courses would you say it is safe?

- Does the order of k-anonymization matter?

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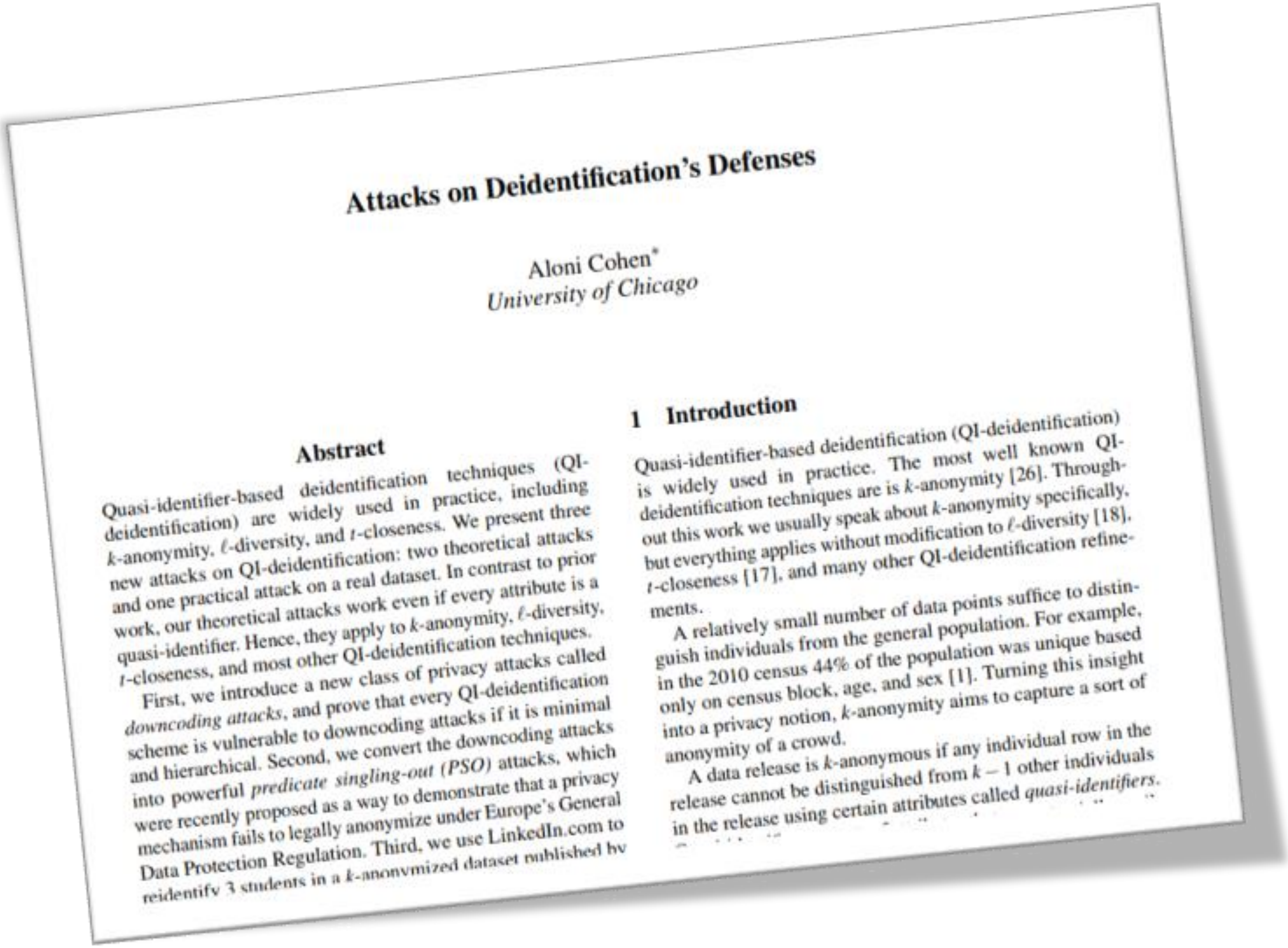
- If you were a student of one of these courses would you say it is safe?

- Does the order of k-anonymization matter?

- If you found a unique record… how would you re-identify?

More on the Xed fiasco and other attacks



Attacks on Deidentification's Defenses

Aloni Cohen*
University of Chicago

Abstract

Quasi-identifier-based deidentification techniques (QI-deidentification) are widely used in practice, including k-anonymity, ℓ-diversity, and t-closeness. We present three new attacks on QI-deidentification: two theoretical attacks and one practical attack on a real dataset. In contrast to prior work, our theoretical attacks work even if every attribute is a quasi-identifier. Hence, they apply to k-anonymity, ℓ-diversity, t-closeness, and most other QI-deidentification techniques.

First, we introduce a new class of privacy attacks called *downcoding attacks*, and prove that every QI-deidentification scheme is vulnerable to downcoding attacks if it is minimal and hierarchical. Second, we convert the downcoding attacks into powerful *predicate singling-out (PSO)* attacks, which were recently proposed as a way to demonstrate that a privacy mechanism fails to legally anonymize under Europe's General Data Protection Regulation. Third, we use LinkedIn.com to reidentify 3 students in a k-anonymized dataset published by

1 Introduction

Quasi-identifier-based deidentification (QI-deidentification) is widely used in practice. The most well known QI-deidentification techniques are is k-anonymity [26]. Throughout this work we usually speak about k-anonymity specifically, but everything applies without modification to ℓ-diversity [18], t-closeness [17], and many other QI-deidentification refinements.

A relatively small number of data points suffice to distinguish individuals from the general population. For example, in the 2010 census 44% of the population was unique based only on census block, age, and sex [1]. Turning this insight into a privacy notion, k-anonymity aims to capture a sort of anonymity of a crowd.

A data release is k-anonymous if any individual row in the release cannot be distinguished from $k-1$ other individuals in the release using certain attributes called *quasi-identifiers*.