18734: Foundations of Privacy

Database Privacy: k-anonymity and de-anonymization attacks

Anupam Datta
CMU

Fall 2016

Publicly Released Large Datasets

- Useful for improving recommendation systems, collaborative research
- Contain personal information
- Mechanisms to protect privacy, e.g. anonymization by removing names
- Yet, private information leaked by attacks on anonymization mechanisms

NETFLIX

movielens
helping you find the *right* movies

PACER
PUBLIC ACCESS TO COURT ELECTRONIC RECORDS

amazon.com

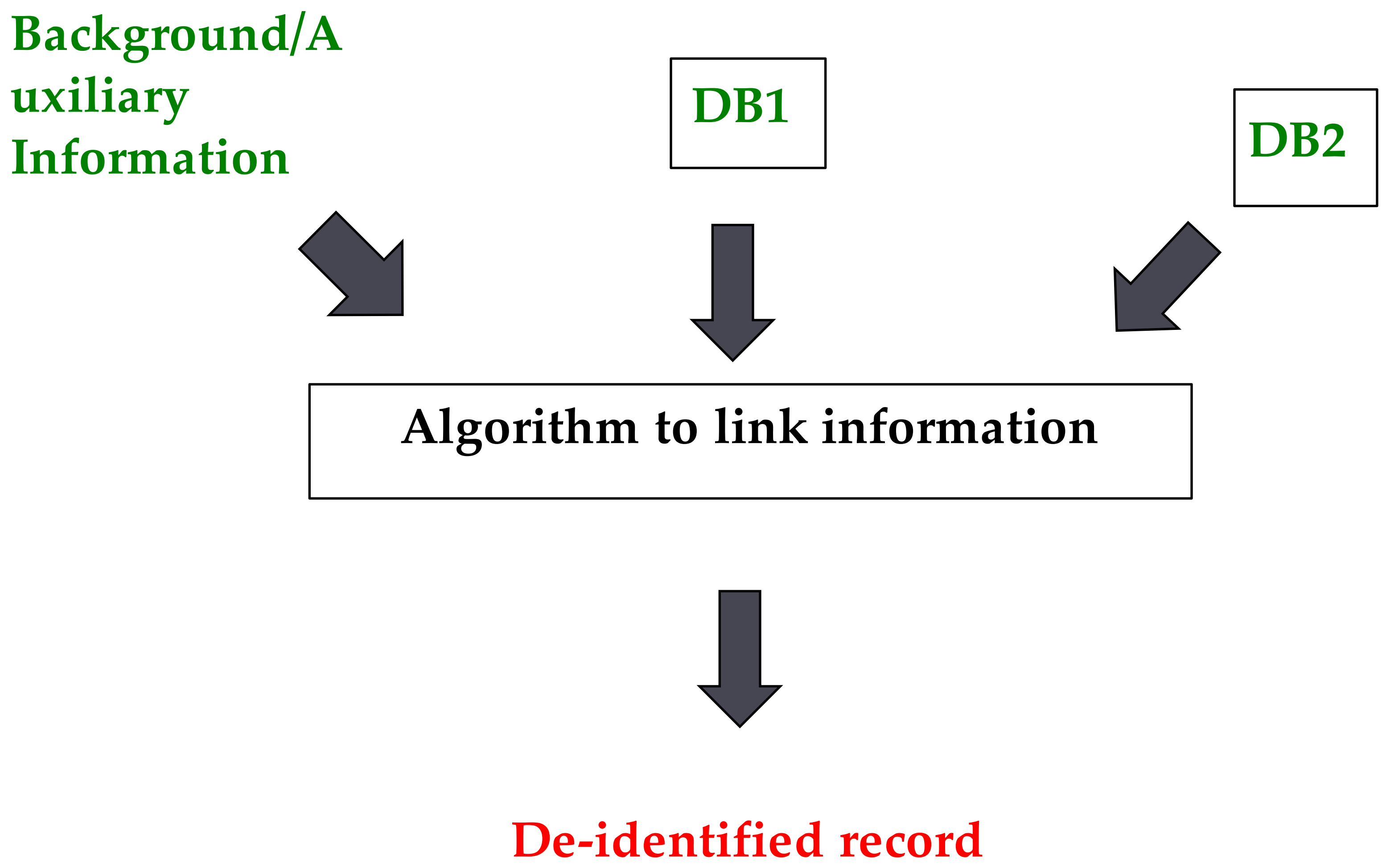
WIKIPEDIA
The Free Encyclopedia

Article Discussion

AOL search data leak

From Wikipedia, the free encyclopedia

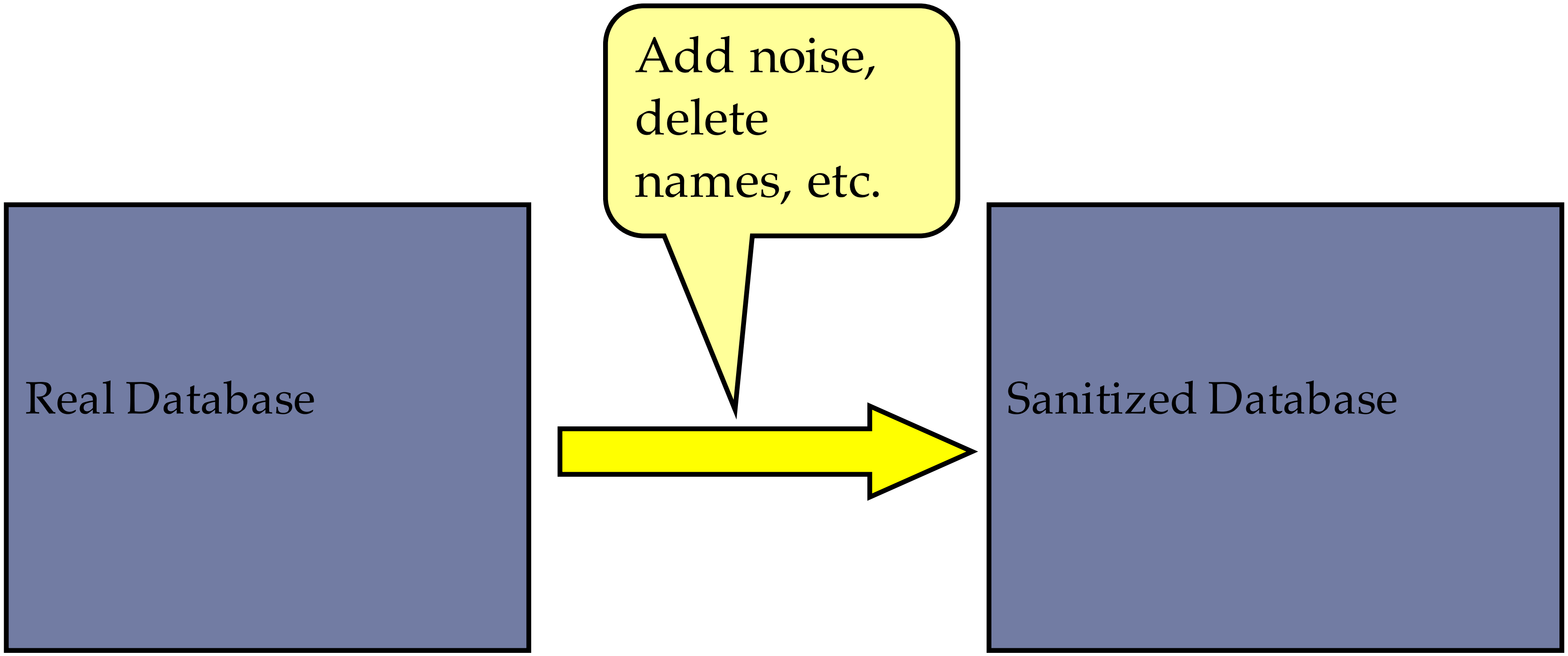
Non-Interactive Linking



Roadmap

- ~~Motivation~~
- Privacy definitions
- Netflix-IMDb attack
- Theoretical analysis
- Empirical verification of assumptions
- Conclusion

Sanitization of Databases



Health records

Census data

Protect privacy

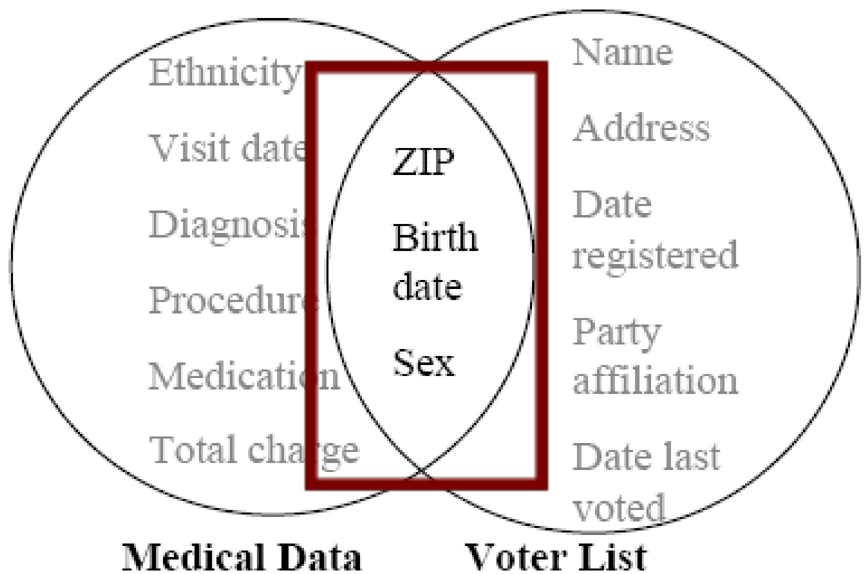
Provide useful information (utility)

Database Privacy

- Releasing sanitized databases
  1. k-anonymity [Samarati 2001; Sweeney 2002]
  2. Differential privacy [Dwork et al. 2006] (*future lecture*)

Re-identification by linking

Linking two sets of data on shared attributes may uniquely identify some individuals:



87 % of US population uniquely identifiable by 5-digit ZIP, gender, DOB

K-anonymity

- Quasi-identifier: Set of attributes that can be linked with external data to uniquely identify individuals
- Make every record in the table indistinguishable from at least *k-1* other records with respect to quasi-identifiers
- Linking on quasi-identifiers yields at least *k* records for each possible value of the quasi-identifier

K-anonymity and beyond

	Non-Sensitive			Sensitive
	Zip Code	Age	Nationality	Condition
1	13053	28	Russian	Heart Disease
2	13068	29	American	Heart Disease
3	13068	21	Japanese	Viral Infection
4	13053	23	American	Viral Infection
5	14853	50	Indian	Cancer
6	14853	55	Russian	Heart Disease
7	14850	47	American	Viral Infection
8	14850	49	American	Viral Infection
9	13053	31	American	Cancer
10	13053	37	Indian	Cancer
11	13068	36	Japanese	Cancer
12	13068	35	American	Cancer

Figure 1. Inpatient Microdata

	Non-Sensitive			Sensitive
	Zip Code	Age	Nationality	Condition
1	130**	< 30	*	Heart Disease
2	130**	< 30	*	Heart Disease
3	130**	< 30	*	Viral Infection
4	130**	< 30	*	Viral Infection
5	1485*	≥ 40	*	Cancer
6	1485*	≥ 40	*	Heart Disease
7	1485*	≥ 40	*	Viral Infection
8	1485*	≥ 40	*	Viral Infection
9	130**	3*	*	Cancer
10	130**	3*	*	Cancer
11	130**	3*	*	Cancer
12	130**	3*	*	Cancer

Figure 2. 4-anonymous Inpatient Microdata

Provides some protection: linking on ZIP, age, nationality yields 4 records

Limitations: lack of diversity in sensitive attributes, background knowledge, subsequent releases on the same data set

l-diversity, m-invariance, t-closeness, …

Re-identification Attacks in Practice

Examples:

- Netflix-IMDB
- Movielens attack
- Twitter-Flicker
- Recommendation systems – Amazon, Hunch,..

Goal of De-anonymization: To find information about a record in the released dataset

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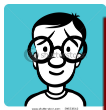
Anonymization Mechanism



	Gladiator	Titanic	Heidi
Bob	5	2	1
Alice	3	2.5	2
Charlie	1.5	2	2

Each row corresponds to an individual

Each column corresponds to an attribute, e.g. movie

Delete name identifiers and add noise

	Gladiator	Titanic	Heidi
r_1	4	1	0
r_2	2	1.5	1
r_3	0.5	1	1

Anonymized Netflix DB

De-anonymization Attacks Still Possible

- Isolation Attacks
  - Recover individual's record from anonymized database
  - E.g., find user's record in anonymized Netflix movie database
- Information Amplification Attacks
  - Find more information about individual in anonymized database
  - E.g. find ratings for specific movie for user in Netflix database

Netflix-IMDb Empirical Attack [Narayanan et al 2008]

Anonymized Netflix DB

	Gladiator	Titanic	Heidi
r_1	4	1	0
r_2	2	1.5	1
r_3	0.5	1	1

Publicly available IMDb ratings (noisy)

	Titanic	Heidi
Bob	2	1

Used as auxiliary information

Weighted Scoring Algorithm

Isolation Attack!

r_1	4	1	0

Problem Statement

Anonymized database

	Gladiator	Titanic	Heidi
r_1	4	1	0
r_2	2	1.5	1
r_3	0.5	1	1

Auxiliary information about a record (noisy)

	Titanic	Heidi
Bob	2	1

Attacker uses algorithm to find record

Attacker's goal: Find r_1 or record similar to Bob's record

Enhance theoretical understanding of why empirical de-anonymization attacks work

Research Goal

Characterize classes of auxiliary information and properties of database for which re-identification is possible

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Netflix-IMDb Empirical Attack [Narayanan et al 2008]

Anonymized Netflix DB

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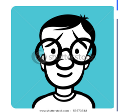


	Titanic	Heidi
Bob	2	1

Used as auxiliary information

What does **auxiliary information** about a record mean?

Weighted Scoring Algorithm

How do you measure similarity of this record with Bob's record? **(Similarity Metric)**

r_1	4	1	0

Definition: Asymmetric Similarity Metric

	Gladiator v_1	Titanic v_2	Heidi v_3
y	5	0	-
r	0	2	3

Individual Attribute Similarity

$$T(y(i),r(i)) = 1 - \frac{|y(i) - r(i)|}{p(i)}$$

$$T(y(v_1),r(v_1)) = 1 - \frac{|5-0|}{5} = 0$$

p(i): range of attribute *i*

Intuition: Measures how closely two people's ratings match on one movie

Movie (i)	T(y(i), r(i))
Gladiator	0
Titanic	0.6
Heidi	0

Similarity Metric

$$S(y,r) = \sum_{i \in supp(y)} \frac{T(y(i),r(i))}{|supp(y)|}$$

supp(y): non null attributes in *y*

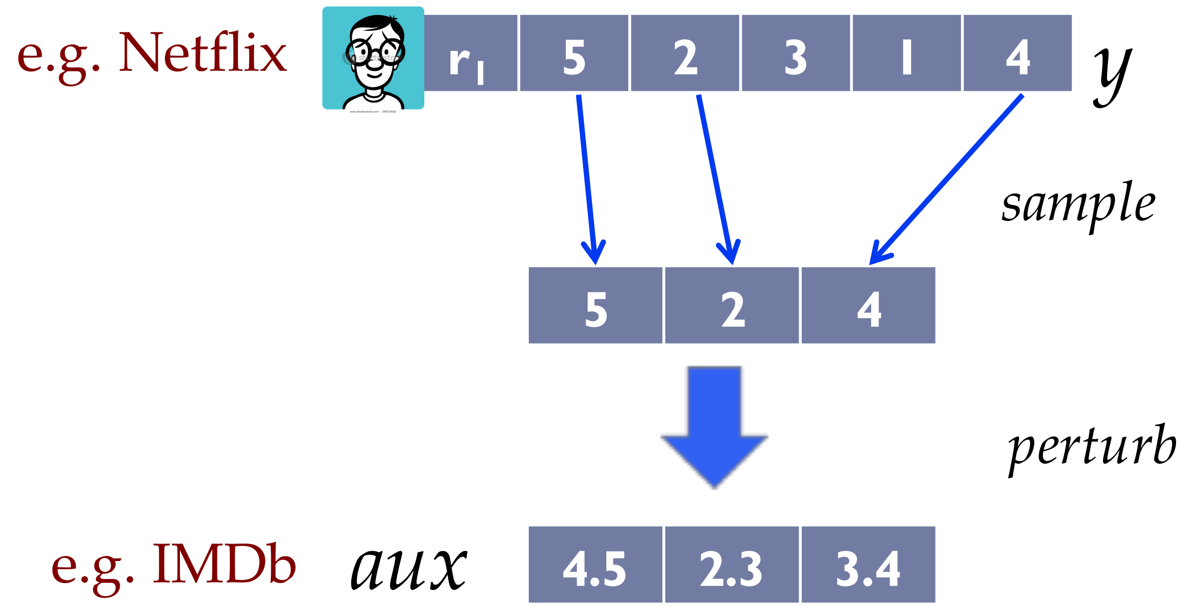
Intuition: Measures how closely two people's ratings match overall

S(y,r)	0.6 / 2 = 3

Definition: Auxiliary Information

Intuition:
aux about *y* should be a subset of record *y*
aux can be noisy

aux captures information available outside normal data release process



Bound level of perturbation in *aux*

$$\gamma \in [0,1]$$

(m,γ)-perturbed auxiliary information

$$\forall i \in \mathrm{supp}(aux)\ T(y(i), aux(i)) \geq 1 - \gamma$$

$|\mathrm{supp}(aux)| = m =$ no. of non null attributes in *aux*

Weighted Scoring [Narayanan et al 2008, Frankowski et al 2006]

Intuition: The fewer the number of people who watched a movie, the rarer it is

Weight of an attribute *i*

$$\boxed{w(i) = \frac{1}{\log(|\mathrm{supp}(i)|)}}$$

$|\mathrm{supp}(i)|$ = no. of non null entries in column i

Use weight as an indicator of rarity

Score gives a weighted average of how closely two people match on every movie, giving higher weight to rare movies

Scoring Methodology

$$Score(aux, r_j) = \sum_{i \in \mathrm{supp}(aux)} \frac{\boxed{w(i)} * T(aux(i), r_j(i))}{|\mathrm{supp}(aux)|}$$

$|\mathrm{supp}(aux)|$ = m = no. of non null attributes in aux

Compute *Score* for every record *r* in anonymized DB to find out which one is closest to target record *y*

Weighted Scoring Algorithm [Narayanan et al 2008]

Compute *Score* for every *r* in *D*

$$Score(aux, r_j) = \sum_{i \in supp(aux)} \frac{w(i) * T(aux(i), r_j(i))}{|supp(aux)|}$$

w_i	0.63	0.5	0.63
	v_1	v_2	v_3
r_1	5	2	-
r_2	3	1	4
r_3	-	2	4

$Score(aux, r_j)$
0.52
0.40
0.23

v_1	v_2
4.5	2.3

aux

One of the records *r* in anonymized database is *y*, which row is it?

Eccentricity measure > threshold

$$e(aux, D) = \max_{r \in D}(Score(aux, r)) - \max_{2, r \in D}(Score(aux, r))$$

Output record with max Score

r_1	5	2	-

Score(aux, r) used to predict *S(y,r)*

Where do Theorems Fit?

4.5	2.3

Computed:

Score of all records *r* in *D* with *aux*

r_1	5	2	-

Theorems help bridge the gap

4.5	2.3

Desired:

Guarantee about *Similarity*

r_1	5	2	-

Theorems

- Theorem 1: When Isolation Attacks work?
- Theorem 2: Why Information Amplification Attacks work?

Theorem 1: When Isolation Attacks work?

Intuition: If eccentricity is high, algorithm always finds the record corresponding to auxiliary information!

Eccentricity: Highest score - Second highest score

If

aux is (m,γ)-perturbed

Eccentricity threshold > γM

γ: Indicator of perturbation in aux
M : Average of weights in aux
$\breve{O}$: Record output by algorithm
y : Target record

then

$$Score(aux,\breve{O}) = Score(aux,y)$$

If $\breve{O}$ is the only record with the highest score then $\breve{O} = y$

Isolation Attack: Theorem

Theorem IV.1 *Let y denote the target record from a given database D. Let aux_y denote (m, γ)-perturbed auxiliary information about record y. If the eccentricity measure $e(aux_y, D) > \gamma M$ where $M = \frac{\sum_{i \in supp(aux_y)} w_i}{|supp(aux_y)|}$ is the scaled sum of weights of attributes in aux_y, then*

1) $\max_{r \in D}(Score(aux_y, r)) = Score(aux_y, y)$.
2) *Additionally, if only one record has maximum score value $= Score(aux_y, y)$, then the record o returned by the algorithm is the same as target record y.*

A. Datta, D. Sharma and A. Sinha. Provable De-anonymization of Large Datasets with Sparse Dimensions. In proceedings of *ETAPS First Conference on Principles of Security and Trust (POST 2012)*

Theorems

- ~~Theorem 1: When Isolation Attacks work?~~
- Theorem 2: Why Information Amplification Attacks work?

Intuition: Why Information Amplification Attacks work?

- If two records agree on rare attributes, then with high probability they agree on other attributes too

- Use intuition to find record *r* similar to *aux* on many rare attributes (using *aux* as *'proxy'* for *y*)

Intuition: Why Information Amplification Attacks work?

For > 90%
of records

> 0.75

- If a high **fraction** of attributes in *aux* are **rare**, then any record *r* that is **similar to** ***aux***, is **similar to *y***

Similarity
> 0.75

Similarity
> 0.65

Theorem 2: Why Information Amplification Attacks work?

Define Function

$$f_D(\eta_1, \eta_2, \eta_3)$$

If a high **fraction** of attributes in *aux* are **rare**, then any record *r* **similar to *aux***, is **similar to *y***

- Measure overall similarity between target record y and r that depends on:

η_1 : Fraction of rare attributes in *aux*

η_2 : Lower bound on similarity between r and *aux*

η_3 : Fraction of target records for which guarantee holds

$$S(y, r) \geq f_D(\eta_1, \eta_2, \eta_3)$$

Theorem 2: Why Information Amplification Attacks work?

Using Function

$$f_D(\eta_1, \eta_2, \eta_3)$$

$$S(y, r) \geq f_D(\eta_1, \eta_2, \eta_3)$$

Theorem gives guarantee about similarity of record output by algorithm with target record

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Empirical verification

- Use `anonymized' Netflix database with 480,189 users and 17,770 movies

- Percentage values claimed in our results = percentage of records not filtered out because of
  - insufficient attributes required to form aux OR
  - insufficient rare or non-rare attributes required to form aux

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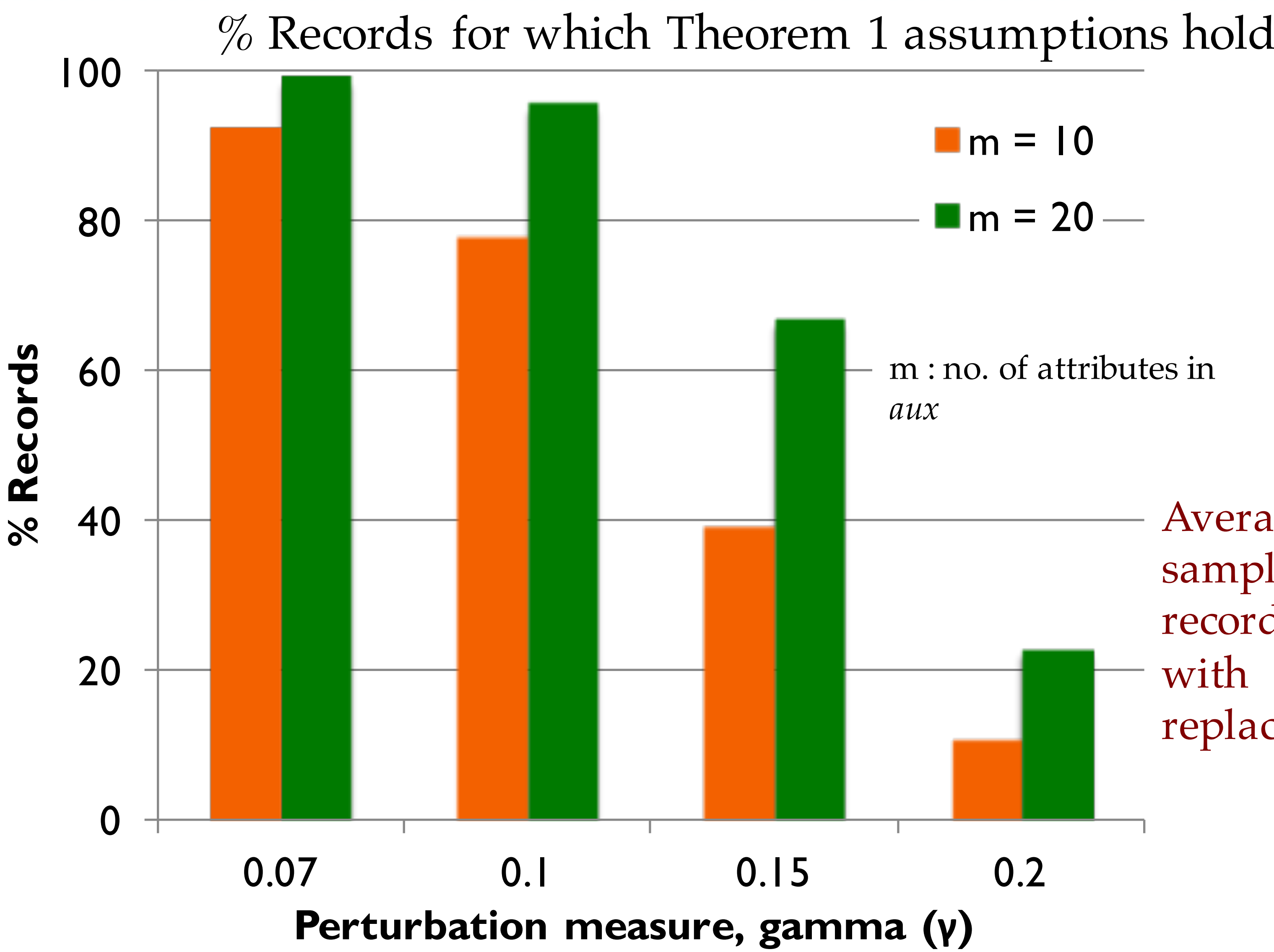
Do Assumptions hold over Netflix Database?



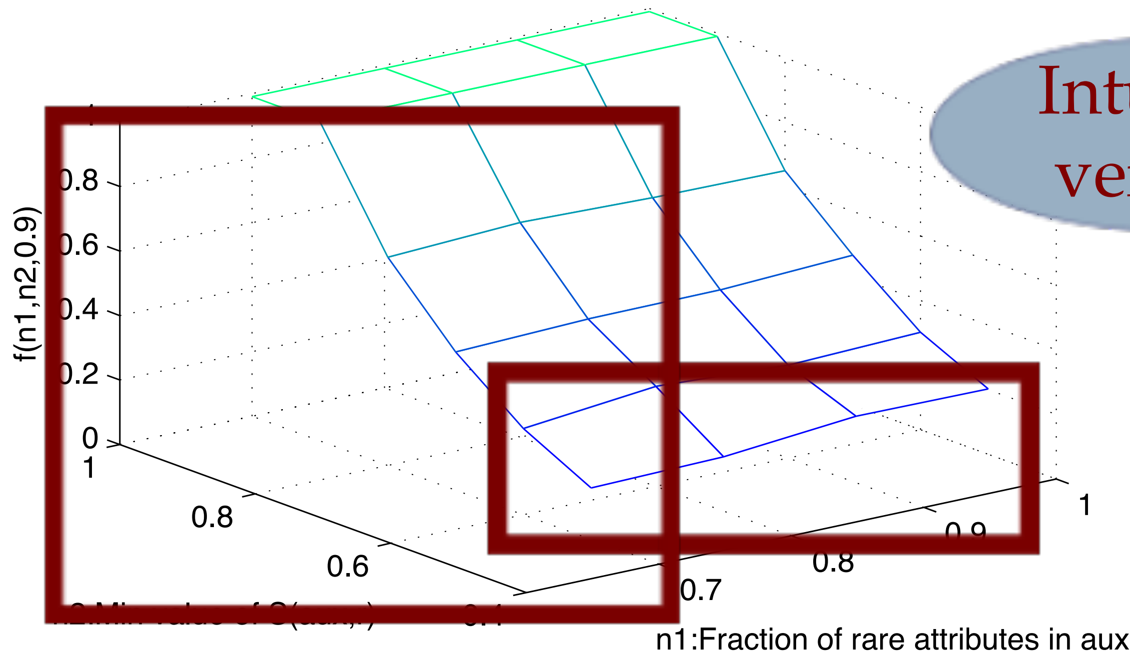
Averaged over sample of 10000 records chosen with replacement

A. Datta, D. Sharma and A. Sinha. Provable De-anonymization of Large Datasets with Sparse Dimensions. In proceedings of *ETAPS First Conference on Principles of Security and Trust (POST 2012)*

Does Intuition about f_D hold for Netflix Database?

$f_D(\eta_1, \eta_2, \eta_3)$ can be evaluated given D

$$S(y, r) \geq f_D(\eta_1, \eta_2, \eta_3)$$



Intuition verified

For Netflix DB,

$f_D(\eta_1, \eta_2, \eta_3)$ is monotonically increasing in $\boxed{\eta_1}$ and $\boxed{\eta_2}$ and tends to 1 as η_2 increases

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Conclusion

- Naïve anonymization mechanisms do not work
- We obtain **provable** bounds about, and **verify empirically**, why some de-anonymization attacks work in practice
- Even perturbed auxiliary information can be used to launch de-anonymization attacks if:
  - *Database* has many **rare dimensions** and
  - *Auxiliary information* has information about these rare dimensions

- Questions?