

The Community as a Learning System for Health:
Using Local Data to Improve Community Health

National Center for Health Statistics, CDC
May 12, 2011

Are there limits to privacy preserving sharing of data?

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Take Home Point

Context: Sharing of patient information for research.

A general and purely technological solution to privacy preserving sharing of patient data might not be possible.

Current State

- Sharing of data
 - Complete (needs oversight)
 - Limited data set (“almost” de-identified, needs oversight)
 - De-identified data
- De-identification by HIPAA standard
 - Safe Harbor (removal of 18 predefined information items)
 - Statistical Standard (expert declares data re-identification risk as “very small”)

Problems

- Oversight (IRB)
 - Costly (administration, time)
 - Researcher: write IRB protocol and wait for approval
 - Institution: process protocol and administrate it
 - Difficult across institutions



Problems

- De-identification
 - by Safe Harbor yields data with limited utility¹
 - by Safe Harbor does not prevent re-identification²
 - by Statistical Standard is vaguely defined:
 - “A person with appropriate knowledge” [...] “determines that the risk [of re-identification] is very small”
- Inferences about sensitive information can be made without re-identification

¹Beyond the HIPAA Privacy Rule: Enhancing Privacy, Improving Health Through Research. IOM 2009

²The disclosure of diagnosis codes can breach research participants' privacy. Loukides G, Denny JC, Malin B. J Am Med Inform Assoc. 2010 May 1;17(3):322-7

Insufficiency of de-identification: inferences about known individuals

Query Editor (I)

[Diagnosis](#) [Encounters](#) [Age](#) [Gender](#)

Find number of patients with

[Diagnosis](#) [Encounters](#) [Age](#) [Gender](#) : secondary diabetes mellitus, without mention of complication (249.0) ✕

and

[Diagnosis](#) [Encounters](#) [Age](#) [Gender](#) : Age ✕
between 30 and 31

and

[Diagnosis](#) [Encounters](#) [Age](#) [Gender](#) : Gender ✕
Male (1001.1)

= 3

Query Editor (I)

[Diagnosis](#) [Encounters](#) [Age](#) [Gender](#)

Find number of patients with

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[Diagnosis](#) [Encounters](#) [Age](#) [Gender](#) : Age ✕
between 30 and 31

and

[Diagnosis](#) [Encounters](#) [Age](#) [Gender](#) : Gender ✕
Male (1001.1)

and

[Diagnosis](#) [Encounters](#) [Age](#) [Gender](#) : human immunodeficiency virus (hiv) disease (042) ✕

= 3

(We know that neighbor Bob is 30 and has secondary diabetes)

Points of Discussion

- Are insufficiencies of de-identification too esoteric to be of practical concern?
 - Is heuristic and empirical risk assessment^{1,2} convincing?
 - “we were able to re-identify x %”: not a valid upper bound!
 - Can we use media attention as a guide?
 - Note:
 - HITECH breach reporting does not apply to de-identified data
 - There are no tracking requirements for de-identified data

¹Evaluating re-identification risks with respect to the HIPAA privacy rule. K Benitez, B Malin. *JAMIA* 2010;17:169-177

²A method for managing re-identification risk from small geographic areas in Canada. El Emam et al. *BMC Medical Informatics and Decision Making* 2010, **10**:18

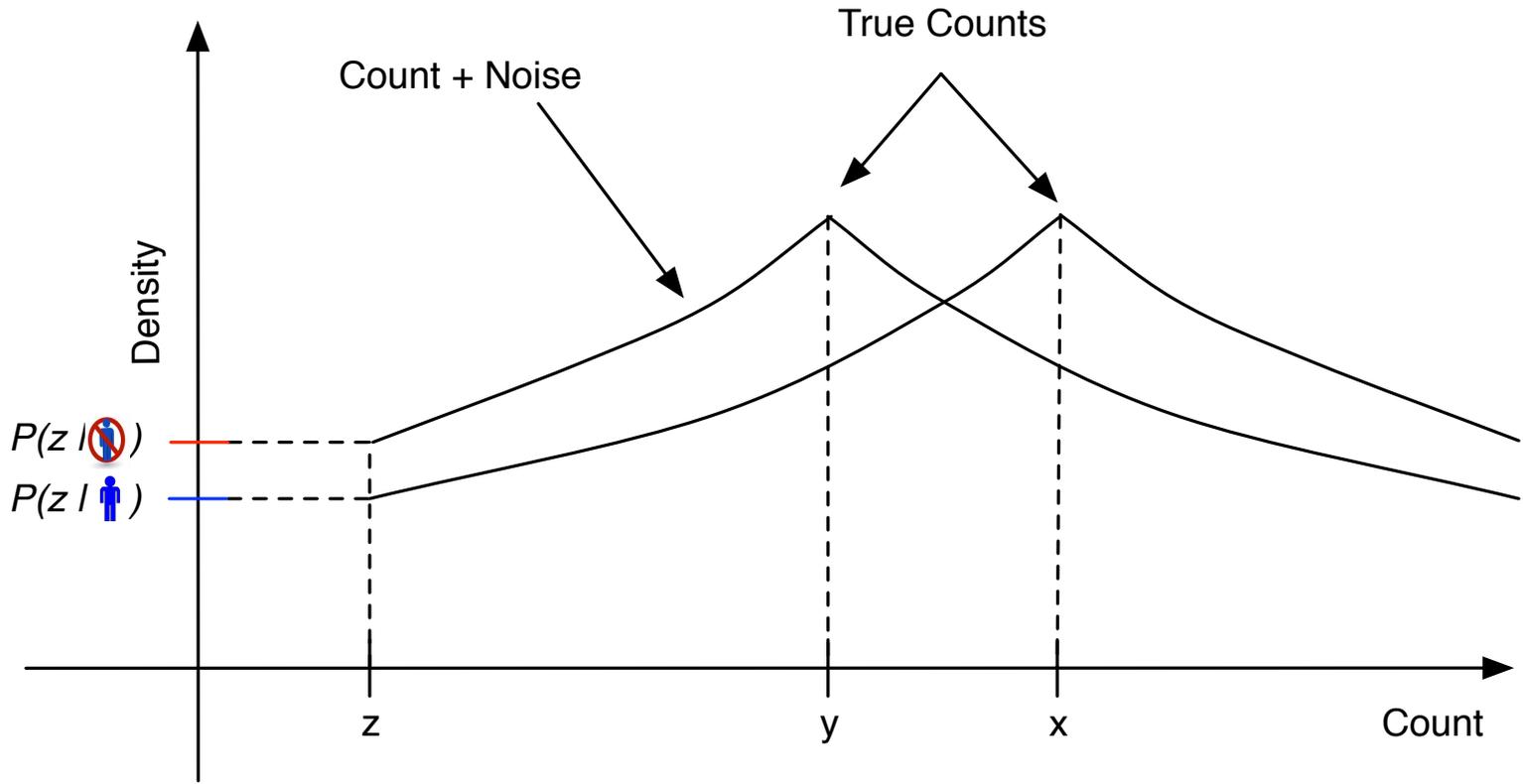
A possible alternative view?

- Ideal for individual privacy: “*information is privacy preserving if what can be learned about any **individual** is independent of this information*”
- Consequence: we are allowed to share information about *populations*.
- Implies de-identification
- Complete independence not feasible: requires infinite populations

Towards the ideal: Differential Privacy

- Differential Privacy* bounds the change in likelihood of learning anything about an individual by his inclusion in the data
- Is a property of an access method (as opposed to a property of data)
- Access methods to data that provably guarantee differential privacy exist

Differential Privacy and Noisy Counts



$$\frac{P(z | \text{person with red icon})}{P(z | \text{person with blue icon})} = \text{differential privacy}$$

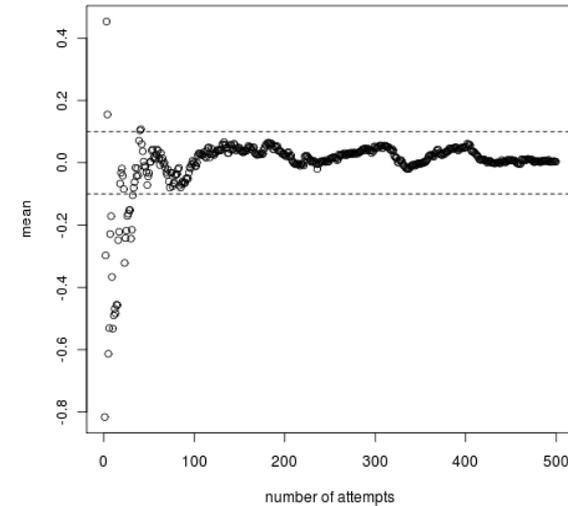


$$\leq 1$$

The Finite Privacy Budget



Example: Adding noise to counts does not protect against averaging multiple trials



Suggests* a general property of a finite “privacy budget”: only small # of privacy preserving accesses can be allowed, beyond which privacy can no longer be guaranteed

Increase information about each patient:
decrease in budget!

Dealing with a finite budget

- Use all allowed information accesses up front to extract all privacy preserving information
 - Never allow privacy preserving access again
 - Different uses might need different information
 - Very high-dimensional data: budget very small
- Leverage environment to “extend budget”
 - Principle: substitute some “treatment” (punishment) for some “prevention”
 - Requires:
 - Detection of misuse and perpetrator
 - Effective sanctioning of perpetrator (aka. “teeth”)

Conclusion

- De-identification as a definition of privacy seems insufficient for believable privacy
- Current theoretical research suggests that there are limits to truly privacy preserving sharing of data using technological means alone

Acknowledgements

- Collaborators:
 - Kamalika Chaudhuri
 - Anand Sarwate
 - DBMI/iDASH members
- Support
 - NIH R01 LM07273
 - NIH U54 HL108460

