

De-Identification and the Health Insurance Portability and Accountability Act (HIPAA)

Overview and framing of current issues



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National Institute of Standards and Technology



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Non-regulatory federal laboratory.

Mission:

"To promote US innovation and industrial competitiveness by advancing measurement science, standards, and technology in ways that enhance economic security and improve our quality of life."

NISTIR 8053:

De-Identification of Personal Information

Covers:

- Why de-identify?
- De-identification terminology
- Famous re-identification cases
- De-identifying and re-identifying structured data (e.g. survey data, Census data, etc.)
- Challenges with de-identifying unstructured data (e.g. medical text, photographs, medical imagery, genetic information)

NISTIR 8053

De-Identification of Personal Information

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http://nvlpubs.nist.gov/nistpubs/ir/2015/NIST.IR.8053.pdf

October 2015 vi+46 pages

Today there is a significant and growing interest in de-identification.



Controlled Sharing



Open Science



Data Publishing

Big-data is not a new science—it's the future of all science.

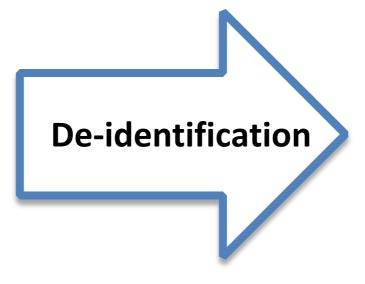


Under the current HIPAA Privacy Rule, de-identified Protected Health Information can be distributed without restriction.



https://en.wikipedia.org/wiki/Medical_record

Medical Records



- X name
- **X** address
- X birthday
- X medical record number etc.



Public Internet

Interest in de-identification extends far beyond healthcare.

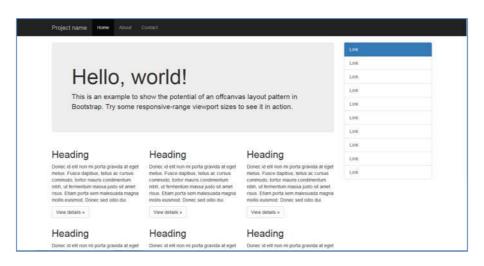


Social Science Data



https://pixabay.com/en/credit-card-bill-bank-statement-1104961/

Consumer Financial Data

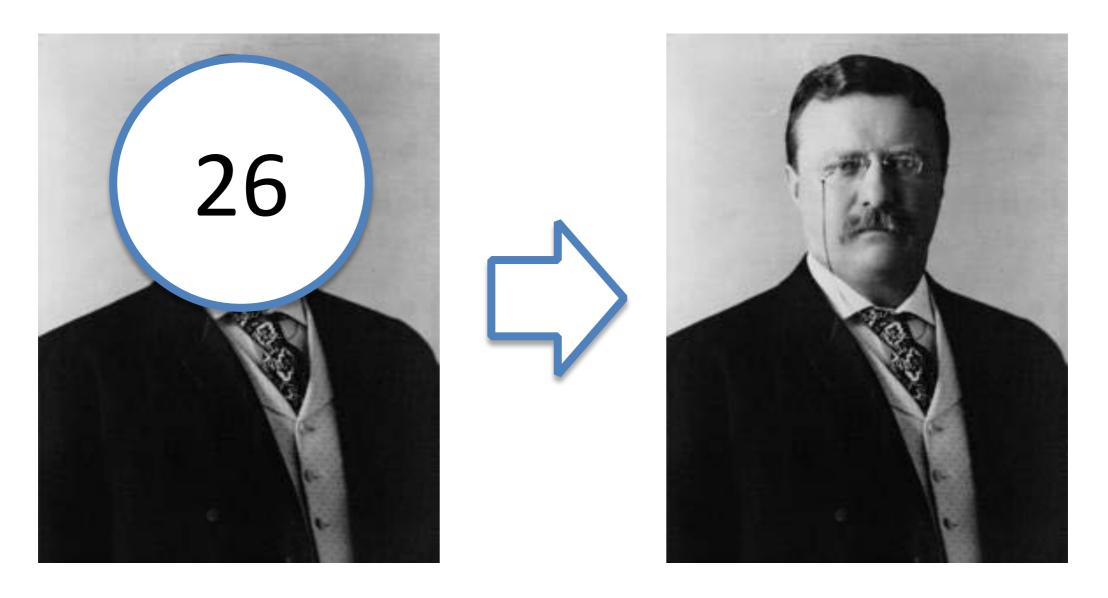


Website

"We will never share your personal information..."

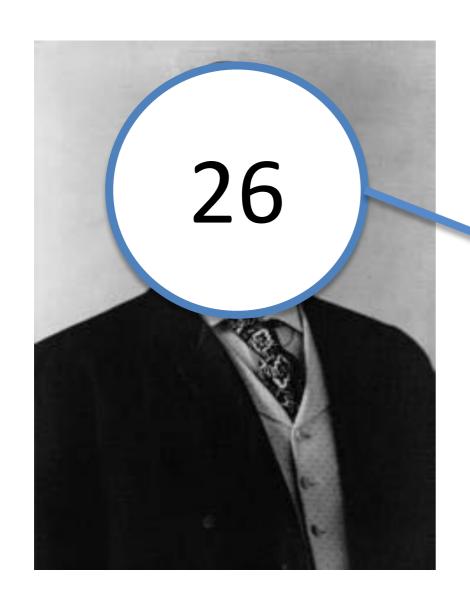


De-identified data can be re-identified



Sometimes data are not properly de-identified.

De-identified data can be re-identified



24	Grover Cleveland
25	William McKinley
26	Theodore Roosevelt
20	Theodole Roosevell
27	William Howard Taft

Sometimes de-identified data can be linked to another dataset

Simple statistics can be identifying.

Title	Age	Sex	Address	ICD-10	Diagnosis
Lab Tech	35	M		K25.0	Gastric Ulcer with hemorrhage
Lab Tech	56	F		J00	Acute nasopharyngitis [Common Cold]
Professor	35	M		C64.1	Malignant neoplasm of right kidney
Professor	69	F		C64.1	Malignant neoplasm of right kidney
Contracts Specialist	52	F		L30.9	Dermatitis, unspecified [Eczema]
University President	56	F		C64.1	Malignant neoplasm of right kidney

Hypothetical dataset from university healthcare system

Re-identified information can link with other data.

Research Database:

Patient 234-334-11

Diagnostic Codes: A98.4, J00, L30.9

•••

Patient 234-334-11

Age: 35

Genetic History. ...

Patient 234-334-11

Psychological Records

• • •

Patient 234-334-11

Social Services History

••



Ebola P	atient	ICD-10	Diagnosis	
Alice	30	F	A98.4	Ebola
Bob	35	M	A98.4	Ebola
Carol	40	F	A98.4	Ebola

Techniques for limiting identity disclosure:

Title	Age	Sex	Address	ICD-10	Diagnosis
University President	56	F		C64.1	Malignant neoplasm of right kidney

Generalization: University President ⇒ Senior Administrator

Age: 56 ⇒ Age: 50-59

Field Swapping: Age: 52 \Rightarrow Age: 56

Age: 56 \Rightarrow Age: 52

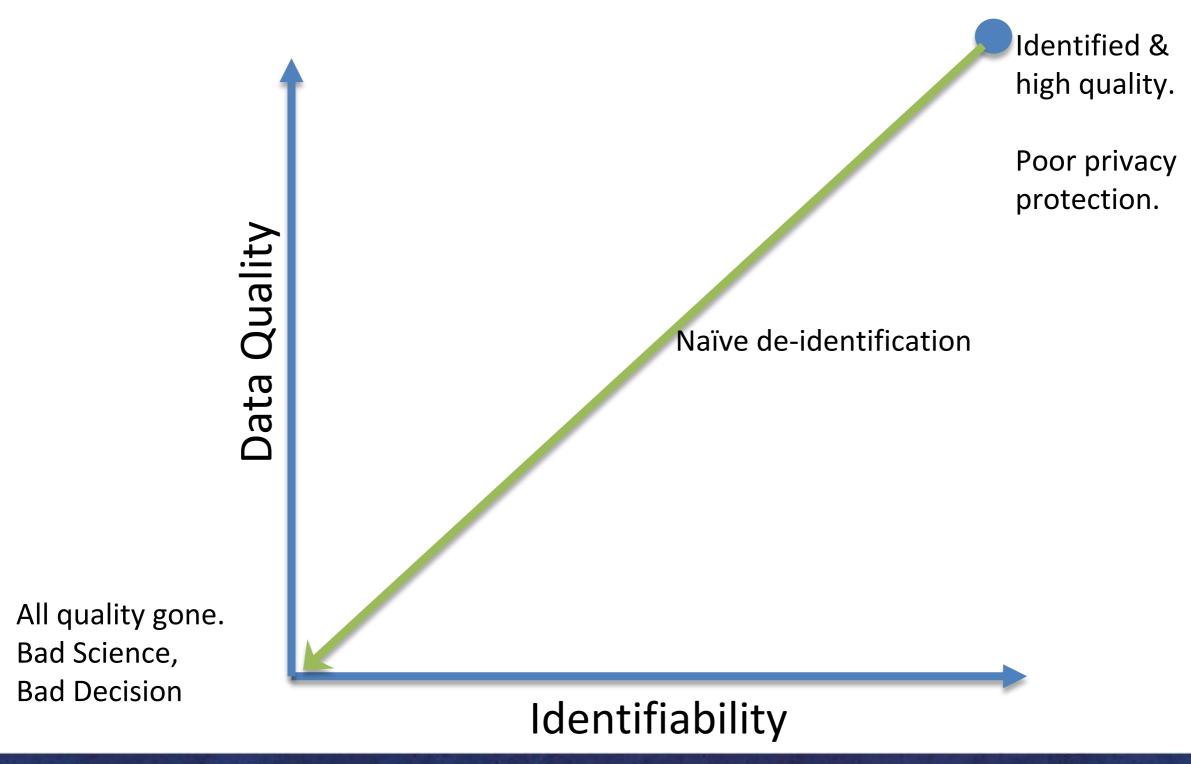
Noise Addition: University President ⇒ VP Finance

Age: 56 \Rightarrow Age: 58 ±5

Suppression: University President ⇒ XXXXXXXXXXXXXX

Age: 56 ⇒ Age: XXX

Lowering identifiability lowers data quality.



HIPAA Privacy Rule "Safe Harbor" Provision: Medical records are de-identified if 18 data elements are removed

Direct Identifiers:

- Names
- Individual numbers: phone, fax, SSN, medical record, account #s, etc.
- Email addresses, IP address, URLs
- Biometrics: fingerprints, voiceprints, photographs, etc.
- Any other uniquely identifying number, characteristic or code.

Indirect Identifiers:

- Geographic subdivisions smaller than a state, except first 3 digits of ZIP, provided the combined ZIP codes contain more than 20,000 people.
- Dates directly related to an individual (except for "age 90 or older")

Geographic information requires special attention

Indirect identifiers		Direct identifier			
Title	Age	Sex	Address	ICD-10	Diagnosis
Lab Tech	35	М	100 Utah St. Anytown, 20124	K25.0	Gastric Ulcer with hemorrhage
Lab Tech	56	F	653 Pleasant St. Uptown, 20321	J00	Acute nasopharyngitis [Common Cold]
Professor	35	М	564 Main St. Nassis, 25312	T25.332S	Burn of third degree of left toe
Professor	69	F	202 Sky Lane Katap, 20134	C64.1	Malignant neoplasm of right kidney
Contracts Specialist	52	F	956 Diablo Rd. Quirky, 23990	L30.9	Dermatitis, unspecified [Eczema]
University President	56	F	451 Termo Dr. Boltz, 25333	C64.1	Malignant neoplasm of right kidney

Hypothetical dataset from university healthcare system

Safe Harbor allows ZIP3 (assuming there are 20,000 people living in the area)

Indirect	t identif	iers	Direct identifier			
Title	Age	Sex	Address	ICD-10	Diagnosis	
Lab Tech	35	M	201 _{XX}	K25.0	Gastric Ulcer with hemorrhage	
Lab Tech	56	F	203:XX	J00	Acute nasopharyngitis [Common Cold]	
Professor	35	M	253 XX	T25.332S	Burn of third degree of left toe	
Professor	69	F	201 XX	C64.1	Malignant neoplasm of right kidney	
Contracts Specialist	52	F	239 XX	L30.9	Dermatitis, unspecified [Eczema]	
University President	56	F	253 XX	C64.1	Malignant neoplasm of right kidney	

Hypothetical dataset from university healthcare system

Results of the 2010 Office of the National Coordinator for Health Information Technology Safe Harbor Re-Identification Test:

15,000 Hispanic Patients

216 distinct by Sex, ZIP3 & age



30,000 Records from InfoUSA

84 distinct by sex, ZIP3 & age

20 match on sex, ZIP3 & age



infoUSA°

Lists

The Highest Quality Mailing

2 actual matches on last name, street address, and phone

Data from 2004-2009

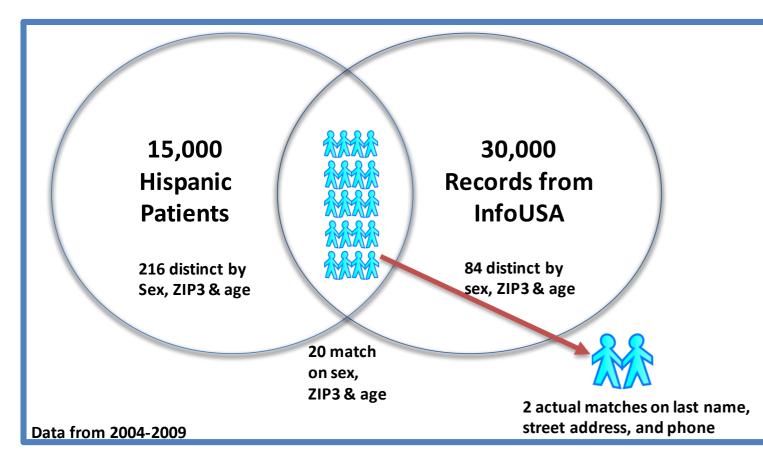
K-anonymity: assure at least "k" records have the same set of indirect identifiers.

Indirect	t identifi	iers	Direct identifier				
Title	Age	Sex	Address	ICD-10	Diagnosis		
Lab Tech	35	М	201 _{XX}	K25.0	Gastric Ulcer with hemorrhage		
Lab Tech	56	F	203:XX	J00	Acute nasopharyngitis [Common Cold]		
Professor	35	М	253 XX	T25.332S	Burn of third degree of left toe		
Professor	69	F	201 XX	C64.1	Malignant neoplasm of right kidney		
Contracts Specialist	52	F	239 XX	L30.9	Dermatitis, unspecified [Eczema]		
University President	56	F	253 XX	C64.1	Malignant neoplasm of right kidney		

Color background indicates values modified for k=2 k-anonymity

"Tiger Teams" are another way to test re-identification.





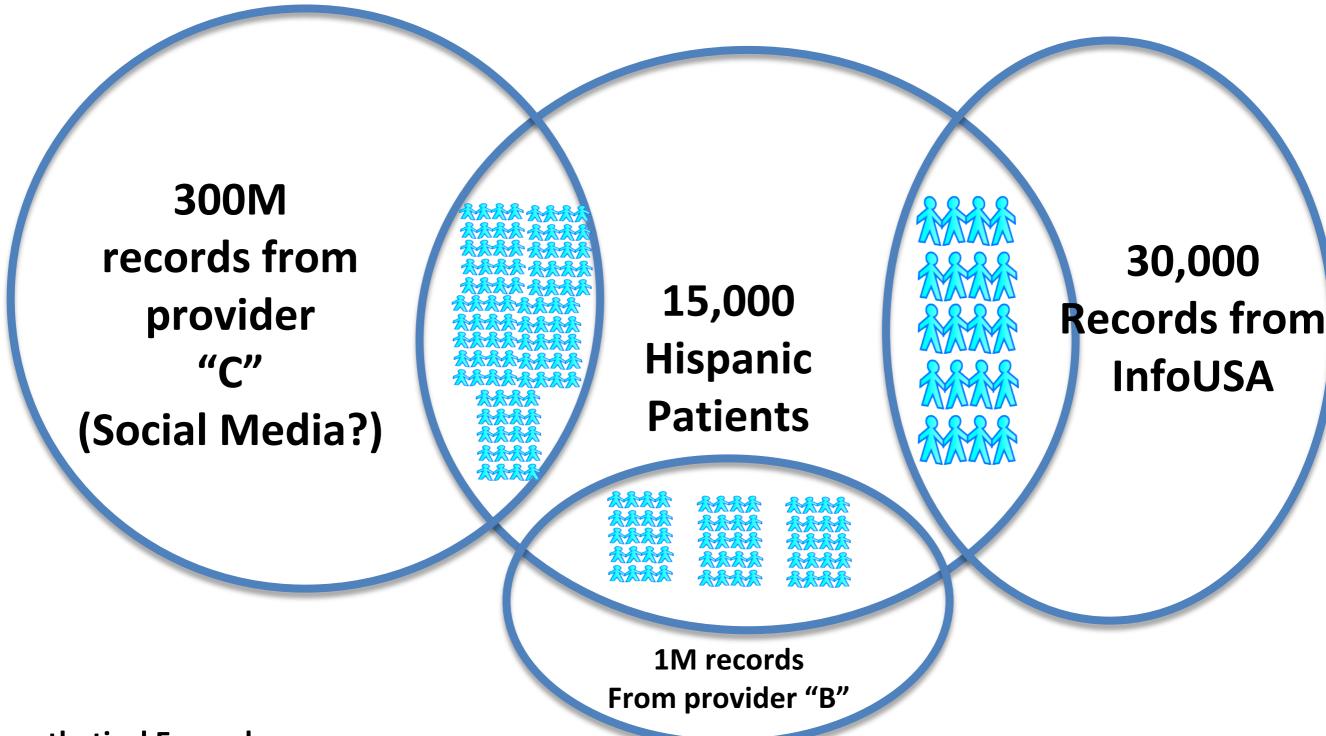


Estimated Re-identification rate:

No verification: 20 in 15,000

Verification: 2 in 15,000

Re-identification tests assume data available to match. As more data become available, re-identification gets easier.



A constellation of diseases can be an identifier

De-identified medical records from provider "N"

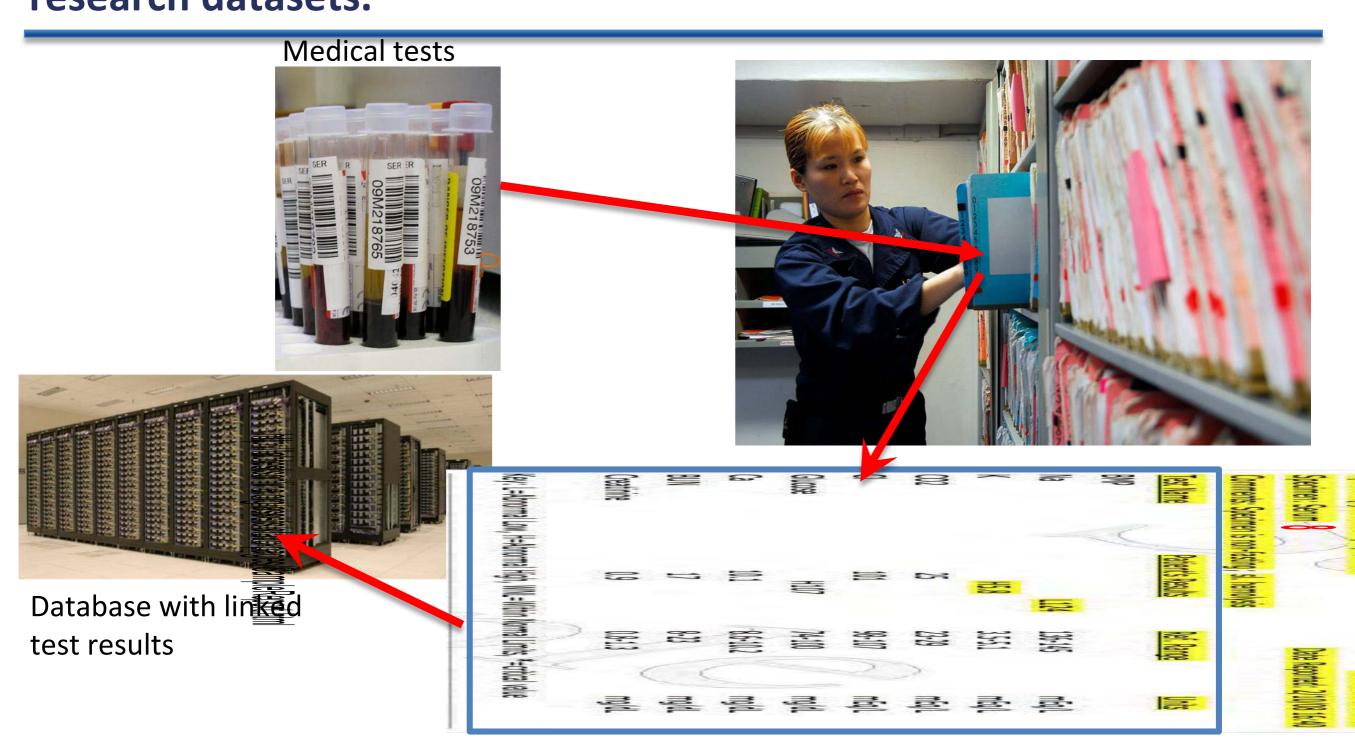


Smallpox

Concussion at age 9
Malaria at age 21
Depression
Fractured jaw

Linked records

Atreya, Smith, McCoy, Malin & Miller (2013) "Reducing patient re-identification risk for laboratory results within research datasets."



A single identified blood test can be the link to dozens of de-identified records

Blood tests can be de-identified by adding noise



_ ₁ Patier	it copy		
University Medical Center 123 University Way, City	er, Dept. of Pathology	7	02/14/2008 16:13
	Doe, Mr. John C	2. 3	
Patient ID No. 9876543	D.O.B. 01/0:	1/1941	671
Ordering MD: Smith, Pe	ter MD 4	Physician Copy f	for Dr: Smith, Jane
PT medications: multivit	tamins 5		
Specimen(s) Collected:	2/10/08 14:30		Lab Acc'n No. 2234
Specimen: Serum		Date Re	ported: 2/10/08 16:
Comments: Specimen is	s non-fasting; sl. hemolysis		
Test Name	// Patient's Results	Ref. Range	Units
ВМР			
Na	L124	136-145	mEq/L
K	H5.8	3.5-5.1	mEq/L
CO2	25	23-29	mEq/L
CI	101	98-107	mEq/L
Glucose	H107	74-100	mg/dL
Ca	10.1	8.6-10.2	mg/dL
BUN	17	8-23	mg/dL
Creatinine	0.9	0.8-1.3	mg/dL

```
Na: 124 \Rightarrow 126

K: 5.8 \Rightarrow 5.9

CO2: 25 \Rightarrow 24

Cl: 101 \Rightarrow 104

Glucose: 107 \Rightarrow 110

Ca: 10.1 \Rightarrow 9.9

BUN: 17 \Rightarrow 17

Creatinine: 0.9 \Rightarrow 1.0

(values for demonstration only)
```

Research database

"Differential Privacy" adds systematic noise to query results

Data Enclave

Real Data + Computation Query



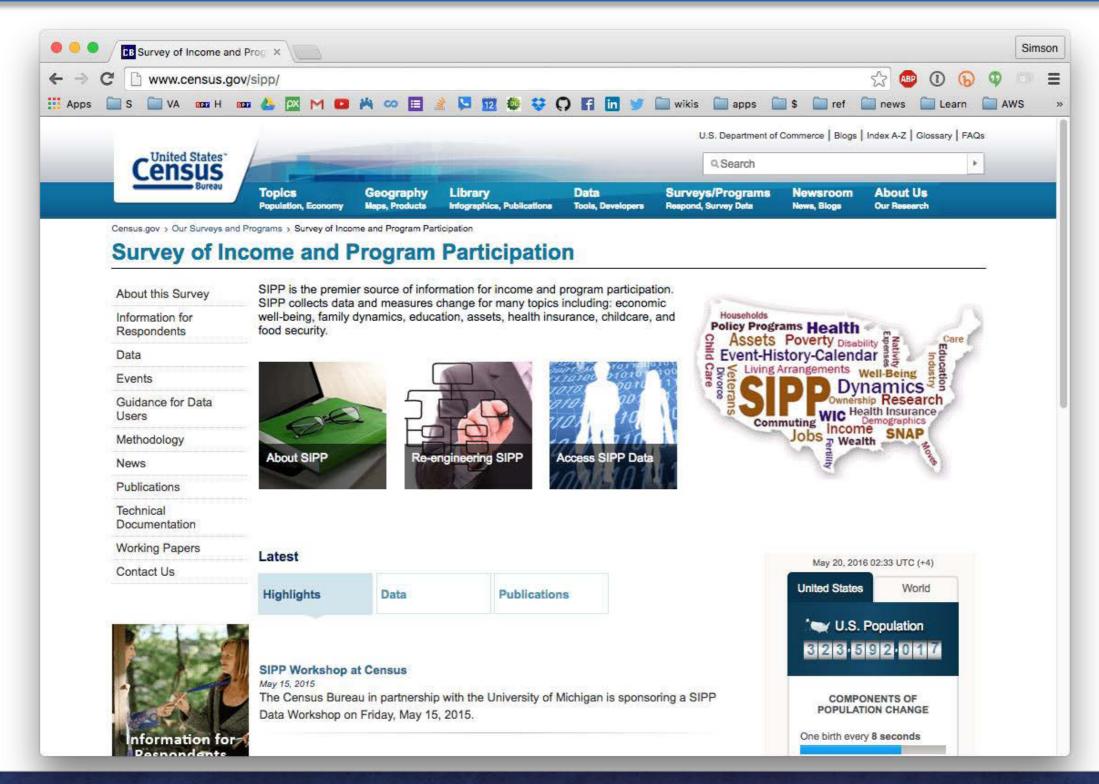
Result

Synthetic Data

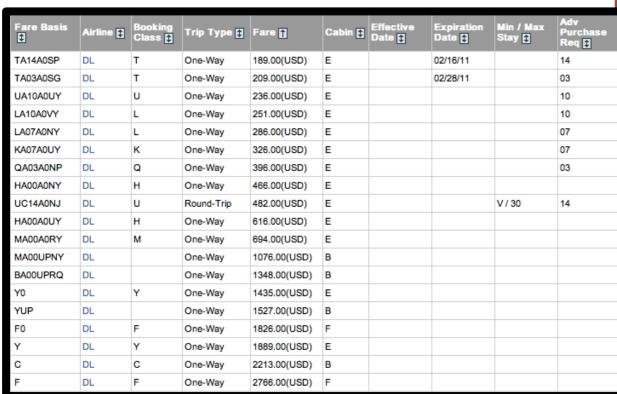


Key concepts: Privacy Budget & Noise

The Census Bureau distributes synthetic data to protect privacy while preserving some data quality.



Can synthetic datasets designed to enable research also be used to promote accountability and transparency?







Animated encounter data



Body-worn camera video with replaced faces

De-identification strategies should be formally evaluated.

Do they meet the stated policy goals?

Does the software faithfully implement the stated algorithm?

Are the statistical privacy guarantees actually met?

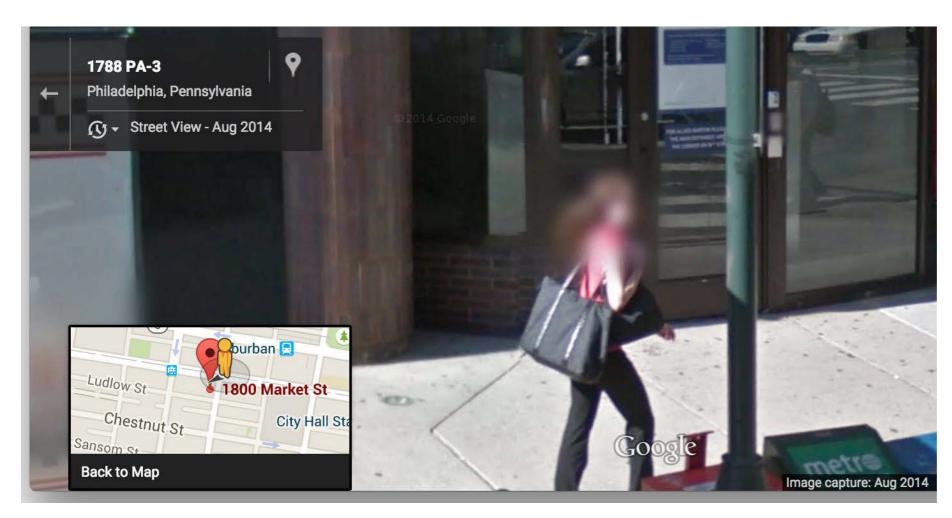
Is the necessary training in place?

Will there be monitoring and auditing?



https://en.wikipedia.org/wiki/EMIDEC 1100

De-identification of non-tabular data poses special problems.



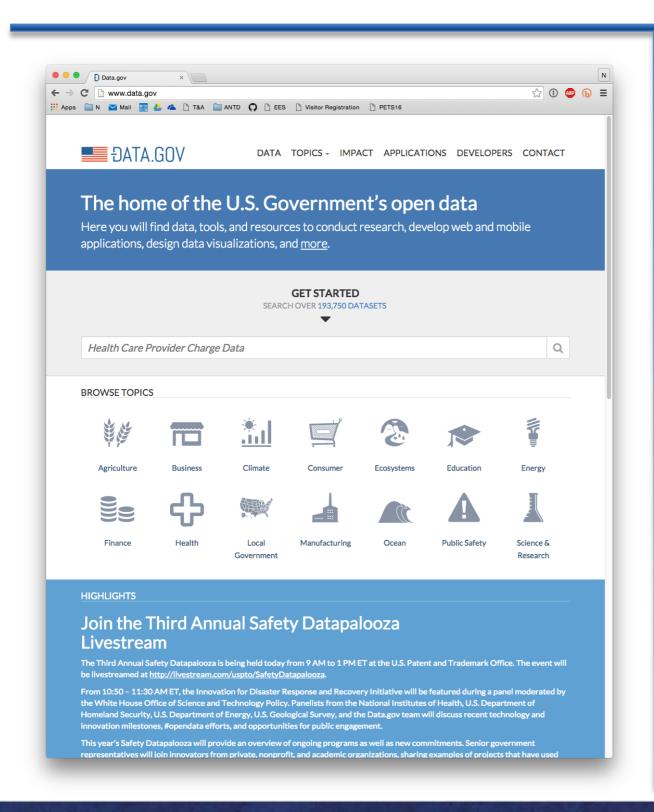


http://www.randomhistory.com/photos/2014/scoliosis-xray.jpg

Medical imagery can be highly identifying.

Google claims 90% of faces and 95% of license plates removed through automated processing.

More research is needed to determine if systems can protect privacy and allow for unlimited use of data.

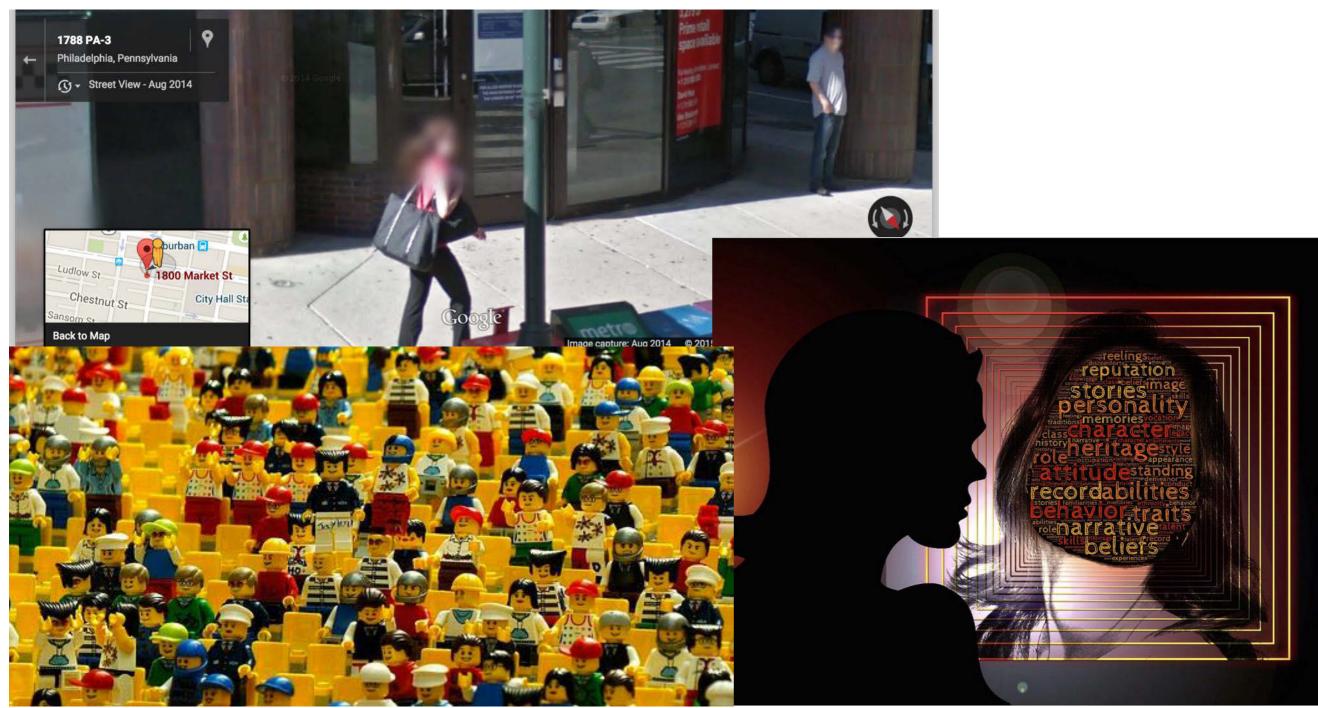








Can raw data be transformed so completely that individuals cannot recognize their own data once they are in a crowd?



https://pixabay.com/en/lego-doll-the-per-amphitheatre-1044891/

https://pixabay.com/en/self-self-image-image-identity-792365/

In summary:

We have learned a lot about de-identification in recent years.

The de-identification "toolkit" has several options

- suppression, generalization commonly used in healthcare
- field swapping, noise addition commonly used in vital statistics

K-anonymity and Differential Privacy are formal models for evaluating the quality of de-identification

We increasingly have the ability to:

- Modify data so that the data subjects' identity is rem leaving information that is somewhat useful.
- But the more useful it is, the more likely it can be re-identified

We need procedures for:

- Evaluating the effectiveness of de-identification
- Evaluating the usefulness of the data that remain.

We need these techniques for a wide range of

• Structured data, text, medical, video

Lowering identifiability lowers data quality.

