Deploying Differential Privacy for the 2020 Census of Population and Housing

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The views in this presentation are those of the author, and not those of the U.S. Census Bureau.

Abstract

When differential privacy was created more than a decade ago, the motivating example was statistics published by an official statistics agency. In theory there is no difference between theory and practice, but in practice there is.

In attempting to transition differential privacy from the theory to practice, and in particular for the 2020 Census of Population and Housing, the U.S. Census Bureau has encountered many challenges unanticipated by differential privacy's creators. Many of these challenges had less to do with the mathematics of differential privacy and more to do with operational requirements that differential privacy's creators had not discussed in their writings. These challenges included obtaining qualified personnel and a suitable computing environment, the difficulty of accounting for all uses of the confidential data, the lack of release mechanisms that align with the needs of data users, the expectation on the part of data users that they will have access to micro-data, the difficulty in setting the value of the privacy-loss parameter, ε (epsilon), and the lack of tools and trained individuals to verify the correctness of differential privacy, and push-back from same members of the data user community.

Addressing these concerns required developing a novel hierarchical algorithm that makes extensive use of a high-performance commercial optimizer; transitioning the computing environment to the cloud; educating insiders about differential privacy; engaging with academics, data users, and the general public; and redesigning both data flows inside the Census Bureau and some of the final data publications to be in line with the demands of formal privacy.

Outline

Motivation

The flow of census response data

Disclosure Avoidance for the 2010 census

Disclosure Avoidance for the 2018 census End-to-End test

Disclosure Avoidance for the 2020 census

Conclusion

Motivation

The 2020 Census of Population and Housing

Count everyone once, only once, and in the right place.

Motivation
Article 1, Section 2

"…The actual Enumeration shall be made within three Years after the first Meeting of the Congress of the United States, and within every subsequent Term of ten Years, in such Manner as they shall by Law direct…"

Federal Register / Vol. 82, No. 215 / Nov 8, 2017 / Notices (for the 2018 End-to-End test)

Dec. 31, 2018

We will report (per block):

P1. RACE/ETHNICITY
Universe: Total population
Group by: BLOCK

P2. RACE/ETHNICITY
Universe: Total population age 18 and over

H1. OCCUPANCY STATUS

P42. GROUP QUARTERS POPULATION
Universe: Population in Group Quarters

DEPARTMENT OF COMMERCE

Bureau of the Census

[Docket Number 170824806–7806–01]

Proposed Content for the Prototype 2020 Census Redistricting Data File

AGENCY: Bureau of the Census, Department of Commerce.

ACTION: Notice and request for comment.

SUMMARY: The 2020 Census Redistricting Data Program provides states the opportunity to specify the small geographic areas for which they wish to receive 2020 decennial population totals for the purpose of reapportionment and redistricting. This notice pertains to Phase 3, the Data Delivery phase of the program, as the U.S. Census Bureau is providing notification and requesting comment on the content of the prototype 2020 Census Redistricting Data File that will be produced from the 2018 End-to-End Census Test. The Census Bureau anticipates publishing the content for the prototype 2020 Census Redistricting Data File from the 2018 End-to-End Census Test in the second quarter of fiscal year 2018 in a final notice. In that final notice, the Census Bureau also will respond to the comments received on this notice.

We need to protect privacy!
13 U.S. Code § 9 - Information as confidential; exception

Neither the Secretary, nor any other officer or employee of the Department of Commerce or bureau or agency thereof, or local government census liaison may…

(2) *Make any publication whereby the data furnished by any particular establishment or individual under this title can be identified*; or

We need to protect privacy!
13 U.S. Code § 9 - Information as confidential; exception

(3) …*Copies of census reports, which have been so retained, shall be immune from legal process, and shall not, without the consent of the individual or establishment concerned, be admitted as evidence or used for any purpose in any action, suit, or other judicial or administrative proceeding.*

Statistical agencies collect data under a *pledge of confidentiality.*

We pledge:

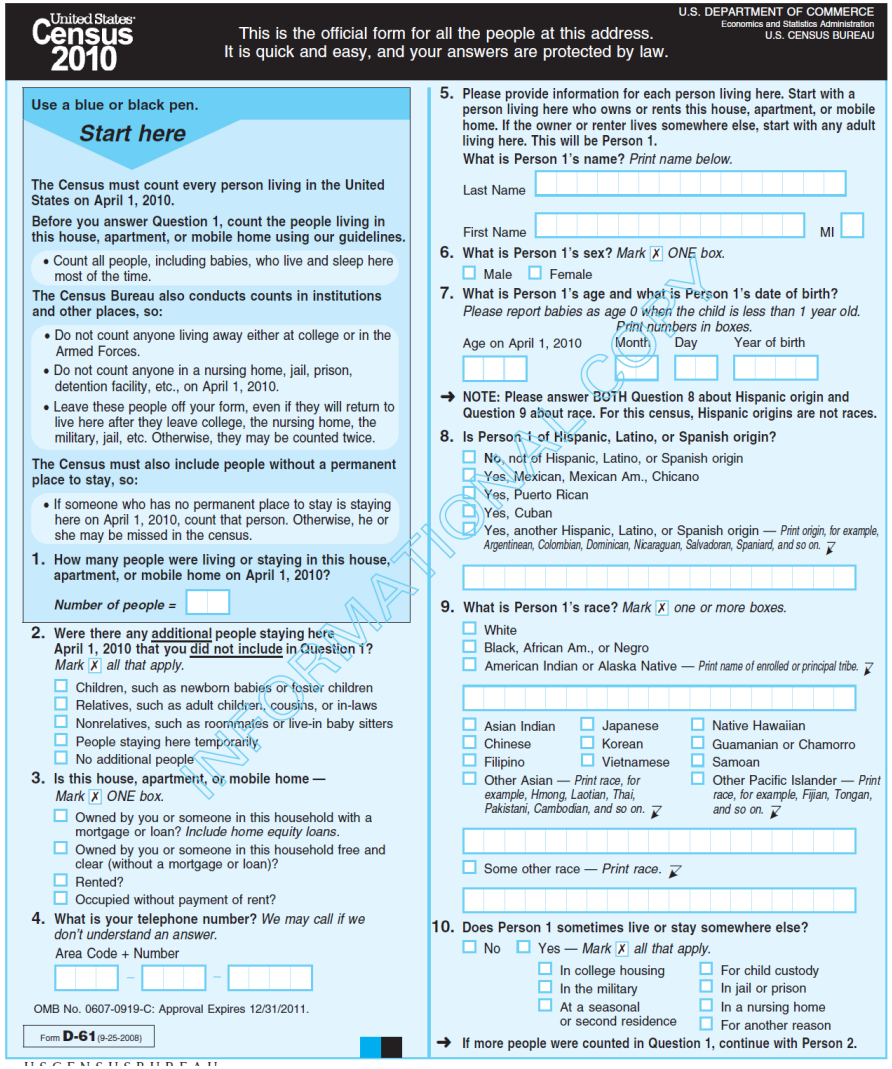
*Collected data will be used **only for statistical purposes.***

Collected data will be kept ***confidential***.

Data from individuals or establishments *won't be identifiable in any publication.*

“Disclosure Avoidance”
means
preventing improper *disclosures.*

“This is the official form for all the people at this address.”



United States Census 2010

This is the official form for all the people at this address.
It is quick and easy, and your answers are protected by law.

U.S. DEPARTMENT OF COMMERCE
Economics and Statistics Administration
U.S. CENSUS BUREAU

Use a blue or black pen.

Start here

The Census must count every person living in the United States on April 1, 2010.

Before you answer Question 1, count the people living in this house, apartment, or mobile home using our guidelines.

- Count all people, including babies, who live and sleep here most of the time.

The Census Bureau also conducts counts in institutions and other places, so:

- Do not count anyone living away either at college or in the Armed Forces.
- Do not count anyone in a nursing home, jail, prison, detention facility, etc., on April 1, 2010.
- Leave these people off your form, even if they will return to live here after they leave college, the nursing home, the military, jail, etc. Otherwise, they may be counted twice.

The Census must also include people without a permanent place to stay, so:

- If someone who has no permanent place to stay is staying here on April 1, 2010, count that person. Otherwise, he or she may be missed in the census.

1. How many people were living or staying in this house, apartment, or mobile home on April 1, 2010?
   Number of people =

2. Were there any additional people staying here April 1, 2010 that you did not include in Question 1? *Mark ✗ all that apply.*
   - Children, such as newborn babies or foster children
   - Relatives, such as adult children, cousins, or in-laws
   - Nonrelatives, such as roommates or live-in baby sitters
   - People staying here temporarily
   - No additional people

3. Is this house, apartment, or mobile home — *Mark ✗ ONE box.*
   - Owned by you or someone in this household with a mortgage or loan? *Include home equity loans.*
   - Owned by you or someone in this household free and clear (without a mortgage or loan)?
   - Rented?
   - Occupied without payment of rent?

4. What is your telephone number? *We may call if we don't understand an answer.*
   Area Code + Number

OMB No. 0607-0919-C: Approval Expires 12/31/2011.

Form D-61 (9-25-2008)

5. Please provide information for each person living here. Start with a person living here who owns or rents this house, apartment, or mobile home. If the owner or renter lives somewhere else, start with any adult living here. This will be Person 1.
   What is Person 1's name? *Print name below.*
   Last Name
   First Name MI

6. What is Person 1's sex? *Mark ✗ ONE box.*
   - Male
   - Female

7. What is Person 1's age and what is Person 1's date of birth?
   Please report babies as age 0 when the child is less than 1 year old.
   Print numbers in boxes.
   Age on April 1, 2010 | Month | Day | Year of birth

→ NOTE: Please answer BOTH Question 8 about Hispanic origin and Question 9 about race. For this census, Hispanic origins are not races.

8. Is Person 1 of Hispanic, Latino, or Spanish origin?
   - No, not of Hispanic, Latino, or Spanish origin
   - Yes, Mexican, Mexican Am., Chicano
   - Yes, Puerto Rican
   - Yes, Cuban
   - Yes, another Hispanic, Latino, or Spanish origin — *Print origin, for example, Argentinean, Colombian, Dominican, Nicaraguan, Salvadoran, Spaniard, and so on.*

9. What is Person 1's race? *Mark ✗ one or more boxes.*
   - White
   - Black, African Am., or Negro
   - American Indian or Alaska Native — *Print name of enrolled or principal tribe.*
   - Asian Indian
   - Chinese
   - Filipino
   - Japanese
   - Korean
   - Vietnamese
   - Native Hawaiian
   - Guamanian or Chamorro
   - Samoan
   - Other Asian — *Print race, for example, Hmong, Laotian, Thai, Pakistani, Cambodian, and so on.*
   - Other Pacific Islander — *Print race, for example, Fijian, Tongan, and so on.*
   - Some other race — *Print race.*

10. Does Person 1 sometimes live or stay somewhere else?
    - No
    - Yes — *Mark ✗ all that apply.*
      - In college housing
      - In the military
      - At a seasonal or second residence
      - For child custody
      - In jail or prison
      - In a nursing home
      - For another reason

→ If more people were counted in Question 1, continue with Person 2.

“It is quick and easy, and your answers are protected by law.”

The 2010 Census collected data on 308,745,538 people.

DRF

Raw data from respondents: **Decennial Response File**

Statistical Processes

HDF

Hundred-percent Detail File

Confidential data

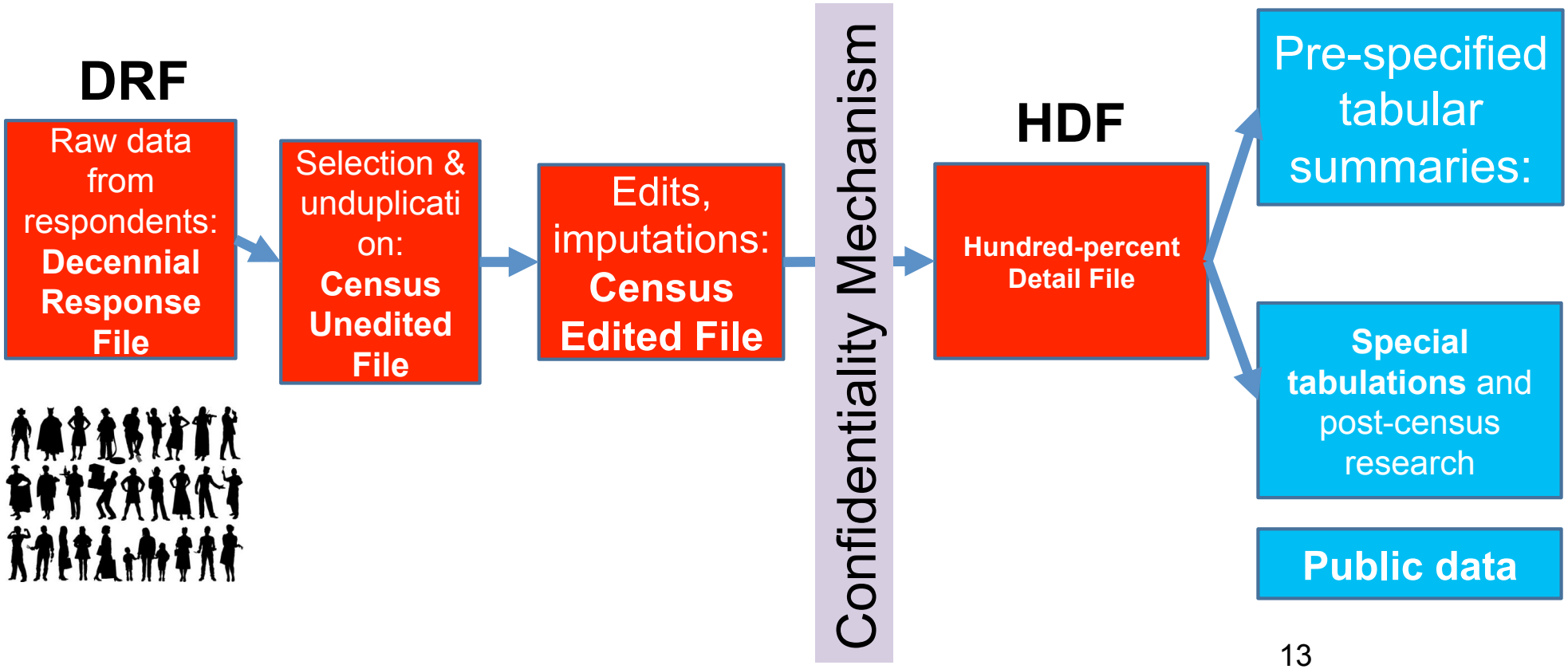
Published data

Pre-specified tabular summaries: **PL94-171, SF1, SF2**

Special tabulations and post-census research

Public data

The 2000 and 2010 Confidentiality Mechanism operated as a filter on the Census Edited File:



For each person, we collected 6 variables (44 bits of data)

Variable	Range	Bits
Block	6,207,027 inhabited blocks	23
Sex	2 (Female/Male)	1
Age	103 (0-99 single age year categories, 100-104, 105-109, 110+)	7
Race	63 allowable race combinations	7
Ethnicity	2 (Hispanic/Not)	1
Relationship	17 values	5
Total		44

308,745,538 people x 6 variables = 1,852,473,228 measurements
308,745,538 people x 44 bits = 13,584,803,672 bits ≈ 1.7 GB

2010 Census: Summary of Publications (approximate counts)

The 2010 Census publication schedule resulted in roughly

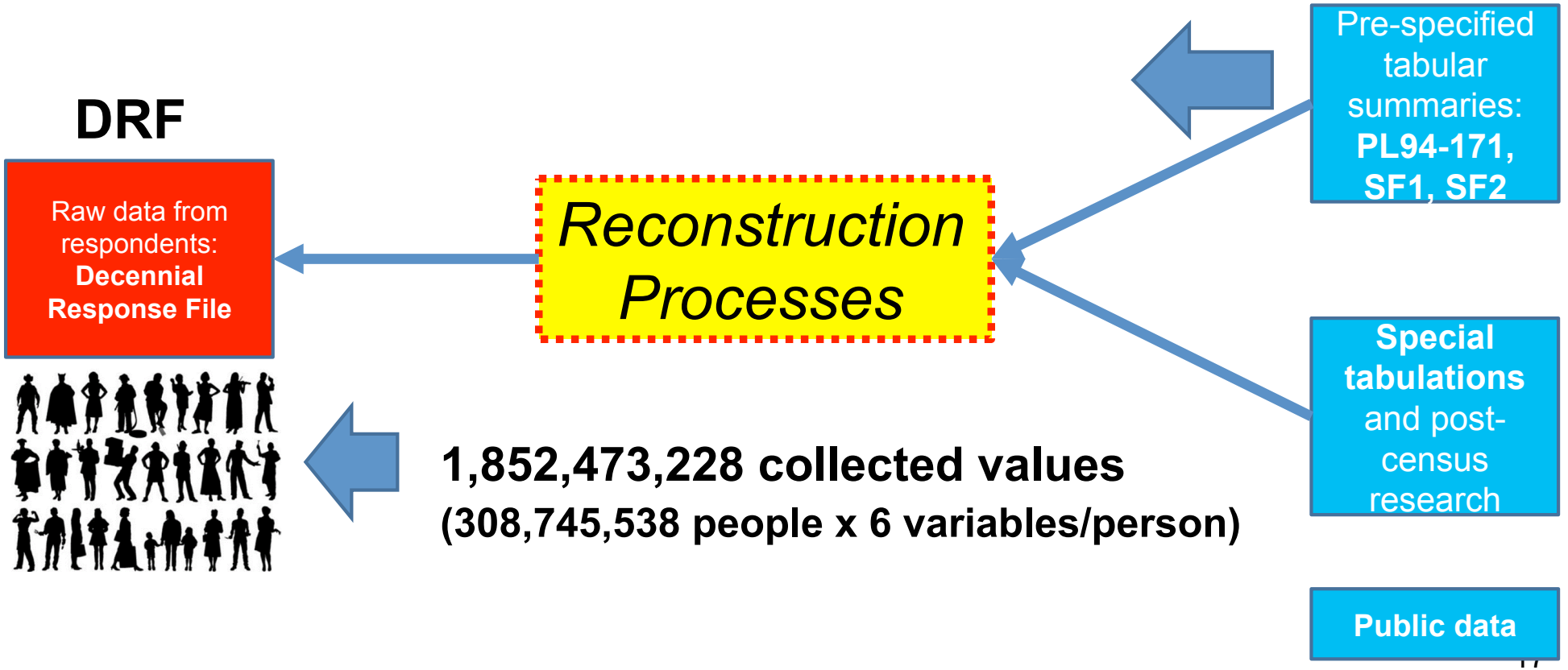
- 2.8 billion counts (including zeros) published in PL94-171,
- 2.8 billion in the rest of SF1, 2 billion in SF2, and
- 30 million in a public-use microdata sample.

Total is roughly 7.7 billion statistics, or 25 per person. That's a lot more than **6** per person (recall 6= variable per person).

2010 Census: Summary of Publications (approximate counts)

Publication	Released counts
PL94-171 Redistricting	2,771,998,263
Balance of Summary File 1	2,806,899,669
Summary File 2	2,093,683,376
Public-use micro data sample	30,874,554
Lower bound on published statistics	7,703,455,862
Published Statistics/person	25
Recall: Collected variables/person:	6
Published Statistics/collected variable	25 / 6 ≈ 4.2

Question:
Is it possible to run the statistical process in reverse?



2003:
Database Reconstruction

ABSTRACT

We examine the tradeoff between privacy and usability of statistical databases. We model a statistical database by an n-bit string $d_1, .., d_n$, with a query being a subset $q \subseteq [n]$ to be answered by $\sum_{i \in q} d_i$. Our main result is a polynomial reconstruction algorithm of data from noisy (perturbed) subset sums. Applying this reconstruction algorithm to statistical databases we show that in order to achieve privacy one has to add perturbation of magnitude $\Omega(\sqrt{n})$. That is, smaller perturbation always results in a strong violation of privacy. We show that this result is tight by exemplifying access algorithms for statistical databases that preserve privacy while adding perturbation of magnitude $\tilde{O}(\sqrt{n})$.

For time-$\mathcal{T}$ bounded adversaries we demonstrate a privacy-preserving access algorithm whose perturbation magnitude is $\approx \sqrt{T}$.

Revealing Information while Preserving Privacy

Irit Dinur Kobbi Nissim*
NEC Research Institute
4 Independence Way
Princeton, NJ 08540
{iritd,kobbi}@research.nj.nec.com

ABSTRACT

We examine the tradeoff between privacy and usability of

research which is based (among other things) on statistics of the information in the database. On the other hand, the hospital is obliged to keep the privacy of its patients, i.e. leak no medical information that could be related to a specific patient. The hospital needs an access mechanism to the database that allows certain 'statistical' queries to be answered, as long as they do not violate the privacy of any single patient.

*Work partly done when the author was at DIMACS, Rutgers University, and while visiting Microsoft Research Silicon Valley Lab.

PODS 2003, June 9-12, 2003, San Diego, CA.

One simple tempting solution is to remove from the database all 'identifying' attributes such as the patients' names and

In their comparative survey of privacy methods for statistical databases, Adam and Wortmann [2] classified the approaches taken into three main categories: (i) query restriction, (ii) data perturbation, and (iii) output perturbation. We give a brief review of these approaches below, and refer the reader to [2] for a detailed survey of the methods and their weaknesses.

Query Restriction. In the query restriction approach, queries are required to obey a special structure, supposedly to prevent the querying adversary from gaining too much information about specific database entries. The limit of this approach is that it allows for a relatively small number of queries.

A related idea is of query auditing [7], i.e. a log of the queries is kept, and every new query is checked for possible compromise, allowing/disallowing the query accordingly.

[1]A patient's gender, approximate age, approximate weight, ethnicity, and marital status – may already suffice for a complete identification of most patients in a database of a thousand patients. The situation is much worse if a relatively 'rare' attribute of some patient is known. For example, a patient having Cystic Fibrosis (frequency $\approx 1/3000$) may be uniquely identified within about a million patients.

Attacking statistical databases

Statistical agencies are trusted curators.

Respondents

Confidential Database

Age Sex Race/MS
8 FBS
18 MWS
24 FWS
30 MWM
36 FBM
66 FBM
84 MBM

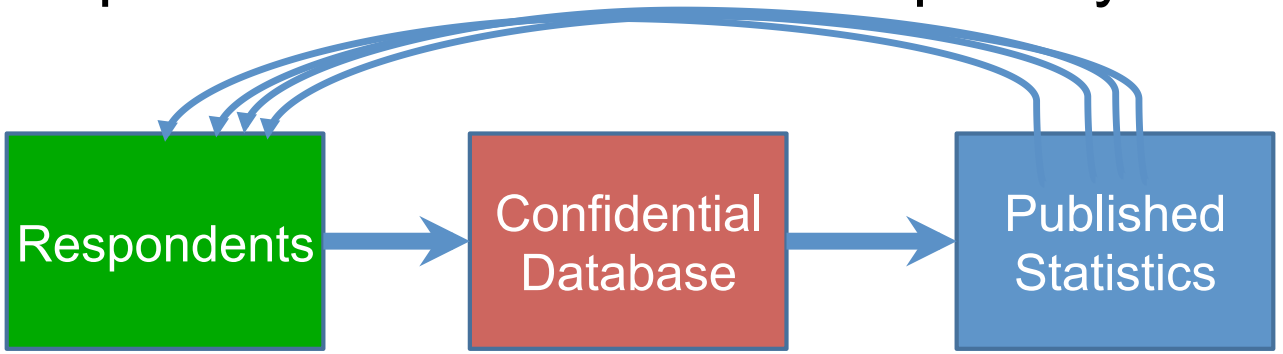
Published Statistics

	#	Median Age	Mean Age
Total	7	30	38
Women	4	30	33.5
Male	3	30	44
Black	4	51	48.5
White	3	24	24
Married	4	51	54
Black F	3	36	36.7

This is the trusted curator model

We now know “trusted curator” model is more complex.

Every data publication results in some privacy loss.



Publishing too many statistics results in the compromise of the entire confidential database.

Consider the statistics from a single household

24 yrs Female White Single (24 FWS)

	Count	Median	Mean
Total	1	24	24
# Female	1	24	24
# white	1	24	24
Single	1	24	24
White F	1	24	24

Publishing statistics for this household alone would result in an improper disclosure.

24 yrs Female White Single (24 FWS)

	Count	Median	Mean
Total	(D)	(D)	(D)
# Female	(D)	(D)	(D)
# white	(D)	(D)	(D)
Single	(D)	(D)	(D)
White F	(D)	(D)	(D)

(D) Means suppressed to prevent an improper disclosure.

In the past, statistical agencies aggregated data from many households together into a single publication.

	Count	Median Age	Mean Age
Total	7	30	38
# Female	4	30	33.5
# male	3	30	44
# black	4	51	48.5
# white	3	24	24
Married	4	51	54
Black F	3	36	36.7

We now know that this publication can be reverse-engineered to reveal the confidential database.

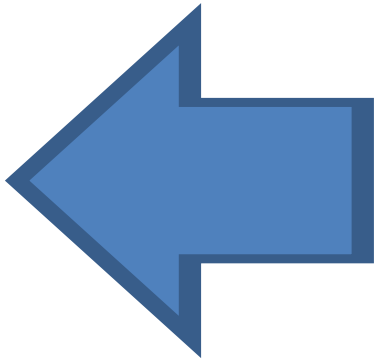
66 FBM & 84 MBM

30 MWM & 36 FBM

8 FBS

18 MWS

24 FWS



	Count	Median	Mean
Total	7	30	38
# Female	4	30	33.5
# male	3	30	44
# black	4	51	48.5
# white	3	24	24
Married	4	51	54
Black F	3	36	36.7

This table can be expressed by 164 equations.
Solving those equations takes
0.2 seconds on a 2013 MacBook Pro.

The problem with publishing fewer statistics: it's hard to know how many statistics is "too many."

Solution #1	Solution #2
8 FBS	2 FBS
18 MWS	12 MWS
24 FWS	24 FWS
30 MWM	30 MBM
36 FBM	36 FWM
66 FBM	72 FBM
84 MBM	90 MBM

	Count	Median	Mean
Total	7	30	38
# Female	4	30	33.5
# male	3	30	44
# black	4	51	48.5
# white	3	24	24
Married	4	51	54
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Lower bound on published statistics	7,703,455,862
Published Statistics/person	25
Recall: Collected variables/person:	6
Published Statistics/collected variable	25 ÷ 6 ≈ 4.2

We performed a database reconstruction and re-identification attack for all 308,745,538 people in 2010 Census

1. Reconstructed 308,745,538 microdata records.
2. Used 4 commercial databases of the 2010 US population acquired 2009-2011 in support of the 2010 Census

   Commercial database had: **NAME, ADDRESS, AGE, SEX**
3. Linked reconstructed records to the commercial database records

   Linked database has: **NAME, ADDRESS, AGE, SEX , ETHNICITY & RACE**

   Link rate: 45%
4. Compared linked database to Census Bureau confidential data

   Question: How often did the attack get the all variables including race and ethnicity right?

   Answer: 38% (17% of US population)

Our attack is good, but not perfect.
An outside attacker would have a harder time.

We confirmed re-identification of 38% (17% of US population)

We did not reconstruct families.

We did not recover detailed self-identified race codes

An outside attacker:

Would not know which re-identifications are correct.

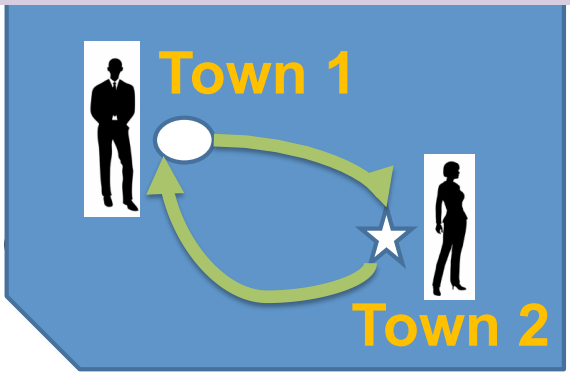
An outside attacker would need to confirm with another external data source.

The protection system used in 2000 and 2010 relied on swapping households.

Some households were swapped with other households

- Swapped households had the same siz
- Swapping limited to within each state.

Confidentiality Mechanism



Any State

Disadvantages:

- Swap rate and details of swapping not disclos
- Privacy protection was not quantified.
- Impact on data quality not quantified.

Swapping is called a “Disclosure Avoidance” technique.
It’s job is to prevent improper disclosures.

We now know that the disclosure avoidance techniques we used in the 2010 Census were flawed

We released *exact population counts* for blocks, tracts and counties.

We did not swap 100% of the households

We released ≈25 statistics per person,
but only collected six pieces of data per person:

Block • Age • Sex • Race • Ethnicity • Relationship to Householder

The Census Bureau did the best possible in 2010.
The math for protecting a decennial census using formal privacy did not [yet] exist.

Faced with “database reconstruction,” statistical agencies have just two choices

Option #1: Publish fewer statistics.

Option #2: Publish statistics with less accuracy.

Faced with “database reconstruction,” statistical agencies have just ~~two~~ one choice

~~Option #1: Publish fewer statistics.~~

The problem with publishing fewer statistics is that we don’t know when we have reached a threshold of having published too many statistics. This is because the information that is published can be combined with external information, or information in the future.

Option #2: Publish statistics with less accuracy.

2006:
Differential Privacy

Abstract. We continue a line of research initiated in [10, 11] on privacy-preserving statistical databases. Consider a trusted server that holds a database of sensitive information. Given a query function f mapping databases to reals, the so-called *true answer* is the result of applying f to the database. To protect privacy, the true answer is perturbed by the addition of random noise generated according to a carefully chosen distribution, and this response, the true answer plus noise, is returned to the user.

Previous work focused on the case of noisy sums, in which $f = \sum_i g(x_i)$, where x_i denotes the ith row of the database and g maps database rows to $[0, 1]$. We extend the study to general functions f, proving that privacy can be preserved by calibrating the standard deviation of the noise according to the *sensitivity* of the function f. Roughly speaking, this is the amount that any single argument to f can change its output. The new analysis shows that for several particular applications substantially less noise is needed than was previously understood to be the case.

The first step is a very clean characterization of privacy in terms of indistinguishability of transcripts. Additionally, we obtain separation results showing the increased value of interactive sanitization mechanisms over non-interactive.

Calibrating Noise to Sensitivity in Private Data Analysis

Cynthia Dwork[1], Frank McSherry[1], Kobbi Nissim[2], and Adam Smith[3]*

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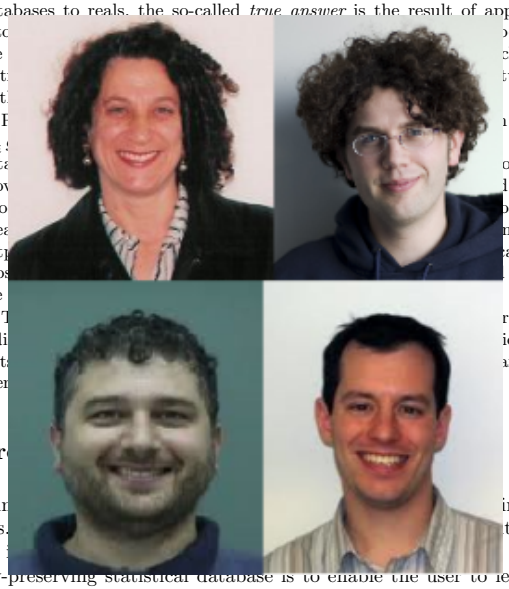
[2] Ben-Gurion University. kobbi@cs.bgu.ac.il
[3] Weizmann Institute of Science. adam.smith@weizmann.ac.il

Abstract. We continue a line of research initiated in [10, 11] on privacy-preserving statistical databases. Consider a trusted server that holds a database of sensitive information. Given a query function f mapping databases to reals, the so-called *true answer* is the result of applying



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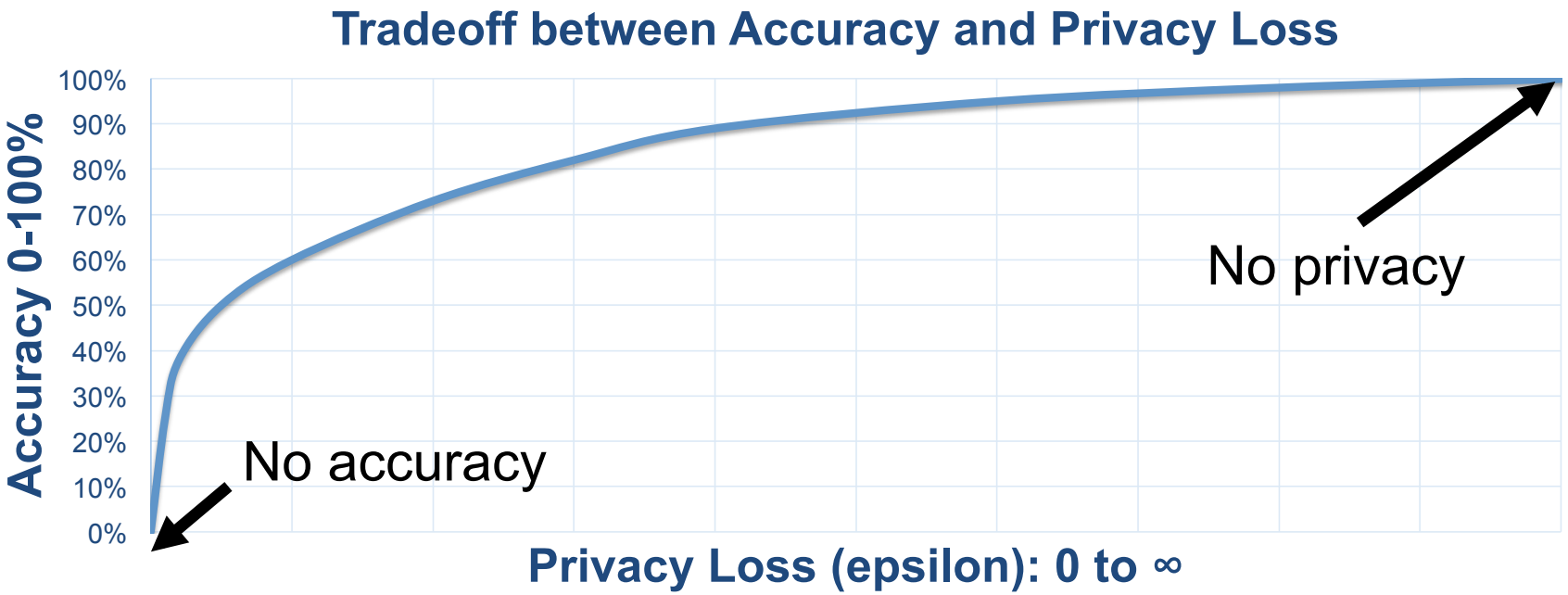
1 Intr

We contin
databases.
database
a privacy-preserving statistical database is to enable the user to learn proper
ties of the population as a whole while protecting the privacy of the individua
contributors.

We assume the database is held by a trusted server. On input a query functio
f mapping databases to reals, the so-called *true answer* is the result of applying f
to the database. To protect privacy, the true answer is perturbed by the additio

* Supported by the Louis L. and Anita M. Perlman Postdoctoral Fellowship.

Differential privacy gives us a mathematical approach for balancing accuracy and privacy loss



“Differential privacy” is really two things

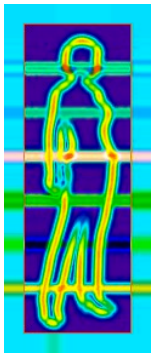
1 – A mathematical definition of privacy loss.

2 – Specific mechanisms that allow us to:

- ✓ *Add the smallest amount of noise necessary for a given privacy outcome*
- ✓ *Structure the noise to have minimal impact on the more important statistics*

Differential privacy — the big idea:
Use “noise” to create uncertainty about private data

NOISE BARRIER



24 yrs Female White Single (24 FWS)

35 yrs Female Black Single (35 FBS)

Impact of the noise ≈ impact of a single person

Impact of noise on aggregate statistics decreases with larger population.

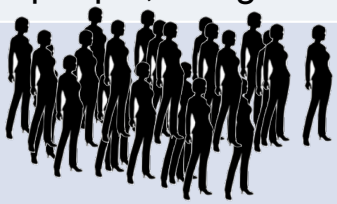
Each time we go through the noise barrier, we get a different number

	NOISE BARRIER	Age	Count
 1 person age 22		25	3
 1 person age 22		17	1
 1 person age 22		27	-1

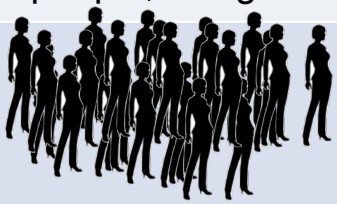
Epsilon controls the amount of noise

	NOISE BARRIER	Epsilon	Age
 1 person age 22		100	22
 1 person age 22		1.0	24
 1 person age 22		0.1	-115

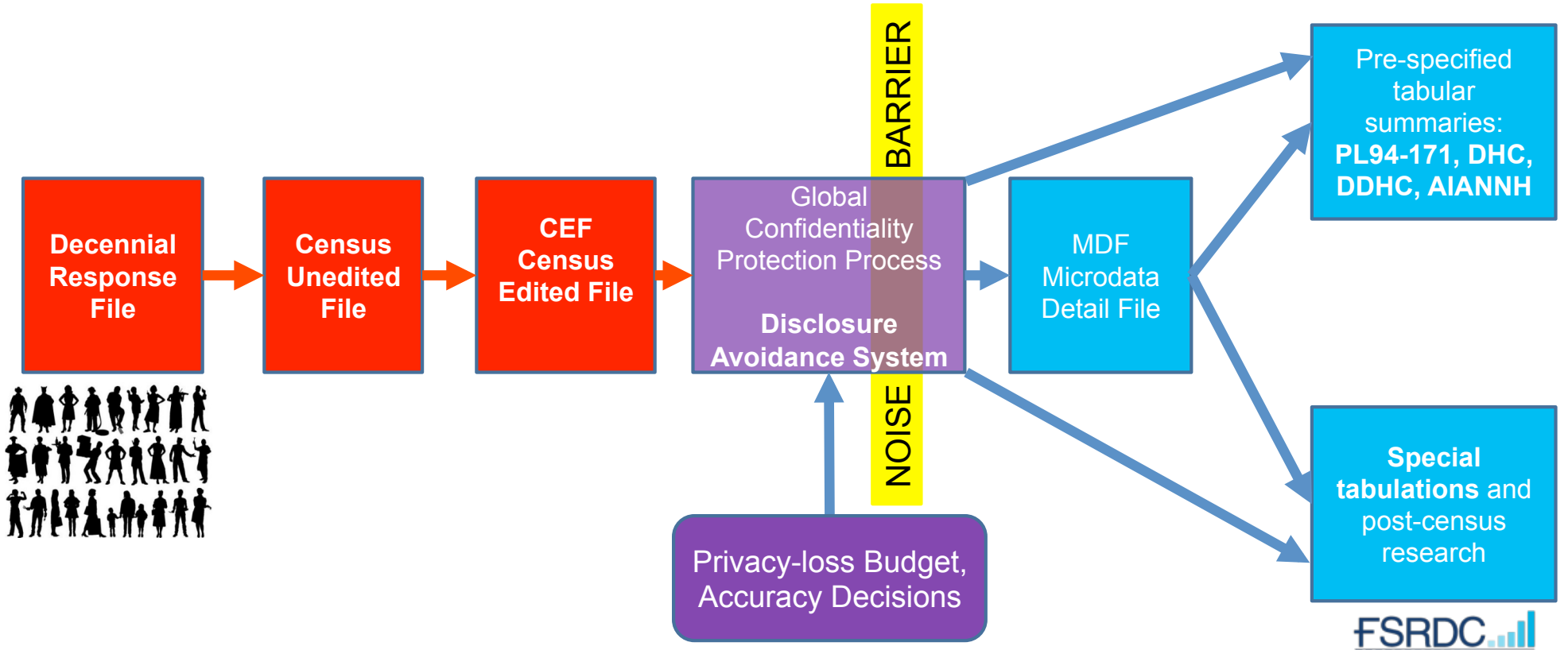
Understanding the impact of “noise:”
Statistics based on 10,000 experiments, epsilon=1.0

	NOISE BARRIER	5,000 (50%) runs	9,500 (95%) runs
 1 person age 22		Median(age): 9 → 73	Median(age): 0→ 104
 10 people, all age 22		Median(age): 17 → 61	Median(age): 0→ 103
 100 people, all age 22		Median(age): 21 → 22	Median(age): 21→ 22

The noise also impacts the person counts

	NOISE BARRIER	5,000 (50%) runs	9,500 (95%) runs
 1 person age 22		Median(age): 9 → 73 # people: -9 → 11	Median(age): 0→ 104 # people: -29 → 30
 10 people, all age 22		Median(age): 17 → 61 # people: 0 → 20	Median(age): 0→ 103 # people: -19 → 38
 100 people, all age 22		Median(age): 21 → 22 # people: 90 → 110	Median(age): 21→ 22 # people: 71 → 129

DAS allows the Census Bureau to enforce global confidentiality protections

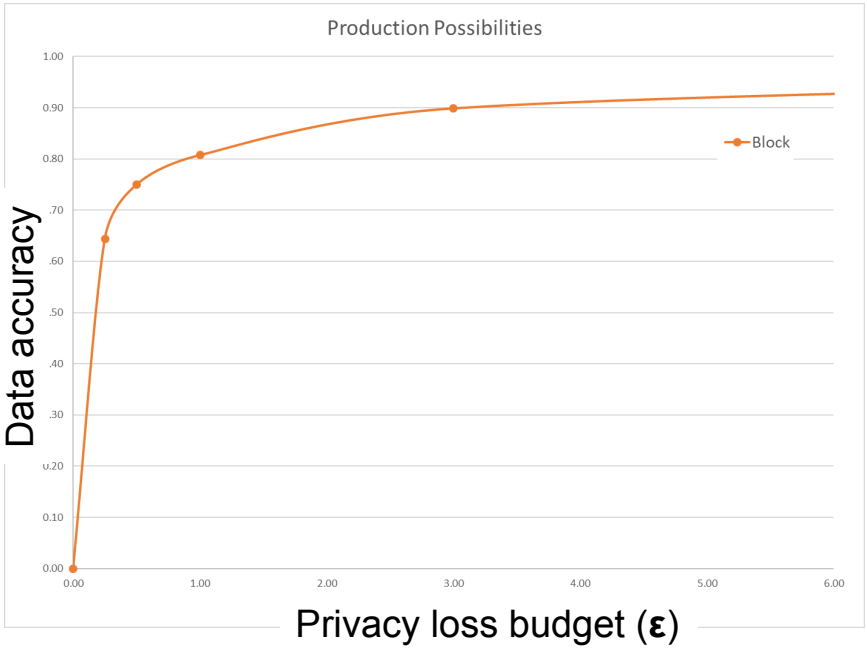


The Census disclosure avoidance system uses differential privacy to defend against an accurate reconstruction attack

Differential privacy provides:

- Provable bounds on the accuracy of the best possible database reconstruction given the released tabulations. (recall reconstruction through equations might give more than one solution)

- Algorithms that allow policy makers to decide the trade-off between accuracy and privacy.

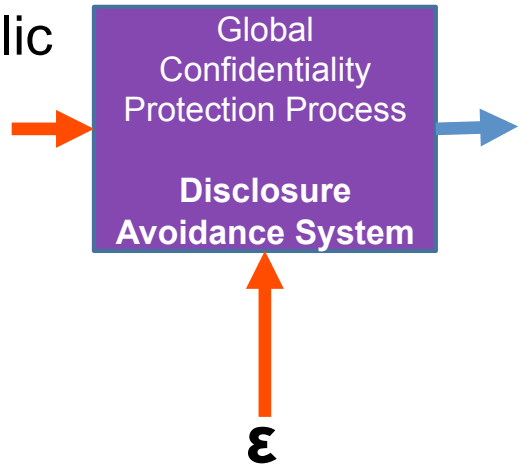


Final privacy-loss budget determined by Data Stewardship Executive Policy Committee (DSEP) with recommendation from Disclosure Review Board (DRB)

The Disclosure Avoidance System relies on injects formally private noise

Advantages of noise injection with formal privacy:

- Transparency: the details can be explained to the public
- Tunable privacy guarantees
- Privacy guarantees do not depend on external data
- Protects against accurate database reconstruction
- Protects every member of the population



Challenges:

- Entire country must be processed at once for best accuracy
- Every use of confidential data must be tallied in the *privacy-loss budget*

There was no off-the-shelf system for applying differential privacy to a national census

We had to create a new system that:

- Produced higher-quality statistics at more densely populated geographies
- Produced consistent tables

We created new differential privacy algorithms and processing systems that:

- Produce highly accurate statistics for large populations (e.g. states, counties)
- Create protected microdata that can be used for any tabulation without additional privacy loss
- Fit into the decennial census production system

How the 2020 System Works: High-level Overview

Every record in the population may be modified

But modifications are bounded by the global privacy budget.

Records in the tabulation data have no exact counterpart in the confidential data

There is no one-to-one mapping between CEF and MDF records (collected data and published data).

Explicitly protected tabulations (PL-94 and SF-1) have provable, public accuracy levels

Basic approach for a DP Census

Treat the *entire census* as a set of queries on histograms.

Select the specific queries to measure

- Six *geolevels* (nation, state, county, tract, block group, block)
- Thousands of queries per *geounit*
- Billions of queries overall
- Histogram has billions of cells

Basic definitions

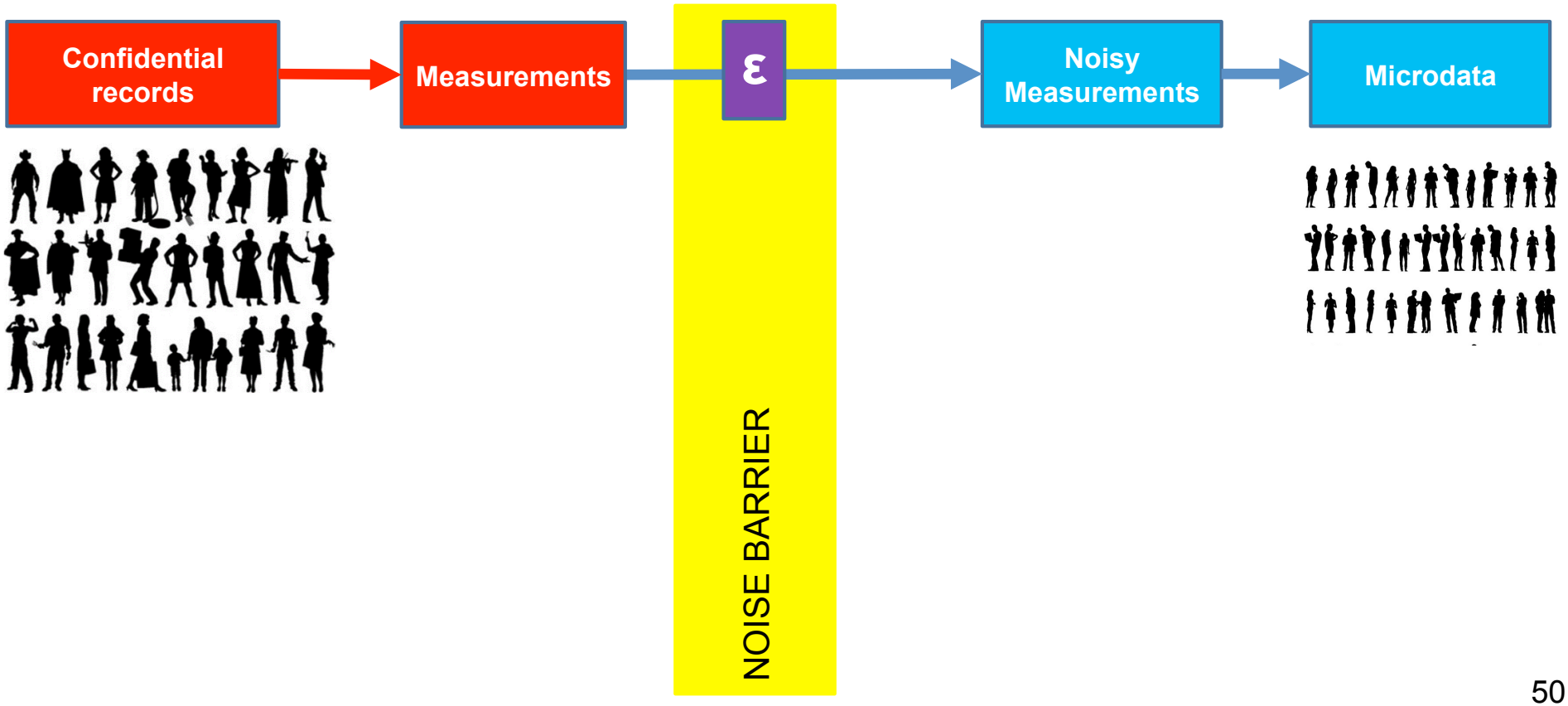
Census block

- the smallest geographic unit used by the for tabulation of data (data collected from all houses, rather than a sample of houses). The number of blocks for the 2010 Census was 11,155,486.
- The population of a census block varies greatly. As of them 2010 census there were 4,871,270 blocks with a reported population of zero, while a block that is entirely occupied by an apartment complex might have several hundred inhabitants.
- There are many blocks (rural areas) with few people (possibility leaks)

Block groups

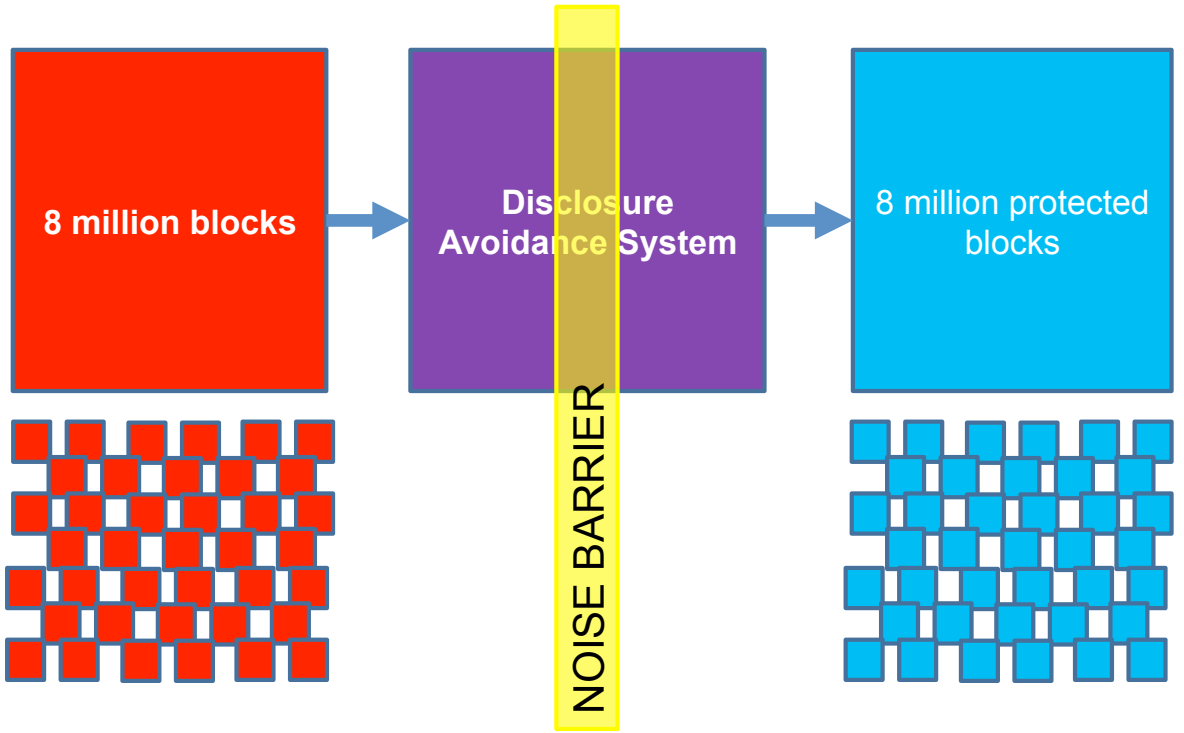
- Census blocks are grouped into block groups, which are grouped into census tracts.

Protecting the data



First effort: The block-by-block algorithm

Independently protect each block (parallel composition)



Measure queries for each block; privatize queries; convert results back to microdata

Block-by-block algorithm (also called bottomUp)

Mechanism:

- Select, Measure, Reconstruct separately on each block

Advantages:

- Simple and easy to parallelize
- Privacy cost does not depend on # of blocks
- Releasing DP for one block has same cost as releasing for all

Disadvantages

- Significant error at higher level
- Error adds up
- Variance of each geounit is proportional to the number of blocks it contains

New algorithm: the top-down mechanism

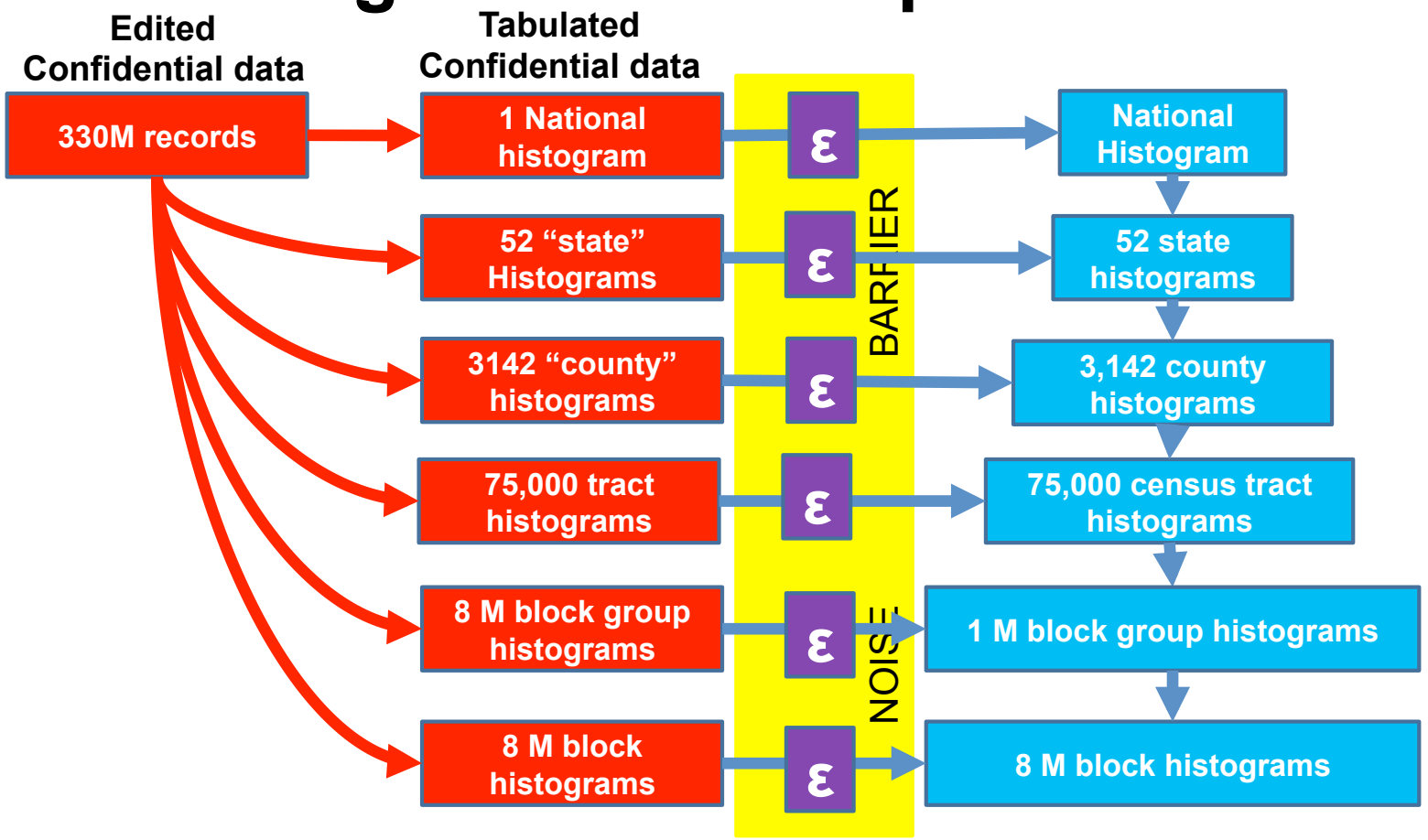
Step 1: Generate national histogram without geographic identifiers.

Step 2: Allocate counts in histogram to each geography "top down."

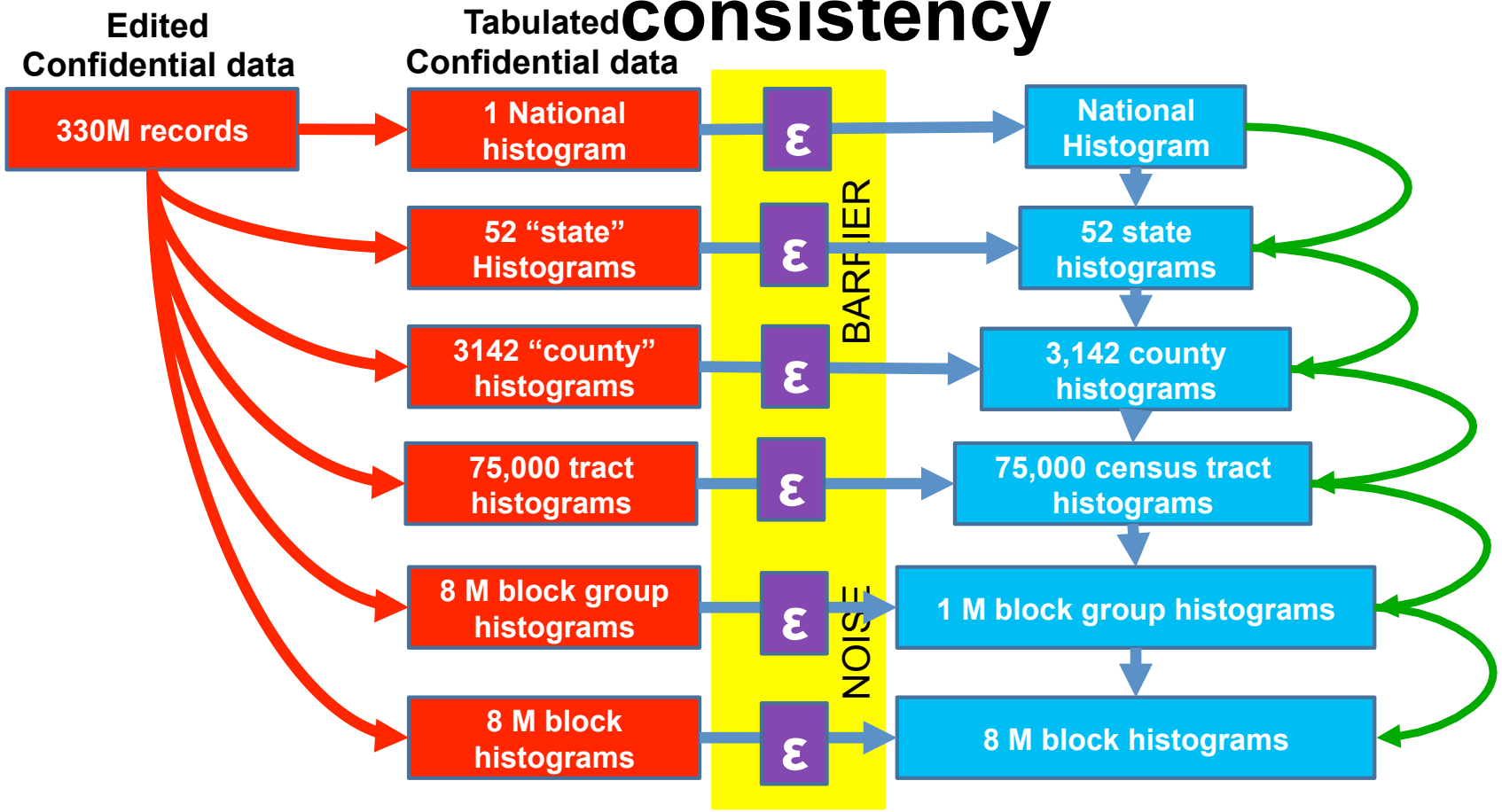
National-level measurements - ε_{nat}
State-level histograms - ε_{state}
County-level histograms - ε_{county}
Tract-level histograms - ε_{tract}
Block-group level histograms - $\varepsilon_{blockgroup}$
Block-level histograms - ε_{block}

$$\varepsilon = \varepsilon_{nat} + \varepsilon_{state} + \varepsilon_{county} + \varepsilon_{tract} + \varepsilon_{blockgroup} + \varepsilon_{block}$$

New algorithm: the top-down mechanism



Post-process for non-negativity and consistency



Top-down framework: alternative view

National histogram equivalent to table of records:

Age	Race	Sex	Ethnicity	HHGQ

Extend to state-level histograms:

Age	Race	Sex	Ethnicity	HHGQ	State

Add county:

Age	Race	Sex	Ethnicity	HHGQ	State	County

Then add tract, block group, block

Top-Down Framework

Advantages:

Easy to parallelize

Each geo-unit can have its own strategy selection

We use High Dimensional Matrix Mechanism [MMHM18]

Parallel composition at each geo-level

Reduced variance for many aggregate regions

Sparsity discovery

- *e.g. very few 100+ aged people: if a region has no such records in county A, no subregion will have them.*

Post-processing

Each distribution involves (at least) two runs of an optimizer

L_2 solve:

- Generates nonnegative fractional demographics histogram
- State histograms must add up to National histogram (etc.)

L_1 solve:

- Converts fractional histogram to non-negative integer histogram
- Maintain consistency: child histograms must add up to parent
- Integer solutions are fast to find

Evaluating the algorithm

We released runs of the top-down algorithm on data from the 1940 Census.

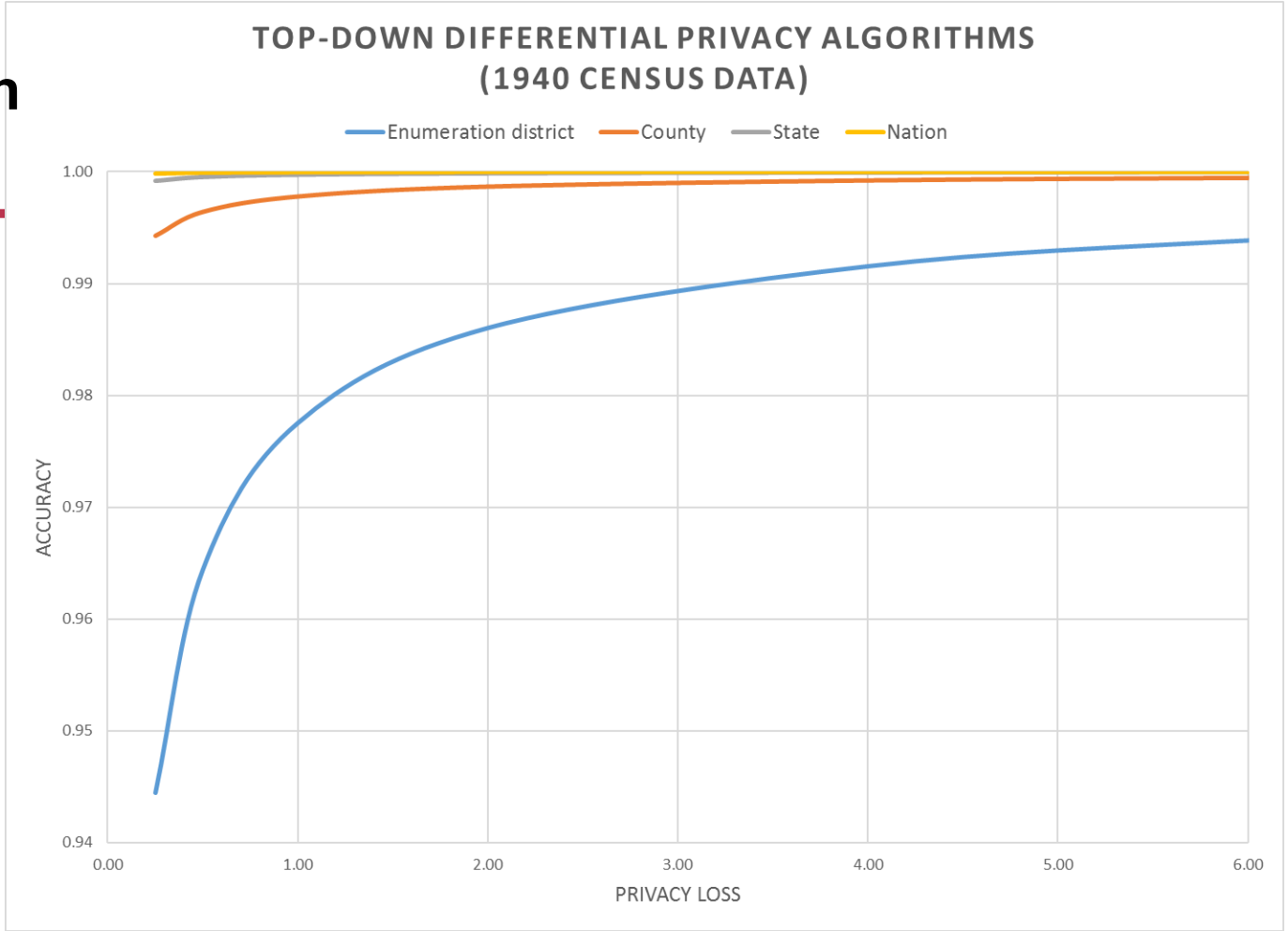
- Epsilon values 0.25 .. 8.0
- Multiple runs at each value of epsilon.

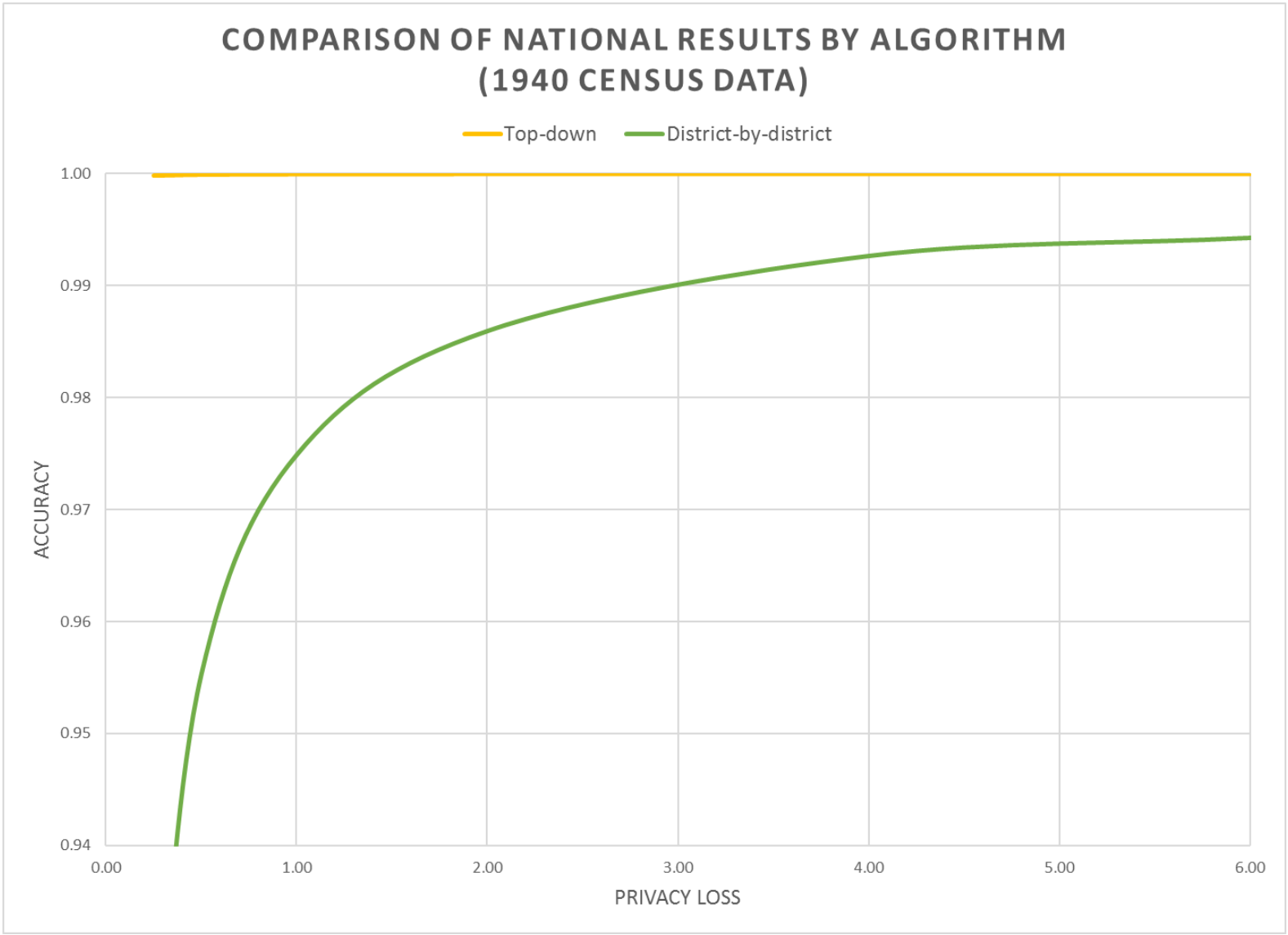
Caveats:

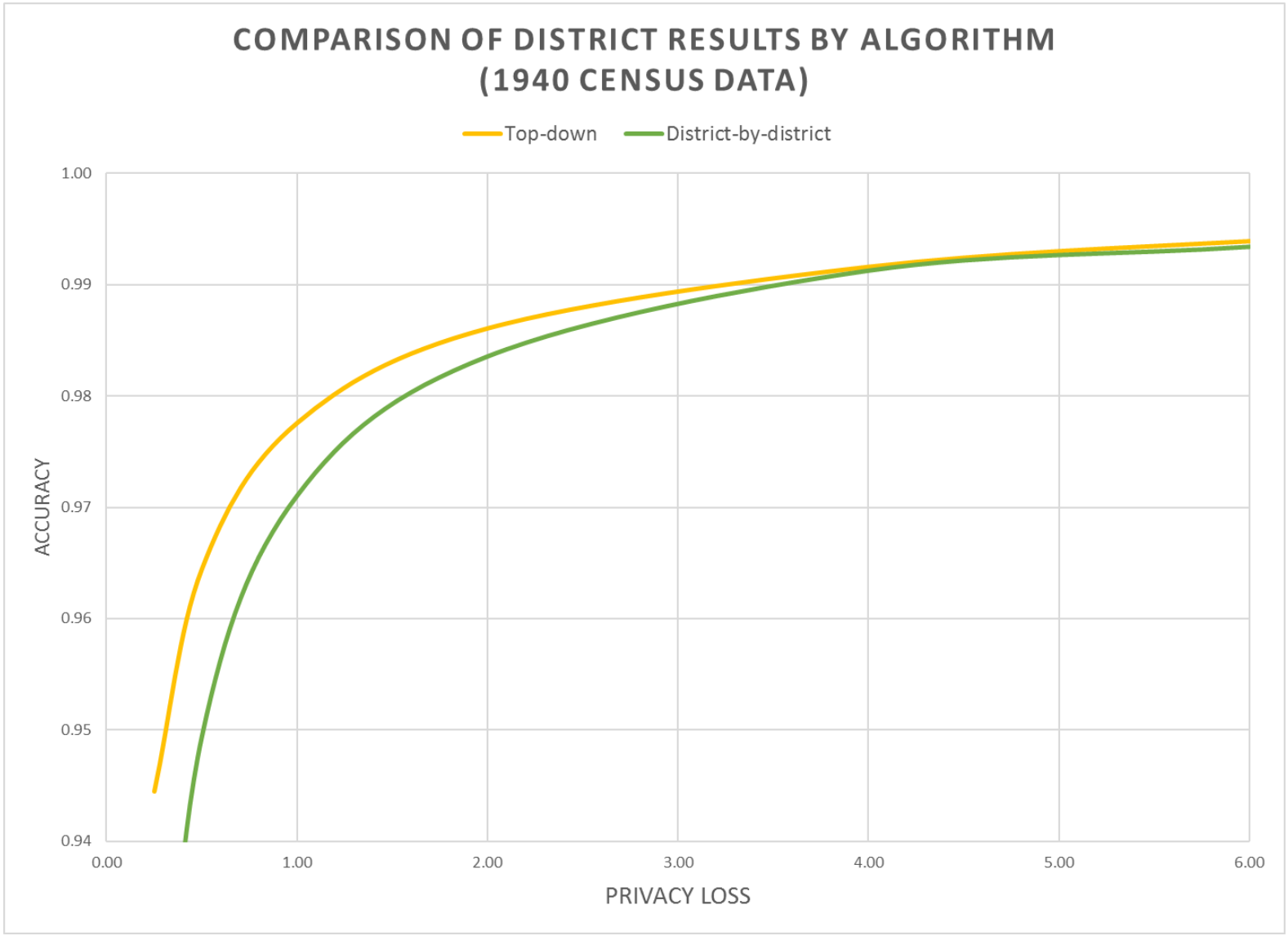
- 1940 data had 4 geography levels: Nation, State, County, Enumeration District.
- 2020 data has 6 levels: Nation, State, County, Tract, Block Group and Block.

- 1940 data has 6 races races / 2020 data has 63 race combinations
- 1940 data has no citizenship (Citizen or non-Citizen)

Top-Down: much more accurate!




COMPARISON OF NATIONAL RESULTS BY ALGORITHM
(1940 CENSUS DATA)
Top-down
District-by-district
1.00
0.99
0.98
0.97
0.96
0.95
0.94
ACCURACY
0.00
1.00
2.00
3.00
4.00
5.00
6.00
PRIVACY LOSS


COMPARISON OF DISTRICT RESULTS BY ALGORITHM
(1940 CENSUS DATA)
Top-down
District-by-district
1.00
0.99
0.98
0.97
0.96
0.95
0.94
ACCURACY
0.00
1.00
2.00
3.00
4.00
5.00
6.00
PRIVACY LOSS

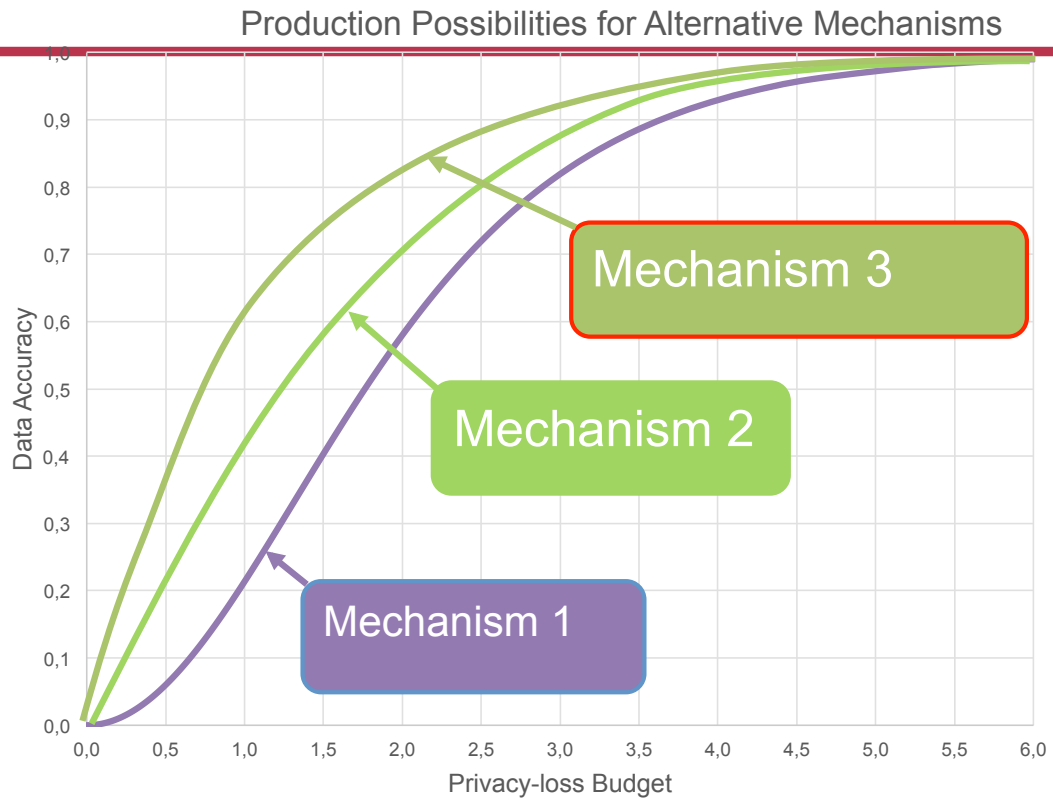
Two public policy choices:

What is the correct value of epsilon?

Where should the accuracy be allocated?

Managing the Tradeoff

Policy Issue: Setting Epsilon



Policy Decisions: Setting privacy loss budget (ε)

Global privacy loss budget

Geographic levels

- Fraction of **ε** allocated to each level

Tables

- Fraction of **ε** allocated to each table or relationship

Policy Issues for the 2020 Census: Invariants

For the 2018 End-to-End test, policy makers wanted exact counts:

- Number of people on each block
- Number of people on each block of voting age
- Number of residences & group quarters on each block

We implemented invariants before we understood their mathematical impact on differential privacy semantics. We then scaled back to four invariants:

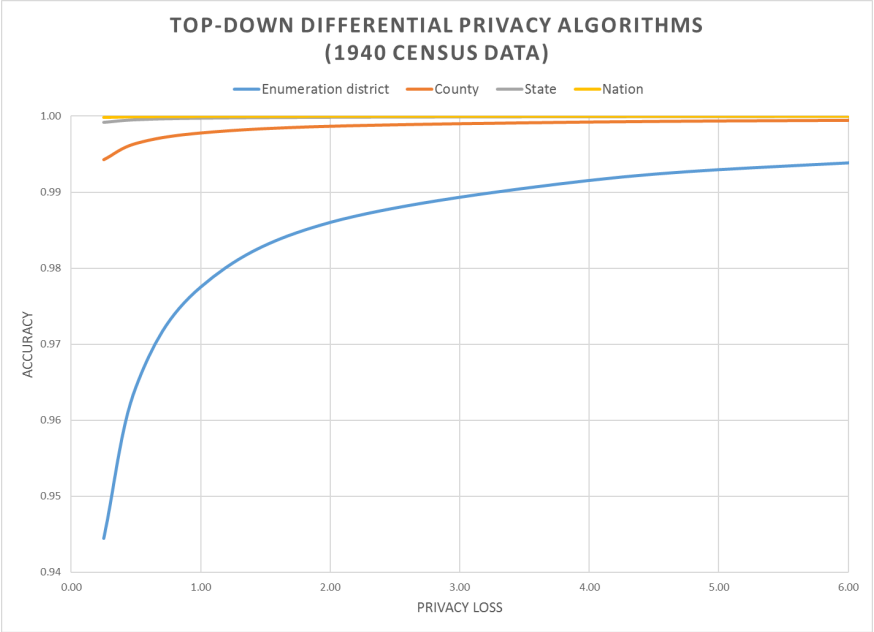
- C1: Total population (invariant at the county level for the 2018 E2E)
- ~~C2: Voting-age population (population age 18 and older)~~ (eliminated for the 2018 E2E)
- C3: Number of housing units (invariant at the block level)
- C4: Number of occupied housing units (invariant at the block level)
- C5: Number of group quarters facilities by group quarters type (invariant at the block level)

Scientific Issue for any use of DP: Quality Metrics

What is the measure of “quality” or “utility” in a complex data product?

Options:

- L1 error between “true” data set and “protected” data set
- Impact on an algorithm that uses the data (e.g., redistricting and Voting Rights Act enforcement)



The Choice Problem for Redistricting Tabulations Is More Challenging

In the redistricting application, the fitness-for-use is based on :

- Supreme Court one-person one-vote decision (All legislative districts must have approximately equal populations; there is judicially approved variation)
- *Is statistical disclosure limitation a "statistical method" (permitted by Utah v. Evans) or "sampling" (prohibited by the Census Act, confirmed in Commerce v. House of Representatives)?*
- Voting Rights Act, Section 2: requires majority-minority districts at all levels, when certain criteria are met

The privacy interest is based on:

- Title 13 requirement not to publish exact identifying information
- The public policy implications of uses of detailed race, ethnicity and citizenship

Organizational Challenges

Process documentation

- All uses of confidential data need to be tracked and accounted.

Workload identification

- All desired queries on MDF should be known in advance.
- Required accuracy for various queries should be understood.
- Queries outside of MDF must also be pre-specified

Correctness and Quality control

- Verifying implementation correctness.
- Data quality checks on tables cannot be done by looking at raw data.

Data User Challenges

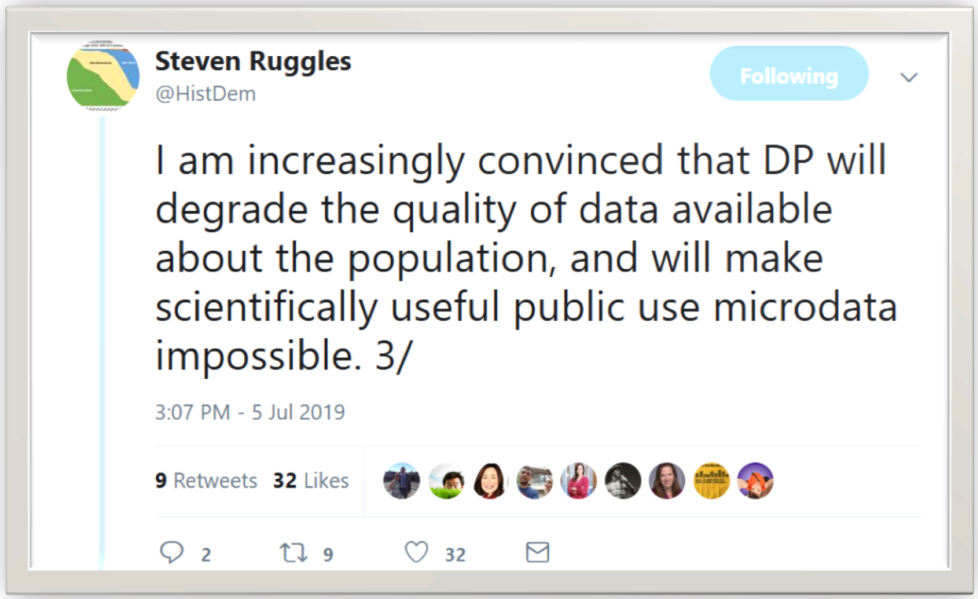
Differential privacy is not widely known or understood.

Many data users want highly accurate data reports on small areas.

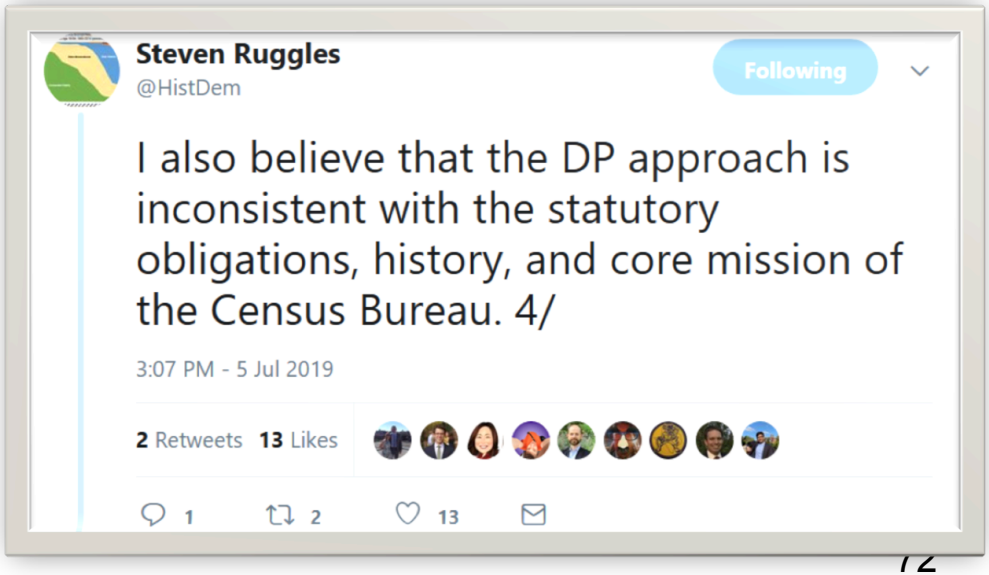
- Some are anxious about the intentional addition of noise.
- Some are concerned that previous studies done with swapped data might not be replicated if they used DP data.

Many data users believe they require access to Public Use Microdata.

Users in 2000 and 2010 didn't know the error introduced by swapping and other protections applied to the tables and PUMS.



Concerns and Responses



Redistricting and Exact Counts

In the US, legislative districts must have equal size.

- Decennial Census counts of each block are the “official counts.”

Some data users are concerned that adding noise to the counts will make them unfit for use.

However:

- Evaluation of districts is based on official decennial counts; these data are used for 10 years.
- Noise added by DP is significantly less than noise added by other statistical methods currently in use

Ruggles Concerns

STEVEN RUGGLES

Regents Professor of History and Population Studies
Director, Institute for Social Research and Data Innovation
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University of Minnesota
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(612) 624-5818

Differential privacy is not a measure of identifiability

Differential privacy does not measure disclosure risk

"Differential Privacy is not concerned with re-identification of respondents

- "DP prohibits revealing *characteristics* of an individual even if the *identity* of that individual is effectively concealed
- "This is a radical departure from established census law and precedent
- "The Census Bureau has been disseminating individual-level *characteristics* routinely since the first microdata in 1962

Organized attack on the move to differential privacy

STEVEN RUGGLES

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Concerns:

- “Differential privacy will degrade the quality of data available about the population, and will probably make scientifically useful public use microdata impossible
- The differential privacy approach is inconsistent with the statutory obligations, history, and core mission of the Census Bureau”

Analysis of population variances
David Van Riper & Tracy Kugler, IPUMS (APDU 2019)

Analysis of population variances
David Van Riper & Tracy Kugler, IPUMS (APDU 2019)

For more information…

practice

DOI:10.1145/3287287

Article development led by queue.acm.org

These attacks on statistical databases are no longer a theoretical danger.

BY SIMSON GARFINKEL, JOHN M. ABOWD, AND CHRISTIAN MARTINDALE

Understanding Database Reconstruction Attacks on Public Data

IN 2020, THE U.S. Census Bureau will conduct the Constitutionally mandated decennial Census of Population and Housing. Because a census involves collecting large amounts of private data under the promise of confidentiality, traditionally statistics are published only at high levels of aggregation. Published statistical tables are vulnerable to *database reconstruction attacks* (DRAs), in which the underlying microdata is recovered merely by finding a set of microdata that is consistent with the published statistical tabulations. A DRA can be performed by using the tables to create a set of mathematical constraints and then solving the resulting set of simultaneous equations. This article shows how such an attack can be addressed by adding noise to the published tabulations, so the reconstruction no longer results in the original data. This has implications for the 2020 census.

The goal of the census is to count every person once, and only once, and in the correct place. The results are used to fulfill the Constitutional requirement to apportion the seats in the U.S. House of Representatives among the states according to their respective numbers.

In addition to this primary purpose of the decennial census, the U.S. Congress has mandated many other uses for the data. For example, the U.S. Department of Justice uses block-by-block counts by race for enforcing the Voting Rights Act. More generally, the results of the decennial census, combined with other data, are used to help distribute more than $675 billion in federal funds to states and local organizations.

Beyond collecting and distributing data on U.S. citizens, the Census Bureau is also charged with protecting the privacy and confidentiality of survey responses. All census publications must uphold the confidentiality standard specified by Title 13, Section 9 of the U.S. Code, which states that Census Bureau publications are prohibited from identifying "the data furnished by any particular establishment or individual." This section prohibits the Census Bureau from publishing respondents' names, addresses, or any other information that might identify a specific person or establishment.

Upholding this confidentiality requirement frequently poses a challenge, because many statistics can inadvertently provide information in a way that can be attributed to a particular entity. For example, if a statistical agency *accurately* reports there are two persons living on a block and the average age of the block's residents is 35, that would constitute an improper disclosure of personal information, because one of the residents could look up the data, subtract their contribution, and infer the age of the other.

Communications of ACM March 2019
Garfinkel & Abowd

Can a set of equations keep U.S. census data private?
By Jeffrey Mervis
Science
Jan. 4, 2019 , 2:50 PM

http://bit.ly/Science2019C1

More Background on the 2020 Disclosure Avoidance System

September 14, 2017 CSAC (overall design)
https://www2.census.gov/cac/sac/meetings/2017-09/garfinkel-modernizing-disclosure-avoidance.pdf

August, 2018 KDD'18 (top-down v. block-by-block)
https://digitalcommons.ilr.cornell.edu/ldi/49/

October, 2018 WPES (implementation issues)
https://arxiv.org/abs/1809.02201

October, 2018 *ACMQueue* (understanding database reconstruction)
https://digitalcommons.ilr.cornell.edu/ldi/50/ or
https://queue.acm.org/detail.cfm?id=3295691

Memorandum 2019.13: Disclosure Avoidance System Design Parameters
https://www.census.gov/programs-surveys/decennial-census/2020-census/planning-management/memo-series/2020-memo-2019_13.html

Conclusions and discussions

1. The Emerging Public Policy Debate About Privacy and Accuracy

The database reconstruction theorem, also known as the fundamental law of information reconstruction, tells us that if you publish too many statistics derived from a confidential data source, at too high a degree of accuracy, then after a finite number of queries you will completely expose the confidential data (Dinur & Nissim, 2003).

All statistical disclosure limitation techniques, including traditional and formally private methods, seek to protect privacy by limiting the quantity of data released (e.g., through suppression) or by reducing the accuracy of the data.

Conclusions and discussions

2. Prioritizing Accuracy for Diverse Use Cases

When implementing differential privacy, the privacy-loss budget makes data accuracy and privacy competing uses of a finite resource: the information (bits) in the underlying data.

It is impossible to protect privacy while also releasing highly accurate data to support every conceivable use case, and vice versa.

While statistics for large populations—for example, for entire states or for major metropolitan areas—can be adequately protected with negligible amounts of noise, many important uses of census data require calculations on smaller populations, where the impacts of noise can be much more significant.

Conclusions and discussions

3. Choose the Right Design: not all statistics are the same

How you implement any disclosure avoidance strategy will impact the accuracy and usability of the resulting data, and this is especially true for differentially private methods.

In fact, the design of the system can often have more of an impact on the accuracy of the resulting data than the selection of the privacy-loss budget.

With differential privacy, the amount of noise you must inject into the data is dependent on the sensitivity of the calculation you are performing. Because that sensitivity depends on the impact that the presence or absence of any individual could have on the resulting calculation, some statistics (e.g., simple counts of individuals) typically require less noise than others (e.g., mean age).

Conclusions and discussions

4. Rethinking Tabular Consistency and Integrality

Consumers of official statistics, particularly those who use data products that have been produced for a long time, are accustomed to the data looking a certain way, and to interpreting those data as the ‘ground truth.’

As such, they are unaccustomed to seeing population counts with fractional or negative values. Because differential privacy injects noise from a symmetric distribution (typically Laplace or geometric), the raw noisy statistics emerging from the privacy protection stage of a formally private algorithm will usually include fractional and negative values, and different tabulations of the same characteristic may not be internally consistent (e.g., the total number of people in a geography may not equal the sum of males and females within that geography).

The process of converting these noisy values into nonnegative integers with tabular consistency therefore introduces more error into the data than is strictly necessary to protect privacy.