Modernizing Disclosure Avoidance: Report on the 2020 Disclosure Avoidance Subsystem as Implemented for the 2018 End-to-End Test (Continued)

Simson L. Garfinkel
Chief, Center for Disclosure Avoidance Research
U.S. Census Bureau

2017 Census Scientific Advisory Committee Fall Meeting
Suitland, MD
11:00AM
September 15, 2017

Acknowledgments

This presentation incorporates work by:

- Dan Kifer (Scientific Lead)
- John Abowd (Chief Scientist)
- Tammy Adams, Robert Ashmead, Aref Dajani, Jason Devine, Michael Hay, Cynthia Hollingsworth, Meriton Ibrahimi, Michael Ikeda, Philip Leclerc, Ashwin Machanavajjhala, Christian Martindale, Gerome Miklau, Brett Moran, Ned Porter, Anne Ross and William Sexton

Outline

Motivation

Differentially private 2020 Disclosure Avoidance System

High-level goals

Flow diagrams

Query examples

Conclusion

Motivation:
To protect the privacy of individual survey responses

2010 Census:

- 5.6 billion independent tabular summaries published.
- Based on 308 million person records

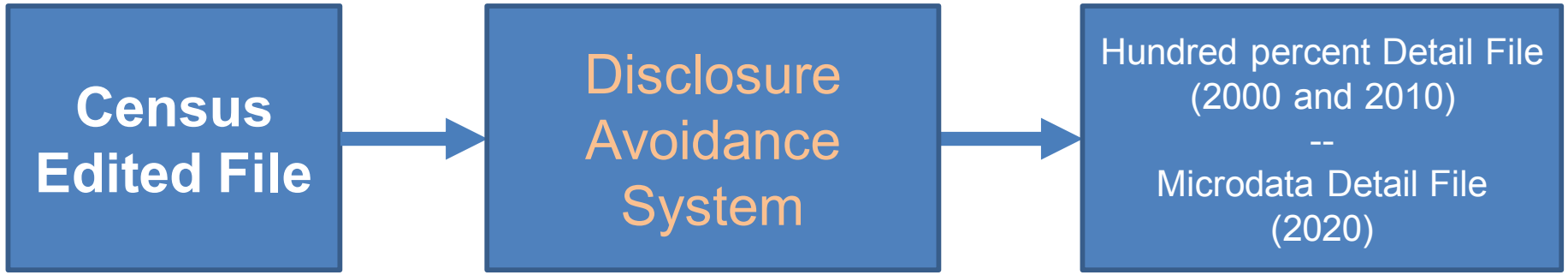
Database reconstruction (Dinur and Nissim 2003) is a serious disclosure threat that all statistical tabulation systems from confidential data must acknowledge.

The confidentiality edits applied to the 2010 Census were not designed to defend against this kind of attack.

The Disclosure Avoidance Subsystem (DAS) implements the privacy protections for the decennial Census.

Features of the DAS:

- Operates on the edited Census records
- Designed to make Census records safe to tabulate



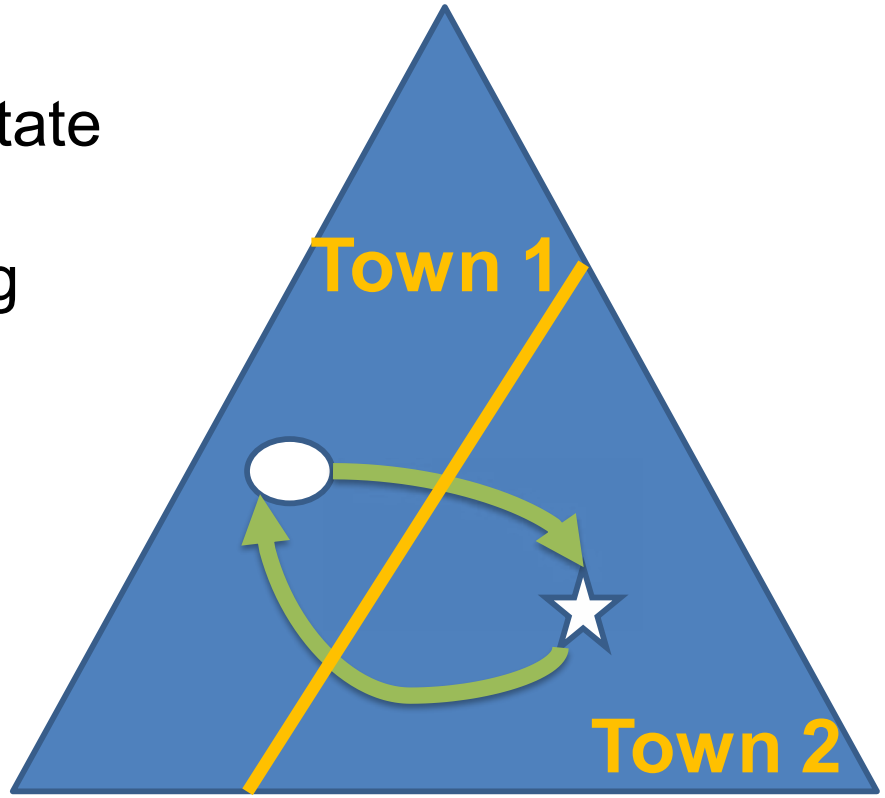
The 2000 and 2010 Disclosure Avoidance Systems relied on swapping households:

Advantages of swapping:

- Easy to understand
- Does not affect state counts if swaps are within a state
- Can be run state-by-state
- Operation is “invisible” to rest of Census processing

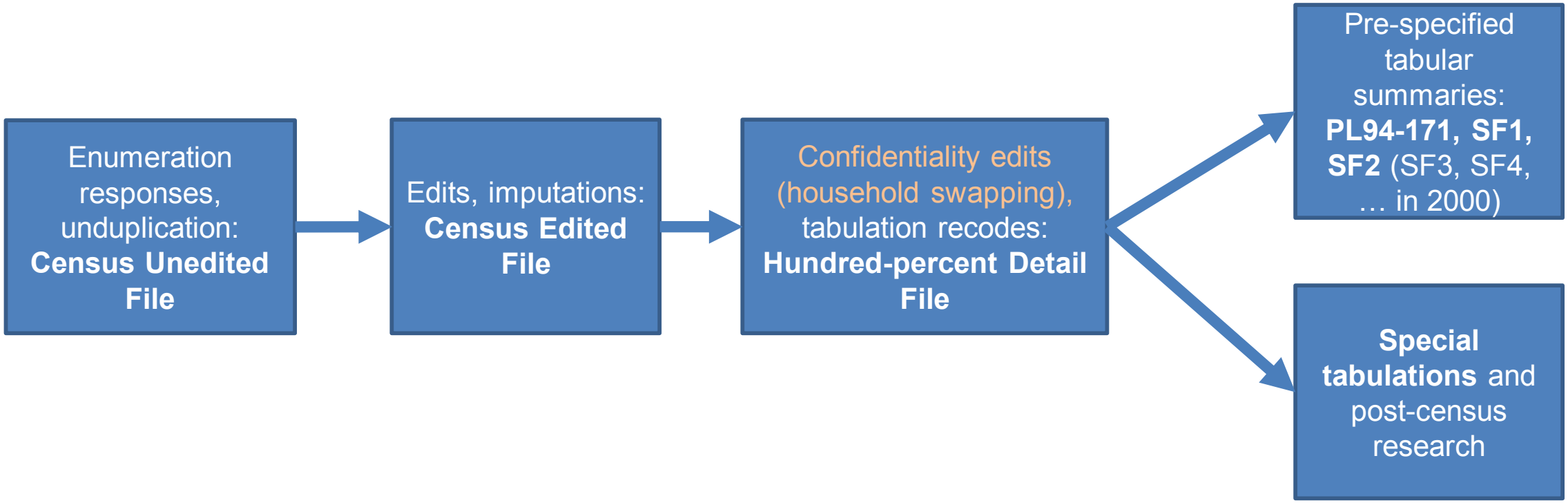
Disadvantages:

- Does not provide formal privacy guarantees
- Does not protect against database reconstruction attacks
- Privacy guarantee relies on lack of external data



State “X”

The 2000 and 2010 Disclosure Avoidance System operated as a filter, on the Census Edited File:

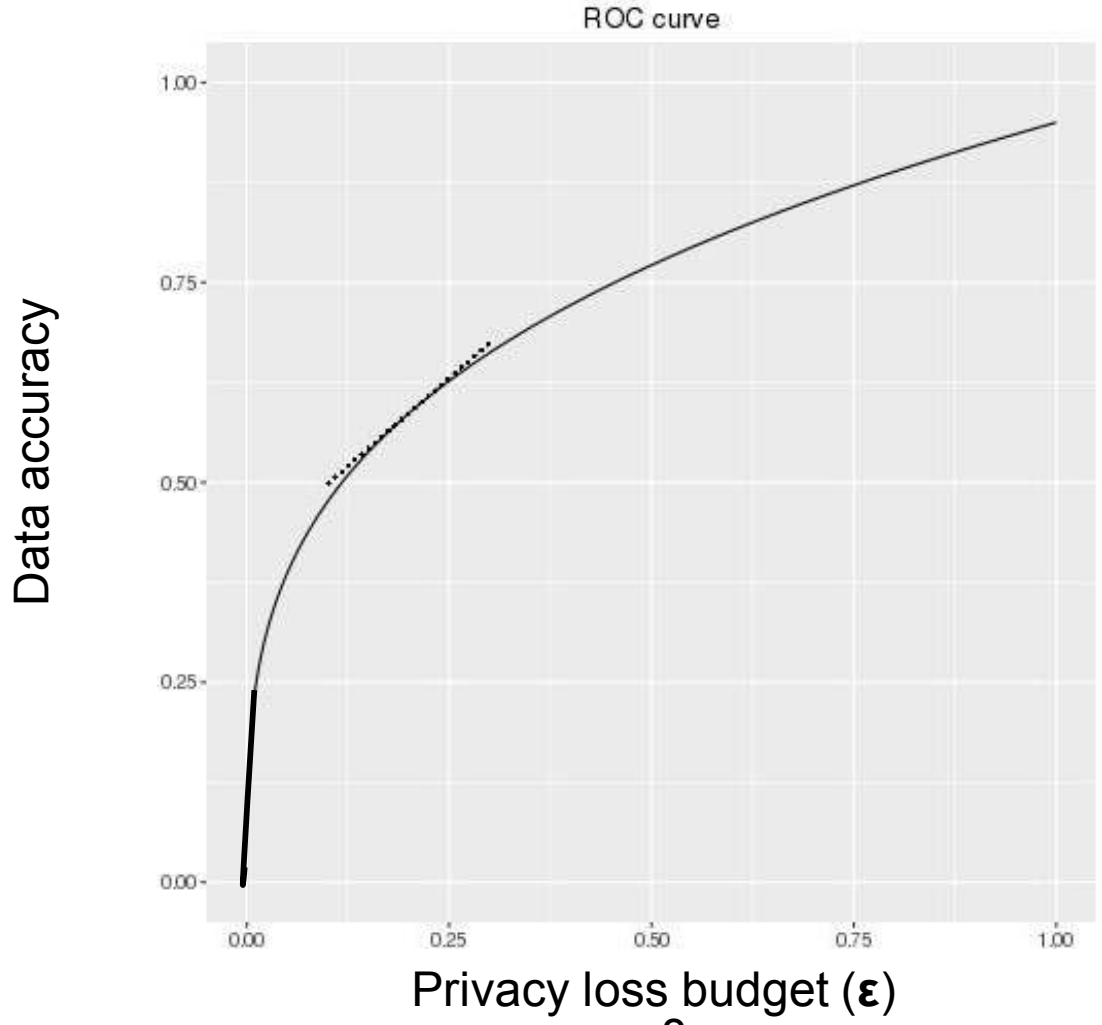


The 2020 Census disclosure avoidance system will use differential privacy to defend against a reconstruction attack,

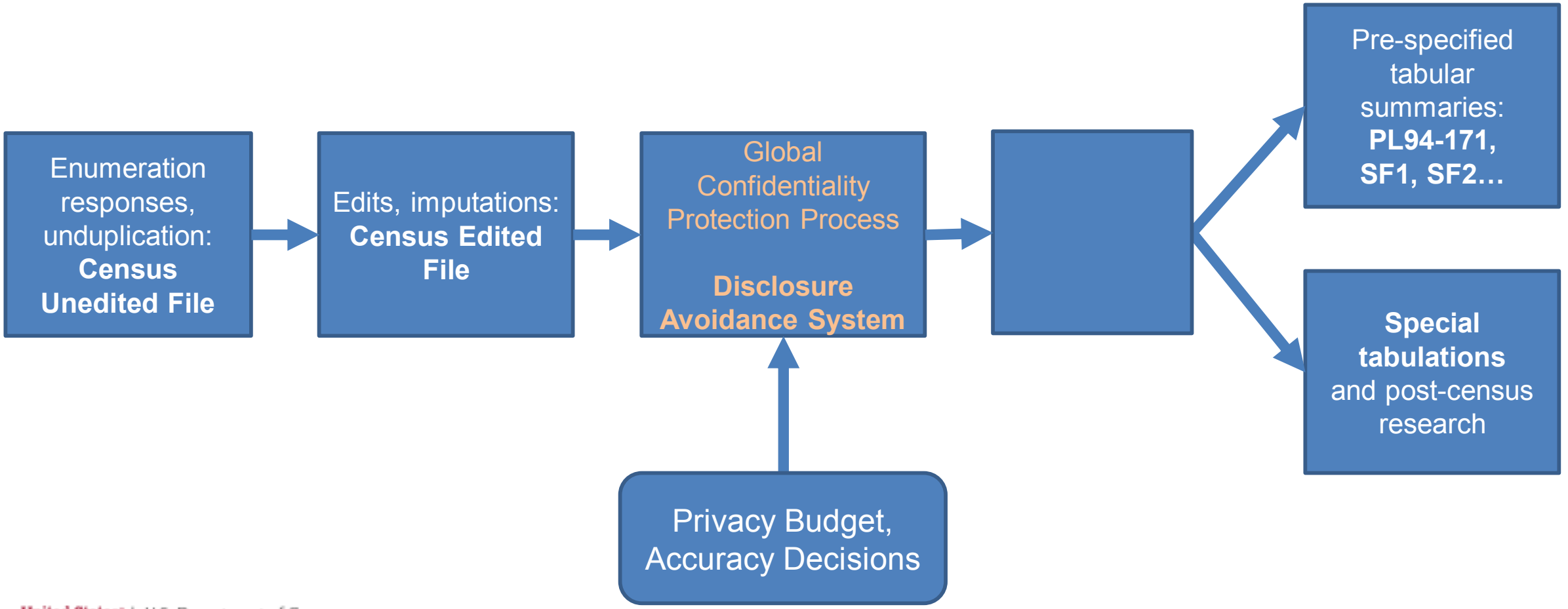
Differential privacy provides:

- Provable bounds on the accuracy of the best possible database reconstruction given the released tabulations.

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



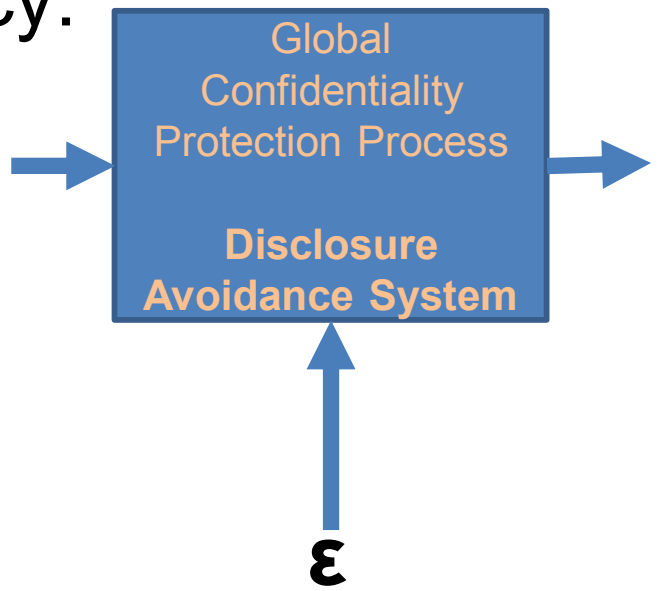
The 2020 Disclosure Avoidance System also operates as a filter… but it's much more visible.



The 2020 Disclosure Avoidance System relies on infusing formally private noise.

Advantages of noise infusion with formal privacy:

- Easy to understand
- Provable and *tunable* privacy guarantees
- Privacy guarantees do not depend on external data
- Protects against database reconstruction attacks
- Privacy operations are *composable*



Disadvantages:

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

Differentially Private Disclosure Avoidance System: Requirements

DAS must be able to read the Census Edited File (CEF):

- CEF must be exactly specified and contain all information necessary for all tabulation recodes
- CEF must be kept confidential after DAS runs (as it was for historical censuses)

DAS must generate the Microdata Detail File (MDF):

- Must contain all information that appears in *any publicly released table* (e.g. PL94-171, SF1, SF2)
- Should not contain *any information* that does *not* appear in a publicly released table
- May be publicly released (in whole or in part)

Non-functional requirements:

- The disclosure avoidance system must provably move information from the CEF to PL94/SF1/SF2 with an adjustable total privacy-loss budget
- The source code and parameters for the DAS will be made publicly available

Why generate a differentially private MDF?

- Familiar to internal and external stakeholders
- Operates with tabulation system to produce PL-94 and SF-1 tabulations
- Guarantees population totals (voting age, non-voting age, householder) exact at all levels of geography
- Consistency among query answers

Some queries must be privacy preserving. Some queries must be exact ("invariant")

Specific PL-94 queries must be exact:

- Block population
- Block voting age population
- Block householders & vacancies

—per 2000 Department of Justice letter to the Director, Kenneth Prewitt

Other PL-94 and SF-1 queries will not be exact:

- Age distribution under 18
- Age distribution 18 and over
- Race and ethnicity distribution
- Household relationship distribution
- Household ownership distribution

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

How the 2020 System Works: High-level Overview

The new system is similar to swapping, with key differences:

- Every record in the population may be modified

  But modifications are bounded by DOJ policy and 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.

  But there are the same number of records for every block.

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

  2020 will publish the algorithms, the parameters and the accuracy of the tabulations.

Proposed "Top-Down" Algorithm

National table of US population

2 x 255 x 17 x 115

Spend ε_1 privacy-loss budget

National table with all 500,000 cells filled, structural zeros imposed with accuracy allowed by ε_1
2 x 255 x 17 x 115

Sex: Male / Female
Race + Hispanic: 255 possible values
Relationship to Householder: 17
Age: 0-114

Reconstruct individual micro-data without geography

325,000,000 records

State-level

State-level tables for only certain queries; structural zeros imposed; dimensions chosen to produce best accuracy for PL-94 and SF-1

Spend ε_2 privacy-loss budget

Target state-level tables required for best accuracy for PL-94 and SF-1
Exact state voting-age, non-voting age, and householder counts as enumerated.

Construct best-fitting individual micro-data with state geography

325,000,000 records now including state identifiers

identifiers

County-level

County-level tables for only certain queries; structural zeros imposed; dimensions chosen to produce best accuracy for PL-94 and SF-1

Spend ε_3 privacy-loss budget

Target county-level tables required for best accuracy for PL-94 and SF-1

Exact county voting-age, non-voting age, and householder counts as enumerated.

Construct best-fitting individual micro-data with state and county geography

325,000,000 records now including state and county identifiers

United States Census Bureau | U.S. Department of Commerce
Economics and Statistics Administration
U.S. CENSUS BUREAU
census.gov

county identifiers

Census tract-level

Tract-level tables for only certain queries; structural zeros imposed; dimensions chosen to produce best accuracy for PL-94 and SF-1

Spend ε_4 privacy-loss budget

Target tract-level tables required for best accuracy for PL-94 and SF-1

Exact tract voting-age, non-voting age, and householder counts as enumerated.

Construct best-fitting individual micro-data with state, county, and tract geography

325,000,000 records now including state, county, and tract identifiers

and tract identifiers

Block-level

Block-level tables for only certain queries; structural zeros imposed; dimensions chosen to produce best accuracy for PL-94 and SF-1

Spend ε_5 privacy-loss budget

Block tract-level tables required for best accuracy for PL-94 and SF-1
Exact block voting-age, non-voting age, and householder counts as enumerated.

Construct best-fitting individual micro-data with state, county, tract and block geography

325,000,000 records now including state, county, tract identifiers

MDF for tabulating

Construct best-fitting individual micro-data with state, county, tract and block geography

325,000,000 records now including state, county, tract, and block identifiers

MDF used for tabulating PL-94, SF-1

MDF for tabulating

How accurate is the MDF?

Disclosure Avoidance Certificate

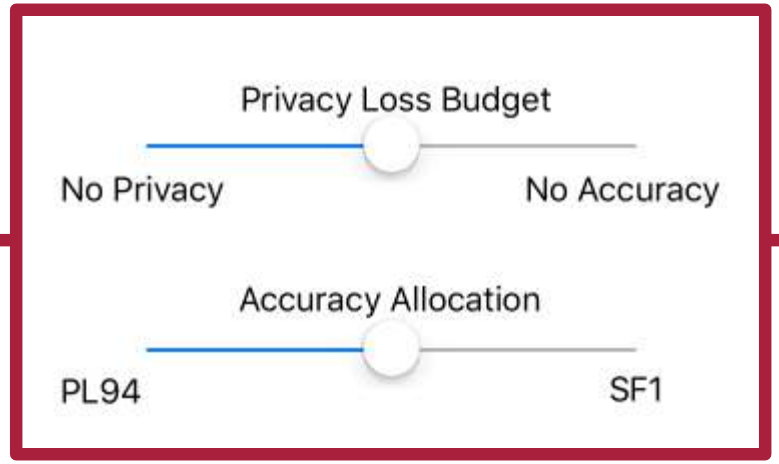
- Certifies that the DAS passed tests
- Reports the accuracy of the MDF
- Requires ε_A

Construct best-fitting individual micro-data with state, county, tract and block geography

325,000,000 records now including state, county, tract, and block identifiers

MDF used for tabulating PL-94, SF-1

Operational Decisions



Set total privacy loss budget: ε

- Ensure that $\varepsilon_1 + \varepsilon_2 + \varepsilon_3 + \varepsilon_4 + \varepsilon_5 + \varepsilon_A = \varepsilon$

Within each stage, allocate privacy-loss budget between:

- PL-94
- Parts of SF-1 not in PL-94

These are policy levers provided by the system.

Levers are set by the Data Stewardship Executive Policy Committee

Inputs Used by the Development Team

Lists of matrices in technical documentation express core queries in the workload

- PL94: https://www.census.gov/prod/cen2010/doc/pl94-171.pdf
- SF1: https://www.census.gov/prod/cen2010/doc/sf1.pdf
- SF2: https://www.census.gov/prod/cen2010/doc/sf2.pdf

Over 1,000 pages of edit specifications for 2010 CEF

Uncurated tabulation recode programs

We are creating

A *framework* for Disclosure Avoidance Systems:

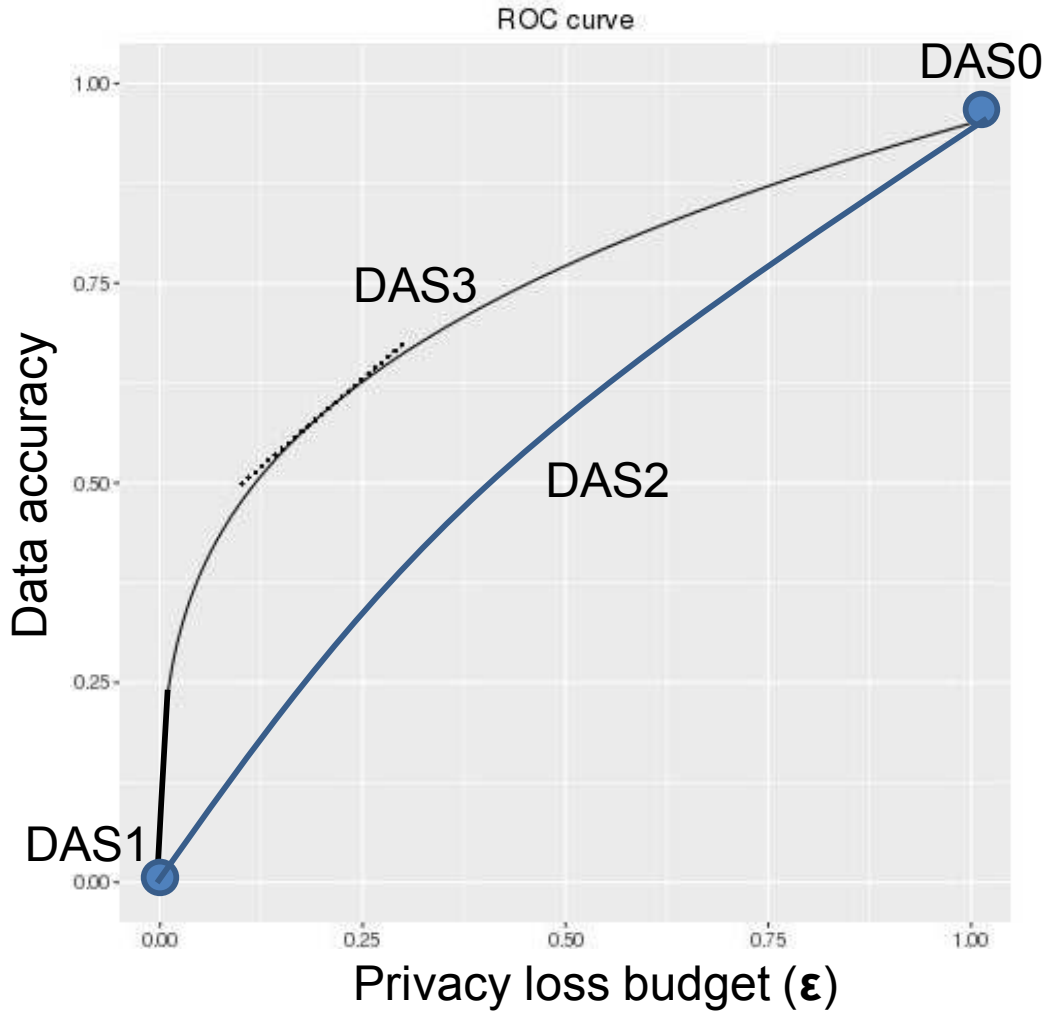
- Development & Test Mode
- Production Mode

Testing Systems:

- DAS0 — 100% accuracy, no privacy
  (No disclosure avoidance)
- DAS1 — 100% privacy, no accuracy
- DAS2 — “bottom-up” engine

Operational System:

- DAS3 — “top-down” engine



Plans for the 2018 End-to-End Test

The 2018 End-to-End test will incorporate differential privacy

- Likely DAS2 — Bottom-up algorithm

Only the prototype PL94-171 files will be produced

No decisions yet regarding the privacy-loss budget or accuracy level

Questions?

Reference

Dinur, Irit and Kobbi Nissim (2003). “Revealing information while preserving privacy.” in *Proceedings of the twenty-second ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems* (PODS '03). ACM, New York, NY, USA, 202-210. DOI: 10.1145/773153.773173.