The U.S. Census Bureau Tries to Be a Good Data Steward in the 21st Century

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The views expressed in this talk are my own and not those of the U.S. Census Bureau. Examples from the 1940 Census are based on public-use micro-data.
Acknowledgments

The challenges of a census:

1. collect all of the data necessary to underpin our democracy
2. protect the privacy of individual data to ensure trust and prevent abuse
Major data products:

• Apportion the House of Representatives  
  (due December 31, 2020)
• Supply data to all state redistricting offices  
  (due April 1, 2021)
• Demographic and housing characteristics  
  (no statutory deadline, target summer 2021)
• Detailed race and ethnicity data  
  (no statutory deadline)
• American Indian, Alaska Native, Native Hawaiian data  
  (no statutory deadline)

For the 2010 Census, this was more than 150 billion statistics from 15GB total data.
Generous estimate: 100GB of data from 2020 Census

Less than 1% of worldwide mobile data use/second
(Source: Cisco VNI Mobile, February 2019 estimate: 11.8TB/second, 29EB/month, mobile data traffic worldwide

The Census Bureau’s data stewardship problem looks very different from the one at Amazon, Apple, Facebook, Google, Microsoft, Netflix ... 

... but appearances are deceiving.
The Database Reconstruction Vulnerability
What we did

• Database reconstruction for all 308,745,538 people in 2010 Census
• Link reconstructed records to commercial databases: acquire PII
• Successful linkage to commercial data: putative re-identification
• Compare putative re-identifications to confidential data
• Successful linkage to confidential data: confirmed re-identification
• Harm: attacker can learn self-response race and ethnicity
What we found

- Census block and voting age (18+) correctly reconstructed in all 6,207,027 inhabited blocks
- Block, sex, age (in years), race (OMB 63 categories), ethnicity reconstructed
  - Exactly: 46% of population (142 million of 308,745,538)
  - Allowing age +/- one year: 71% of population (219 million of 308,745,538)
- Block, sex, age linked to commercial data to acquire PII
  - Putative re-identifications: 45% of population (138 million of 308,745,538)
- Name, block, sex, age, race, ethnicity compared to confidential data
  - Confirmed re-identifications: 38% of putative (52 million; 17% of population)
- For the confirmed re-identifications, race and ethnicity are learned correctly, although the attacker may still have uncertainty
Almost everyone in this room knows that:

Comparing common features allows highly reliable entity resolution (these features belong to the same entity)

Machine learning systems build classifiers, recommenders, and demand management systems that use these amplified entity records

All of this is much harder with provable privacy guarantees for the entities!
The Census Bureau’s 150B tabulations from 15GB of data ...

... and tech industry’s data integration and deep-learning AI systems

are both subject to the fundamental economic problem inherent in privacy protection.
Privacy protection is an economic problem. *Not* a technical problem in computer science or statistics. Allocation of a scarce resource (data in the confidential database) between competing uses: *information products* and *privacy protection.*
Fundamental Tradeoff between Accuracy and Privacy Loss

- Accuracy
- Privacy Loss

No privacy
No accuracy
Fundamental Tradeoff between Accuracy and Privacy Loss

It is infeasible to operate above the frontier.

It is inefficient to operate below the frontier.
Research can move the frontier out.
It is fundamentally a social choice which of these two points is “better.”
The Census Bureau confronted the economic problem inherent in the database reconstruction vulnerability for the 2020 Census by implementing formal privacy guarantees relying on a core of differentially private subroutines that assign:

- the technology to the 2020 Disclosure Avoidance System team,
- the policy to the Data Stewardship Executive Policy committee.
Statistical data, fit for their intended uses, can be produced when the entire publication system is subject to a formal privacy-loss budget.

To date, the team developing these systems has demonstrated that bounded $\varepsilon$-differential privacy can be implemented for the data publications from the 2020 Census used to re-draw every legislative district in the nation (PL94-171 tables).

And many of the person and household level tables in the demographic and housing characteristics.

But there are more than 100 billion other queries published from the 2010 Census that are not easy to make consistent with a finite privacy-loss budget.
The 2020 Disclosure Avoidance team has also developed methods for quantifying and displaying the system-wide trade-offs between the accuracy of the decennial census data products and the privacy-loss budget assigned to sets of tabulations.

Considering that work began in mid-2016 and that no organization anywhere in the world has yet deployed a full, central differential privacy system, this is already a monumental achievement.

Now, let’s see how that system works.
Algorithms Matter
The TopDown Algorithm

National table of US population
2 x 126 x 24 x 115 x 2

Spend $\varepsilon_1$ privacy-loss budget

National table with all 1.5M cells filled, structural zeros imposed with accuracy allowed by $\varepsilon_1$
2 x 126 x 24 x 115 x 2

Sex: Male / Female
Race + Hispanic: 126 possible values
Relationship to Householder/GQ: 24
Age: 0-114

Reconstruct individual micro-data without geography
330,000,000 records
State-level tables for only certain queries; structural zeros imposed; dimensions chosen to produce best accuracy for PL-94 and DHC-P

Spend $\varepsilon_2$ privacy-loss budget

Target state-level tables required for best accuracy for PL94 and DHC-P

Construct best-fitting individual micro-data with state geography

330,000,000 records now including state identifiers
County-level tables for only certain queries; structural zeros imposed; dimensions chosen to produce best accuracy for PL-94 and DHC-P

Spend $\epsilon_3$ privacy-loss budget

Target county-level tables required for best accuracy for PL-94 and DHC-P

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

330,000,000 records now including state and 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 DHC-P

Spend $\epsilon_4$ privacy-loss budget

Target tract-level tables required for best accuracy for PL-94 and DHC-P

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

330,000,000 records now including state, county, and tract identifiers
Block-level tables for only certain queries; structural zeros imposed; dimensions chosen to produce best accuracy for PL-94 and DHC-P

Spend $\epsilon_5$ privacy-loss budget

Target Block tables required for best accuracy for PL-94 and DHC-P

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

330,000,000 records now including state, county, tract, and block identifiers
Tabulation micro-data

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

330,000,000 records now including state, county, tract, and block identifiers

Micro-data used for tabulating PL-94 and DHC-P
Method Summary

• Take differentially private measurements at every level of the hierarchy

• At each level of TopDown post-process:
  • Solve an L2 optimization to get non-negative tables
  • Solve an L1 optimization to get non-negative, integer tables
  • Generate micro-data from the post-processed tables
Naïve Method: BottomUp or Block-by-Block

• Apply differential privacy algorithms to the most detailed level of geography
• Build all geographic aggregates from those components as a post-processing
• This is similar to the local differential privacy implementations in the Chrome browser, iOS, and Windows 10.
DISTRICT-BY-DISTRICT DIFFERENTIAL PRIVACY ALGORITHMS
(1940 CENSUS DATA)
COMPARISON OF DISTRICT RESULTS BY ALGORITHM
(1940 CENSUS DATA)

- TopDown algorithm
- District-by-district algorithm
COMPARISON OF NATIONAL RESULTS BY ALGORITHM
(1940 CENSUS DATA)

- TopDown algorithm
- District-by-district algorithm
But it is only the tip of the iceberg.

Demographic profiles, based on the detailed tables traditionally published in summary files following the publication of redistricting data, have far more diverse uses than the redistricting data.

Summarizing those use cases in a set of queries that can be answered with a reasonable privacy-loss budget is the next challenge.

Internet giants, businesses and statistical agencies around the world should also step-up to these challenges. We can learn from, and help, each other enormously.
Science and policy must address these questions too:

What should the privacy-loss policy be for all uses of the 2020 Census?

How should the Census Bureau handle management-imposed accuracy requirements?

How should the Census Bureau allocate the privacy-loss budget throughout the next seven decades?

Can the Census Bureau insist that researchers present their differentially private analysis programs as part of the project review process?

If so, where do the experts to assess the proposals or certify the implementations come from?
More Background on the 2020 Census 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

• December 6, 2018 CSAC (detailed discussion of algorithms and choices) https://www2.census.gov/cac/sac/meetings/2018-12/abowd-disclosure-avoidance.pdf?

• April 15, 2019 Code base and documentation for the 2018 End-to-End Census Test (E2E) version of the 2020 Disclosure Avoidance System https://github.com/uscensusbureau/census2020-das-e2e

• June 6, 2019 Blog explaining how to use the code base with the 1940 Census public data from IPUMS https://www.census.gov/newsroom/blogs/research-matters/2019/06/disclosure_avoidance.html

• June 11, 2019 Keynote address “The U.S. Census Bureau Tries to Be a Good Data Steward for the 21st Century” ICML 2019 abstract, video

• June 29-31, 2019 Joint Statistical Meetings Census Bureau electronic press kit (See talks by Abowd, Ashmead, Garfinkel, Leclerc, Sexton, and others)
Thank you.

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