The 2020 Census Disclosure Avoidance System

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United States Census 2020

Acknowledgements

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We also acknowledge and greatly appreciate the ongoing feedback we have received from external stakeholder groups that has contributed to the design and improvement of the Disclosure Avoidance System.

For more information and technical details relating to the issues discussed in these slides, please contact the author at michael.b.hawes@census.gov.

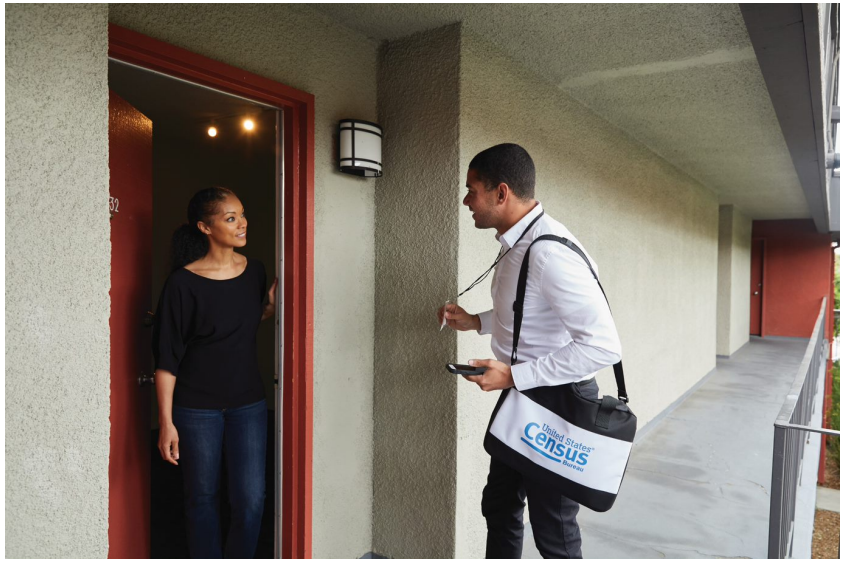
Any opinions and viewpoints expressed in this presentation are the author's own, and do not represent the opinions or viewpoints of the U.S. Census Bureau.

The statistics included in this presentation have been cleared for public dissemination by the Census Bureau's Disclosure Review Board (CBDRB-FY20-DSEP-001, CBDRB-FY20-281, and CBDRB-FY20-101).

Our Commitment to Privacy and Confidentiality

Data stewardship is central to the Census Bureau's mission to produce high-quality statistics about the people and economy of the United States.

Our commitment to protect the privacy of our respondents and the confidentiality of their data is both a legal obligation and a core component of our institutional culture.



Upholding our Promise: Today and Tomorrow

We cannot merely consider privacy threats that exist today.

We must ensure that our disclosure avoidance methods are also sufficient to protect against the threats of tomorrow!

The Census Bureau's Privacy Protections Over Time

Throughout its history, the Census Bureau has been at the forefront of the design and implementation of statistical methods to safeguard respondent data.

Over the decades, as we have increased the number and detail of the data products we release, so too have we improved the statistical techniques we use to protect those data.

The Privacy Challenge

Every time you release any statistic calculated from a confidential data source you "leak" a small amount of private information.

If you release too many statistics, too accurately, you will eventually reveal the entire underlying confidential data source.

Dinur, Irit and Kobbi Nissim (2003) "Revealing Information while Preserving Privacy" PODS, June 9-12, 2003, San Diego, CA

The Growing Privacy Threat

More Data and Faster Computers!

In today's digital age, there has been a proliferation of databases that could potentially be used to attempt to undermine the privacy protections of our statistical data products.

Similarly, today's computers are able to perform complex, large-scale calculations with increasing ease.

These parallel trends represent new threats to our ability to safeguard respondents' data.

Reconstruction

The recreation of individual-level data from tabular or aggregate data.

If you release enough tables or statistics, eventually there will be a unique solution for what the underlying individual-level data were.

Computer algorithms can do this very easily.

	4						2	
			7					4
1		7	8				5	
			9			3		8
5								
			6		8			
3						4		5
	8	5				1		9
		9		7	1			

Reconstruction: A Toy Example

Block 1234	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 Female	3	36	36.7

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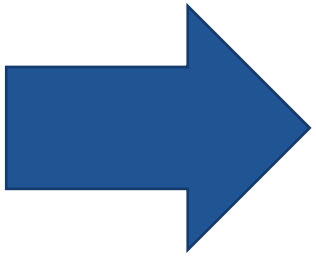


Block	Age	Sex	Race	Relationship
1234	66	Female	Black	Married
1234	84	Male	Black	Married
1234	30	Male	White	Married
1234	36	Female	Black	Married
1234	8	Female	Black	Single
1234	18	Male	White	Single
1234	24	Female	White	Single

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

Re-identification

Linking public data to external data sources to re-identify specific individuals within the data.

Name	Block	Age	Sex		Block	Age	Sex	Race	Relationship
Jane Smith	1234	66	Female	+	1234	66	Female	Black	Married
Joe Public	1234	84	Male		1234	84	Male	Black	Married
John Citizen	1234	30	Male		1234	30	Male	White	Married

External Data

Confidential Data

Reconstructing the 2010 Census

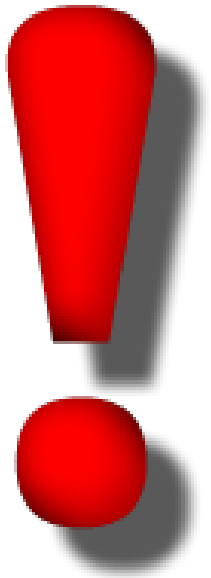
- The 2010 Census collected information on the age, sex, race, ethnicity, and relationship (to householder) status for ~309 Million individuals. (1.9 Billion confidential data points)
- The 2010 Census data products released over 150 billion statistics
- We conducted an internal experiment to see if we could reconstruct and re-identify the 2010 Census records.

Reconstructing the 2010 Census: What Did We Find?

1. On the 309 million reconstructed records, census block and voting age (18+) were correctly reconstructed for all individuals in all 6,207,027 inhabited blocks.
2. Block, sex, age (in years), race (OMB 63 categories), and ethnicity were reconstructed:
    1. Exactly for 46% of the population (142 million individuals)
    2. Within +/- one year for 71% of the population (219 million individuals)
3. Block, sex, and age were then linked to commercial data, which provided presumed re-identification of 45% of the population (138 million individuals).
4. Name, block, sex, age, race, ethnicity were then compared to the confidential data, which yielded confirmed re-identifications for 38% of the presumed re-identifications (52 million individuals).
5. For the confirmed re-identifications, race and ethnicity are learned correctly, though the attacker may still have uncertainty.

The Census Bureau's Decision

- Advances in computing power and the availability of external data sources make database reconstruction and re-identification increasingly likely.
- The Census Bureau recognized that its traditional disclosure avoidance methods are increasingly insufficient to counter these risks.
- To meet its continuing obligations to safeguard respondent information, the Census Bureau has committed to modernizing its approach to privacy protections.



Disclosure Avoidance

Disclosure avoidance methods seek to make reconstruction and re-identification more difficult, by:

- **Reducing precision**
- **Removing vulnerable records, or**
- **Adding uncertainty**

Commonly used (legacy) methods include:

- **Complementary suppression**
- **Rounding**
- **Top/Bottom coding of extreme values**
- **Sampling**
- **Record swapping**
- **Noise injection**

Problem #1 – Impact on Data

All statistical techniques to protect privacy impose a tradeoff between the degree of privacy protection and the resulting accuracy of the data.

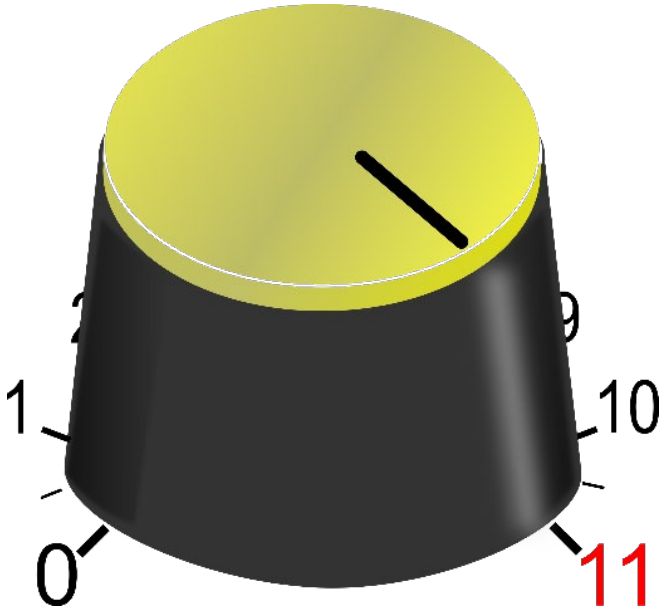
Swap rates, noise injection parameters, cell suppression thresholds, etc. determine this tradeoff.

Problem #2 – How much is enough?

Legacy disclosure avoidance methods provide little ability to quantify privacy protections.

When faced with rising disclosure risk, disclosure avoidance practitioners adjust their implementation parameters.

BUT, this is largely a scattershot solution that over-protects some data, while often under-protecting the most vulnerable records.



Differential Privacy

DP is not a disclosure avoidance "method" as much as it is a framework for defining and then quantifying privacy protection.

Every individual that is reflected in a particular statistic contributes towards that statistic's value.

Every statistic that you publish "leaks" a small amount of private information.

DP as a framework allows you to assess each individual's contribution to the statistic, and to measure (and thus, limit) how much information about them will leak.

Differential Privacy

When combined with noise injection, DP allows you to precisely control the amount of private information leakage in your published statistics.

- **Infinitely tunable – parameter "dials" can be set anywhere from perfect privacy to perfect accuracy.**
- **Privacy guarantee is mathematically provable and future-proof.**
- **The precise calibration of statistical noise enables optimal data accuracy for any given level of privacy protection.***

***Absent post-processing requirements, which can introduce error independent of that needed to protect privacy.**

Privacy vs. Accuracy

The only way to absolutely eliminate all risk of re-identification would be to never release any usable data.

Differential privacy allows you to quantify a precise level of "acceptable risk," and to calibrate your disclosure avoidance mechanism to a precise point on the privacy/accuracy spectrum for the resulting data.

Data Quality | Bnae Kegouqe
Dada Qualitg | Vrkk Jzcfkdy
Data Qaality | Dncb PrhvBln
Dzte Qvality | Dncb Prtnavy
Dfha Quapyti | Tgta Ppijacy
Tgta Qucjity | Dfha Pnjvico
Dncb Qhulitn | Dzhe Njivaci
Ntue Quevdto | Dzte Privecy
Vrkk Zuhnvry | Dada Privacg
Bnaq Denorbe | Data Privacy

Establishing a Privacy-loss Budget

This measure is called the "Privacy-loss Budget" (PLB) or "Epsilon."

- **$\varepsilon=0$ (perfect privacy) would result in completely useless data**
- **$\varepsilon=\infty$ (perfect accuracy) would result in releasing the data in fully identifiable form**

Epsilon

Implications for the 2020 Census

The modernization of our privacy protections using a differential privacy framework does not change the constitutional mandate to apportion the House of Representatives according to the actual enumeration.

As in 2000 and 2010, the Census Bureau will apply privacy protections to the P.L. 94-171 redistricting data, and all subsequent 2020 Census data products.

Privacy-loss Budget Allocation

The Census Bureau's Data Stewardship Executive Policy Committee (DSEP) will be making decisions about the PLB for the 2020 Census. This includes allocation across different 2020 Census data products, including:

- P.L. 94-171 Redistricting data
- Demographic and Housing Characteristics files (DHC)
- Detailed Demographic and Housing Characteristics files (D-DHC)
- …and other uses of Decennial Census data.

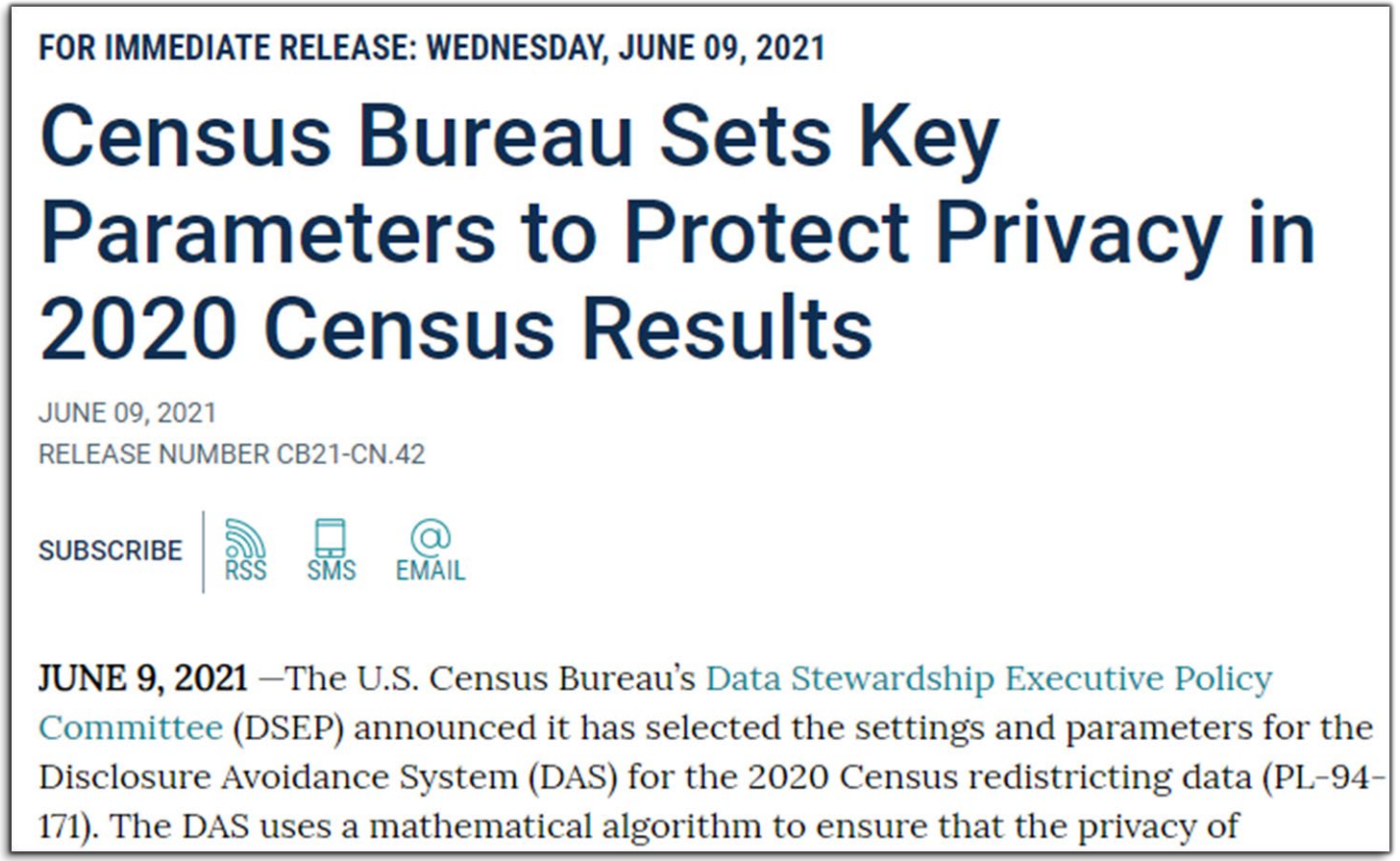
DSEP will also be deciding how to allocate the PLB across the different sets of tabulations *within* each data product (by geographic level and by data element).

Recent Activity: DAS Tuning for the Redistricting Data

P.L. 94-171 Tuning & Privacy-Accuracy Trade-off Experiments

- In December through March, the DAS Team conducted over 600 full-scale TDA runs with the complete P.L. 94-171 data product schema.
- Goal: Evaluating resulting accuracy of varying parameters for:
  - Overall setting of PLB
  - Query strategy
  - Allocation of PLB across geographic levels
  - Allocation of PLB across queries
- Worked with subject matter experts in Demographic and Decennial Directorates to evaluate accuracy of experimental runs to inform parameter setting.

Breaking News



FOR IMMEDIATE RELEASE: WEDNESDAY, JUNE 09, 2021

Census Bureau Sets Key Parameters to Protect Privacy in 2020 Census Results

JUNE 09, 2021
RELEASE NUMBER CB21-CN.42

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JUNE 9, 2021 —The U.S. Census Bureau's Data Stewardship Executive Policy Committee (DSEP) announced it has selected the settings and parameters for the Disclosure Avoidance System (DAS) for the 2020 Census redistricting data (PL-94-171). The DAS uses a mathematical algorithm to ensure that the privacy of

Key Parameters:

- Privacy-loss Budget of ε=19.61 (ε= 17.14 for persons and ε=2.47 for units)
- Improvements to optimized geographic post-processing hierarchy
- Extra PLB allocated to Population Counts
- Extra PLB allocated to Race and Ethnicity statistics

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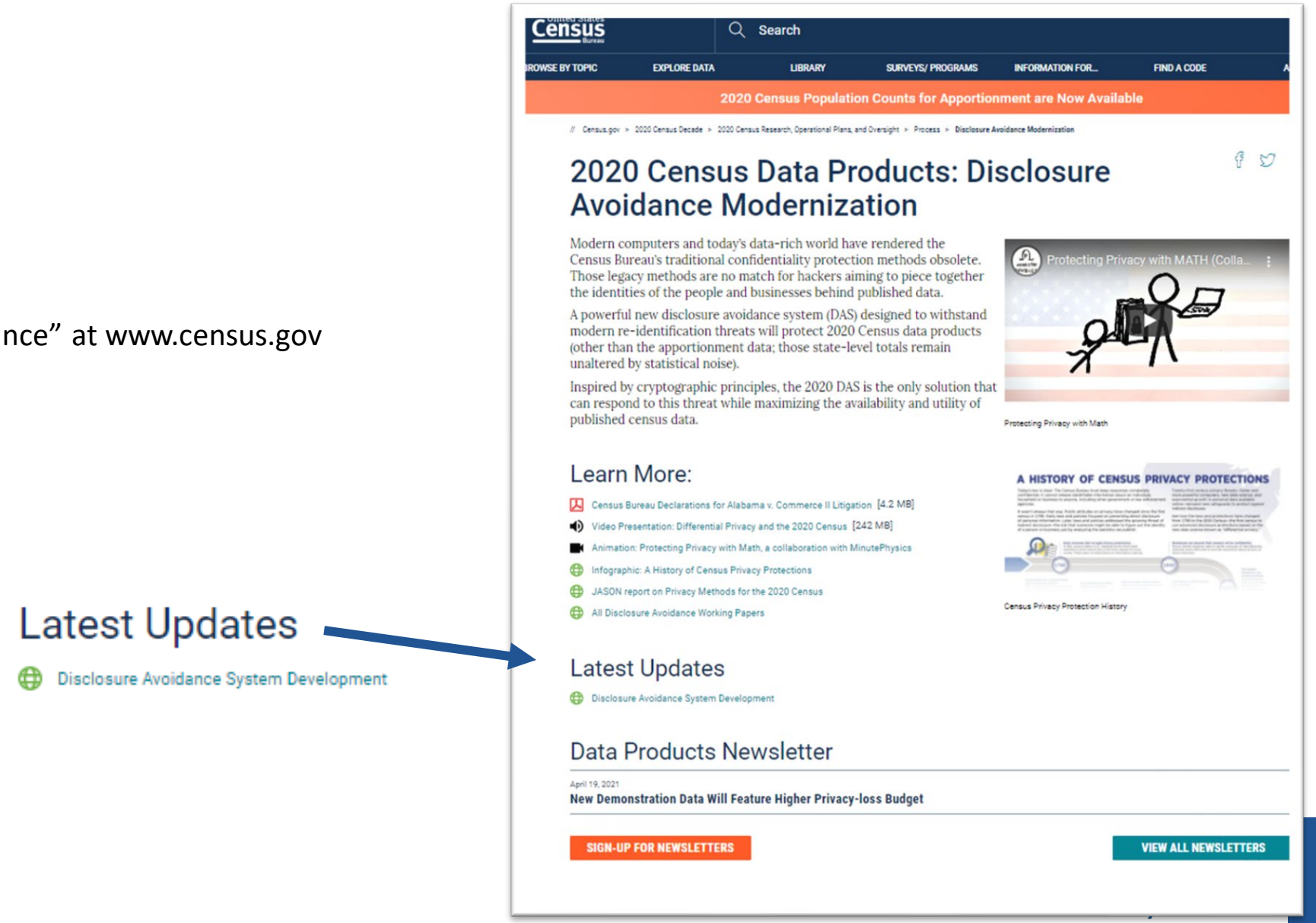

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Questions?