### CBAMS: A Case Study in Differential Privacy at the U.S. Census Bureau

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U.S. Census Bureau



U.S. Department of Commerce Economics and Statistics Administration U.S. CENSUS BUREAU *census.gov*  The views in this presentation are those of the authors and not those of the U.S. Census Bureau.

## The Census Bureau is committed to data quality

- The Census Bureau's *mission* is to serve as the nation's leading provider of **quality** data about its people and economy
- The Census Bureau's *goal* is to provide the best mix of timeliness, relevancy, **quality** and cost for the data we collect and services we provide



## The Census Bureau is also committed to data privacy protection

- The Census Bureau operates, collects data, and publishes statistics under the authority of several titles of the U.S. Code
- Title 13, Sec.9: Neither the Secretary, nor any other officer or employee of the Department of Commerce or bureau or agency thereof [...] may [...] make any publication whereby the data furnished by any particular establishment or individual under this title can be identified



# The Census Bureau is modernizing the way we protect data

#### Traditional

- Include techniques such as
  - Geographic Aggregation
  - Cell Suppression
  - Variable Top-Coding
  - Category Collapsing
- Methods are ad hoc and based on known risks
- May require secrecy of methods and parameters

#### Modern

- Guarantee privacy against broad classes of attacks
- Do not depend on which datasets are now or will be available
- Have a calculable, global privacy loss for a given set of releases at a given accuracy
- Allow for transparency about the method, data accuracy, and privacy loss



## The Census Bureau is pioneering noise injection techniques

- Disciplined and careful noise injection can help provide estimates with favorable properties
- Differential privacy requires that statistical disclosure avoidance techniques, such as noise injection, meet mathematically defined bounds on privacy loss
- We must weigh noise injection against alternative disclosure avoidance methods
  - Even when the properties of the noise injection are sub-optimal, the method can still outperform alternatives
  - Especially true when the alternative is providing less output



## The use of formal privacy is expanding at the Census Bureau

#### In Use or Planned

- OnTheMap
- 2020 Census
- Post-Secondary Education Outcomes (PSEO)
- Census Barriers Attitudes and Motivators Study (CBAMS)

#### **Ongoing Research**

- American Community Survey
- Many more to come!



The Census Barriers Attitudes and Motivators Study (CBAMS) is critical for the 2020 Census

- CBAMS is a nationwide survey designed to identify barriers, attitudes, and motivators toward Census response
- Critical for an accurate and cost efficient Census
  - Emphasizes hard-to-count populations
  - Used to help allocate the media budget and pursue maximum impact of the media campaign
- The 2020 communication campaign requires sharing CBAMS data with external partners



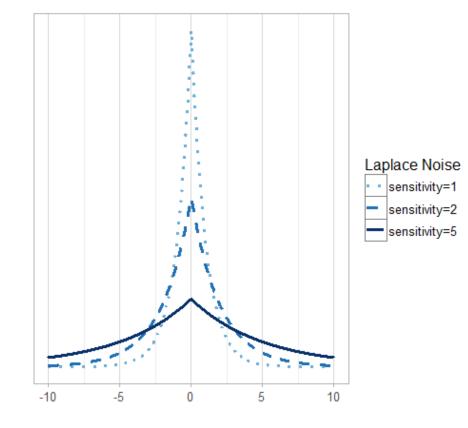
### We choose modern methods for CBAMS

- The communications team needs tens of thousands of estimates from crosstabs
- Cell suppression was considered but it would be complex and time consuming
  - Anytime a cell needs to be suppressed, adjacent cells within a table and across linked tables would need to be suppressed to avoid reconstruction of the suppressed cell
  - Combining categories to reduce the number of offending cells would result in some proportion of lost information
- We provide a protected microdata file using differentially private noise injection
  - Provides partners with higher quality data than they would have otherwise received with traditional methods
  - The communication strategy would need to be drastically changed without this solution
- We employ the local model with two differentially private noise injection mechanisms to produce the protected CBAMS microdata file



### We add Laplace noise to continuous variables

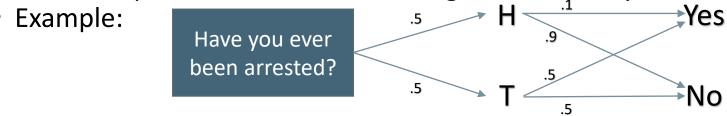
- For a value x we return  $x + \omega$ , where  $\omega \sim \text{Laplace}(0, \frac{\delta_x}{\epsilon})$
- $S_{\chi}$  is called the sensitivity
  - For this model, it is calculated as the difference between the maximum and minimum possible values
  - All continuous values are percentages, so we have  $S_{\chi}$ = 100 0 = 100
- $\epsilon$  is the privacy parameter





### Randomized response is a valuable differentially private mechanism for categorical variables

 Originally developed as a survey method that allows respondent to respond to sensitive questions while maintaining confidentiality



• Assume that the true percentage of respondents who have been arrested is 10%. Then we'll have the expected proportion of answers:

YES	.5(.1) + .5(.5) = .3
NO	.5(.9) + .5(.5) = .7

• Given that the true proportion of 'yes' answers is unknown, it can be reconstructed as

$$YES = \frac{YES_{answered} - P(T)P(H)}{P(H)}$$



## We apply randomized response to discrete variables

- Many survey questions have categorical responses
  - Example: Is the Census used to decide how much money communities will get from the government?
    - (1) Yes, used for this
    - (2) No, not used
    - (3) Don't know
- For a two-category variable the noise injection is displayed in the following design matrix, where ε is the differential privacy parameter

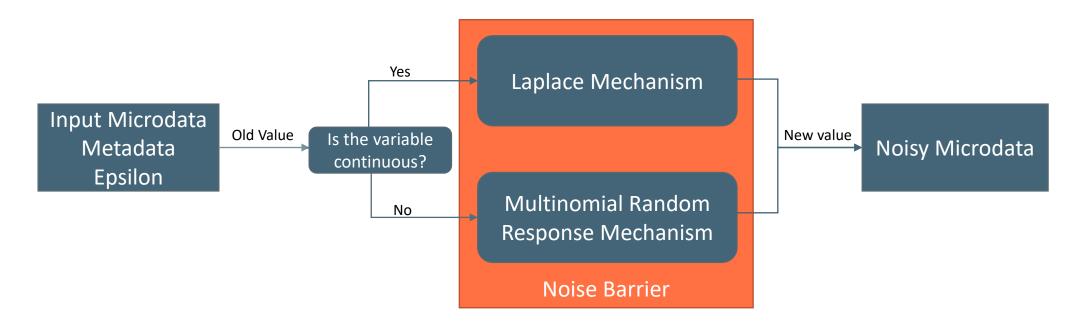
$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} = \begin{pmatrix} \frac{e^{\epsilon}}{1+e^{\epsilon}} & \frac{1}{1+e^{\epsilon}} \\ \frac{1}{1+e^{\epsilon}} & \frac{e^{\epsilon}}{1+e^{\epsilon}} \end{pmatrix}$$

• We use a multinomial version of randomized response to perturb each categorical variable



### We proceed record by record to create the microdata

• Implement noise injection on each record variable-by-variable



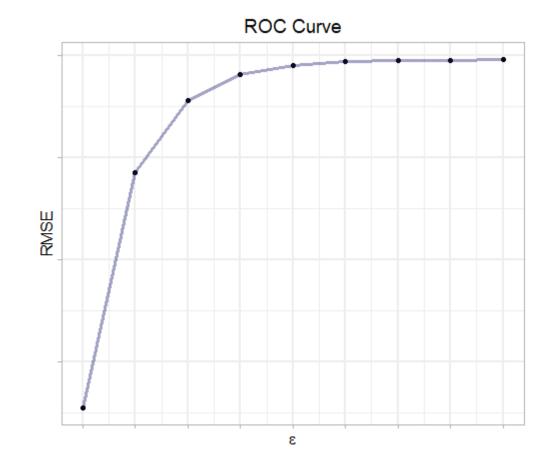
• All data items must pass through the noise barrier



### The ROC curve displays the necessary tradeoff

- Shows the tradeoff between the amount of privacy lost and the accuracy of the data
  - $\epsilon$  is our privacy parameter
  - The root mean squared error (RMSE) is our measure of accuracy
- Quantifying the tradeoff is a key feature of differentially private methods
- Allows policy makers to balance important social goods – data accuracy and data privacy
- We use  $\epsilon = 7$  for each variable
- Publicly available via the Census Bureau's FOIA page





New methods provide an opportunity for greater data privacy and data accuracy

- These techniques allow us to deliver a wealth of data to support the 2020 Census communication team, and to help ensure the success of the Census itself
- The Census Bureau is actively expanding the use of new methods
- These methods allow us to fulfill our obligations to data users and to respondents
- These changes will let the Census Bureau better serve data users
  - Transparency
  - Data-driven decisions about balancing data privacy with data accuracy
  - Continue to have a quality, trusted, reputable product for years to come



### Thank You!

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#### FOIA link

https://www2.census.gov/programs-surveys/decennial/2020/program-management/censusresearch/cbams/2020-CBAMS-Survey.zip

