

General Comments on TDA/DAS

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My Remarks Today

- I haven't had time to adequately assess Michael Hawes's presentation slides, given their (necessary) late arrival to me.
- I will offer some ***general comments*** – less directly responsive to Michael's presentation – about ***TDA for 2020 Census DHC & its DP underpinnings***.
- I will draw on the following:
 - JASON (2020), [Formal Privacy Methods for the 2020 Census](#) (April).
 - JASON (2022), JASON (2022), [Formal Consistency of Data Products and Formal Privacy Methods for the 2020 Census](#) (January).
 - boyd & Sarathy, "Differential Perspectives: Epistemic Disconnects Surrounding the US Census Bureau's Use of Differential Privacy," forthcoming in *Harvard Data Science Review*.
 - Hotz & Salvo, "A Chronicle of the Application of Differential Privacy to 2020 Census," forthcoming in *Harvard Data Science Review*.
 - Hotz, Bollinger, Komarova, Manski, Moffitt, Nekipelov, Sojourner & Spencer, "Balancing Privacy and Usability in the Federal Statistical System," forthcoming in *Proceedings of the National Academy of Sciences*.

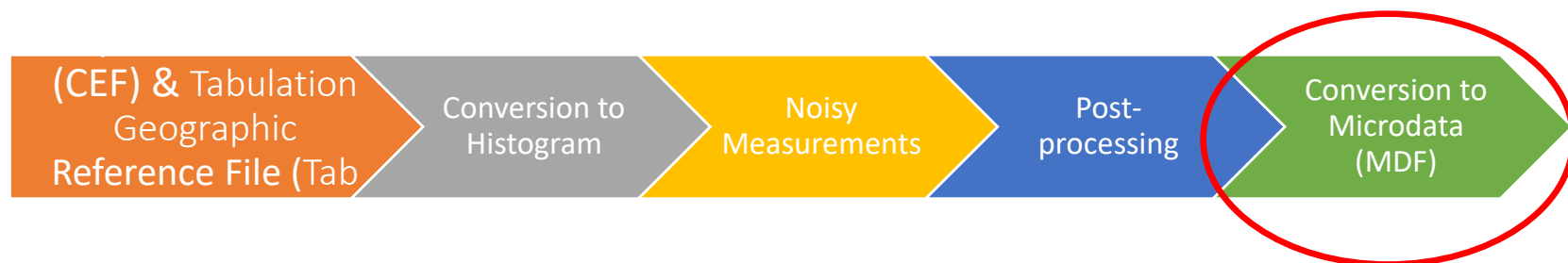
Giving Credit to Census Bureau

- There is ***clear evidence*** that ***TDA improved*** from Oct. 2019 to March 2022 Versions!
- Changes included:
 - Move from TDA based on “pure DP” with Laplace Mechanism to “Zero Concentrated DP” (zCDP) with Gaussian mechanism
 - Move to Optimized Geographic Spine
 - Better handling of Post-Processing constraints (more below)
- They improved ***accuracy*** of ***many statistics*** in both PL and DHC data – JASON Report (2022).
- Much of this, although not all, was in ***response to input from user communities***.

Some Remaining Issues

- **Synthetic Microdata Step** of TDA (see next slide).
 - Due to inherited ***production system*** for data products, TDA is required to produce ***synthetic microdata*** file in same form as Census Edited File (CEF)
 - JASON (2022) argues this step wasn't needed, may have introduced additional errors & certainly ***added to complexity*** of TDA
 - I understand this won't change for 2020 Census data, but...
 - It would be good to assess & report on its consequences
 - More importantly, this step needs to be ***eliminated*** for 2030 Census & other data products.

The TopDown Algorithm

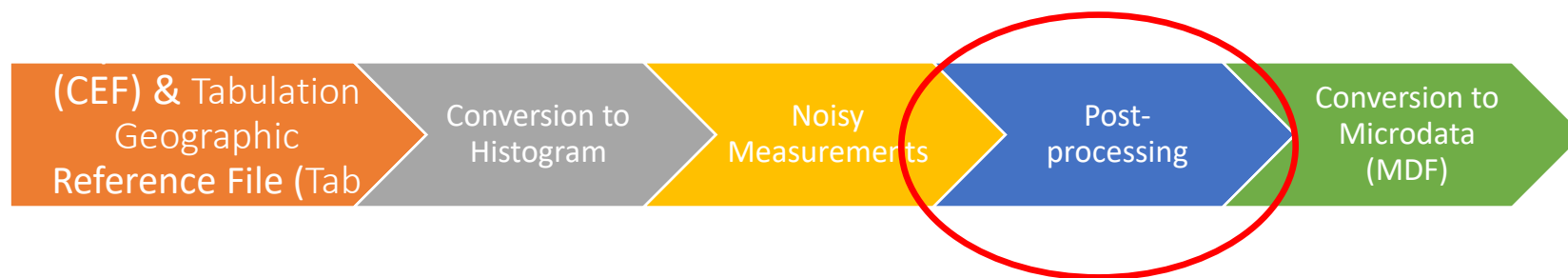


For complete details see: Abowd, J., Ashmead, R., Cumings-Menon, R., Garfinkel, S., Heineck, M., Heiss, C., Johns, R., Kifer, D., Leclerc, P., Machanavajjhala, A., Moran, B., Sexton, W., Spence, M., & Zhuravlev, P. (2022). The 2020 Census Disclosure Avoidance System TopDown Algorithm. *Harvard Data Science Review*. (June) <https://doi.org/10.1162/99608f92.529e3cb9>

Some Remaining Issues

- ***Imposing constraints*** in TDA
 - This the ***post processing*** step in the TDA (next slide).
 - Post-processing within TDA was ***improved, but issues remain.***
 - Evidence suggested this imposed additional errors/inaccuracies in TDA processing. (JASON, 2022)
 - Important to ***explore other ways to impose constraints*** in advance of 2030 Census & other Census products. (Wang & Reiter, 2021)
 - Important to ***provide more information*** to users ***about uncertainties post processing imposed*** on data (more below).

The TopDown Algorithm



For complete details see: Abowd, J., Ashmead, R., Cumings-Menon, R., Garfinkel, S., Heineck, M., Heiss, C., Johns, R., Kifer, D., Leclerc, P., Machanavajjhala, A., Moran, B., Sexton, W., Spence, M., & Zhuravlev, P. (2022). The 2020 Census Disclosure Avoidance System TopDown Algorithm. *Harvard Data Science Review*. (June) <https://doi.org/10.1162/99608f92.529e3cb9>

Some Remaining Issues

- ***Understanding sources of uncertainty*** in data
 - Important to understand contributions of components of TDA to *uncertainty* (margins of error) in DHC & other data products.
 - ***Noise injection*** based on DP criterion is ***relatively straightforward & transparent***.
 - ***Uncertainties due to post-processing & synthetic microdata step*** are ***not!***
 - But also ***essential*** for Census to provide ***more full accounting of other non-sampling sources of error/uncertainty*** and ***soon!*** – JASON (2022); boyd & Sarathy (2022)
 - Users will need this to make informed & effective use of data.
 - Software & documentation will need to be developed & made known & available to users. – JASON (2022).
- ***Related point:*** as part of this, ***Census needs to either release noisy measurements file or close proximity*** to it. – JASON (2022) & others.

Communication, Communication, Communication!

- ***Essential for Census to improve communication about DAS/TDA for all levels of users***
 - This is ***really essential*** on multiple levels:
 - Essential for ***users & public*** – other than CS experts – ***to better understand Census's DAS***.
 - Deal with ***misconceptions*** that are replete & need to be addressed.
 - ***Clearer & more transparent explanations of DAS/TDA*** – including what it did & didn't do – will ***help users to make more effective use of DHC, DDHC, other Census products***.
- See JASON (2022), boyd & Sarathy (2022), among others.

Absolute vs Relative Disclosure Risk

- Following slides draw on:
 - Hotz, V.J., C. Bollinger, T. Komarova, C.F. Manski, R.A., Moffitt, D. Nekipelov, A. Sojourner & B.D. Spencer, “Balancing Privacy and Usability in the Federal Statistical System,” forthcoming in *Proceedings of the National Academy of Sciences*.
 - Hotz, V.J. & J.J. Salvo, “A Chronicle of the Application of Differential Privacy to 2020 Census,” forthcoming in *Harvard Data Science Review*.

Absolute vs Relative Disclosure Risk

- **Absolute Disclosure Risk:**

$$\Pr(J = j, Y_j | D^*, A)$$

where J is **target individual** in an **intruder's information set**, A ;

j is **individual** in **released data set**, D^* ;

D is **confidential data set**;

Y_j is **true value** of j 's (**sensitive**) **data** in D ;

- Using Bayes Rule:

$$\Pr(J = j, Y_j | D^*, A) = [\Pr(D^* | J = j, Y_j, A) / \Pr(D^* | A)] \Pr(J = j, Y_j | A)$$

where $\Pr(J = j, Y_j | A)$ is **intruder's prior** about j being J & her data being Y_j , **based on just intruder's info**, A , and,

$$\Pr(D^* | J = j, Y_j, A) / \Pr(D^* | A) = \Pr(J = j, Y_j | D^*, A) / \Pr(J = j, Y_j | A)$$

where RHS (blue) is **Relative Disclosure Risk**, i.e., **increase** in (or **incremental**) **disclosure risk from releasing** D^* .

Absolute vs Relative Disclosure Risk

- Consider ***analogy*** to ***mortality risks from diseases/health conditions***:
 - Epidemiological studies often focus on ***relative risks*** of ***dying*** from ***one disease/condition vs. another***.
 - These risks may be ***easier to estimate***, as they ***abstract from differences*** in individuals' ***underlying health conditions*** (their ***prior risks***), which are harder to adequately measure.
 - But ***most individuals*** – & their health care providers – ***care about absolute risk of their dying from disease/condition they have***.
 - Individuals ***may not worry*** about even a ***large relative increase in risk of dying*** from condition if they are in “good health.”
 - But, individuals ***may worry*** a lot about even a ***small relative increase in risk of dying*** from condition if they aren't in good health.

Absolute vs Relative Disclosure Risk

- ***Case of privacy loss due to a data release.***
 - One can argue that ***individuals in confidential data set*** – & maybe stat agencies – ***may (should) care*** about ***absolute risk of disclosure*** from ***releasing their data***.
 - Individuals **may care** a lot about even **small relative increase in disclosure risk** due to data release **if prior prob of disclosure is high**, all else equal.
 - May **not be bothered** by even **large relative increase in disclosure risk** due to data release **if prior prob of disclosure risk is low**.

Two Observations concerning Disclosure Risks from Data Releases

1. One can show (Gong & Meng, 2020*, among others) that **DP criterion** – and **DP-based DASs** – **bound *relative disclosure risks*, not *absolute ones***.
 - ***Rationale for DP focus on relative risks***: Serious challenges to quantifying or knowing what information potential intruders may know.
 - DP-based mechanisms address ***worst-case scenarios***.
 - And, importantly, DP-mechanisms can quantify and “**guarantee**” control over the *relative increase in disclosure risks* from data releases in ***transparent way***.

*Gong, R. and X.-L. Meng. 2020. "Congenial Differential Privacy under Mandated Disclosure," *Proceedings of the 2020 ACM-IMS on Foundations of Data Science Conference*. Virtual Event, USA: Association for Computing Machinery, 59–70.

Two Observations concerning Disclosure Risks from Data Releases

2. But, there are “**risks**” to ***not paying more attention to absolute disclosure risks*** in designing DAS for data releases:
 - Will have ***harder time communicating disclosure risks individuals do face.***
 - May have ***harder time complying with privacy protection mandates*** (Title 13 & 26).
 - And, ***not paying attention to absolute disclosure risks will limit:***
 - a) *assessing extent of these risks, e.g., doing further reconstruction and re-identification assessments for 2020 Census data;*
 - b) *assessing how magnitudes of risks differ across groups & types of information;*
 - c) *Improving our understanding which external data (priors) contribute to risks of disclosure.*

Thanks for Listening!