How Modern Disclosure Avoidance Methods Could Change the Way Statistical Agencies Operate

John M. Abowd
Chief Scientist and Associate Director for Research and Methodology
U.S. Census Bureau
Federal Economic Statistics Advisory Committee
December 14, 2018

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

Three Lessons from Cryptography

1. Too many statistics, published too accurately, expose the confidential database with near certainty (database reconstruction)
2. Add noise to every statistic, calibrated to control the worst-case global disclosure risk, called a privacy-loss budget (formal privacy)
3. Transparency can’t be the harm: Kerckhoffs's principle applied to data privacy says that the protection should be provable and secure even when every aspect of the algorithm and all of its parameters are public, only the actual random numbers used must be kept secret

The database reconstruction theorem is the death knell for traditional data publication systems from confidential sources.

And One Giant Silver Lining

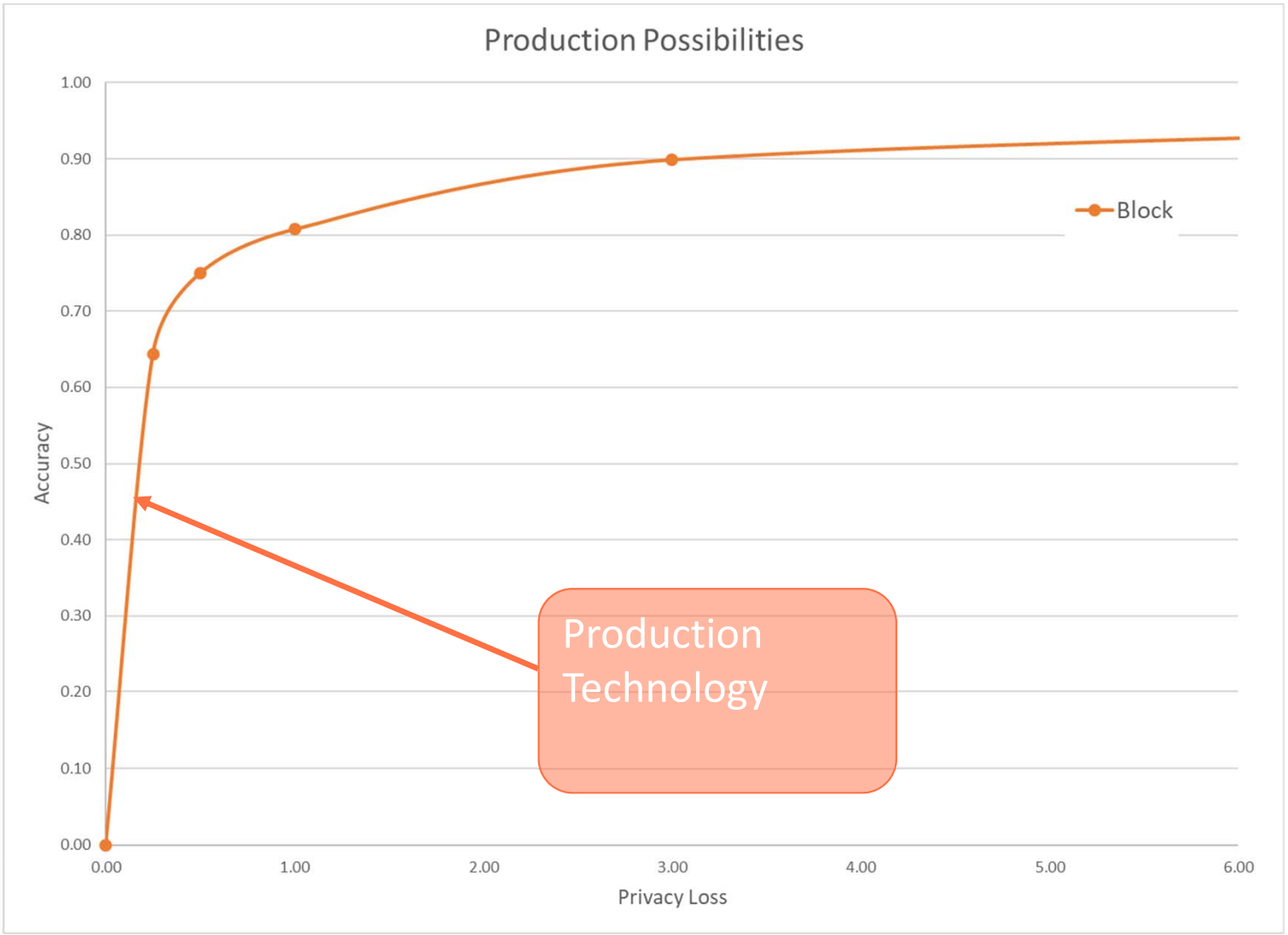
- Formal privacy methods like differential privacy provide technologies that quantify the relationship between accuracy (in multiple dimensions) and privacy-loss
- When you use formal methods, the scientific inferences are valid, provided the analysis incorporates the noise injection from the confidentiality protection
- Traditional SDL doesn't, and can't, do this—it is inherently scientifically dishonest

Database Reconstruction

Internal Experiments Using the 2010 Census

- Confirm that the micro-data from the confidential 2010 Hundred-percent Detail File (HDF) can be accurately reconstructed from PL94 + balance of SF1
- While there is a reconstruction vulnerability, the risk of re-identification is apparently still relatively small
- Experiments are at the person level, not household
- Experiments have led to the declaration that reconstruction of Title 13-sensitive data is an issue, no longer a risk
- Strong motivation for the adoption of differential privacy for the 2018 End-to-End Census Test and 2020 Census
- The only reason that quantitative details are being withheld is to permit external peer-review before they are released

Implemented Differential Privacy System for the 2018 End-to-End Census Test



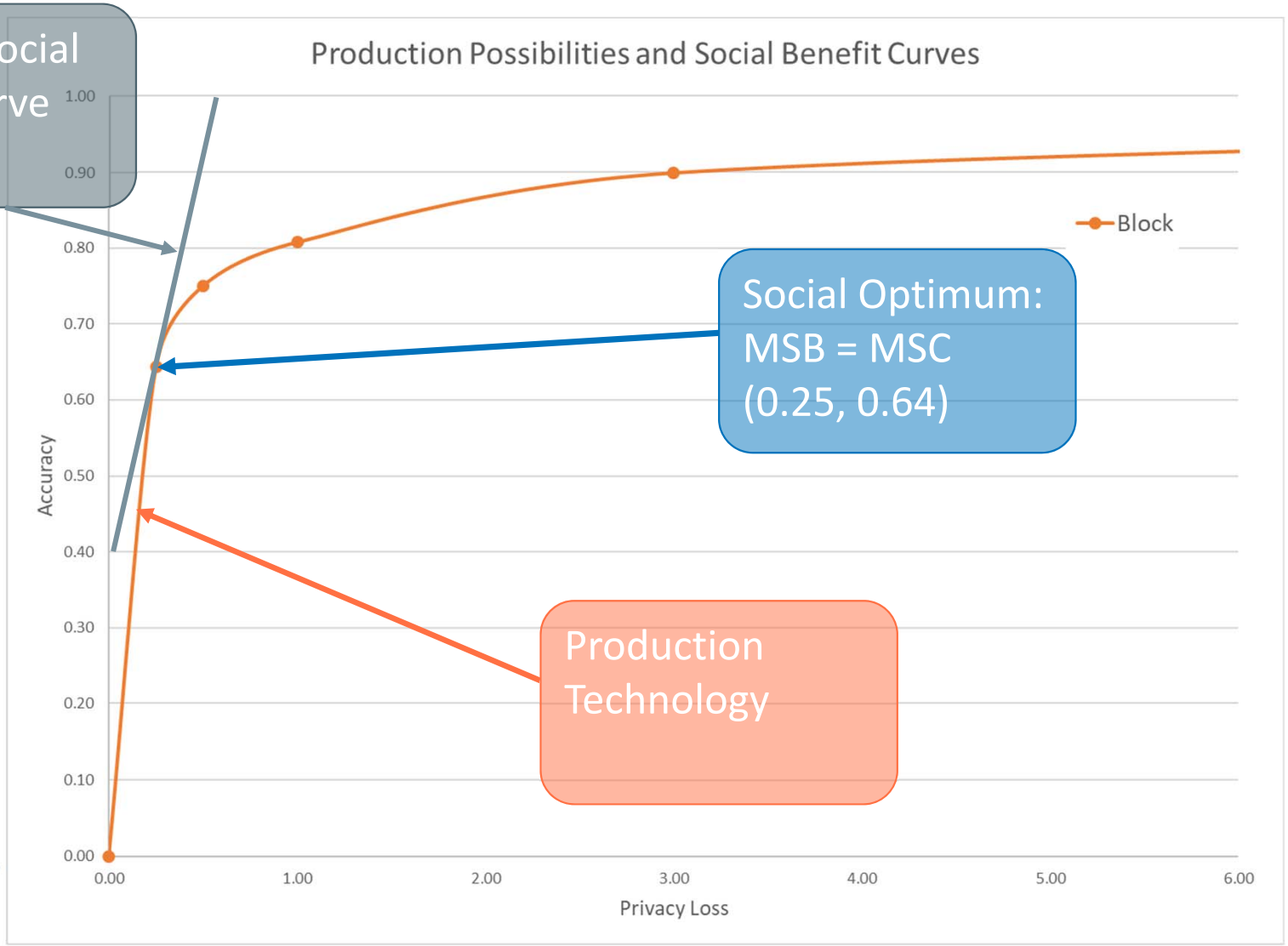
United States Census Bureau

Managing the Tradeoff

Basic Principles

- Based on recent economics (2019, *American Economic Review*) https://digitalcommons.ilr.cornell.edu/ldi/48/ or https://arxiv.org/abs/1808.06303
- The marginal social benefit is the sum of all persons' willingness-to-pay for data accuracy with increased privacy loss
- The marginal rate of transformation is the slope of the privacy-loss v. accuracy graphs we have been examining
- This is exactly the same problem being addressed by Google in RAPPOR or PROCHLO, Apple in iOS 11, and Microsoft in Windows 10 telemetry

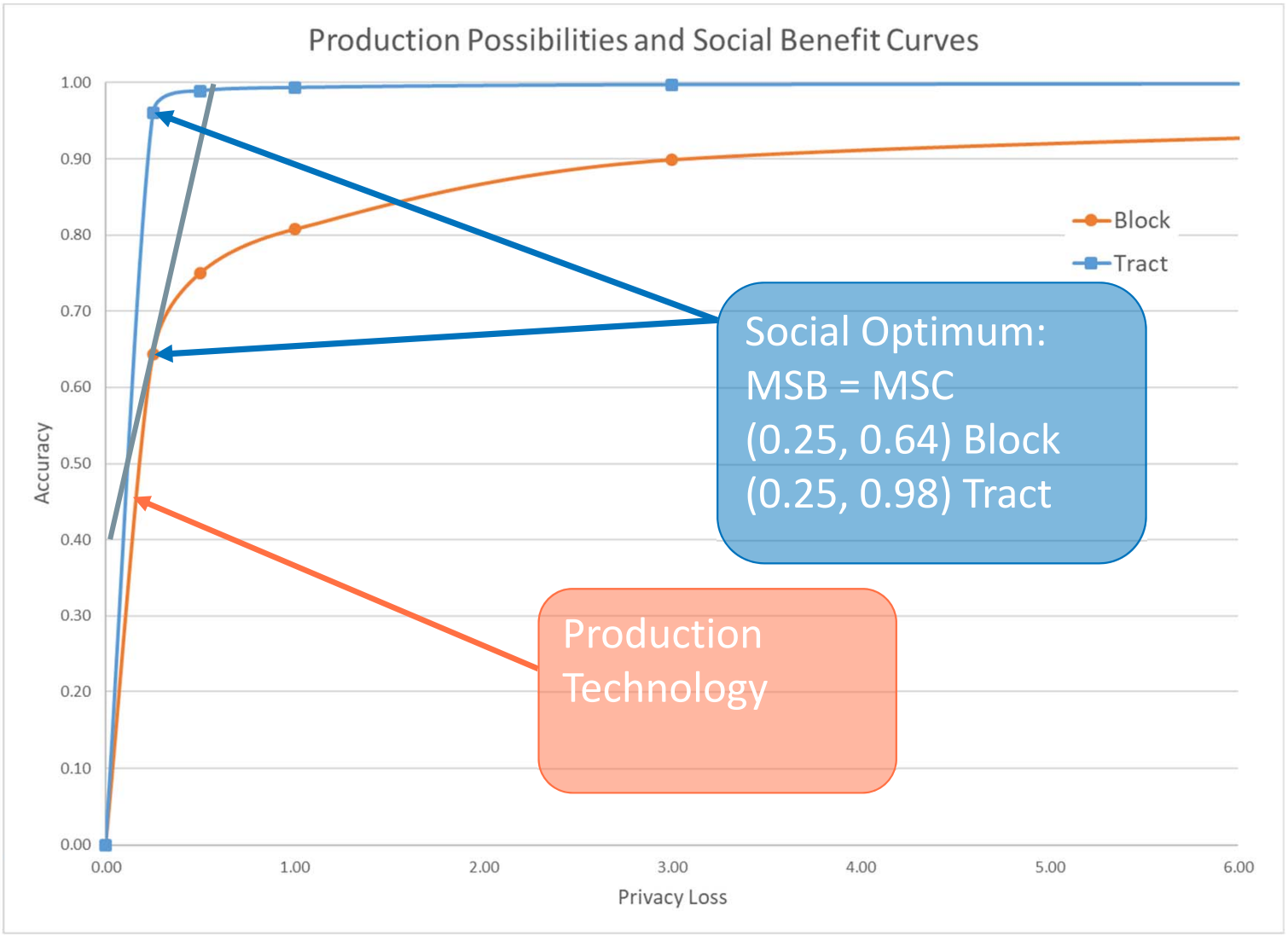
Marginal Social Benefit Curve



Social Optimum: MSB = MSC (0.25, 0.64)

Production Technology

United States Census Bureau



United States Census Bureau

More Background on the 2020 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, 2010 CSAC (detailed discussion of algorithms and choices) https://www2.census.gov/cac/sac/meetings/2018-12/abowd-disclosure-avoidance.pdf?#

Four Examples from Abowd & Schmutte

- Legislative redistricting
- Economic censuses and national accounts
- Tax data and tax simulations
- General purpose public-use micro-data

Legislative Redistricting

- In the redistricting application, the fitness-for-use is based on
  - Supreme Court one-person one-vote decision (All legislative districts must have approximately equal populations; there is judicially approved variation)
  - *Is statistical disclosure limitation a "statistical method" (permitted by Utah v. Evans) or "sampling" (prohibited by the Census Act, confirmed in Commerce v. House of Representatives)?*
  - Voting Rights Act, Section 2: requires majority-minority districts at all levels, when certain criteria are met
- The privacy interest is based on
  - Title 13 requirement not to publish exact identifying information
  - The public policy implications of uses of race, ethnicity and citizenship tabulations at detailed geography

Economic Censuses and National Accounts

- The major client for the detailed tabulations from economic censuses is the producer of national accounts
- In most countries these activities are consolidated in a single agency
- Fitness-for-use: accuracy of the national accounts
- Privacy considerations: sensitivity of detailed industry and product data, which may have been supplied by only a few firms
- Detailed tables can be produced using formal privacy, with far less suppression bias than in current methods
- But, its an inefficient use of the global privacy-loss budget when the accounts are published at much more aggregated levels
- Optimize the accuracy v. privacy loss by sharing confidential data (as permitted under CIPSEA) and applying formal privacy at publication level

Tax Data and Tax Simulations

- Simulating the effects of tax policy changes is an important use of tax micro-data
- Traditional disclosure limitation methods aggravate these simulations by smoothing over important kinks and breaking audit consistency
- Fitness-for-use: quality of the simulated tax policy effects
- Privacy: sensitivity of the income tax returns
- Optimize the accuracy v. privacy loss by doing the simulations inside the IRS firewall and applying formal privacy protection to outputs

General Purpose Public-use Micro-data

- Hierarchy of users
  - Educational
  - Commercial
  - Scientific
- Fitness-for-use: valid scientific inferences on arbitrary hypotheses estimable within the design of the confidential data product
- Privacy: database reconstruction-abetted re-identification attacks make every variable a potential identifier, especially in combination
- Traditional SDL fails the fitness-for-use
- Formal privacy guarantees the fitness-for-use for hypotheses in the set supported by its query workload (serves educational and commercial uses very well)
- For other hypotheses, supervised use (perhaps via a validation server) maintains fitness for use
- Same model as used by IPUMS https://international.ipums.org/international/irde.shtml
- We need to build these cooperatively

Thank you.

John.Maron.Abowd@census.gov

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

Selected References

- 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.
- Dwork, Cynthia, Frank McSherry, Kobbi Nissim, and Adam Smith. 2006. in Halevi, S. & Rabin, T. *(Eds.)* Calibrating Noise to Sensitivity in Private Data Analysis *Theory of Cryptography: Third Theory of Cryptography Conference, TCC 2006, New York, NY, USA, March 4-7, 2006. Proceedings, Springer Berlin Heidelberg*, 265-284, DOI: 10.1007/11681878_14.
- Dwork, Cynthia. 2006. Differential Privacy, *33rd International Colloquium on Automata, Languages and Programming, part II (ICALP 2006), Springer Verlag, 4052*, 1-12, ISBN: 3-540-35907-9.
- Dwork, Cynthia and Aaron Roth. 2014. *The Algorithmic Foundations of Differential Privacy*. Foundations and Trends in Theoretical Computer Science. Vol. 9, Nos. 3–4. 211–407, DOI: 10.1561/0400000042.
- Dwork, Cynthia, Frank McSherry and Kunal Talwar. 2007. The price of privacy and the limits of LP decoding. In *Proceedings of the thirty-ninth annual ACM symposium on Theory of computing*(STOC '07). ACM, New York, NY, USA, 85-94. DOI:10.1145/1250790.1250804.
- Machanavajjhala, Ashwin, Daniel Kifer, John M. Abowd , Johannes Gehrke, and Lars Vilhuber. 2008. Privacy: Theory Meets Practice on the Map, International Conference on Data Engineering (ICDE) 2008: 277-286, doi:10.1109/ICDE.2008.4497436.
- Dwork, Cynthia and Moni Naor. 2010. On the Difficulties of Disclosure Prevention in Statistical Databases or The Case for Differential Privacy, *Journal of Privacy and Confidentiality*: Vol. 2: Iss. 1, Article 8. Available at: http://repository.cmu.edu/jpc/vol2/iss1/8.
- Kifer, Daniel and Ashwin Machanavajjhala. 2011. No free lunch in data privacy. In *Proceedings of the 2011 ACM SIGMOD International Conference on Management of data* (SIGMOD '11). ACM, New York, NY, USA, 193-204. DOI:10.1145/1989323.1989345.
- Abowd, John M. and Ian M. Schmutte. Forthcoming. An Economic Analysis of Privacy Protection and Statistical Accuracy as Social Choices. American Economic Review, at https://arxiv.org/abs/1808.06303
- Erlingsson, Úlfar, Vasyl Pihur and Aleksandra Korolova. 2014. RAPPOR: Randomized Aggregatable Privacy-Preserving Ordinal Response. In *Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security* (CCS '14). ACM, New York, NY, USA, 1054-1067. DOI:10.1145/2660267.2660348.
- Apple, Inc. 2016. Apple previews iOS 10, the biggest iOS release ever. Press Release (June 13). URL=http://www.apple.com/newsroom/2016/06/apple-previews-ios-10-biggest-ios-release-ever.html.
- Ding, Bolin, Janardhan Kulkarni, and Sergey Yekhanin 2017. Collecting Telemetry Data Privately, NIPS 2017.
- Bittau , Andrea, Úlfar Erlingsson, Petros Maniatis, Ilya Mironov, Ananth Raghunathan, David Lie, Mitch Rudominer, Usharsee Kode, Julien Tinnes, and Bernhard Seefeld 2017. Prochlo: Strong Privacy for Analytics in the Crowd, https://arxiv.org/abs/1710.00901.