Statistically Valid Inferences from Privacy Protected Data

Gary King[1]

Institute for Quantitative Social Science
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Quantitative Social Science Colloquium, Princeton University, 10/7/2022

[1]GaryKing.org/privacy. Based on APSR/AJPS/PA articles with subsets of {Georgie Evans, Meg Schwenzfeier, Abhradeep Thakurta, Adam D. Smith}

Science Magazine, 1995

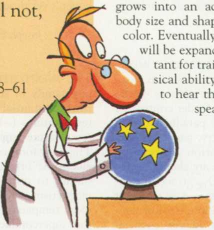
Science Magazine, 1995

VIEWPOINT: THE FUTURE

Through the Glass Lightly

A collection of scientists at the frontier were asked what they see in the future for science.* Here are their views....

> If you can look into the seeds of time,
> And say which grain will grow and which will not,
> Speak then to me, who neither beg nor fear
> Your favors nor your hate.
>
> Shakespeare, *Macbeth*, 1.3.58–61



ILLUSTRATIONS BY TERRY E. SMITH

THERE WILL BE ENORMOUS INROADS INTO human biology and human disease via genomics, gene therapy, and mouse knockout models; a revolution in drug design by combinatorial chemistry; an understanding of the specificity of nerve connections and cognition; and the basic logic of development will be solved (if it is not solved already). New technologies will be developed for studying the structure, function, and dynamics of multiprotein ensembles—for example, the eukaryotic transcription complexes. New methodologies will be developed for studying the behavior of single, live cells in isolation or in the context of an embryo. This includes studying the activity of the cell itself as well as various subcellular structures.

Hal Weintraub
Fred Hutchinson Cancer Research Center
Seattle, Washington

individuals at risk for diabetes, schizophrenia, obesity, and many other diseases. In many cases, disease will be either avoidable by modification of behavior or ameliorated by therapeutic intervention. For societies with socialized health care programs, the economic cost of screening will need to be balanced by the overall savings in disease reduction. If individuals refuse preventive treatment, screening is not cost-effective. For societies with private health care systems, the rich will become healthier and the poor sicker. In both systems, balancing the rights of individuals against the needs of society is going to be difficult.

Peter N. Goodfellow
Department of Genetics
University of Cambridge

toxins, sunlight, and so forth. The output will be a color movie in which the embryo develops into a fetus, is born, and then grows into an adult, explicitly depicting body size and shape and hair, skin, and eye color. Eventually the DNA sequence base will be expanded to cover genes important for traits such as speech and musical ability; the mother will be able to hear the embryo—as an adult—speak or sing.

Harvey F. Lodish
Whitehead Institute for Biomedical Research
Cambridge, Massachusetts

THE OLD PHRASE "YOU can't get blood from a turnip" may be proven incorrect, at least partially. Transgenic plants hold promise as biomanufacturing systems for a wide variety of human proteins, including those found in blood plasma. Serum albumin, for instance, has been shown to be expressed and processed correctly when the gene encoding it was introduced into plants. The missing element in this scenario is process technology, which will make it possible to do large-scale protein purification from plant tissues. Advances in high-level protein expression in specialized plant tissues (such as seeds, fruits, or tubers) coupled to engineering improve-

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- Summary. Progress came from: Novel data, novel methods

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  - How? Solving political problems technologically

Solving Political Problems Technologically

Differential Privacy & Inferential Validity

A General Purpose, Statistically Valid DP Algorithm

The Algorithm in Practice

Convincing Facebook to Make Data Available

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Solving a Political Problem Technologically (via "constitutional design")

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Solving Political Problems Technologically

Differential Privacy & Inferential Validity

A General Purpose, Statistically Valid DP Algorithm

The Algorithm in Practice

Theories of Inference: Statistics vs. CS

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Population
⋮
Rocío
John
Marc
Brandon
Yu Xie
Gleason
Saad
Leonard
Kristopher
Zhou

Mean income: \$48

Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample
⋮	✗
Rocío	✓
John	✓
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Population	Sample	$
⋮	✗	?
Rocío	✓	122
John	✓	76
Marc	✓	145
Brandon	✓	96
Yu Xie	✓	86
Gleason	✓	127
Saad	✓	72
Leonard	✓	132
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$48		$108

Mean income:

Classical Inference

Quantity of Interest

Usually no direct relevance

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Classical Inference

Query-Response

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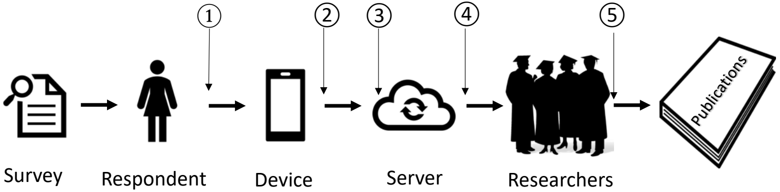
Classical Inference

Query-Response

Statistically Valid Inferences from Privacy Protected Data

Protecting Survey Data



Differential Privacy and its Inferential Challenges

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for all D, D', m

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A Differentially Private Estimator

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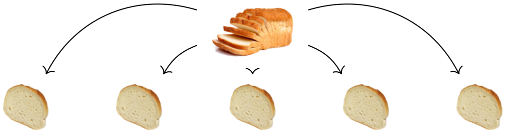
Private data

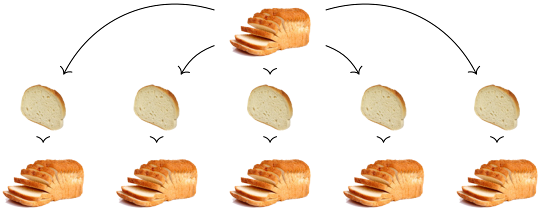
A Differentially Private Estimator



Private data

Partition

A Differentially Private Estimator



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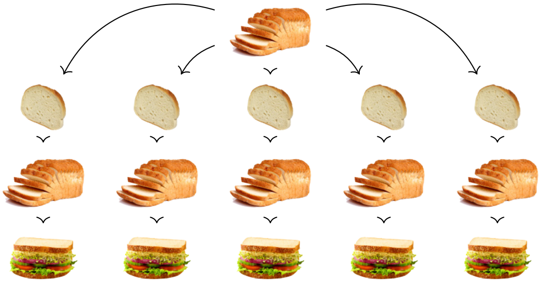
Bag of little bootstraps

A Differentially Private Estimator



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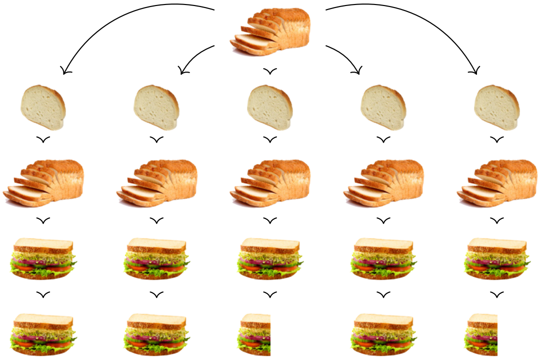

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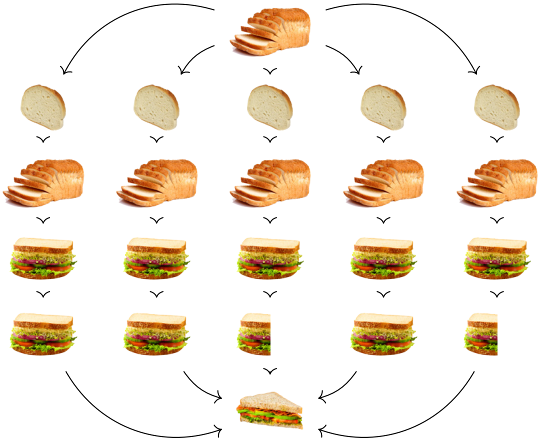

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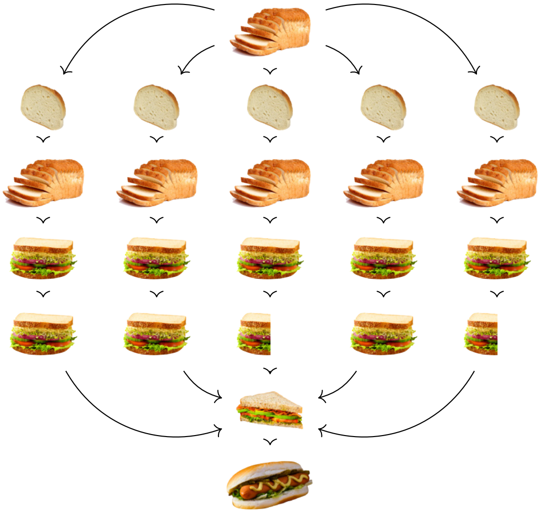

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Noise

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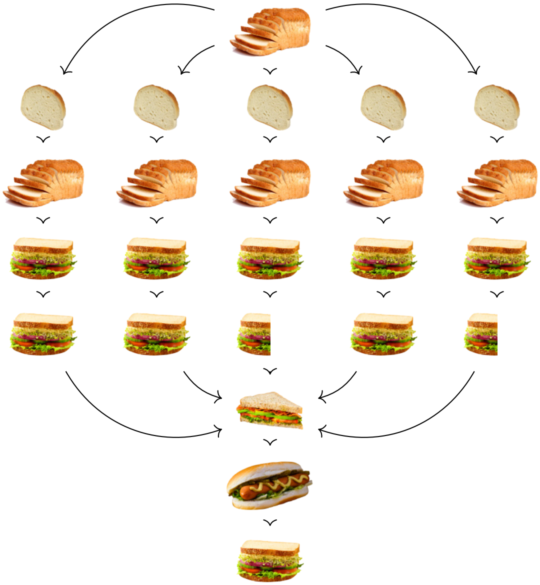

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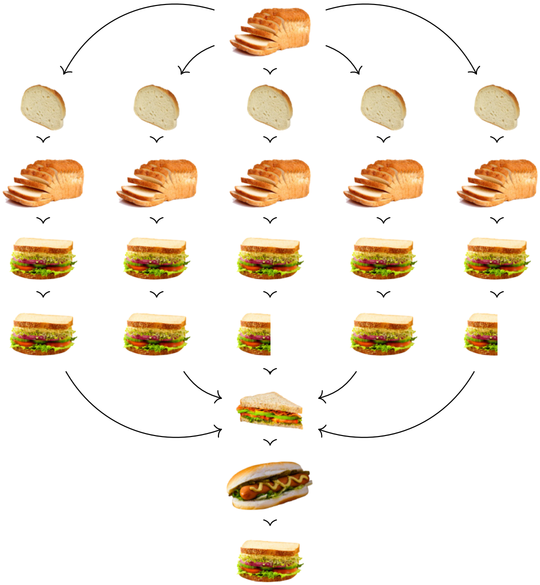

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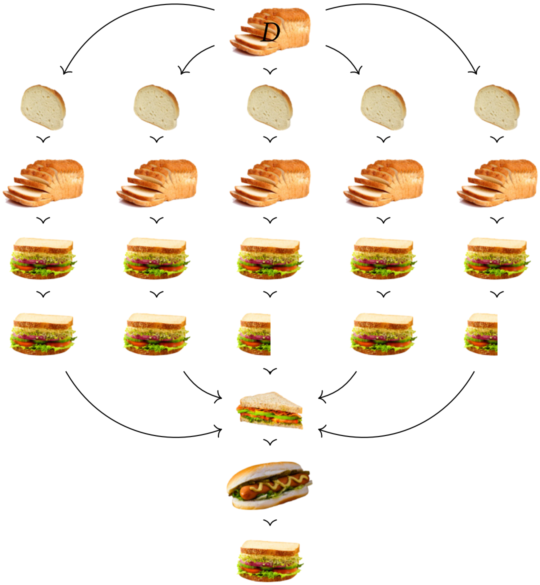

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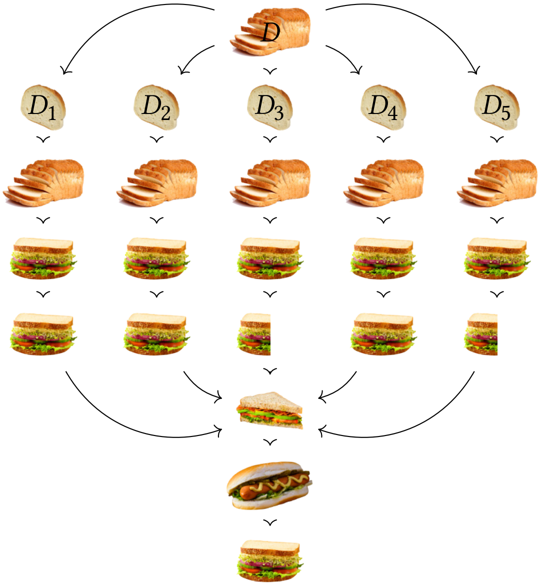

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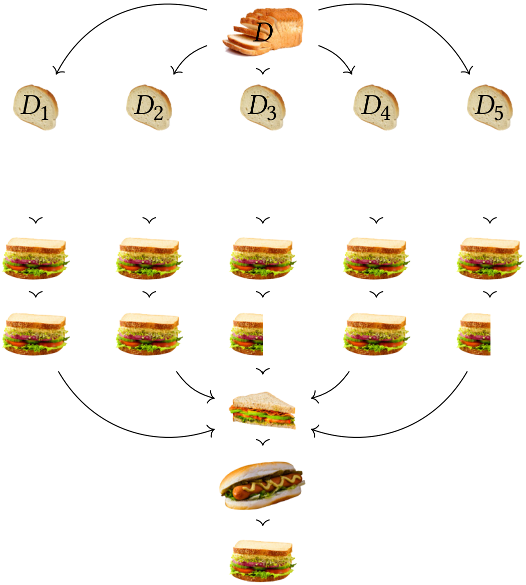

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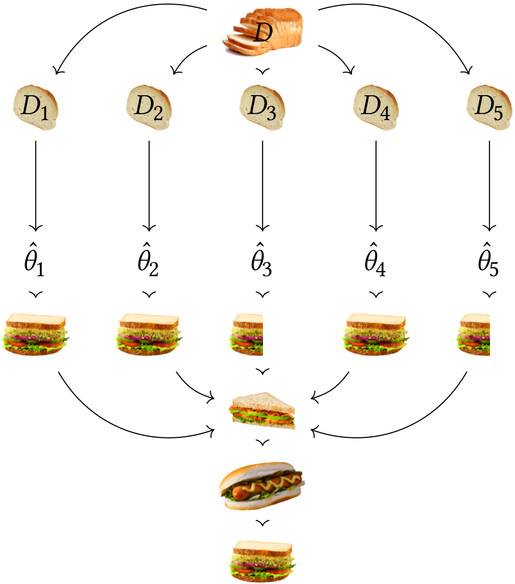

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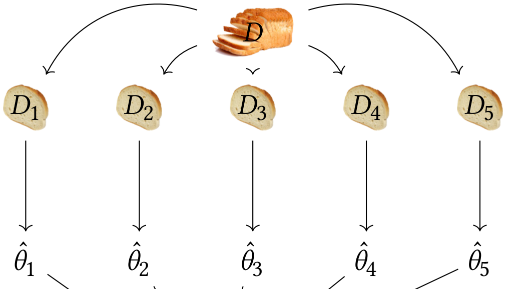

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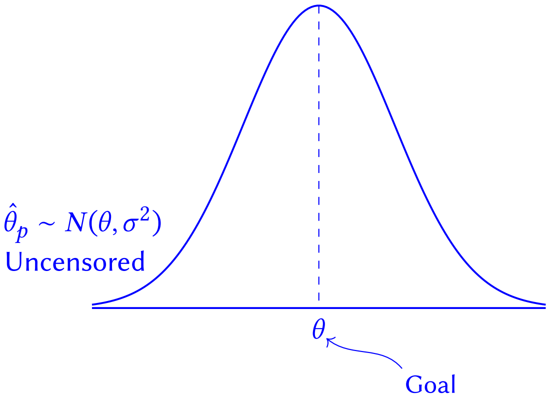

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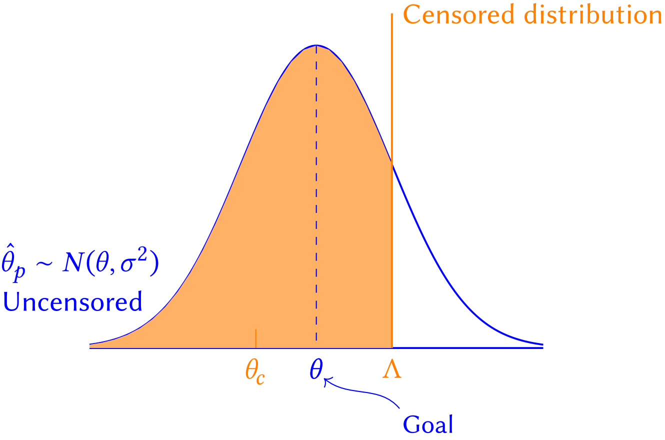

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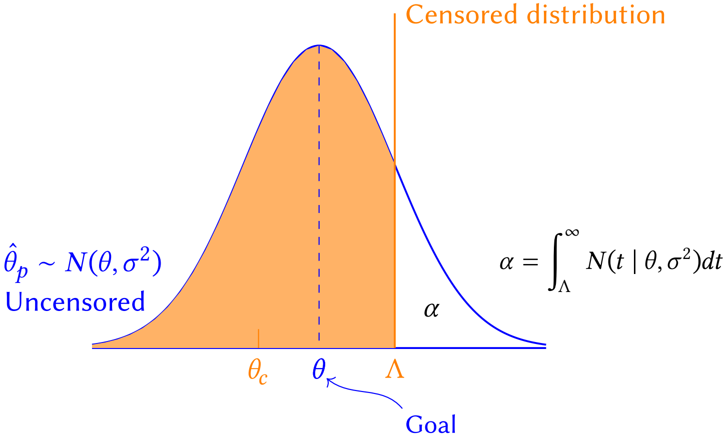

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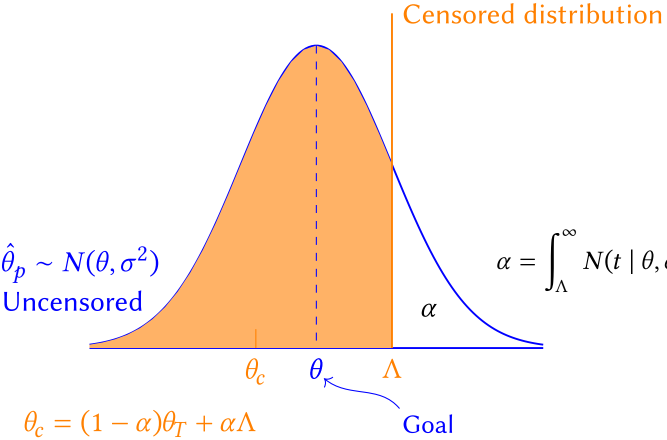

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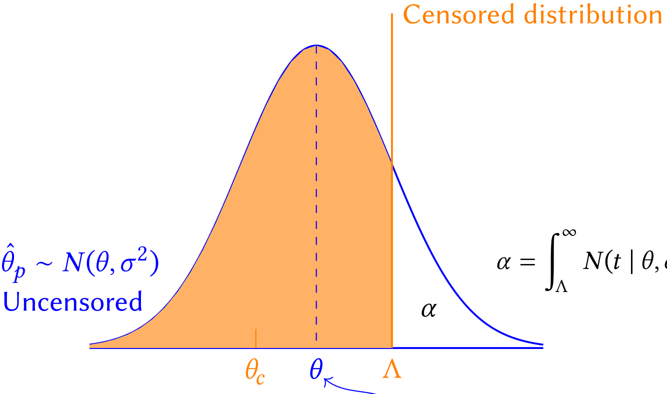

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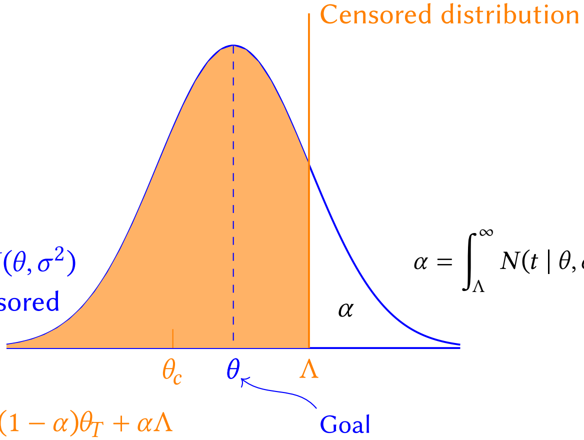

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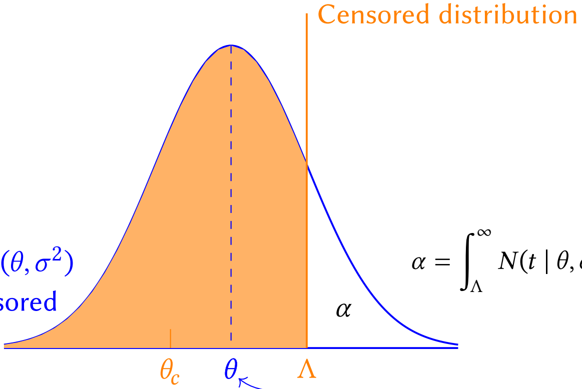

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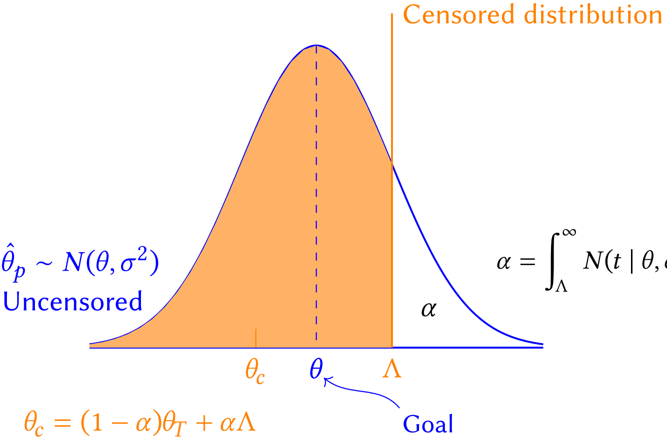

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Variance Estimation

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- Simulate estimates via standard (Clarify) procedures:

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Solving Political Problems Technologically

Differential Privacy & Inferential Validity

A General Purpose, Statistically Valid DP Algorithm

The Algorithm in Practice

Simulations: Finite Sample Evaluation

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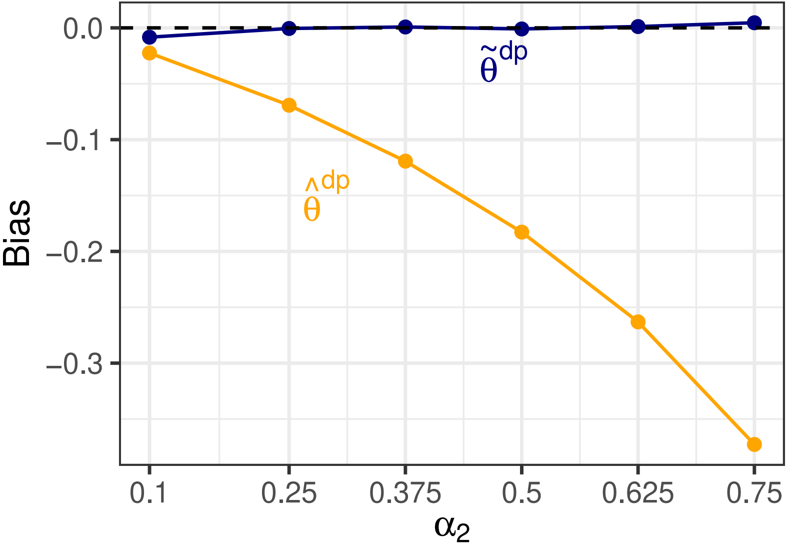

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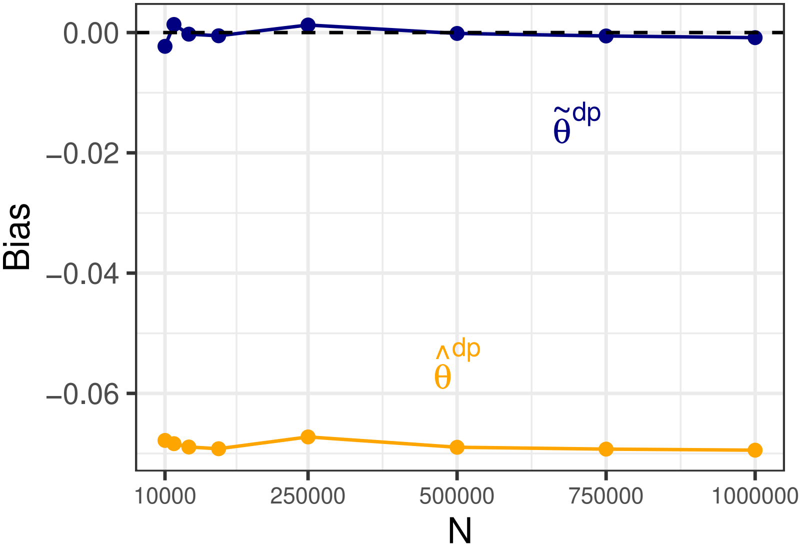

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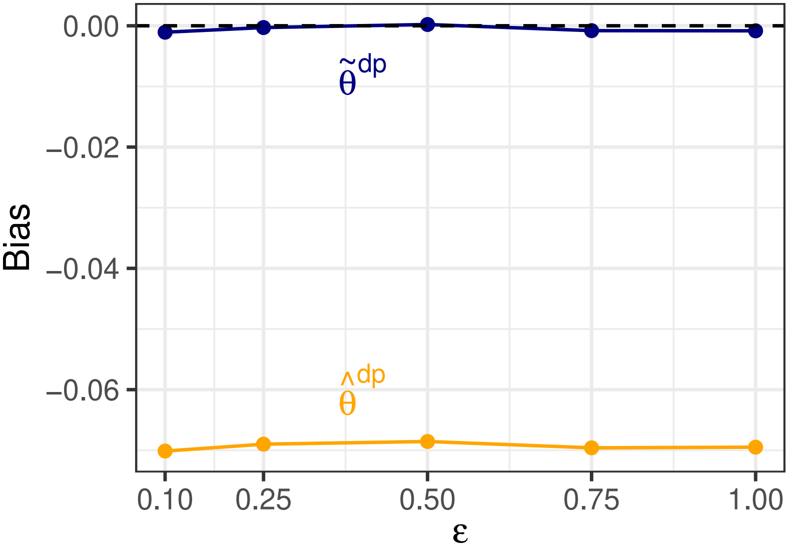

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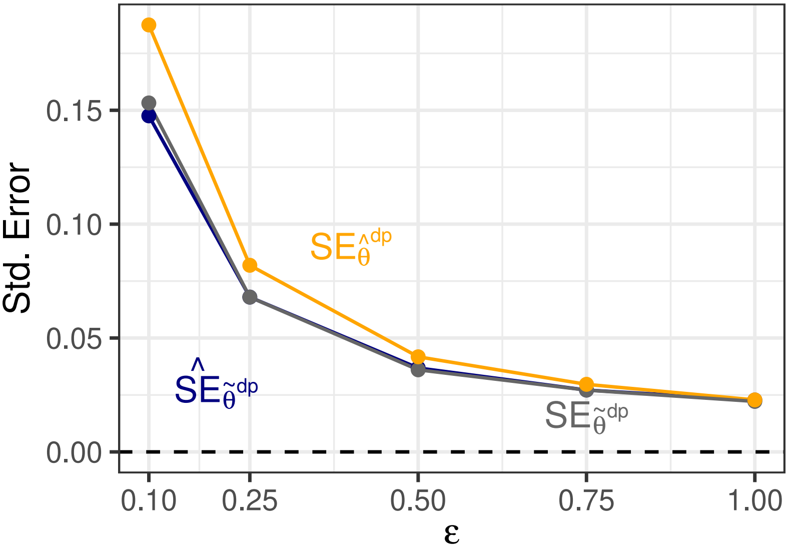

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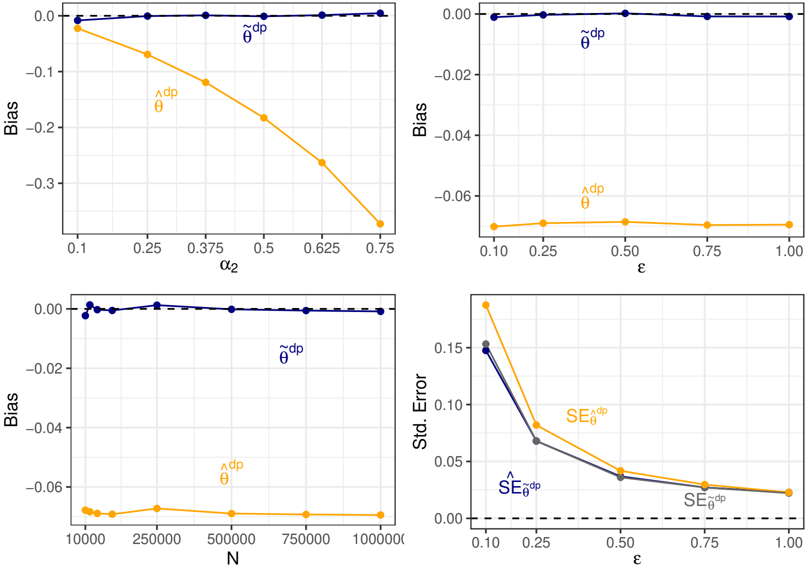
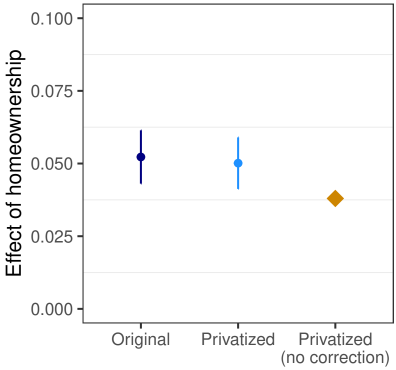
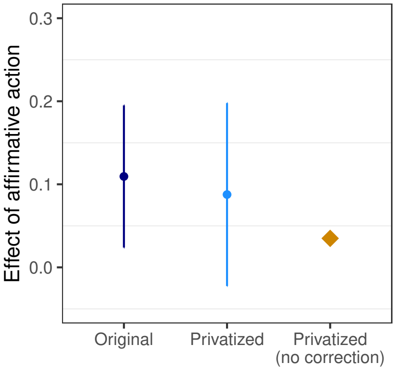


Similar Empirical Results, Larger CIs



(a) Yoder (APSR, 2020)



(b) Bhavnani and Lee (AJPS, 2019)

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- Community based, Open Source Software: OpenDP.org

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Appendix

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- Privacy risk quantified (ϵ), instead of 0/1 for re-ID
  - Helpful mathematically; insufficient in applications
- Real privacy loss $\ll$ maximum privacy loss
  - OK for worst case scenerio; unhelpful in practice
- Privacy Budget
  - Composition: ϵ_1-DP and ϵ_2-DP is $(\epsilon_1 + \epsilon_2)$-DP
  - Can limit maximum risks across analyses & researchers
  - When the budget is used, no new analyses can ever be run
- Completely changes statistical best practices
  - Without DP, we balance worries:
    - P-hacking $\rightsquigarrow$ pre-registration (e.g., clinical trials, Mars lander)
    - Threats to inference $\rightsquigarrow$ diagnostics, exploration, serendipity (e.g., observational data)
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Properties of Differential Privacy

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