Statistically Valid Inferences from Privacy Protected Data

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SICSS, University of Rochester, 5/9/2022

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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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- New Problem: Sharing data without it leaving Facebook

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    - *no* uncertainty estimates

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A General Purpose, Statistically Valid DP Algorithm

The Algorithm in Practice

Theories of Inference: Statistics vs. CS

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Population
⋮
Maria
Adel
Károly
Connor
Georgie
Gary
Meg
Abhradeep
Tim
John

Mean income: $48

Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample
⋮	✗
Maria	✓
Adel	✓
Károly	✓
Connor	✓
Georgie	✓
Gary	✓
Meg	✓
Abhradeep	✓
Tim	✓
John	✓

Mean income: \$48

Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample	$
⋮	✗	?
Maria	✓	122
Adel	✓	76
Károly	✓	145
Connor	✓	96
Georgie	✓	86
Gary	✓	127
Meg	✓	72
Abhradeep	✓	132
Tim	✓	95
John	✓	134
Mean income: $48		$108

Classical Inference

Quantity of Interest

Usually no direct relevance

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Classical Inference

Quantity of Interest

Usually no direct relevance

Theories of Inference: Statistics vs. CS

Population	Sample	$	+Privacy
⋮	✗	?	
Maria	✓	122	Noise & Censoring
Adel	✓	76	
Károly	✓	145	
Connor	✓	96	
Georgie	✓	86	
Gary	✓	127	
Meg	✓	72	
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Mean income: $48   Classical Inference $108

Quantity of Interest

Usually no direct relevance

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	Population	Sample	$	+Privacy	=dp$
	⋮	✗	?		
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	Adel	✓	76		103
	Károly	✓	145		75
	Connor	✓	96		113
	Georgie	✓	86	Noise & Censoring	125
	Gary	✓	127		97
	Meg	✓	72		101
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	Tim	✓	95		83
	John	✓	134		201
Mean income:	$48		$108		$111

Classical Inference

Query-Response

Quantity of Interest

Usually no direct relevance

No direct relevance

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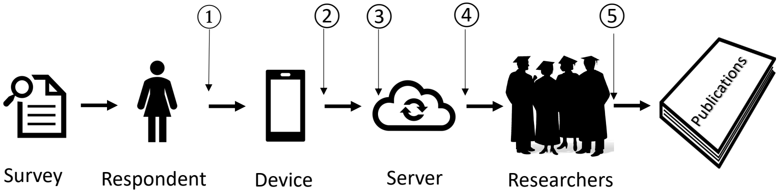
Classical Inference

Query-Response

Statistically Valid Inferences from Privacy Protected Data

Protecting Survey Data



Differential Privacy and its Inferential Challenges

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  - DP Mechanism: $M(s, D)$, with noise & censoring
    - Essential components of ensuring privacy

Differential Privacy and its Inferential Challenges

- Estimators
  - Classical Statistics: Apply statistic s to dataset D, $s(D)$
  - DP Mechanism: $M(s, D)$, with noise & censoring
    - Essential components of ensuring privacy
    - Fundamental problems for statistical inference

Differential Privacy and its Inferential Challenges

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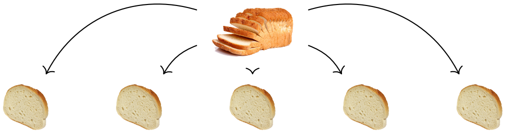
A Differentially Private Estimator

A Differentially Private Estimator

Private data

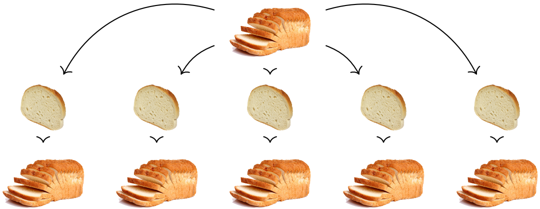
A Differentially Private Estimator



Private data

Partition

A Differentially Private Estimator



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Bag of little bootstraps

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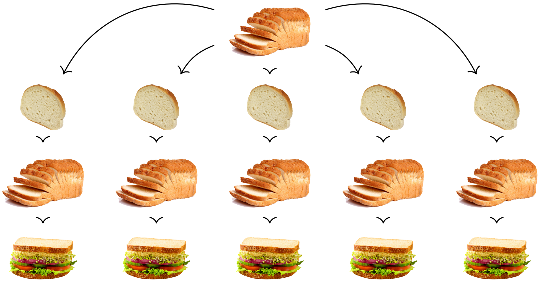

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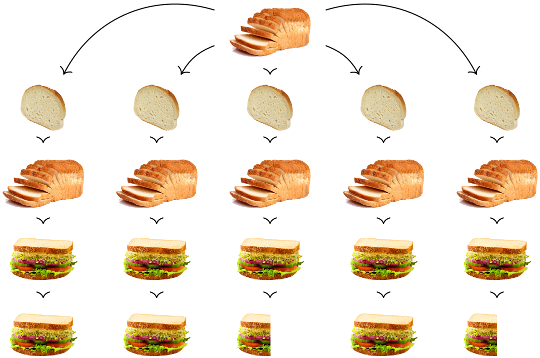

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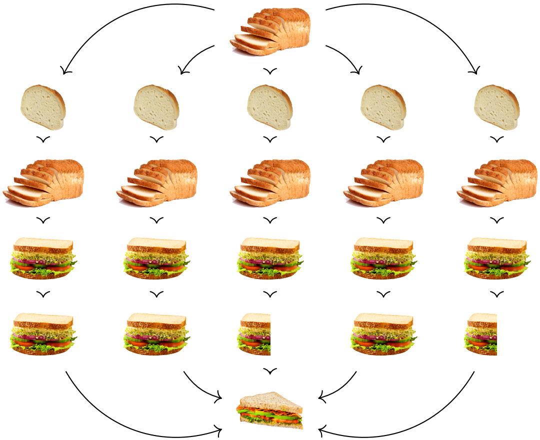

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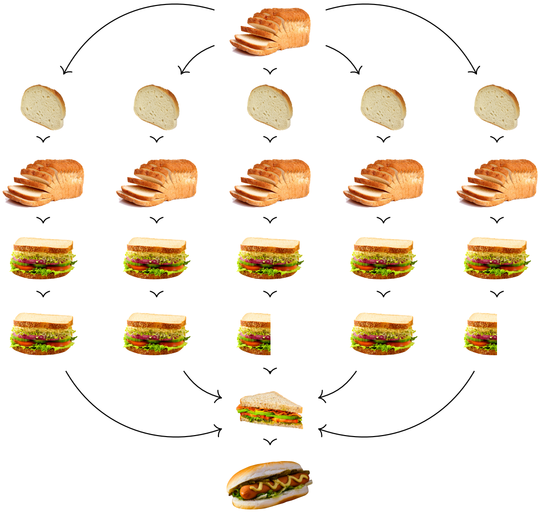

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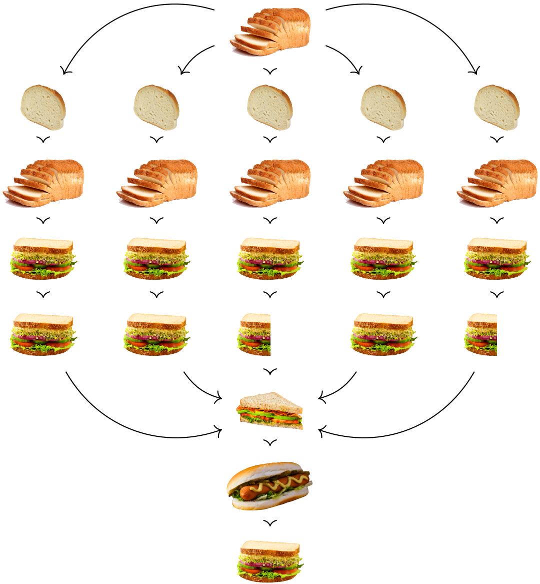

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Bias Correction

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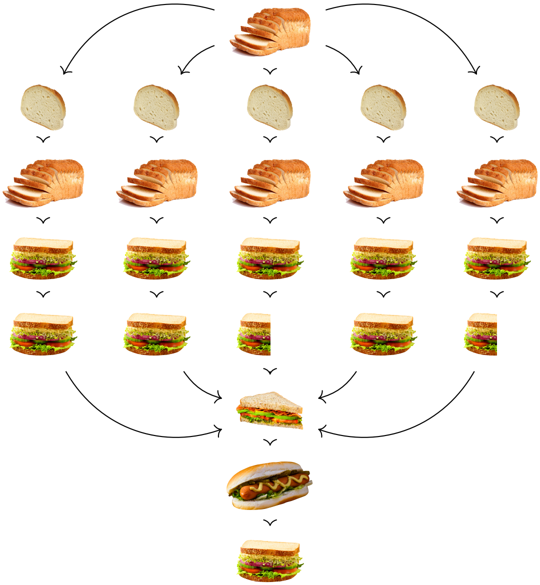

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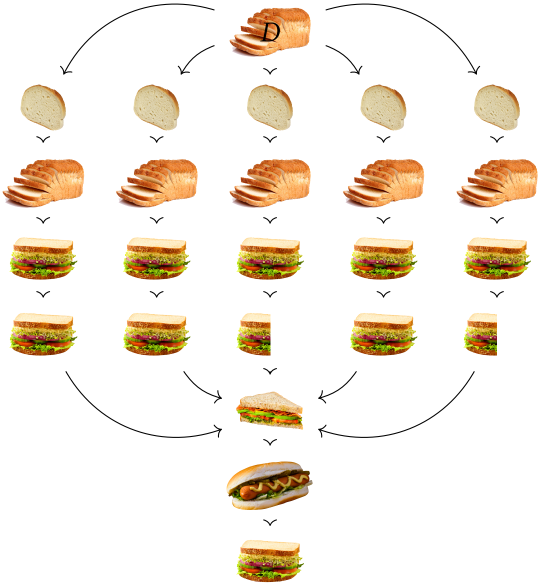

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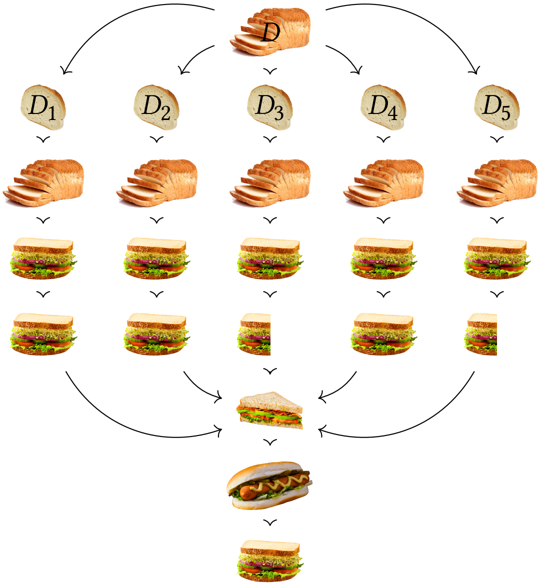

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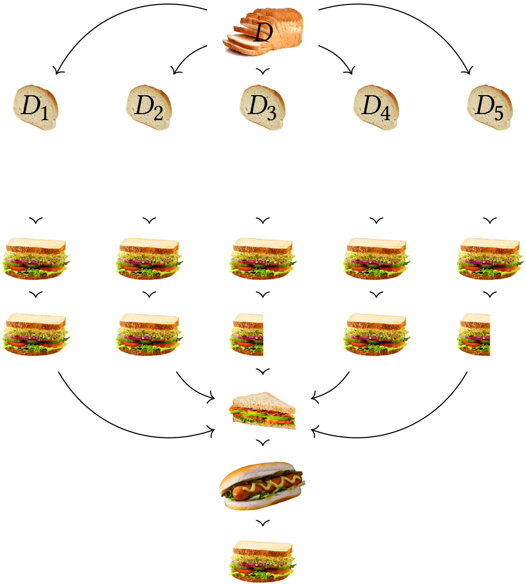

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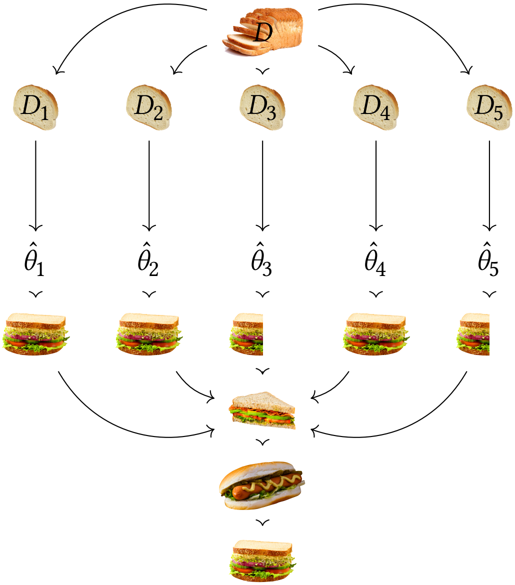

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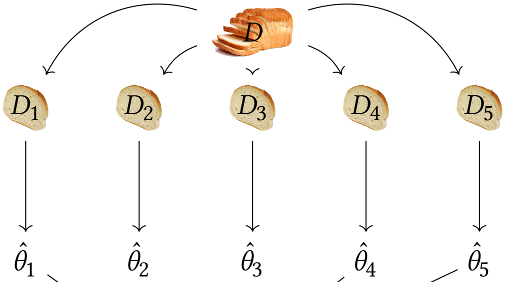

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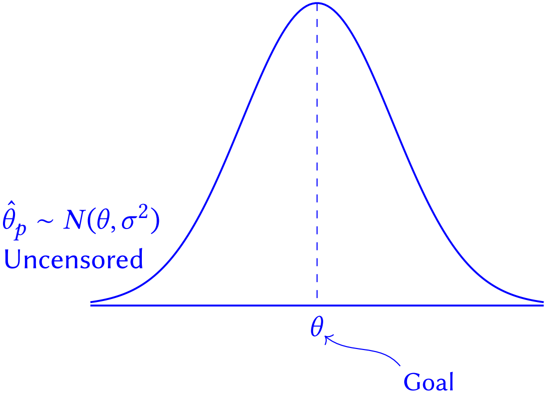

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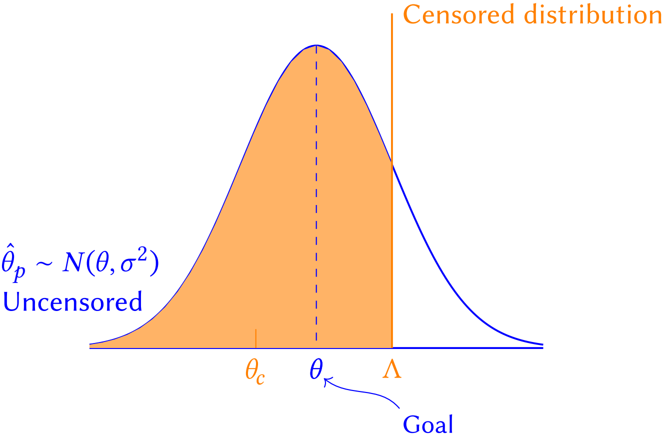

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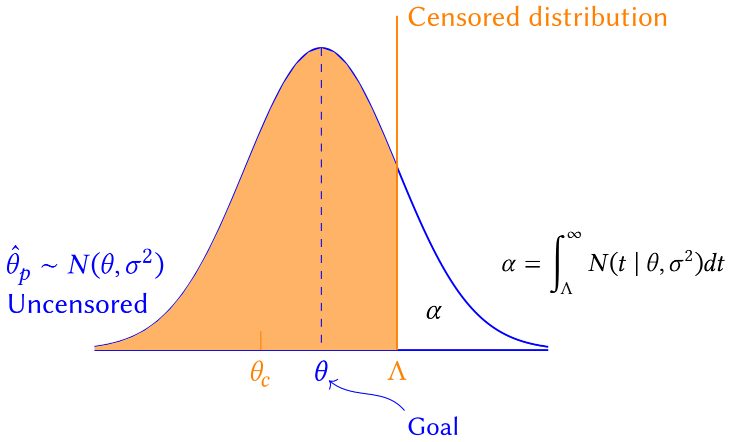

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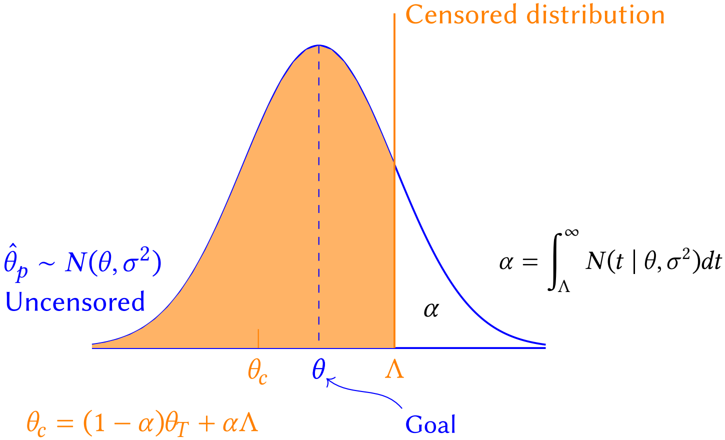

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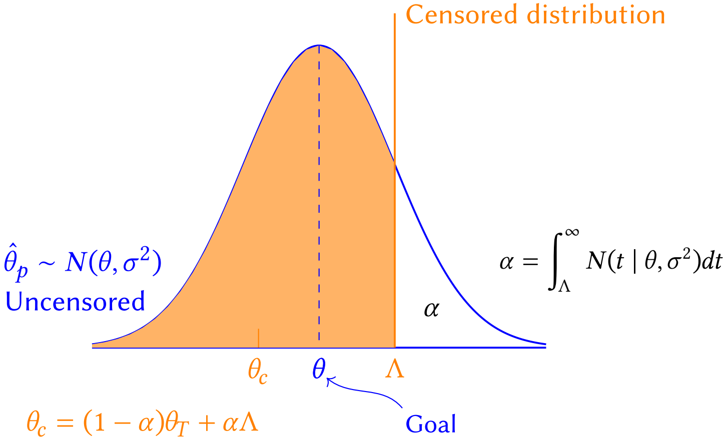

Equations: 2

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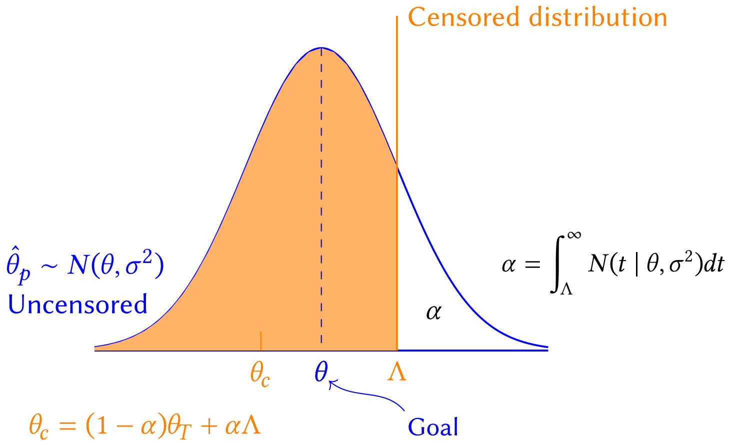

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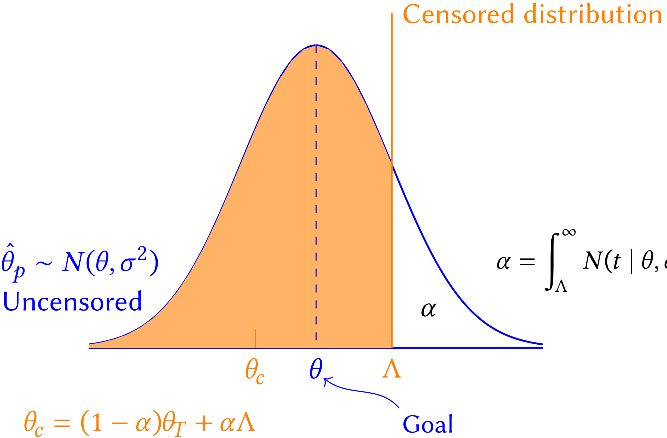

$$\alpha = \int_{\Lambda}^{\infty} N(t \mid \theta, \sigma^2)dt$$

$$\theta_c = (1-\alpha)\theta_T + \alpha\Lambda$$

Disclose: $\hat{\theta}^{\text{dp}}$

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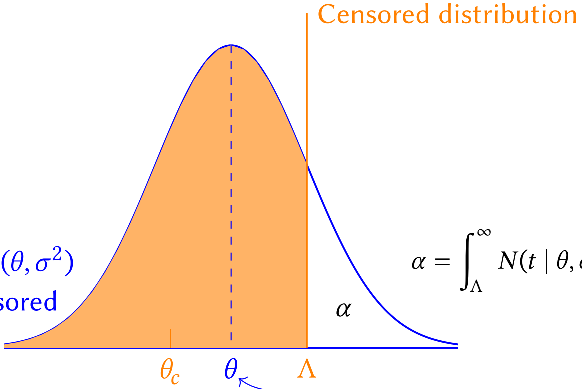

$\hat{\theta}_p \sim N(\theta, \sigma^2)$

Uncensored

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Goal

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Variance Estimation

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- Simulate estimates via standard (Clarify) procedures:

$$\hat{\theta}^{\mathrm{dp}}, \hat{\alpha}^{\mathrm{dp}} \sim N\left(\begin{bmatrix} \hat{\theta}^{\mathrm{dp}} \\ \hat{\alpha}^{\mathrm{dp}} \end{bmatrix}, \begin{bmatrix} \hat{V}(\hat{\theta}^{\mathrm{dp}}) & \widehat{\mathrm{Cov}}(\hat{\alpha}^{\mathrm{dp}}, \hat{\theta}^{\mathrm{dp}}) \\ \widehat{\mathrm{Cov}}(\hat{\alpha}^{\mathrm{dp}}, \hat{\theta}^{\mathrm{dp}}) & \hat{V}(\hat{\alpha}^{\mathrm{dp}}) \end{bmatrix} \right)$$

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Simulations: Finite Sample Evaluation

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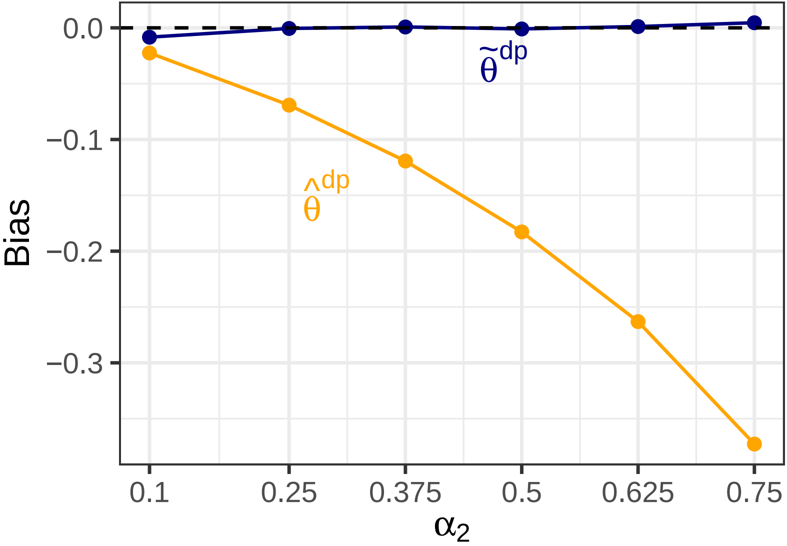

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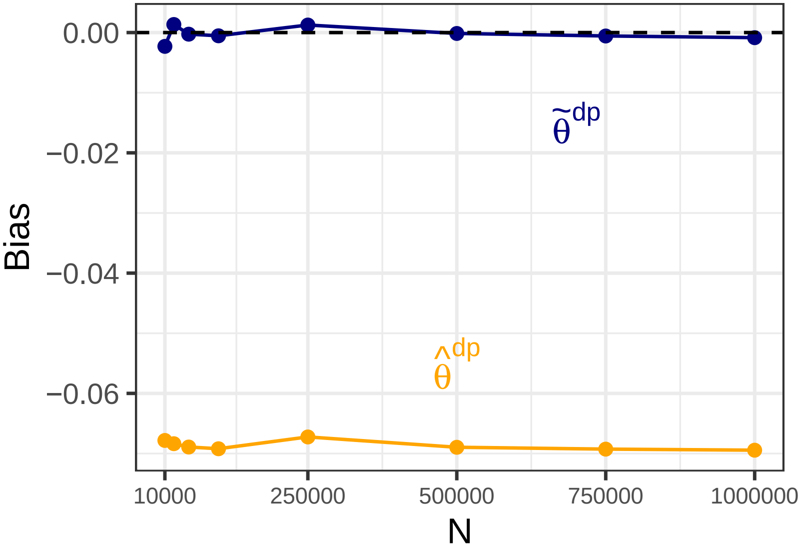

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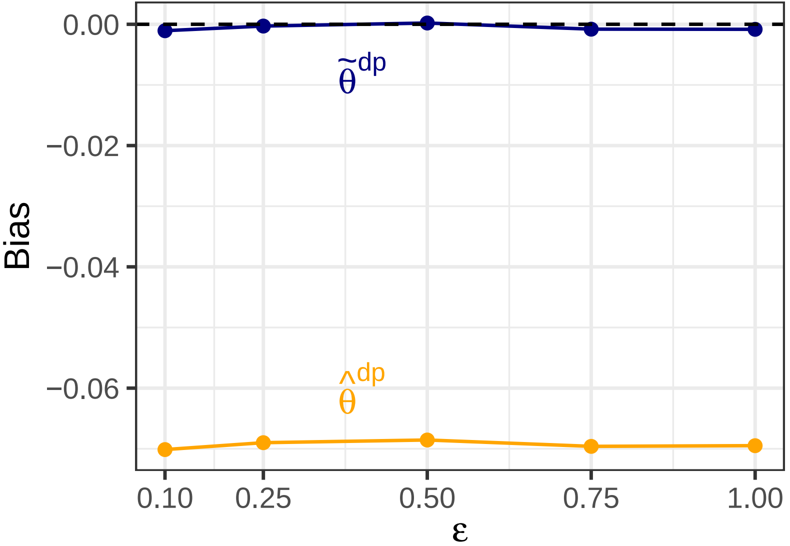

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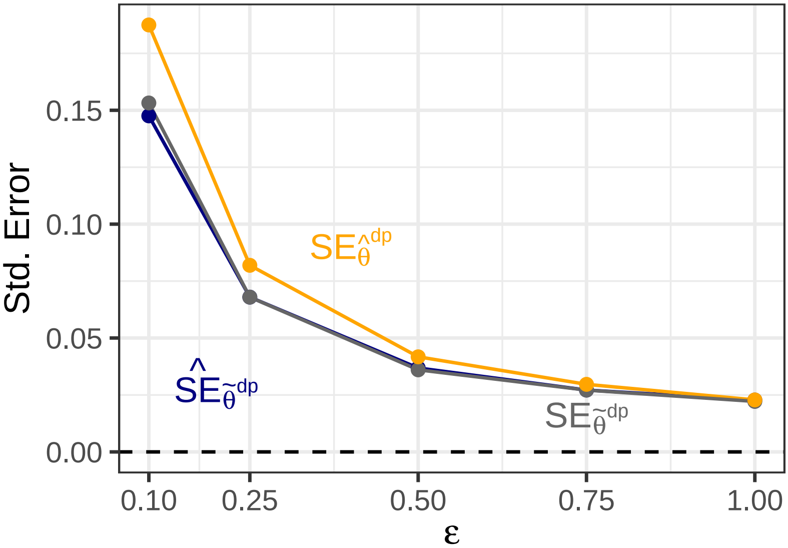

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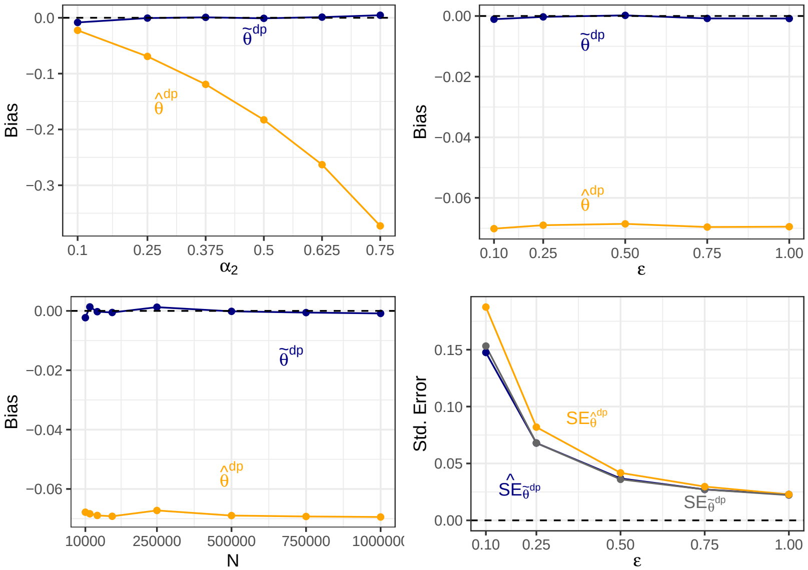
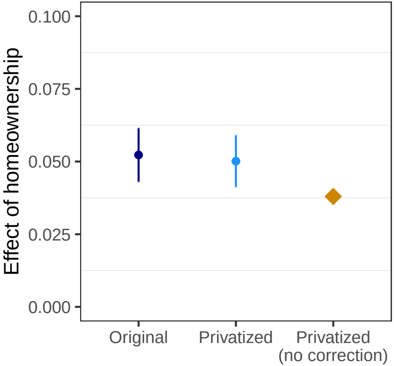
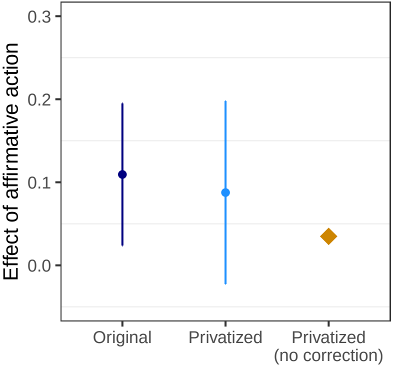


Similar Empirical Results, Larger CIs



(a) Yoder (2020)



(b) Bhavnani and Lee (2019)

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  - Statistically unbiased, lower variance
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  - Implementations:

Concluding Remarks

- Data sharing $\rightsquigarrow$ data access
  - DP protects individual privacy
  - Enables inference to private database, not population
  - Usually biased, no uncertainty estimates
  - Fails to protect society from fallacious scientific conclusions
- Inferential validity
  - A scientific statement: not necessarily correct, but must have:
  - known statistical properties & valid uncertainty estimates
- Proposed algorithm
  - Generic: almost any statistical method or quantity of interest
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  - Solves political problems technologically
  - Implementations:
    - Facebook, Microsoft+Harvard/IQSS, OpenDP

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Appendix

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