Statistically Valid Inferences from Privacy Protected Data

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Deloitte Data Science Seminar, 7/14/2022

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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

Who Needs to Share Data (Safely)?

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- One division of a company $\rightsquigarrow$ another division

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- One company $\rightsquigarrow$ another company
- A Company or Government $\rightsquigarrow$ Academic Researchers

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The Algorithm in Practice

Theories of Inference: Statistics vs. CS

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	Population
	⋮
	James
	Mohammad
	Tysen
	Heather
	Georgie
	Gary
	Meg
	Abhradeep
	Tim
	Cathy
Mean income:	\$48

Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample
⋮	✗
James	✓
Mohammad	✓
Tysen	✓
Heather	✓
Georgie	✓
Gary	✓
Meg	✓
Abhradeep	✓
Tim	✓
Cathy	✓
Mean income: $48	

Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample	$
$\vdots$	✗	?
James	✓	122
Mohammad	✓	76
Tysen	✓	145
Heather	✓	96
Georgie	✓	86
Gary	✓	127
Meg	✓	72
Abhradeep	✓	132
Tim	✓	95
Cathy	✓	134
Mean income: $48		$108

Classical Inference

Quantity of Interest

Usually no direct relevance

Theories of Inference: Statistics vs. CS

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Classical Inference

Quantity of Interest

Usually no direct relevance

Theories of Inference: Statistics vs. CS

Population	Sample	$	+Privacy
⋮	✗	?	Noise & Censoring
James	✓	122	
Mohammad	✓	76	
Tysen	✓	145	
Heather	✓	96	
Georgie	✓	86	
Gary	✓	127	
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Mean income: $48		$108	

Classical Inference

Quantity of Interest

Usually no direct relevance

Theories of Inference: Statistics vs. CS

Population	Sample	$	+Privacy	=dp$
⋮	✗	?		
James	✓	122		85
Mohammad	✓	76		103
Tysen	✓	145		75
Heather	✓	96		113
Georgie	✓	86	Noise & Censoring	125
Gary	✓	127		97
Meg	✓	72		101
Abhradeep	✓	132		128
Tim	✓	95		83
Cathy	✓	134		201

Mean income: $48 — $108 — $111

Classical Inference

Query-Response

Quantity of Interest

Usually no direct relevance

No direct relevance

Theories of Inference: Statistics vs. CS

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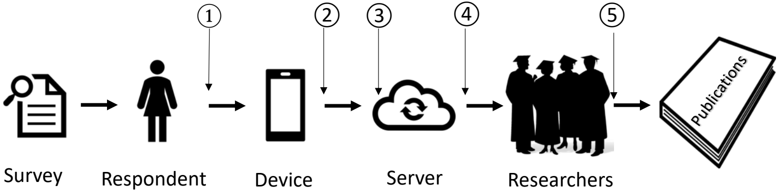
Mean income: $48		$108		$111

Classical Inference

Query-Response

Statistically Valid Inferences from Privacy Protected Data

Protecting Survey Data



Differential Privacy and its Inferential Challenges

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- Estimators

Differential Privacy and its Inferential Challenges

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  - Or: mess with gradients, $X_i'X_i$, data, QOIs, etc.
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A Differentially Private Estimator

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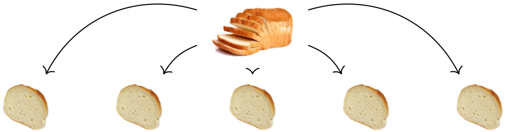
Private data

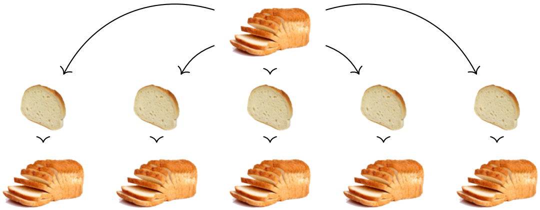
A Differentially Private Estimator



Private data

Partition

A Differentially Private Estimator



Private data

Partition

Bag of little bootstraps

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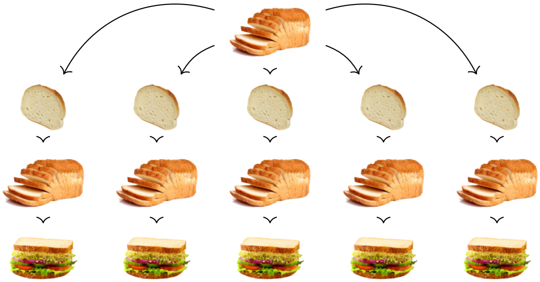

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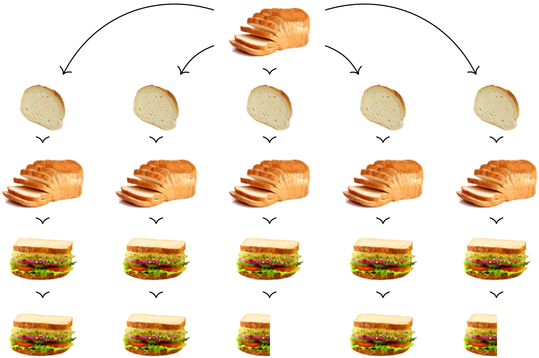

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Estimator

Censor

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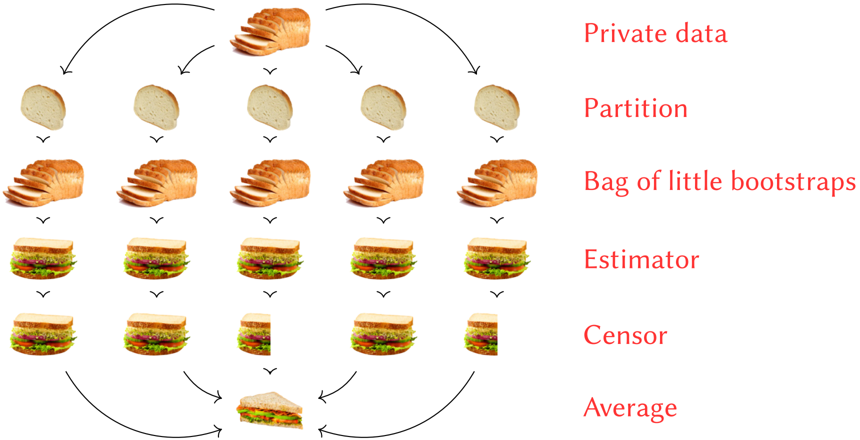

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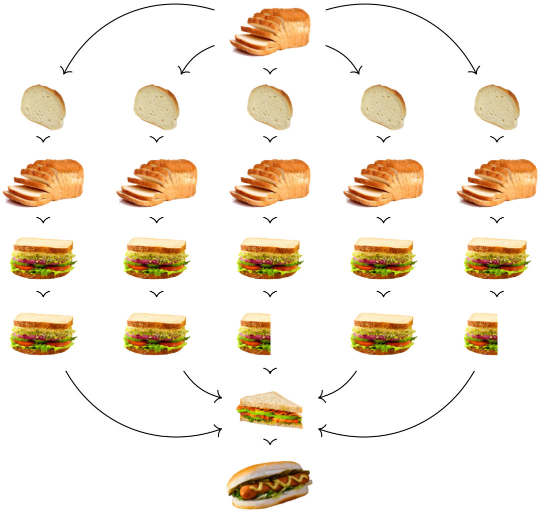

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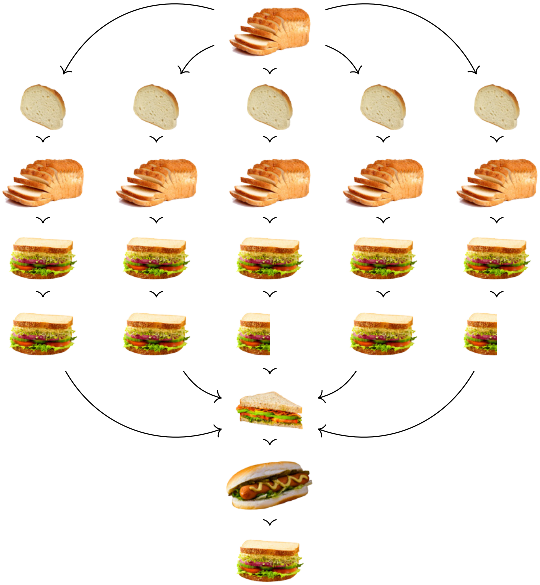

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Bias Correction

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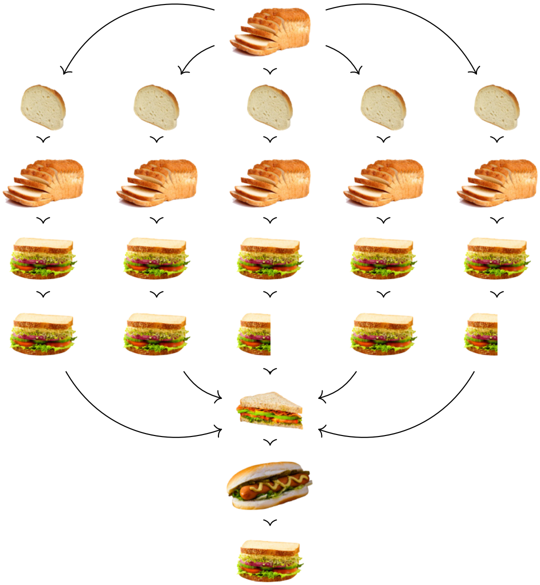

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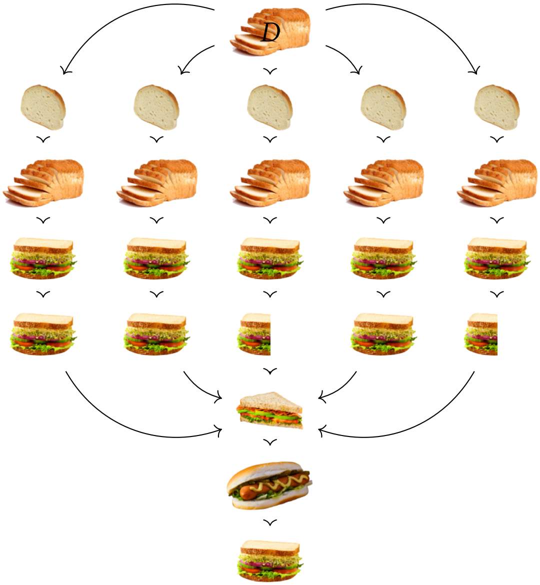

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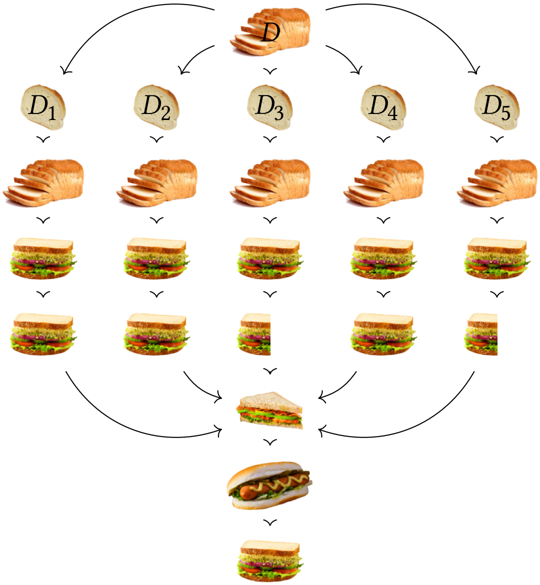

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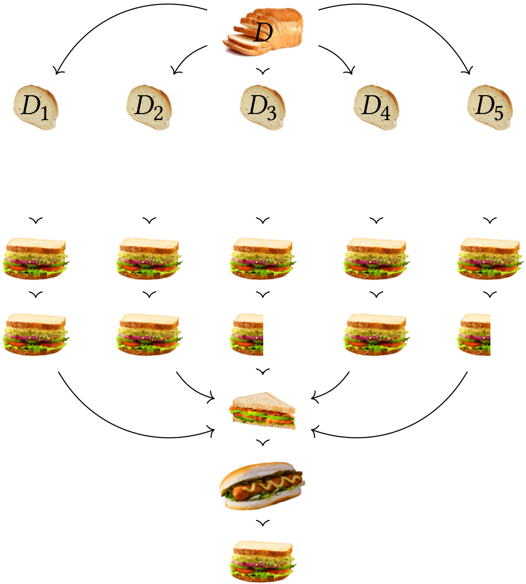

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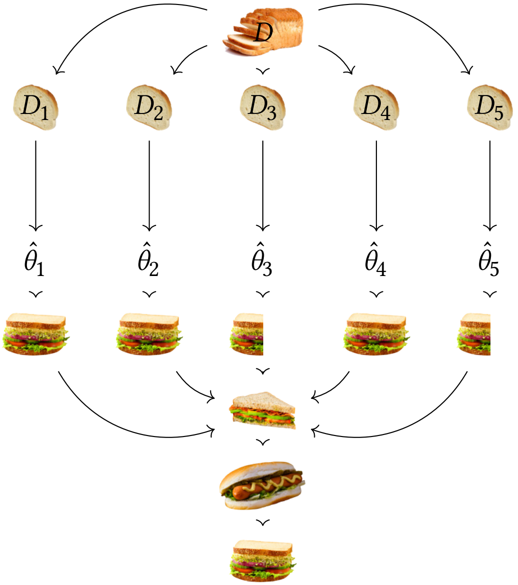

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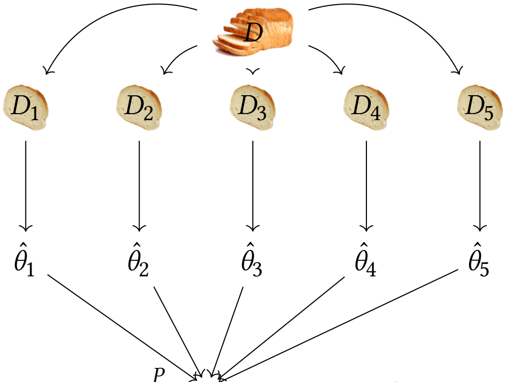

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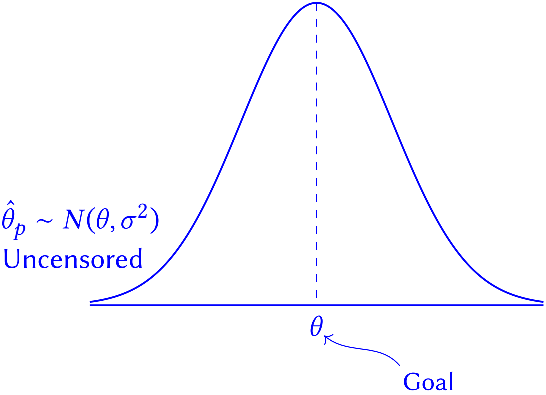

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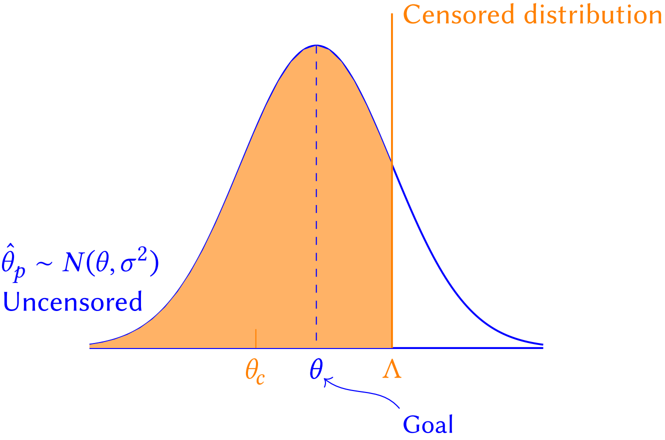

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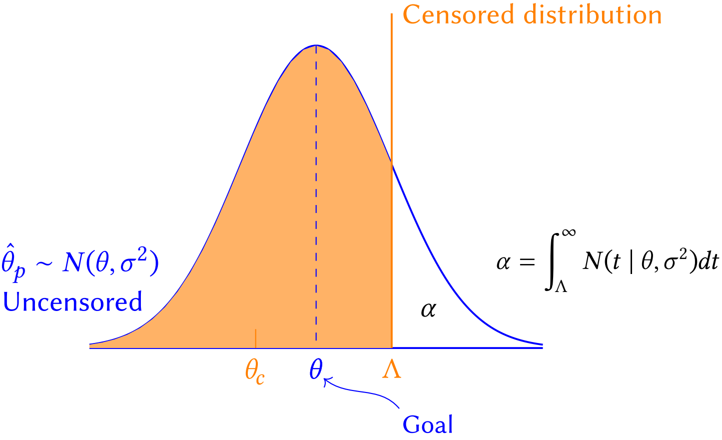

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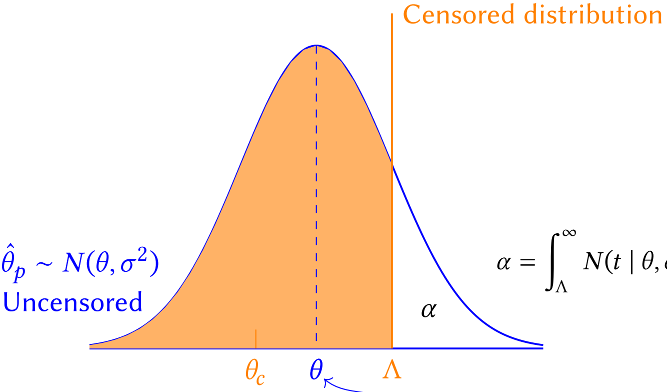

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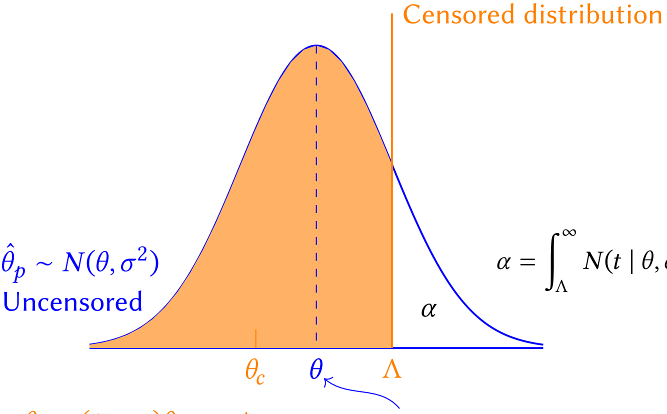

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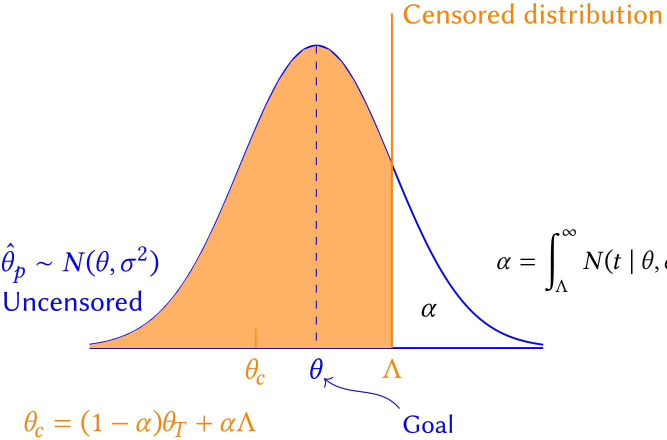

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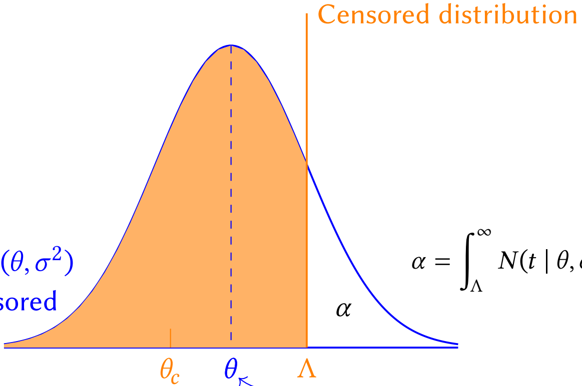

$\hat{\theta}_p \sim N(\theta, \sigma^2)$

Uncensored

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

Goal

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

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

Equations: 2

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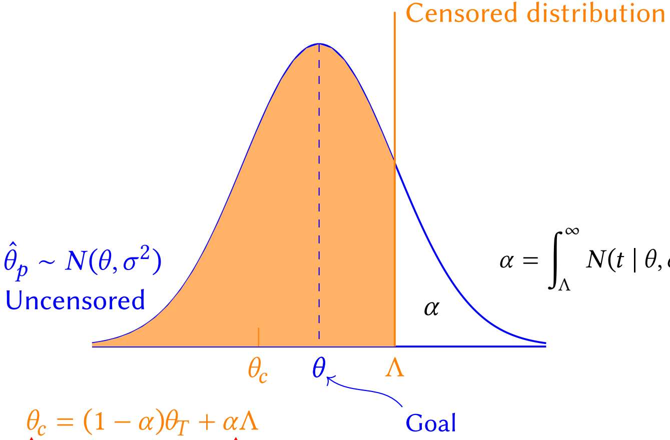

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Variance Estimation

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- Simulate estimates via standard (Clarify) procedures:

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

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Simulations: Finite Sample Evaluation

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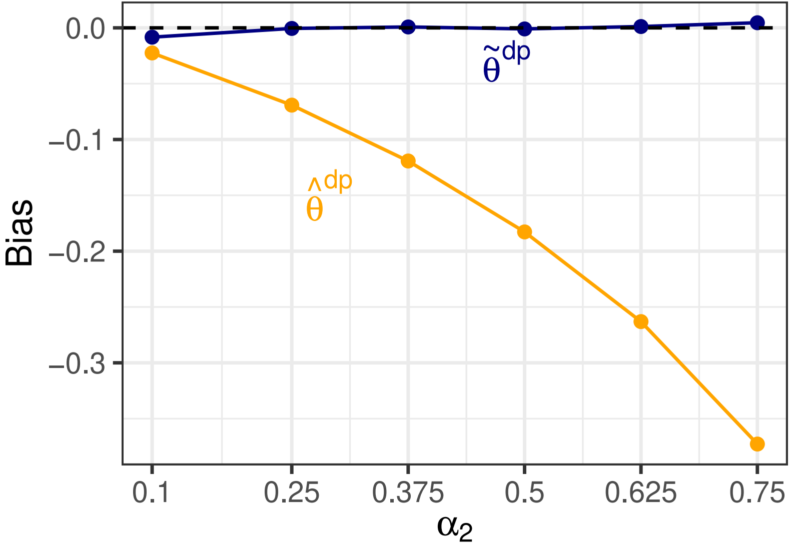

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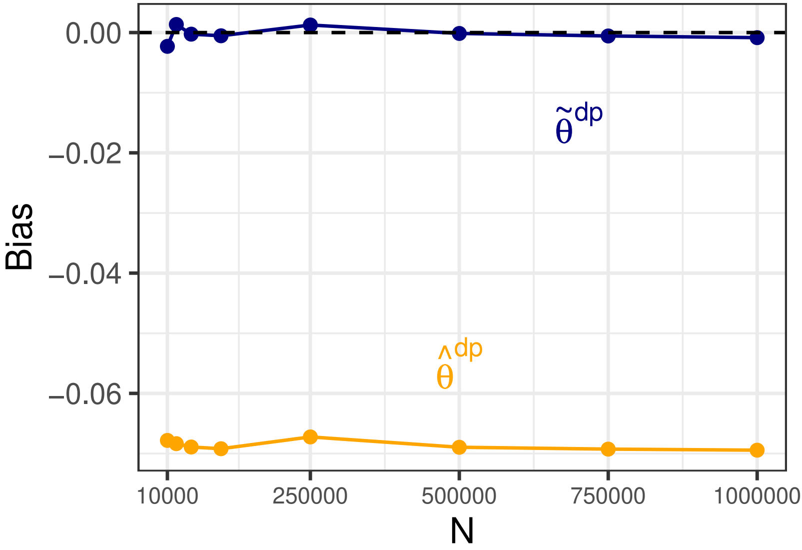

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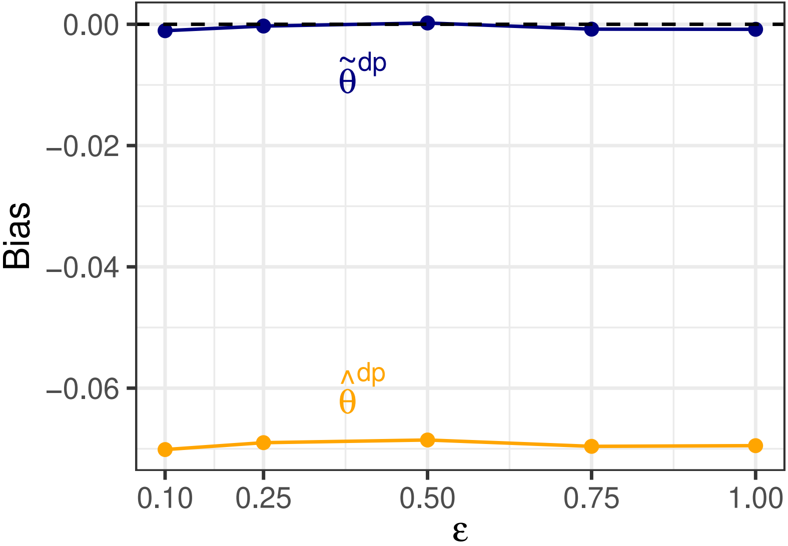

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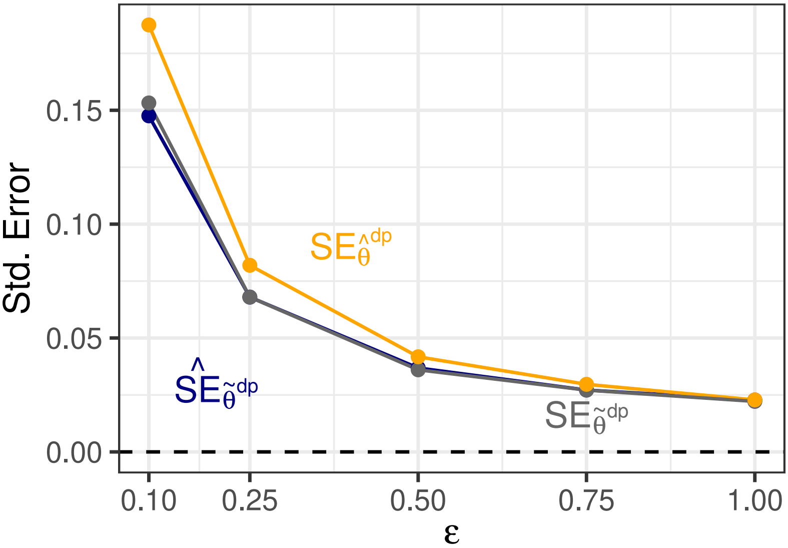

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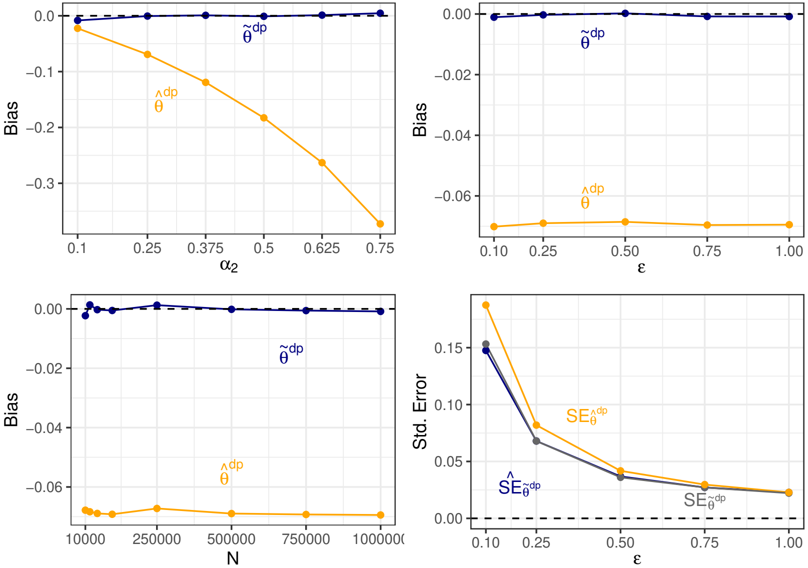
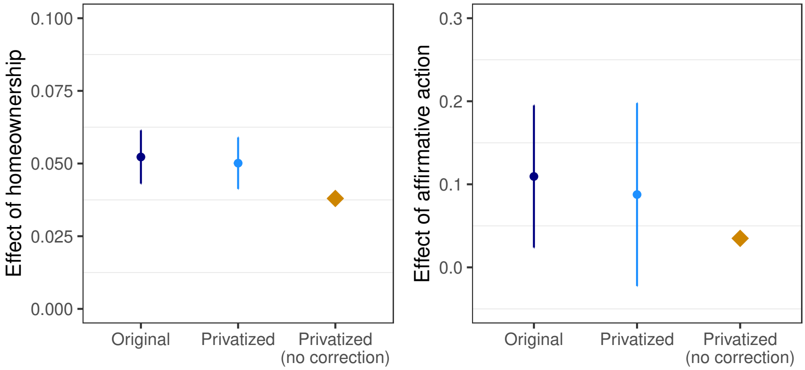


Similar Empirical Results, Larger CIs



(a) Yoder (2020)

(b) Bhavnani and Lee (2019)

Concluding Remarks

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- Community based, Open Source Software: OpenDP.org

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- Georgina Evans, Gary King, Margaret Schwenzfeier, and Abhradeep Thakurta. Forthcoming. "Statistically Valid Inferences from Privacy Protected Data" *American Political Science Review*

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- Georgina Evans and Gary King. Forthcoming. "Statistically Valid Inferences from Differentially Private Data Releases, with Application to the Facebook URLs Dataset" *Political Analysis*

Appendix

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