Statistically Valid Inferences from Privacy Protected Data[1]

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Privacy Tools Project, SEAS, Harvard University, 4/20/2020

[1]Joint work with Georgina Evans, Margaret Schwenzfeier, Abhradeep Thakurta.
[2]GaryKing.org/dp

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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The Algorithm in Practice

Theories of Inference: Statistics vs. CS

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	Population
	⋮
	Lindsay
	Salil
	Georgie
	Gary
	Meg
	Abhradeep
	Joshua
	Annie
	Bob
	Ellen
Mean income:	$48

Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample
⋮	✗
Lindsay	✓
Salil	✓
Georgie	✓
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Meg	✓
Abhradeep	✓
Joshua	✓
Annie	✓
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Ellen	✓
Mean income: \$48	

Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample	$
⋮	✗	?
Lindsay	✓	122
Salil	✓	76
Georgie	✓	145
Gary	✓	96
Meg	✓	86
Abhradeep	✓	127
Joshua	✓	72
Annie	✓	132
Bob	✓	95
Ellen	✓	134
Mean income: $48		$108

Classical Inference

Quantity of Interest

Usually no direct relevance

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Theories of Inference: Statistics vs. CS

Population	Sample	$	+Privacy
⋮	✗	?	
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Salil	✓	76	
Georgie	✓	145	
Gary	✓	96	
Meg	✓	86	
Abhradeep	✓	127	
Joshua	✓	72	
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Mean income: $48 Classical Inference $108

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Meg	✓	86		125
Abhradeep	✓	127		97
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Bob	✓	95		83
Ellen	✓	134		201
Mean income: \$48		\$108		\$111

\$108 $\xrightarrow{\text{Classical Inference}}$ \$48

\$111 $\xrightarrow{\text{Query-Response}}$ \$108

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Classical Inference

Query-Response

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Differential Privacy and its Inferential Challenges

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        - Essential components of ensuring privacy

Differential Privacy and its Inferential Challenges

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  - 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

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  - Can address with: careful software design & education

A Differentially Private Estimator

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Private data

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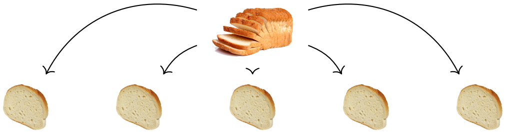
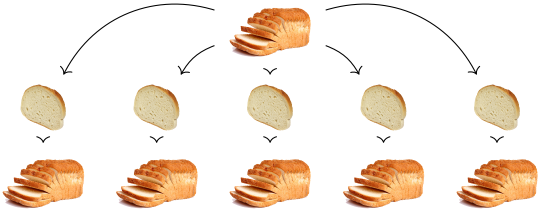


Private data

Partition

A Differentially Private Estimator



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Bag of little bootstraps

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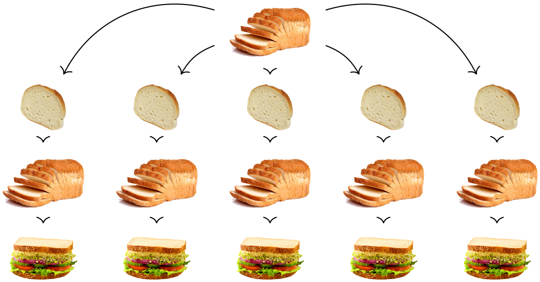

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Estimator

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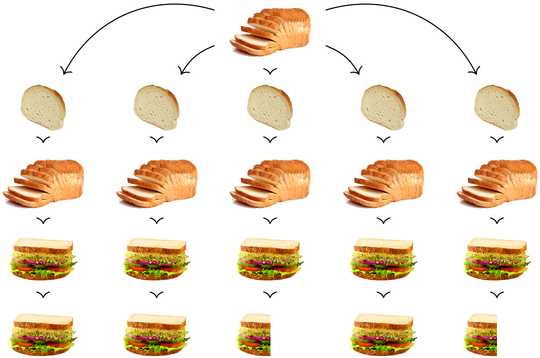

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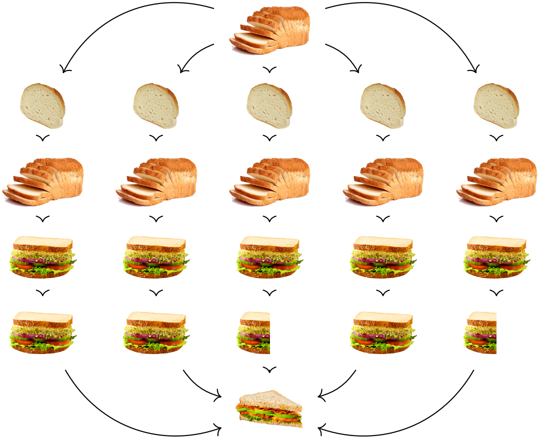

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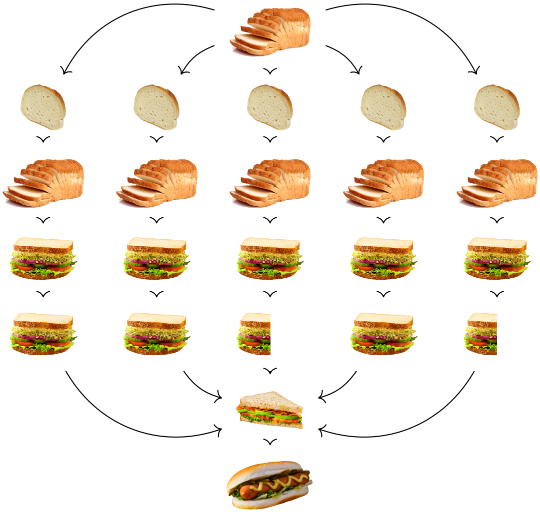

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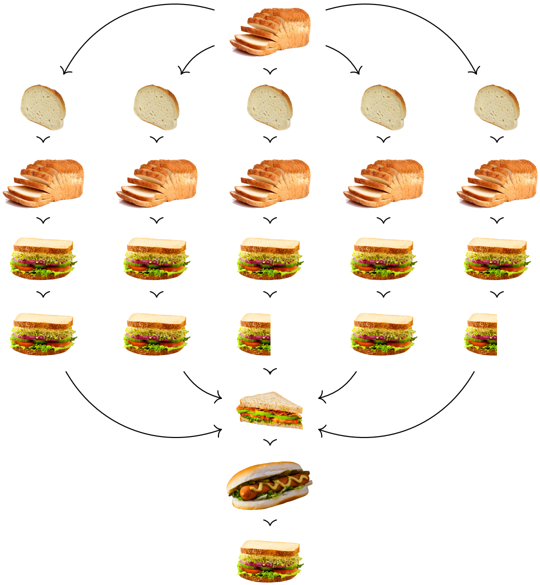

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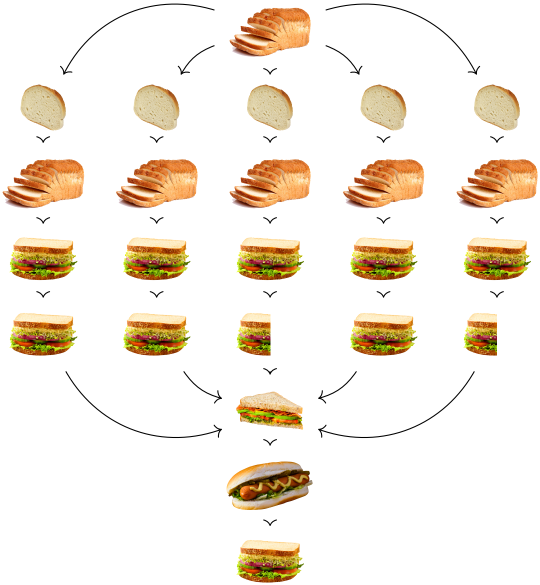

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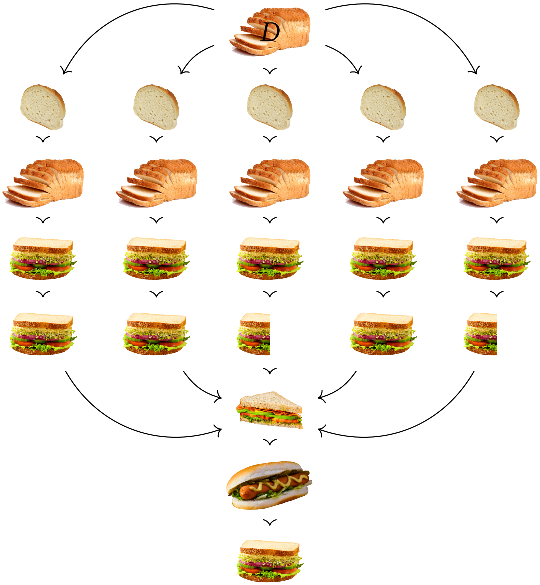

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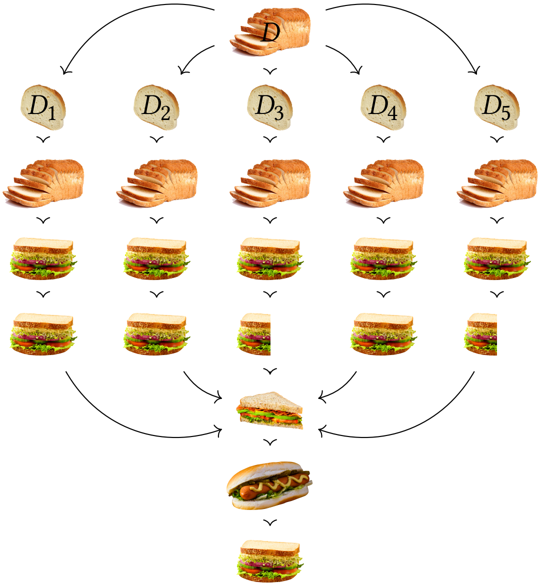

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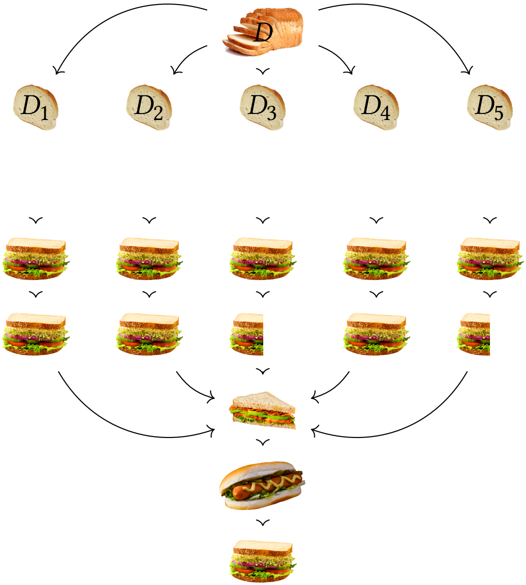

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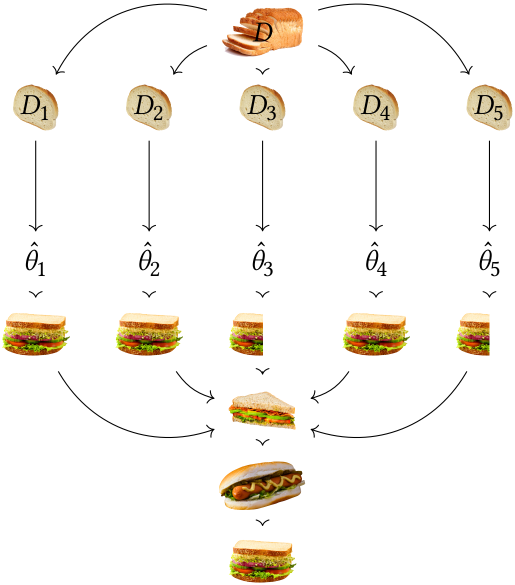

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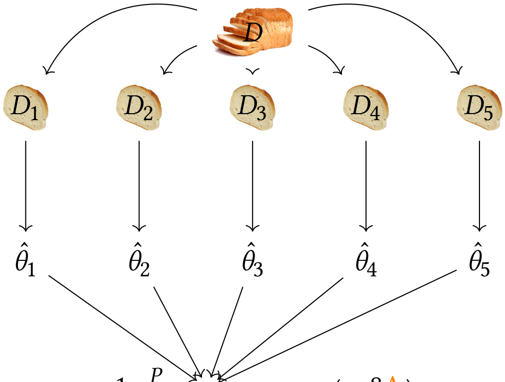

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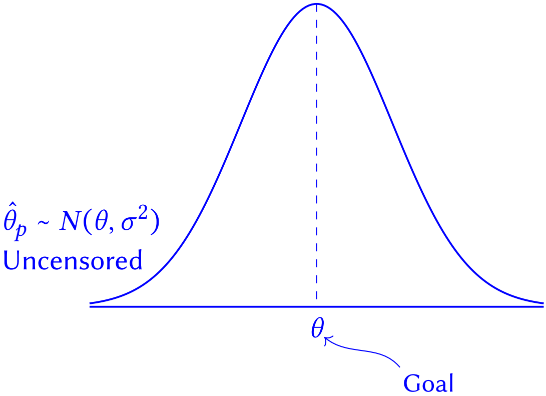

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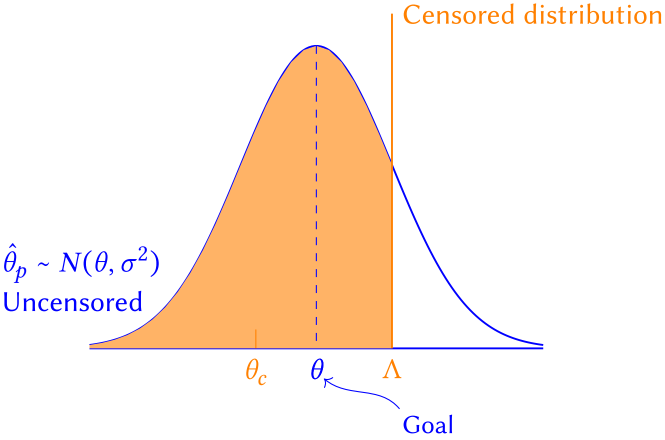

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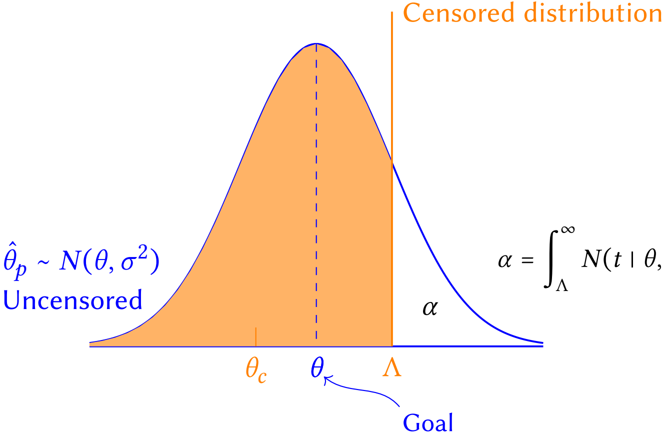

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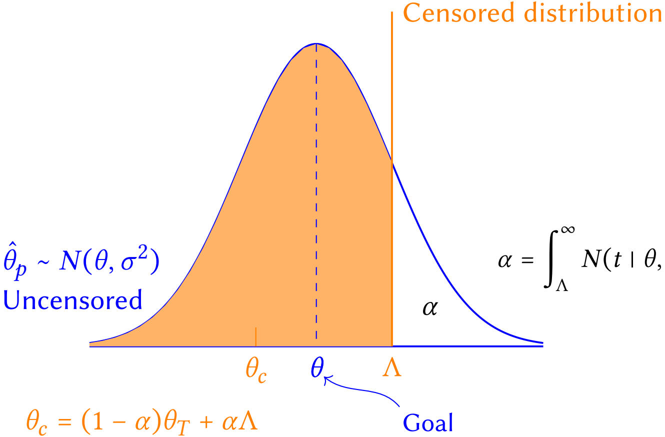

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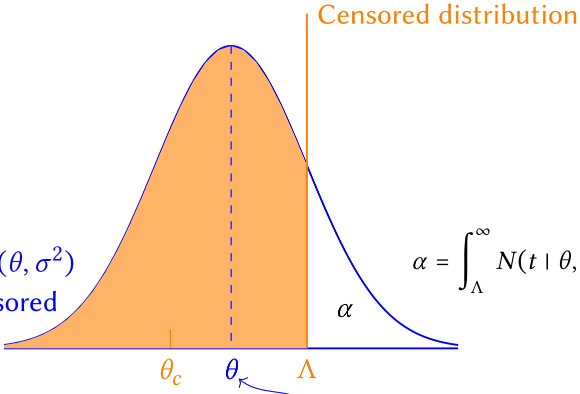

$\hat{\theta}_p \sim N(\theta, \sigma^2)$
Uncensored

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Goal

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

Equations: 2

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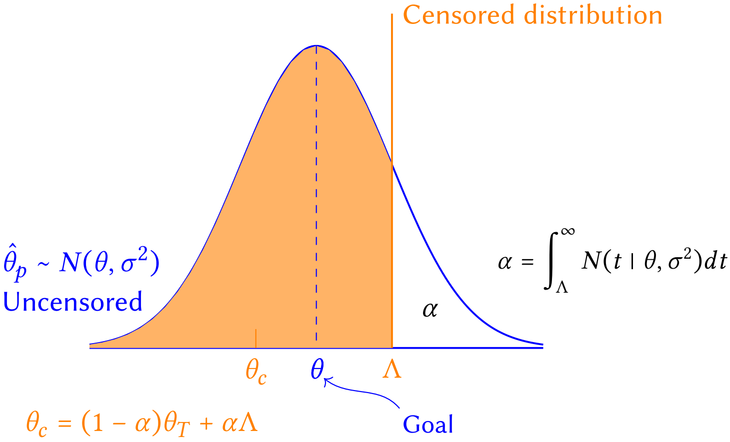

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Unknowns: $\theta, \sigma^2, \alpha, \theta_c$

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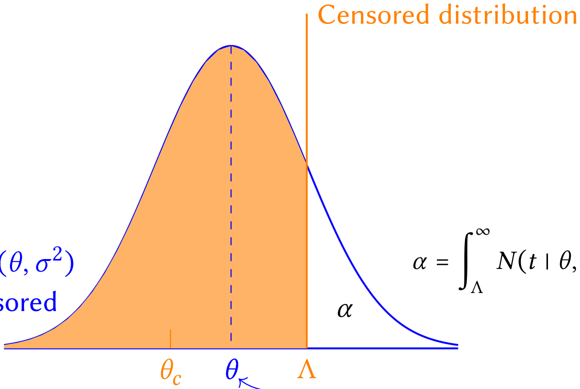

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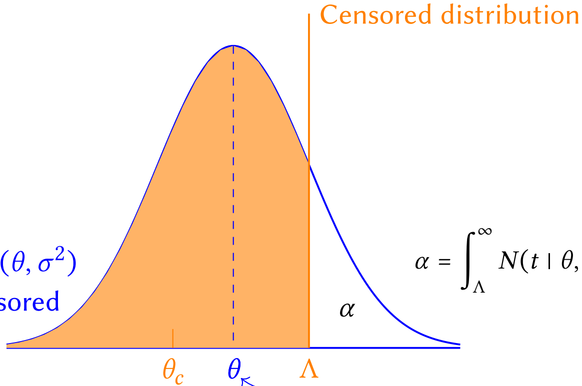

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- Standard error: Standard deviation of $\tilde{\theta}^{\text{dp}}$ over simulations
- Bias correction: reduces bias *and* variance:

$$E(\tilde{\theta}^{\text{dp}}) \approx \theta, \qquad V(\tilde{\theta}^{\text{dp}}) \lesssim V(\hat{\theta}^{\text{dp}})$$

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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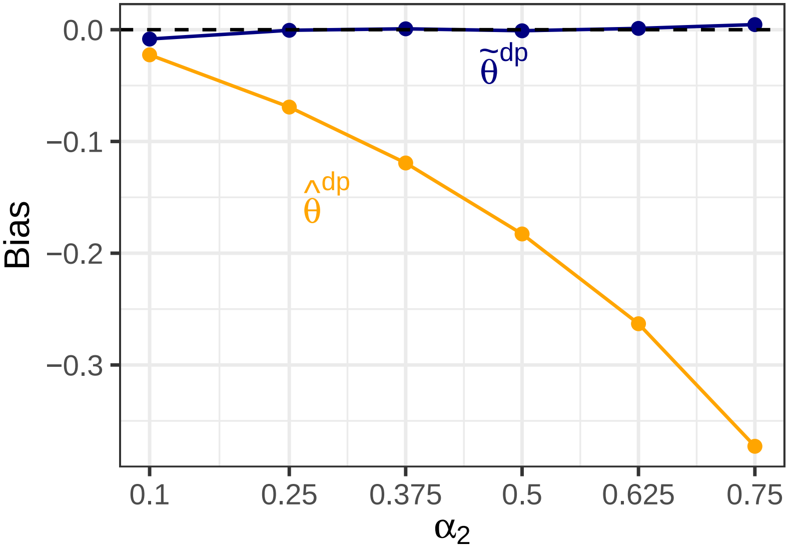
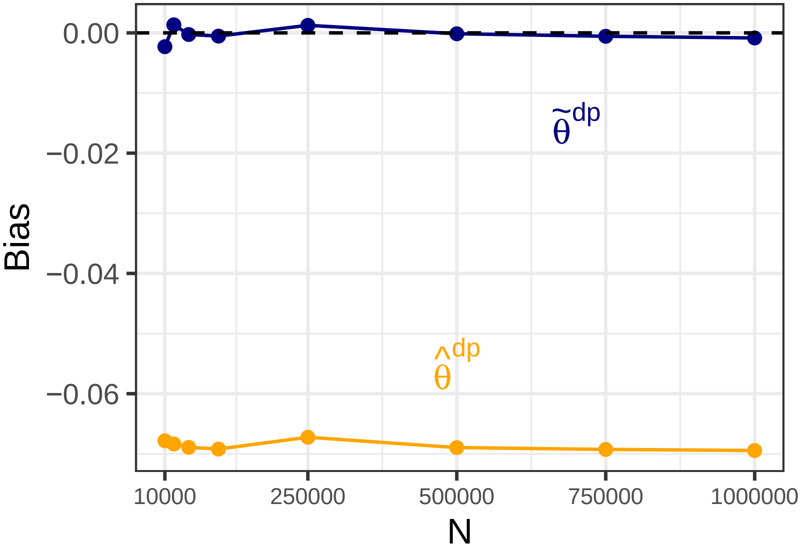


Simulations: Finite Sample Evaluation



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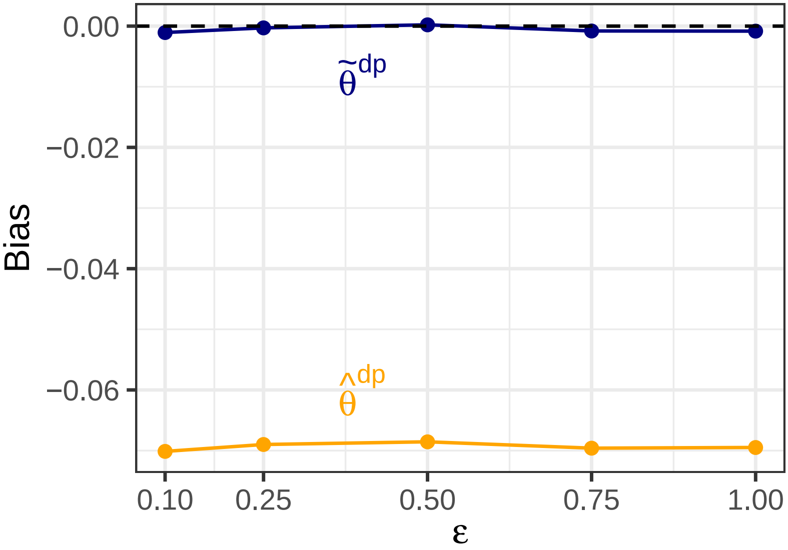

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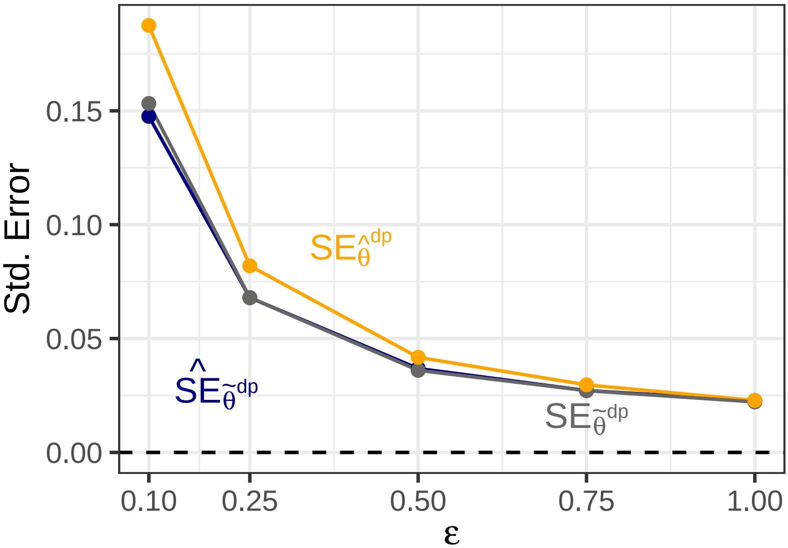

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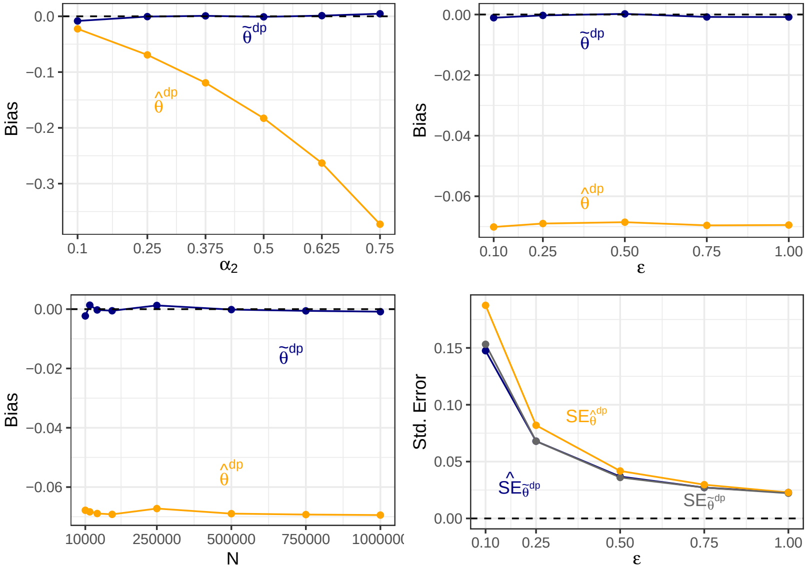

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