Statistically Valid Inferences from Privacy Protected Data[1]

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Harvard University

Google, 3/20/2020

[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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The Algorithm in Practice

Theories of Inference: Statistics vs. CS

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Population
⋮
Michele
Daniel
Georgie
Gary
Meg
Abhradeep
Scott
Larsy
Keith
Elise

Mean income: $48

Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample
⋮	✗
Michele	✓
Daniel	✓
Georgie	✓
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Theories of Inference: Statistics vs. CS

Population	Sample	$
⋮	✗	
Michele	✓	76
Daniel	✓	122
Georgie	✓	145
Gary	✓	96
Meg	✓	86
Abhradeep	✓	127
Scott	✓	72
Larsy	✓	132
Keith	✓	95
Elise	✓	134
Mean income: $48		$108

Classical Inference

Quantity of Interest

Usually no direct relevance

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Mean income: $48   Classical Inference $108   Query-Response $111

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Classical Inference

Query-Response

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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

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
- The DP Standard (simplifying)

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
- The DP Standard (simplifying)
  - Including (D) or excluding (D') you doesn't change conclusions

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- Statistical properties: usually biased, no uncertainty estimates

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  - Can address with: careful software design & education

Solving Political Problems Technologically

Differential Privacy & Inferential Validity

A General Purpose, Statistically Valid DP Algorithm

The Algorithm in Practice

A Differentially Private Estimator

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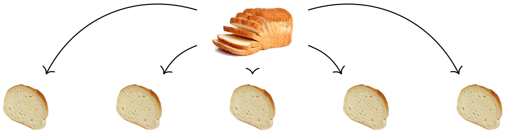
Private data

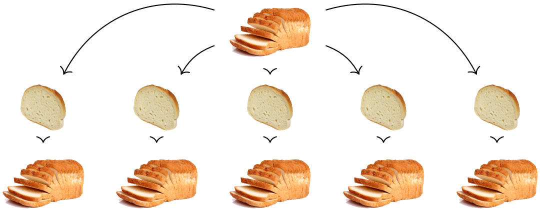
A Differentially Private Estimator



Private data

Partition

A Differentially Private Estimator



Private data

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Bag of little bootstraps

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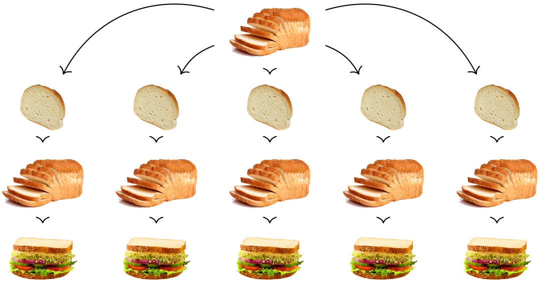

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Estimator

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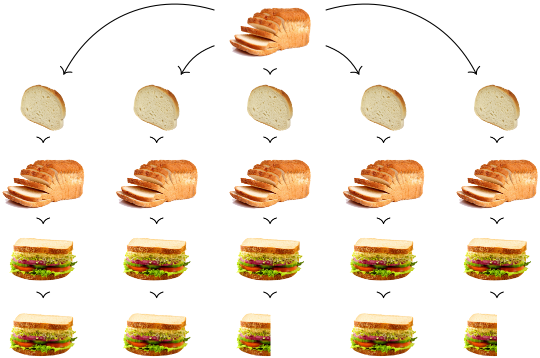

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Estimator

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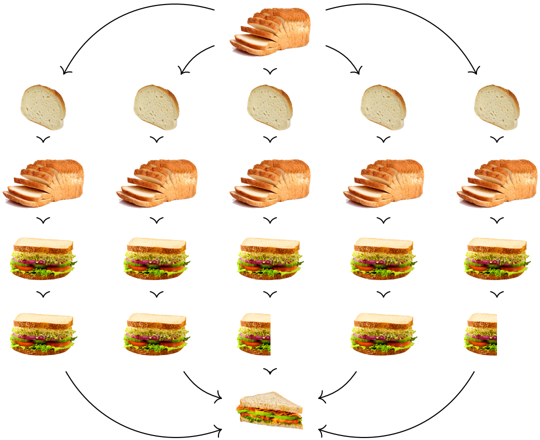

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Estimator

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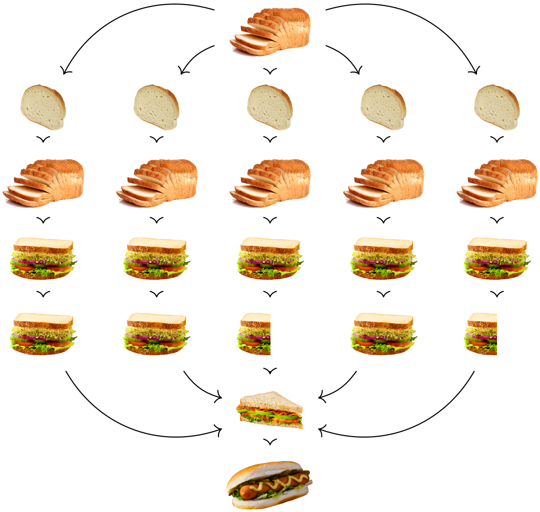

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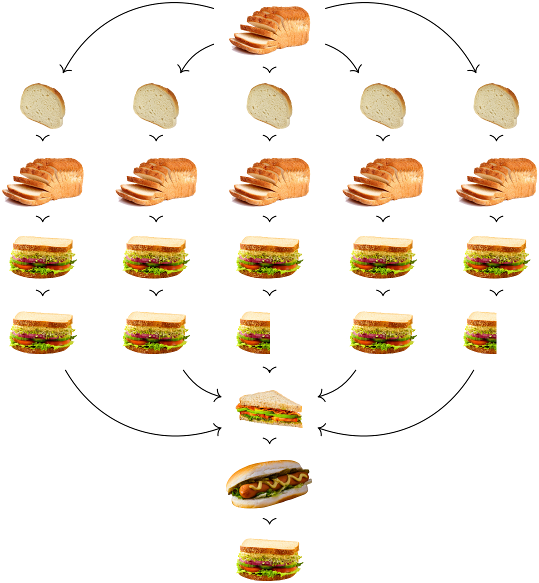
A Differentially Private Estimator



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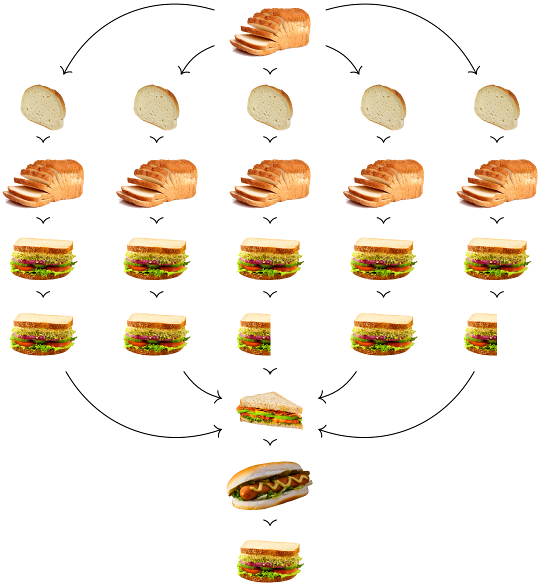

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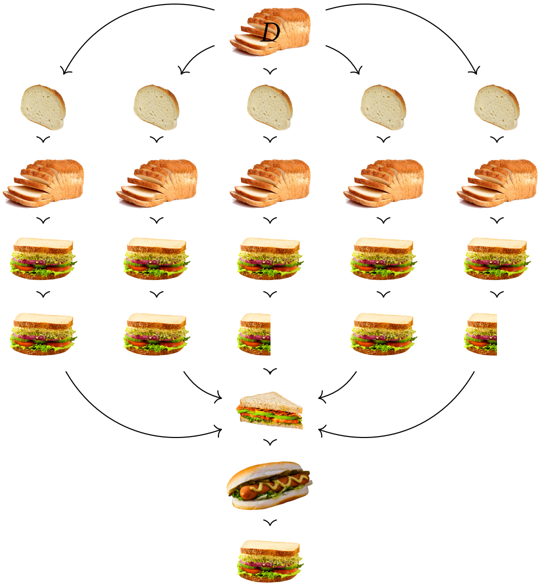

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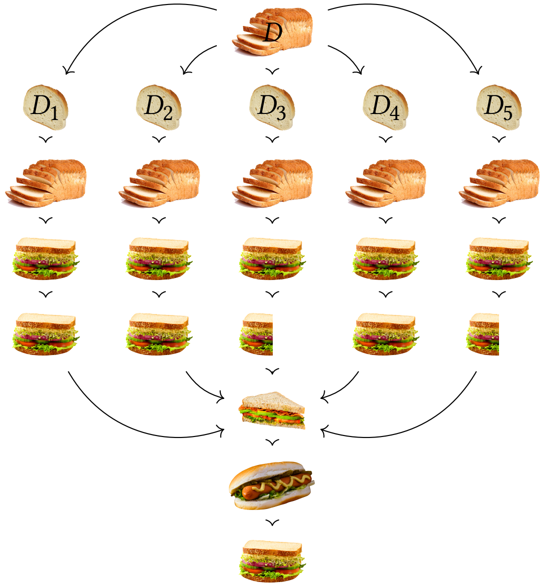

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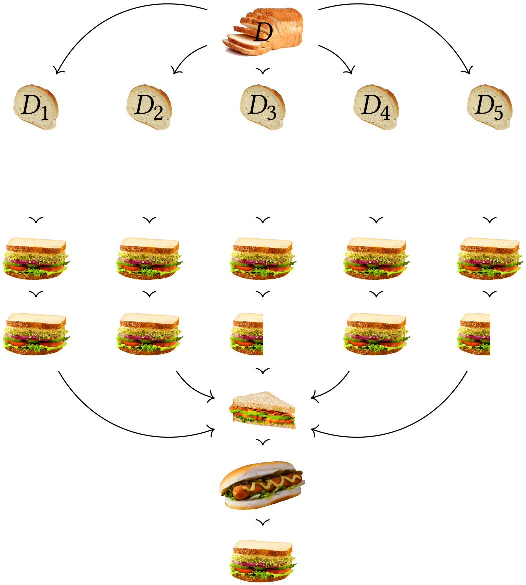

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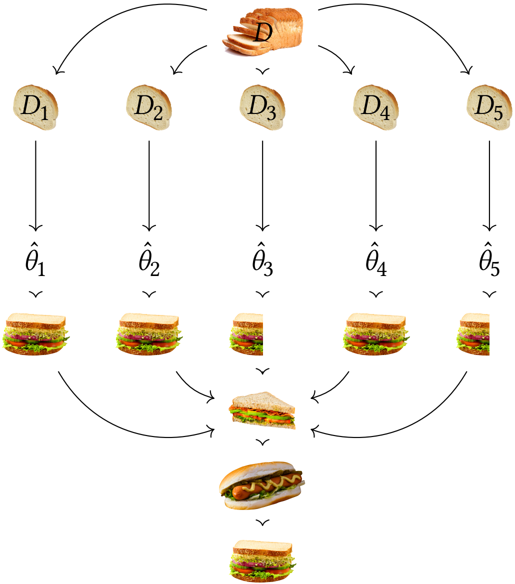

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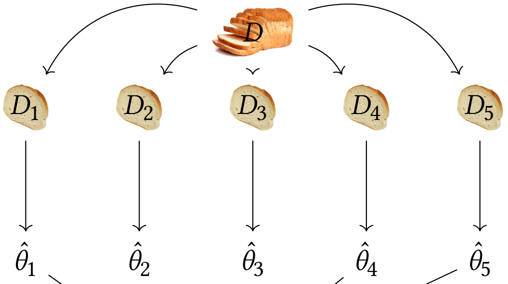

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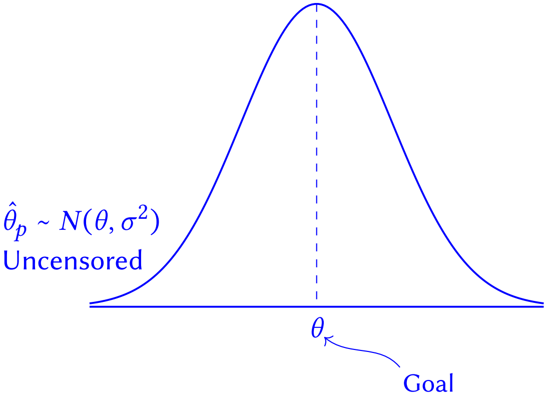

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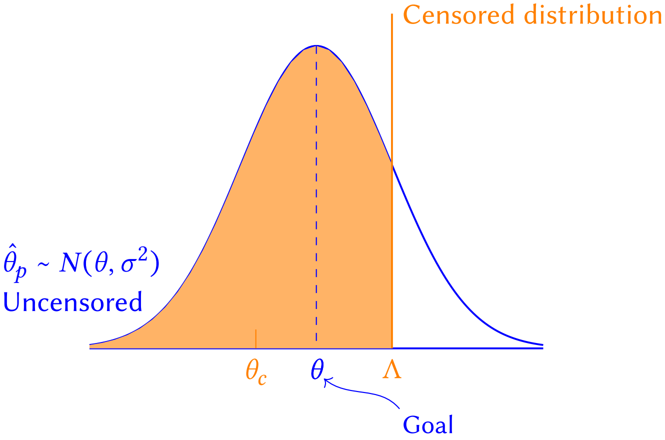

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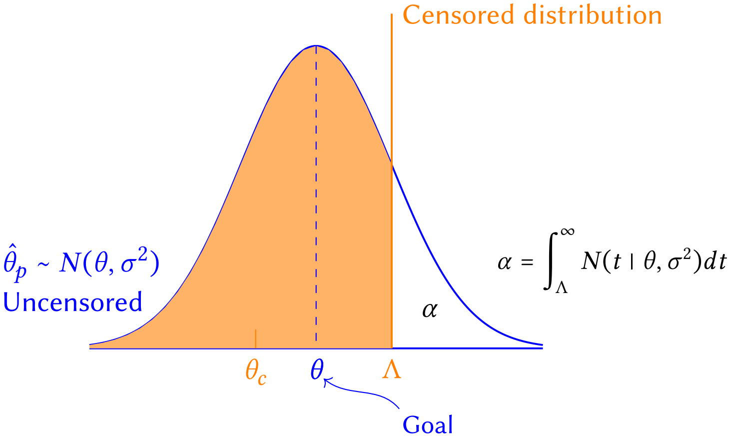

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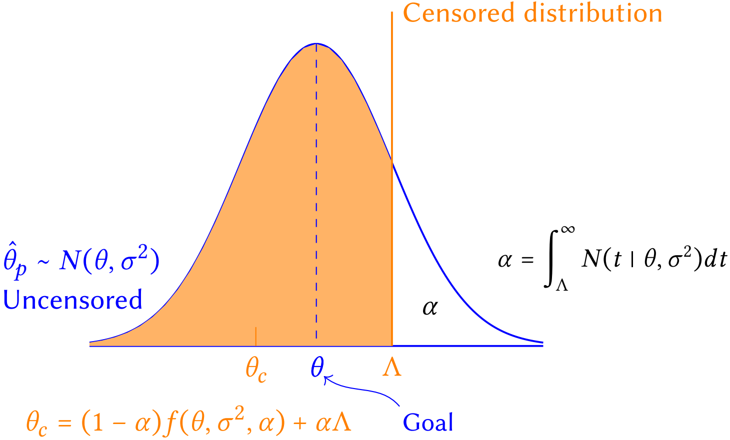

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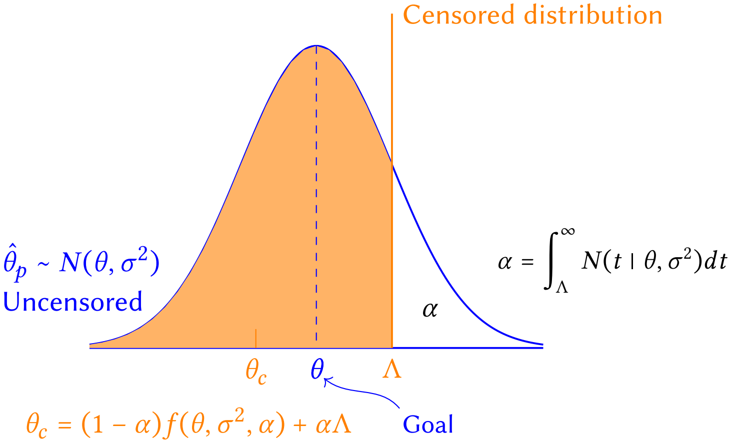

Equations: 2

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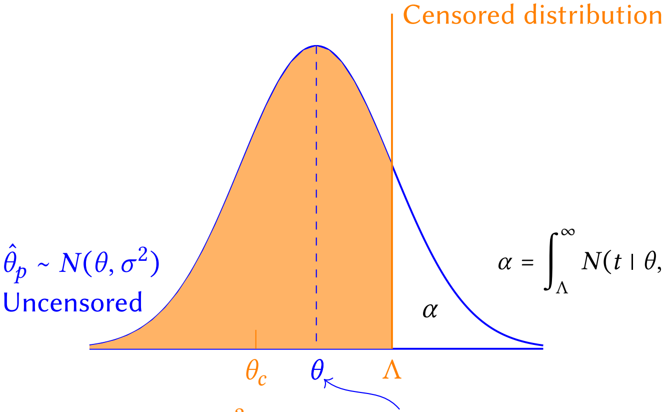

$$\alpha = \int_{\Lambda}^{\infty} N(t \mid \theta, \sigma^2) dt$$

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Equations: 2

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

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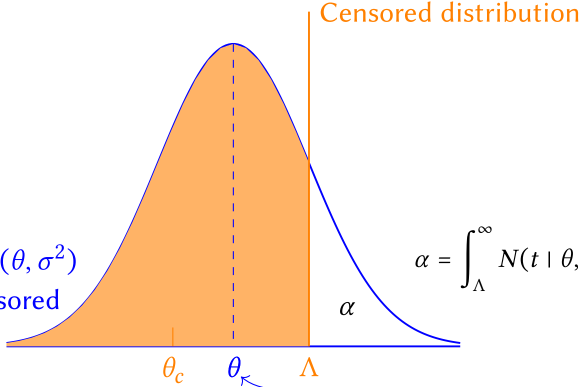

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Goal

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

Equations: 2
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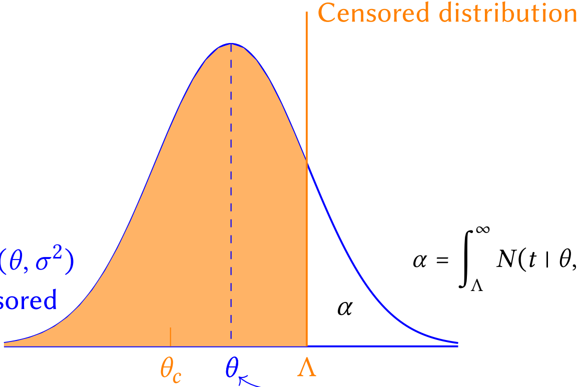

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$$E(\tilde{\theta}^{\text{dp}}) \approx \theta, \qquad V(\tilde{\theta}^{\text{dp}}) \lesssim V(\hat{\theta}^{\text{dp}})$$

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Simulations: Finite Sample Evaluation

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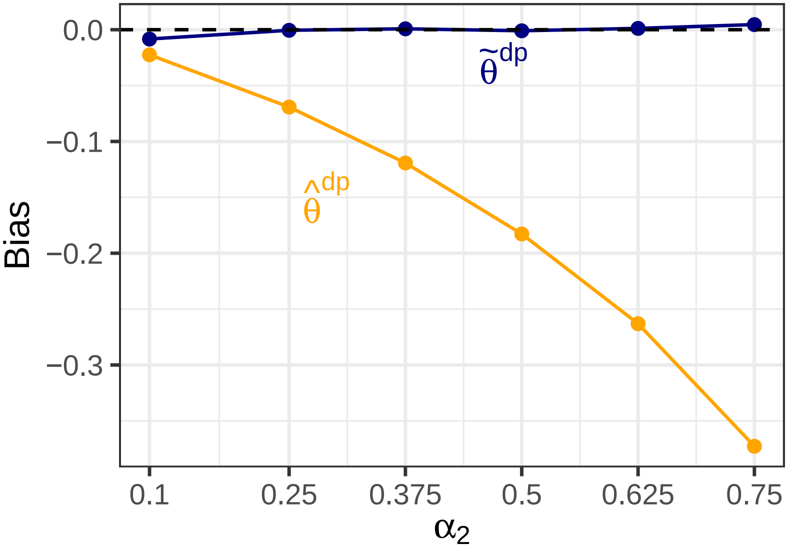

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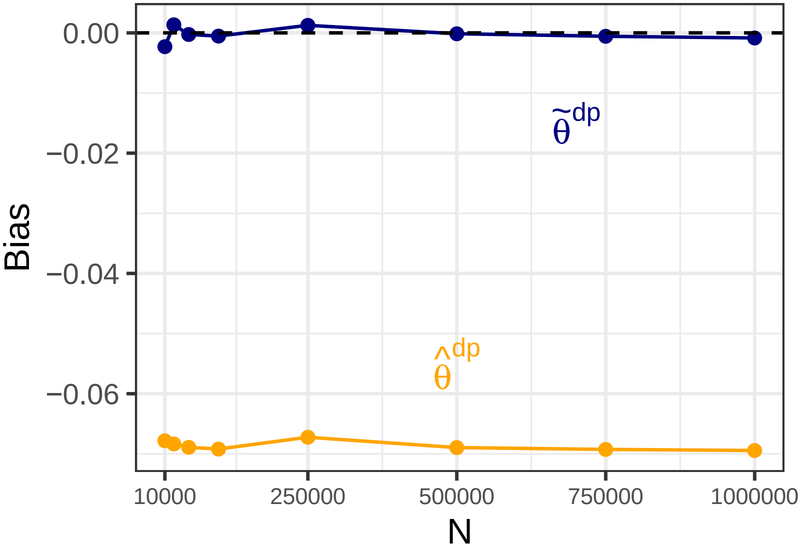

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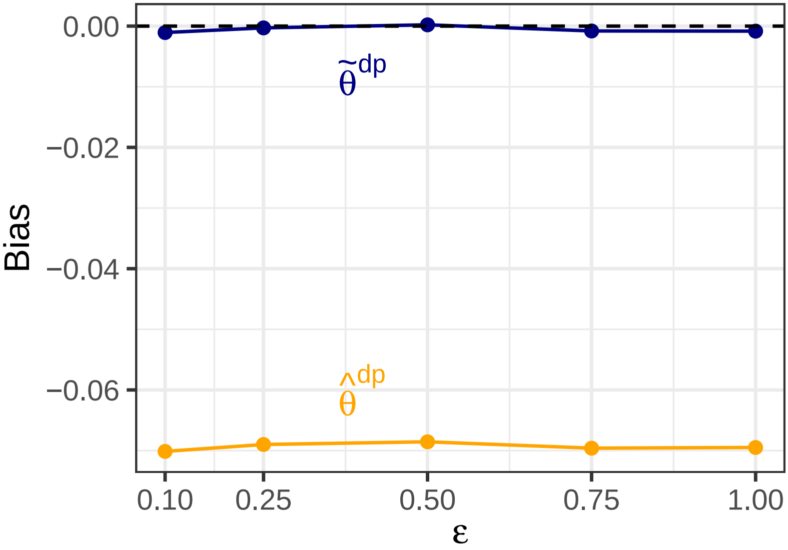

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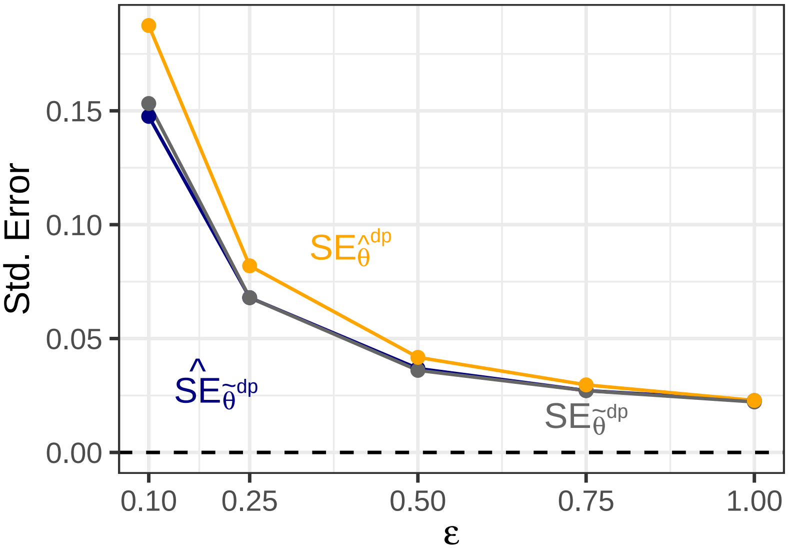

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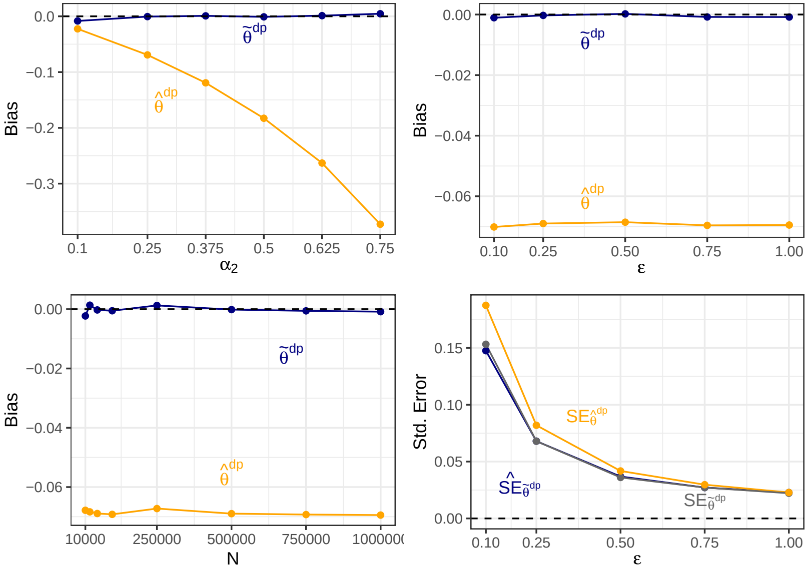

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