# Statistically Valid Inferences from Privacy Protected Data[1]

Gary King[2]

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University of Chicago, 11/8/2019

[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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- New Problem: Sharing data without it leaving Facebook

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| | Population |
|---|---|
| | ⋮ |
| | Mary |
| | Andrey |
| | Georgie |
| | Gary |
| | Meg |
| | Abhradeep |
| | Ella |
| | Anya |
| | Greg |
| | Max |
| **Mean income:** | $48 |

**Quantity of Interest**

# Theories of Inference: Statistics vs. CS

| Population | Sample |
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|---|---|---|
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| Mary | ✓ | 76 |
| Andrey | ✓ | 96 |
| Georgie | ✓ | 145 |
| Gary | ✓ | 122 |
| Meg | ✓ | 86 |
| Abhradeep | ✓ | 127 |
| Ella | ✓ | 72 |
| Anya | ✓ | 132 |
| Greg | ✓ | 95 |
| Max | ✓ | 134 |
| **Mean income:** $48 | | $108 |

Classical Inference

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**Usually no direct relevance**

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| Andrey | ✓ | 96 | |
| Georgie | ✓ | 145 | |
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Classical Inference

Query-Response

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- Statistical properties: usually biased, no uncertainty estimates

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  - $\rightsquigarrow$ We need both DP and inferential validity

# A Differentially Private Estimator

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Private data

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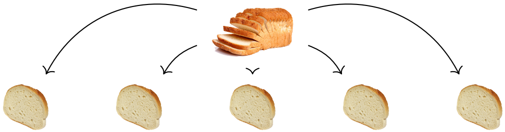

Private data

Partition

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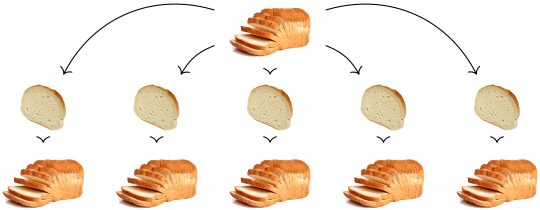

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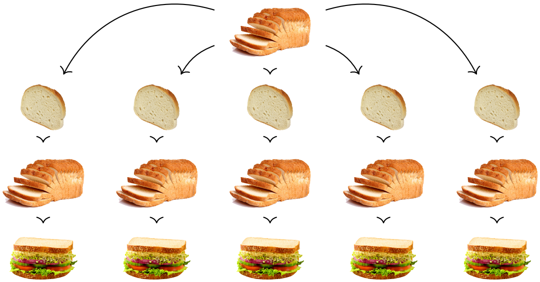

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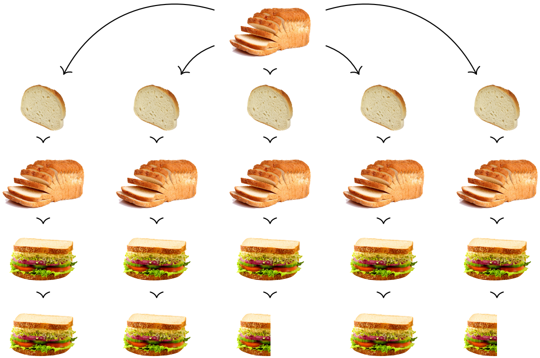

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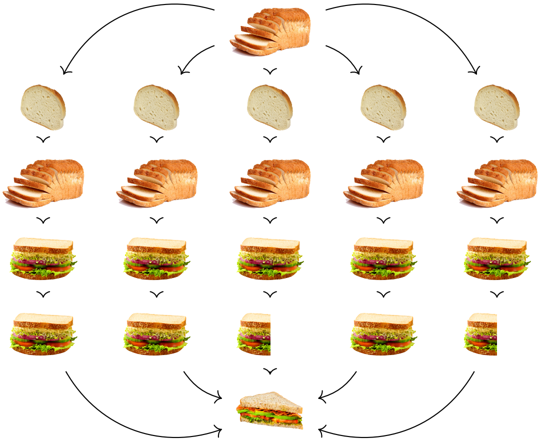

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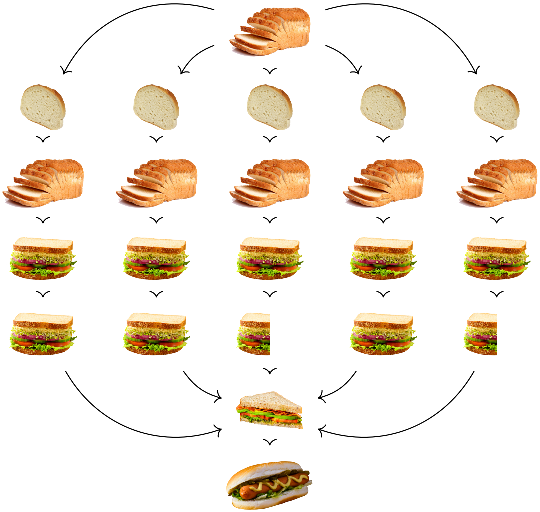

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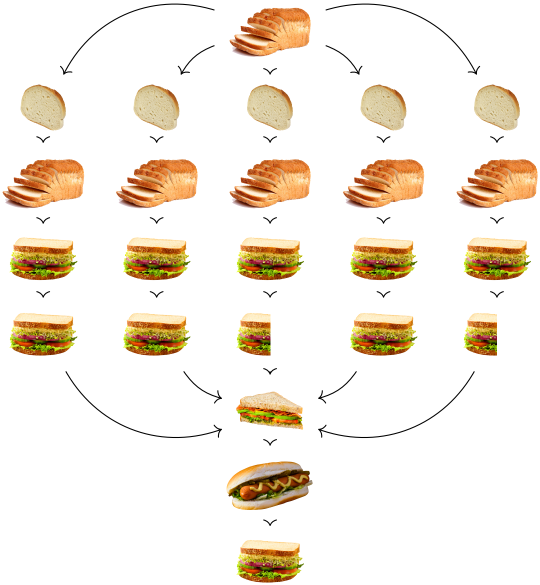

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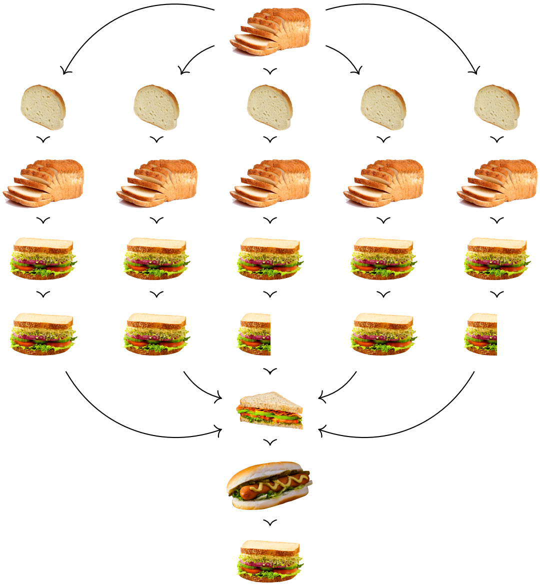

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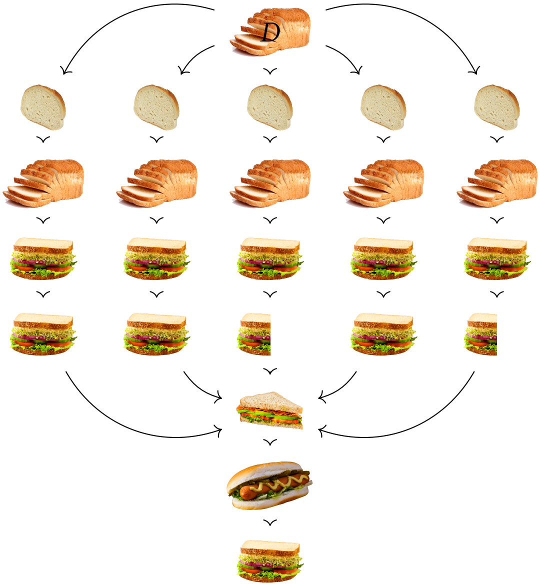


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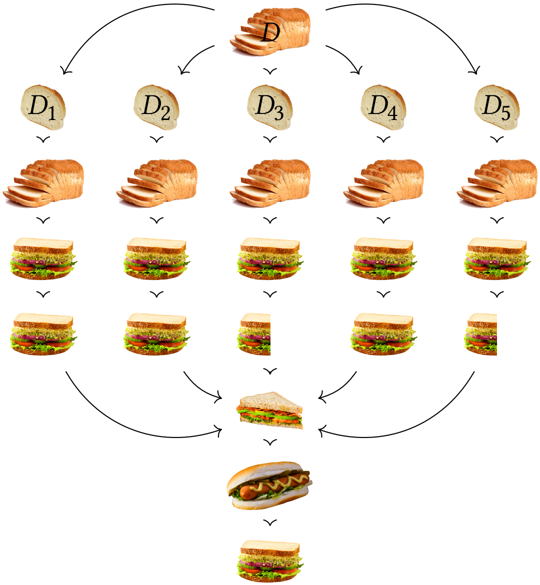


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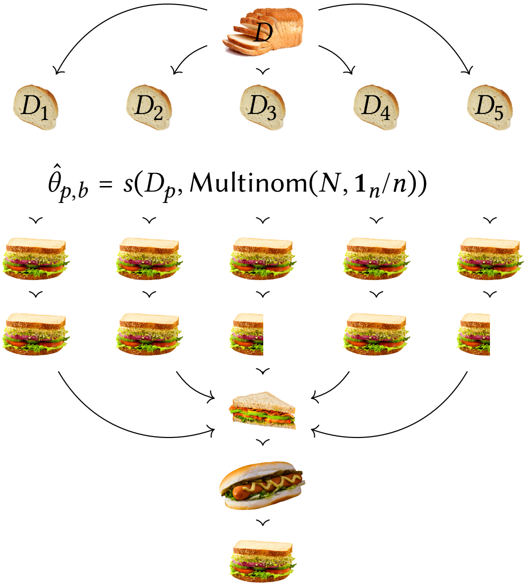


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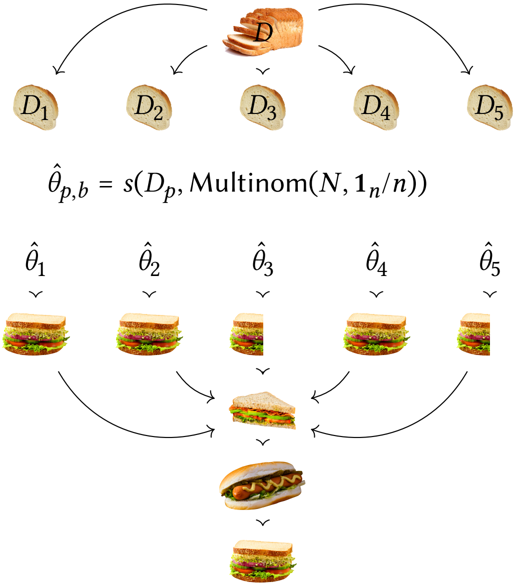


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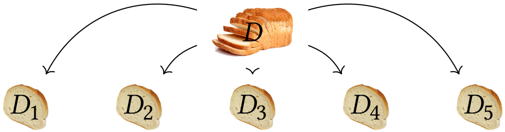


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Partition

$$\hat{\theta}_{p,b} = s(D_p, \mathrm{Multinom}(N, \mathbf{1}_n/n))$$

Bag of little bootstraps

$$\hat{\theta}_1 \quad \hat{\theta}_2 \quad \hat{\theta}_3 \quad \hat{\theta}_4 \quad \hat{\theta}_5$$

Estimator

$$\hat{\theta}^{\mathrm{dp}} = \frac{1}{P}\sum_{p=1}^{P} c(\hat{\theta}_p, \Lambda) + N\left(0, \frac{4\Lambda}{\epsilon P}\right)$$

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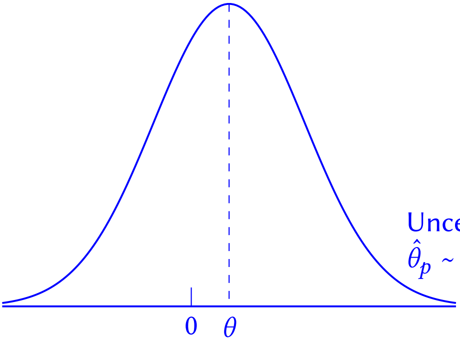


Uncensored distribution
$\hat{\theta}_p \sim N(\theta, \sigma^2)$

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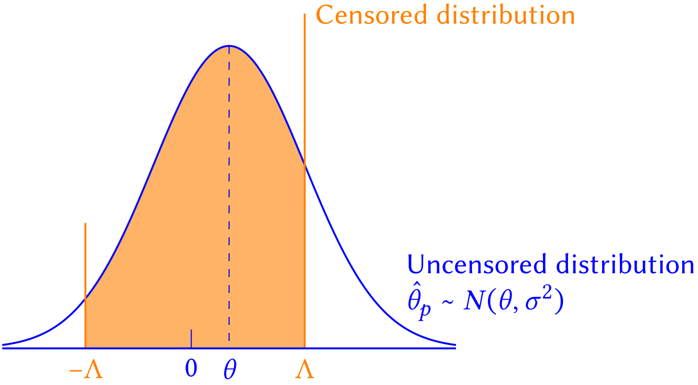

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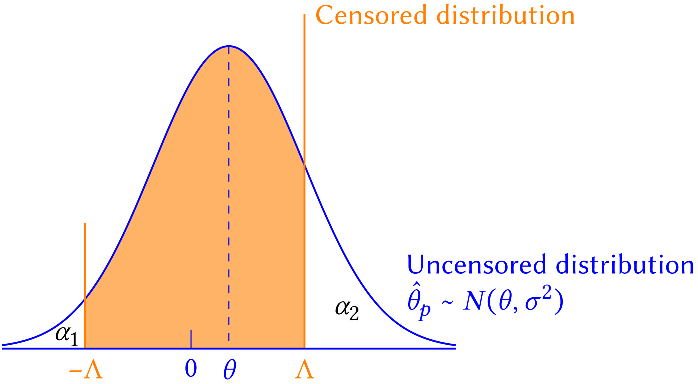


$$\int_{-\infty}^{-\Lambda} N(t \mid \theta, \sigma^2)dt \qquad \int_{\Lambda}^{\infty} N(t \mid \theta, \sigma^2)dt$$

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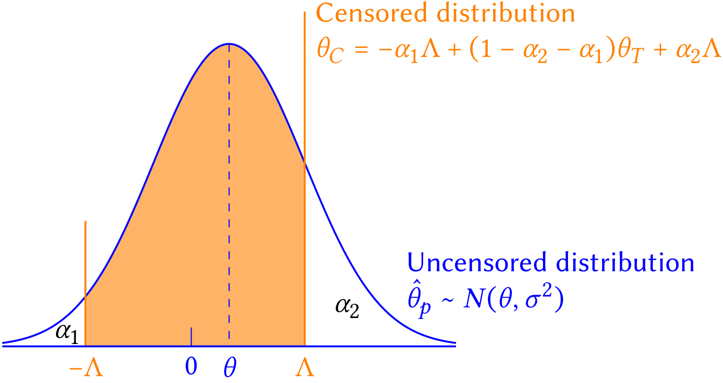


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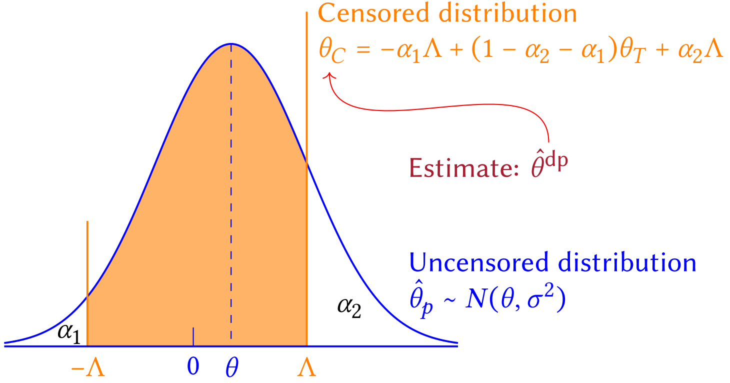


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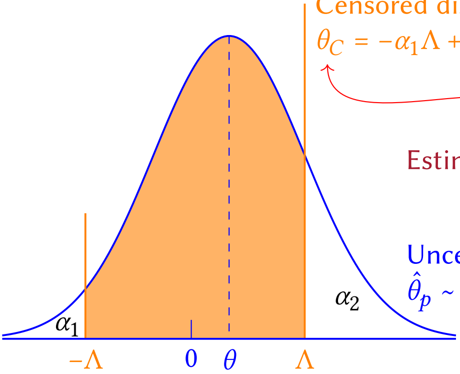


Censored distribution

$\theta_C = -\alpha_1\Lambda + (1 - \alpha_2 - \alpha_1)\theta_T + \alpha_2\Lambda$

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

Uncensored distribution

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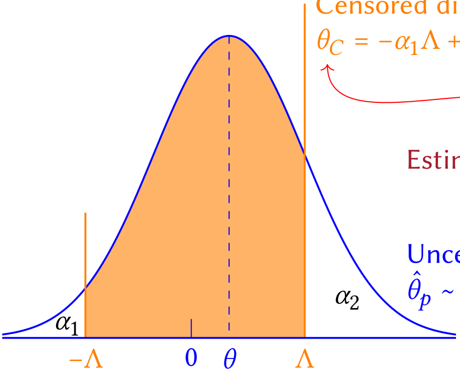


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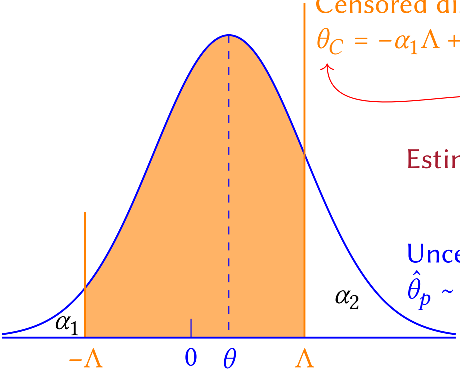


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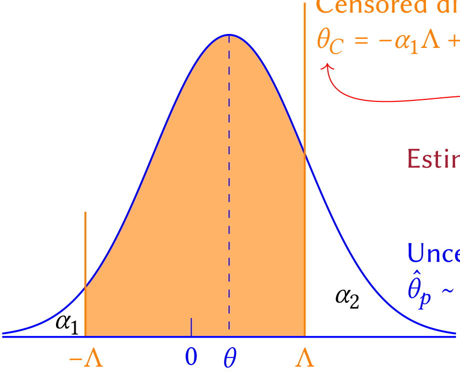


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$$\int_{-\infty}^{-\Lambda} N(t \mid \theta, \sigma^2)dt \qquad \int_{\Lambda}^{\infty} N(t \mid \theta, \sigma^2)dt$$

~~3 eqns, 4 unknowns $\theta, \sigma^2, \alpha_1, \alpha_2$~~

Solve for $\theta$ (and $\sigma^2, \alpha_1$)

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Solving Political Problems Technologically

Differential Privacy & Inferential Validity

A General Purpose, Statistically Valid DP Algorithm

The Algorithm in Practice

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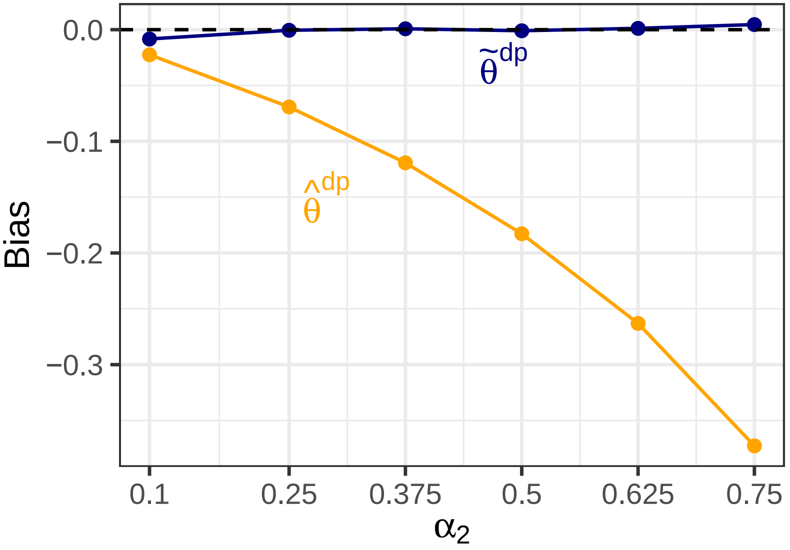

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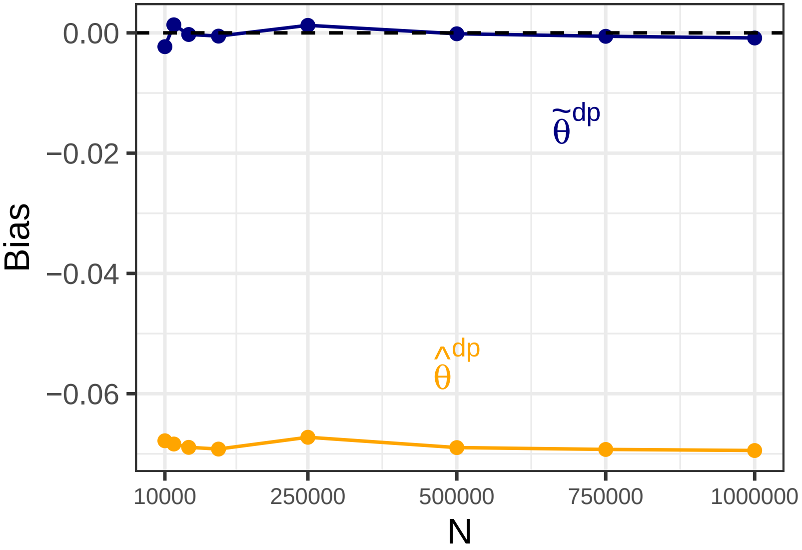

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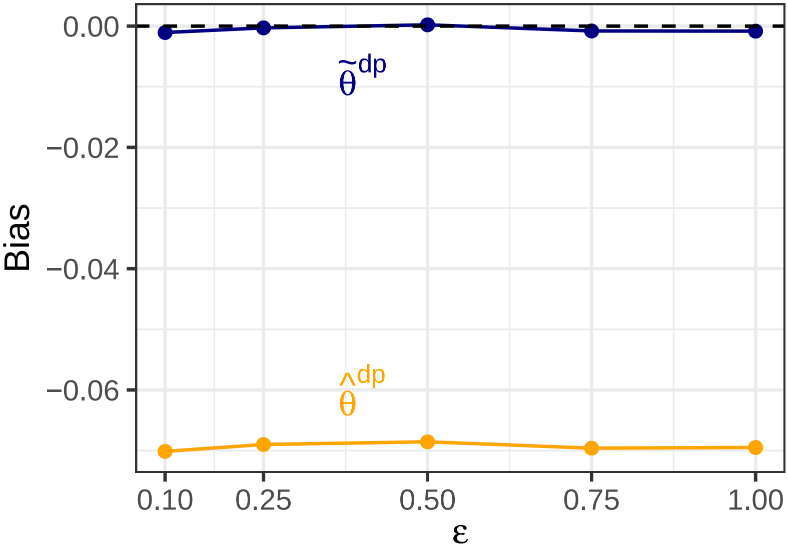

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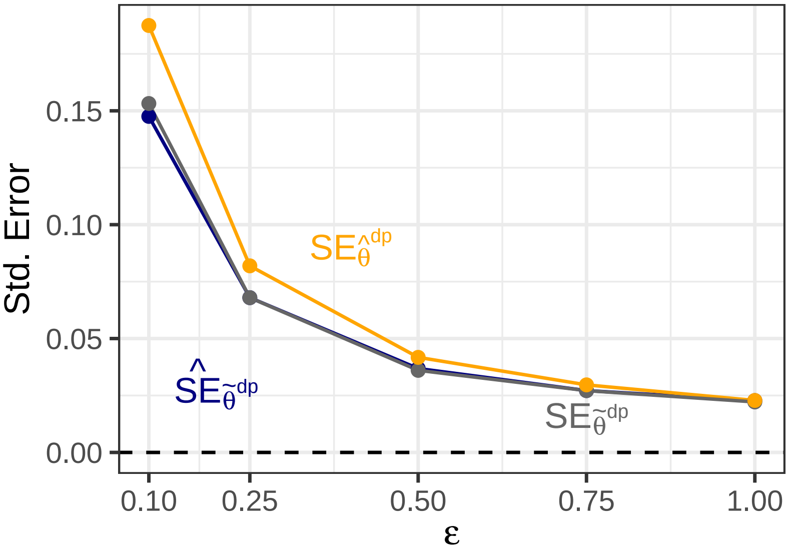

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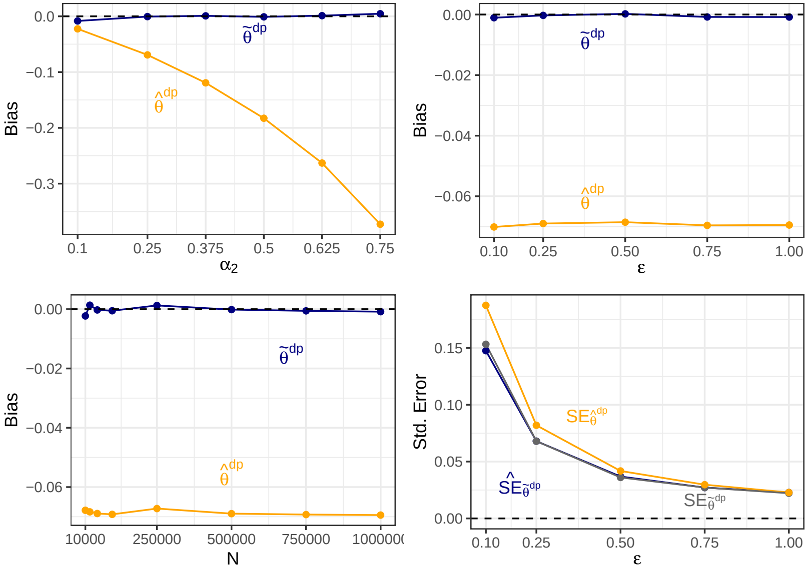

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# For more information

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