Statistically Valid Inferences from Privacy Protected Data[1]

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Harvard University, Applied Statistics Workshop, 2/5/2020

[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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Theories of Inference: Statistics vs. CS

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Georgie
Gary
Meg
Abhradeep
Ryan
Xiang
Dustin
Matt

Mean income: \$48

Quantity of Interest

Theories of Inference: Statistics vs. CS

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Chris	✓
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Kosuke	✓	122
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Gary	✓	96
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Abhradeep	✓	127
Ryan	✓	72
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Usually no direct relevance

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    - Essential components of ensuring privacy

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

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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
- The DP Standard

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

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- Statistical properties: usually biased, no uncertainty estimates

Properties of Differential Privacy

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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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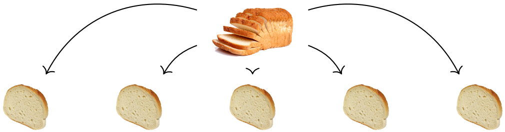
Private data

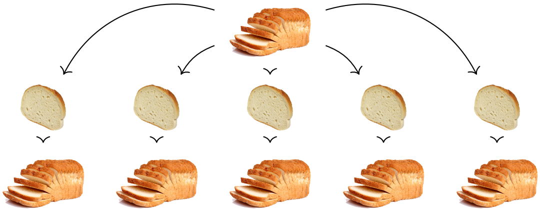
A Differentially Private Estimator



Private data

Partition

A Differentially Private Estimator



Private data

Partition

Bag of little bootstraps

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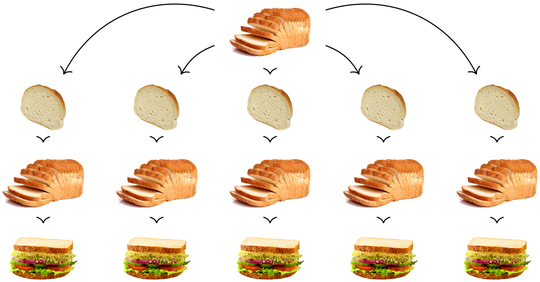

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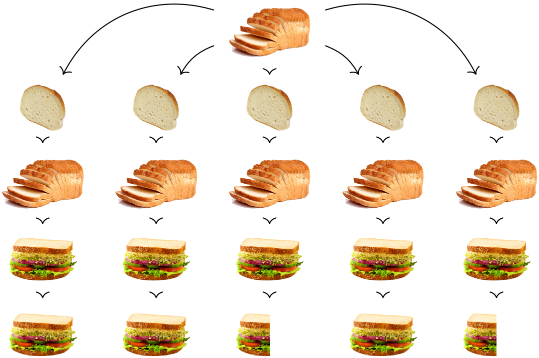
Estimator

A Differentially Private Estimator



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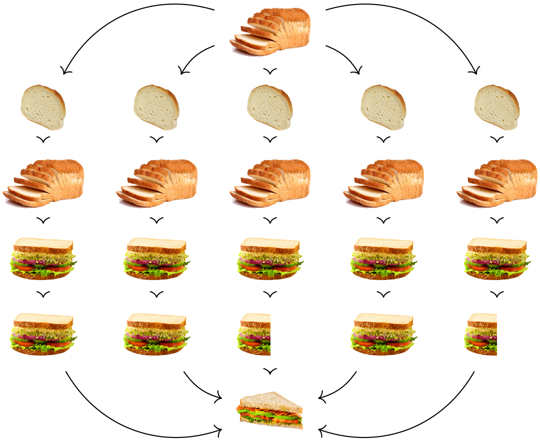
Estimator

Censor

A Differentially Private Estimator



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Estimator

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Average

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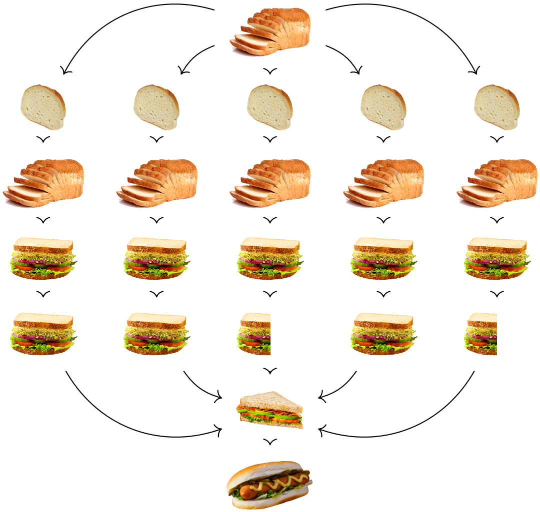

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Average

Noise

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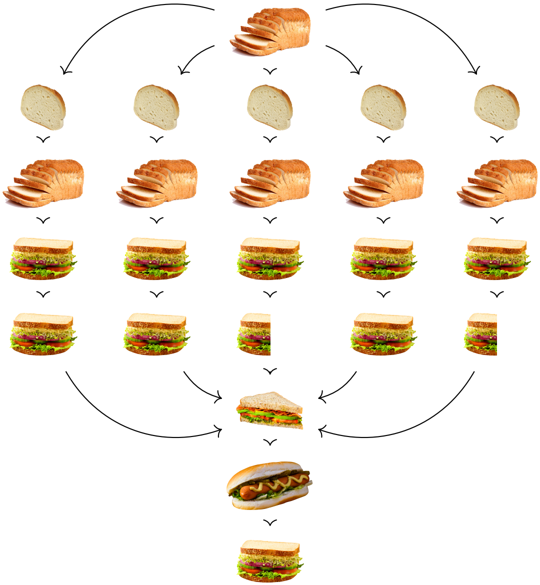

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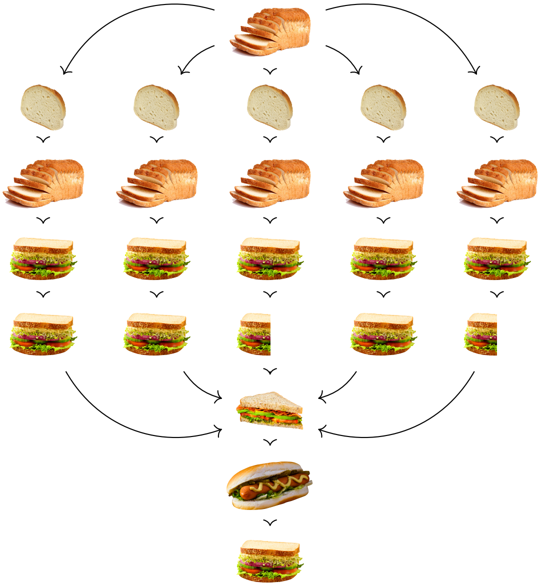

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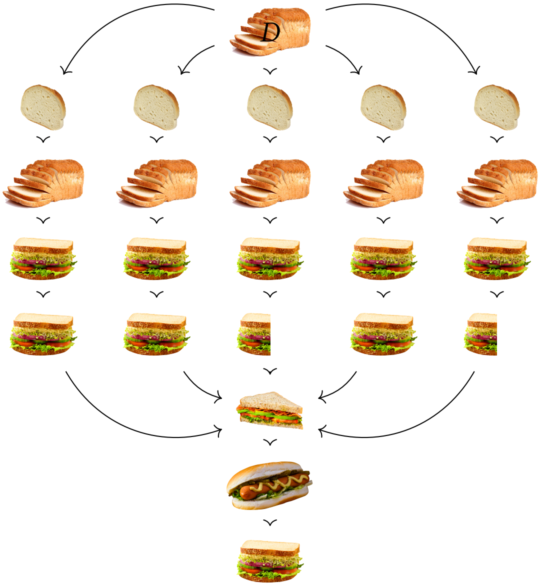

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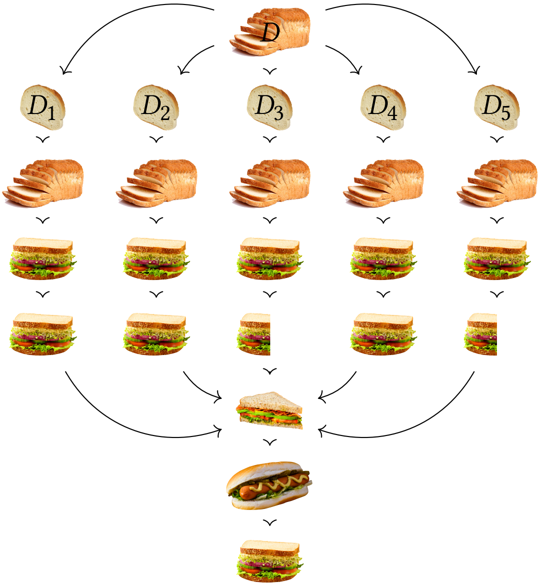

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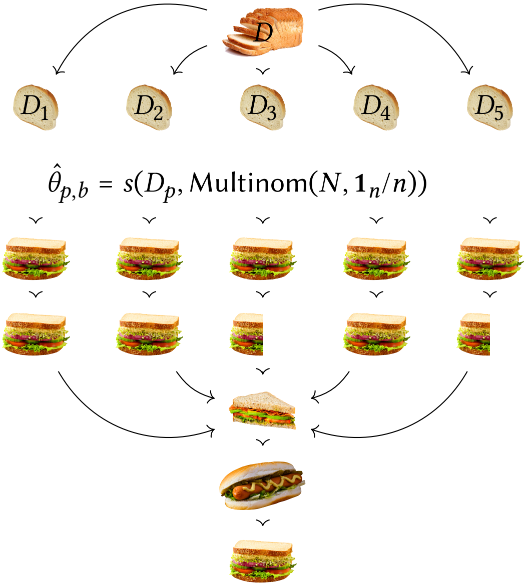

$$\hat{\theta}_{p,b} = s(D_p, \mathrm{Multinom}(N, \mathbf{1}_n/n))$$

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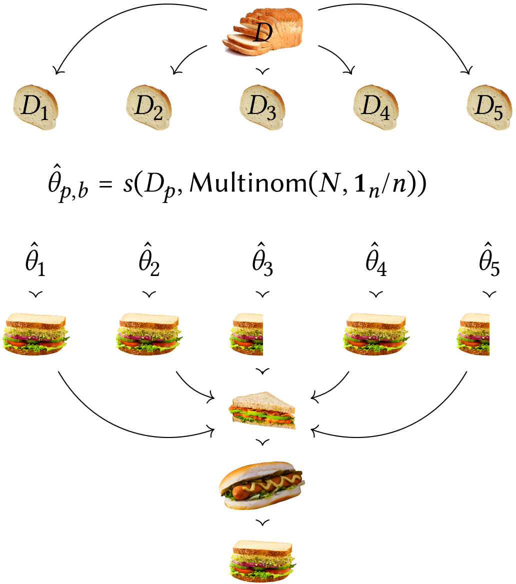

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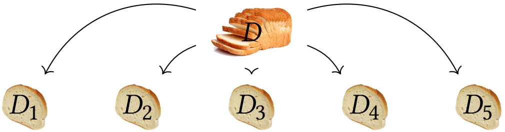

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Bag of little bootstraps

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

Estimator

$$\hat{\theta}^{\text{dp}} = \frac{1}{P} \sum_{p=1}^{P} c(\hat{\theta}_p, \Lambda) + N\left(0, \frac{8\Lambda}{\epsilon P}\right)$$

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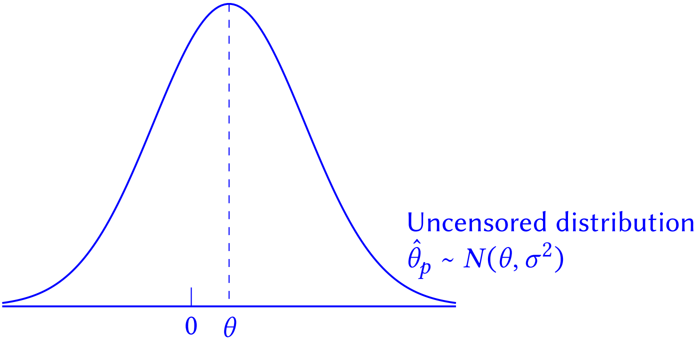

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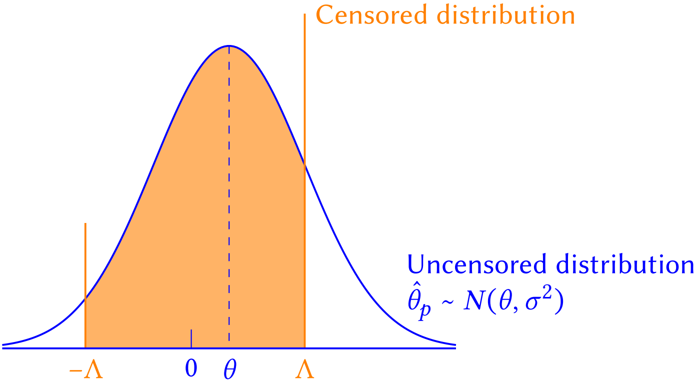

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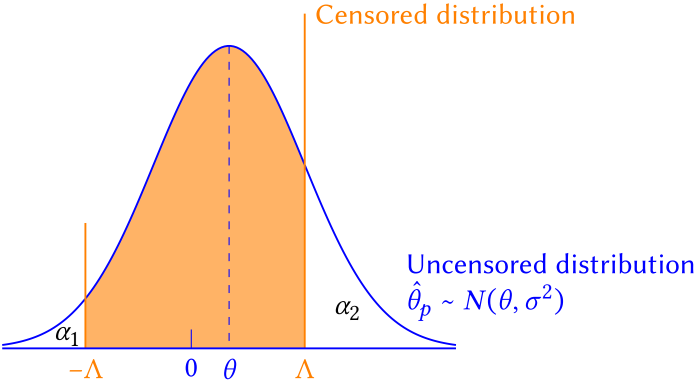

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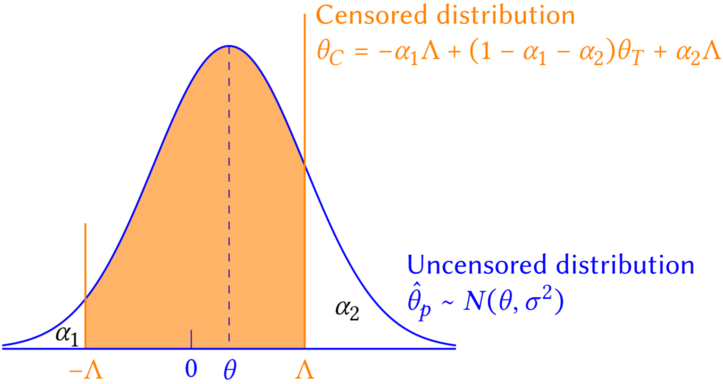

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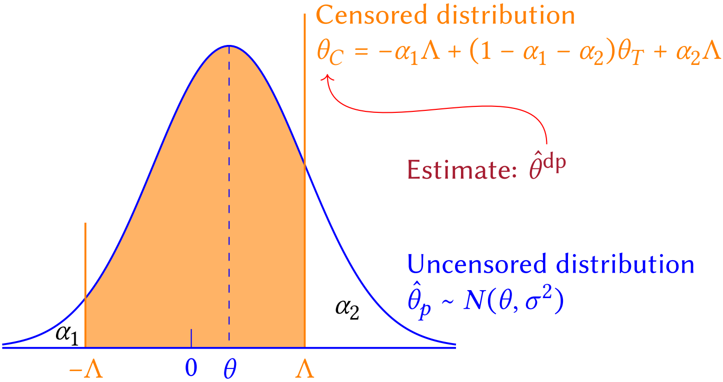

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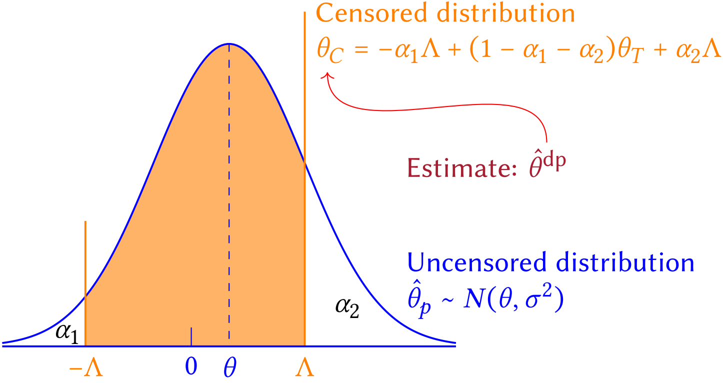

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3 eqns, 4 unknowns $\theta, \sigma^2, \alpha_1, \alpha_2$

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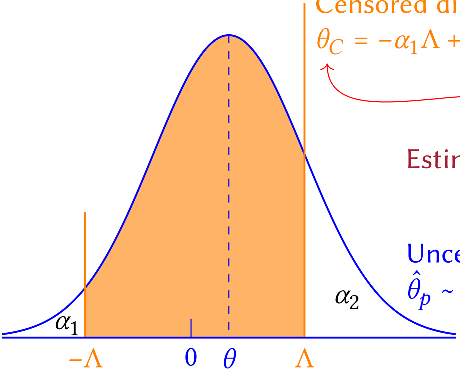
Censored distribution

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

Estimate: $\hat{\theta}^{\mathrm{dp}}$, $\hat{\alpha}_2^{\mathrm{dp}}$



Uncensored distribution

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

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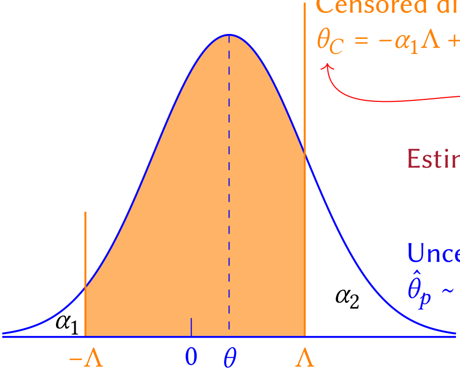

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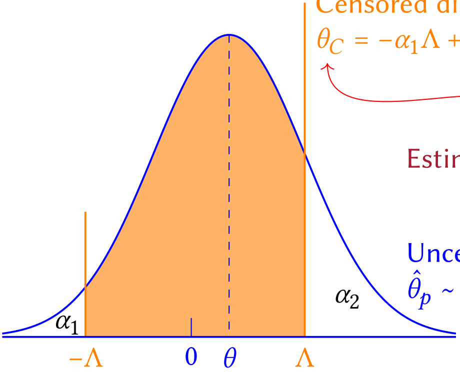

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Solve for θ (and σ^2, α_1)

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Functions of disclosed params

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Functions of disclosed params

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- Standard error: Standard deviation of $\tilde{\theta}^{\text{dp}}(i)$ over i

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- DP Variance is unhelpful: $V(\hat{\theta})^{\text{dp}} \neq V(\hat{\theta}^{\text{dp}})$
- Simulate estimates via standard (Clarify) procedures:

$$\hat{\theta}^{\text{dp}}(i), \hat{\alpha}_2^{\text{dp}}(i) \sim N\left(\begin{bmatrix} \hat{\theta}^{\text{dp}} \\ \hat{\alpha}_2^{\text{dp}} \end{bmatrix}, \begin{bmatrix} \hat{V}(\hat{\theta}^{\text{dp}}) & \widehat{\text{Cov}}(\hat{\alpha}_2^{\text{dp}}, \hat{\theta}^{\text{dp}}) \\ \widehat{\text{Cov}}(\hat{\alpha}_2^{\text{dp}}, \hat{\theta}^{\text{dp}}) & \hat{V}(\hat{\alpha}_2^{\text{dp}}) \end{bmatrix} \right)$$

Functions of disclosed params

- Bias correct simulated params:

$$\{\tilde{\theta}^{\text{dp}}(i), \hat{\alpha}_1^{\text{dp}}(i), \hat{\sigma}^2_{\text{dp}}(i)\} = \text{BiasCorrect}\left[\hat{\theta}^{\text{dp}}(i), \hat{\alpha}_2^{\text{dp}}(i)\right]$$

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

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

Simulations: Finite Sample Evaluation

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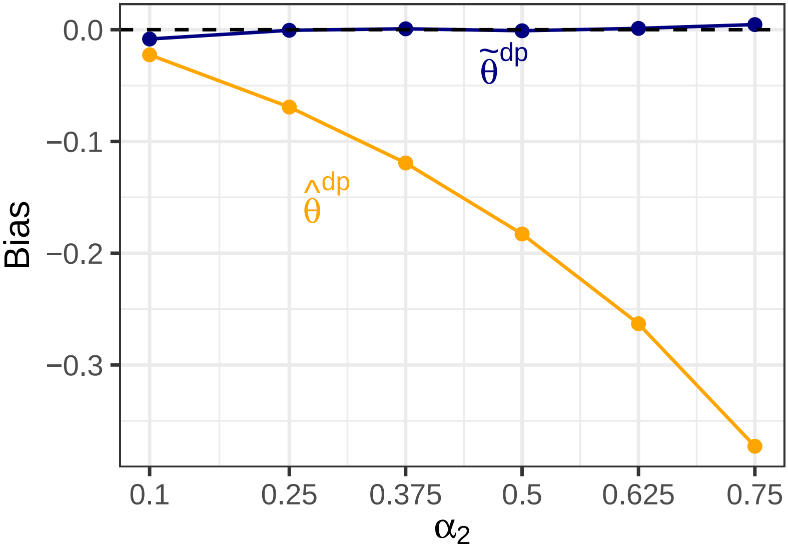

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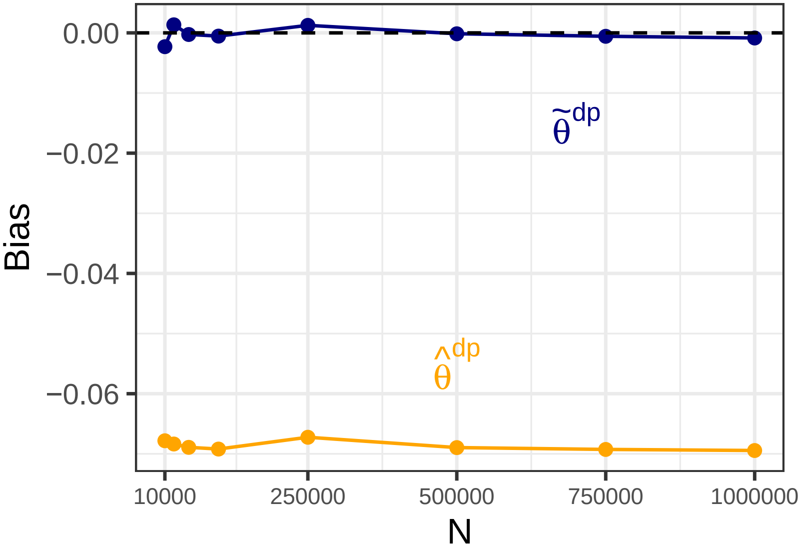

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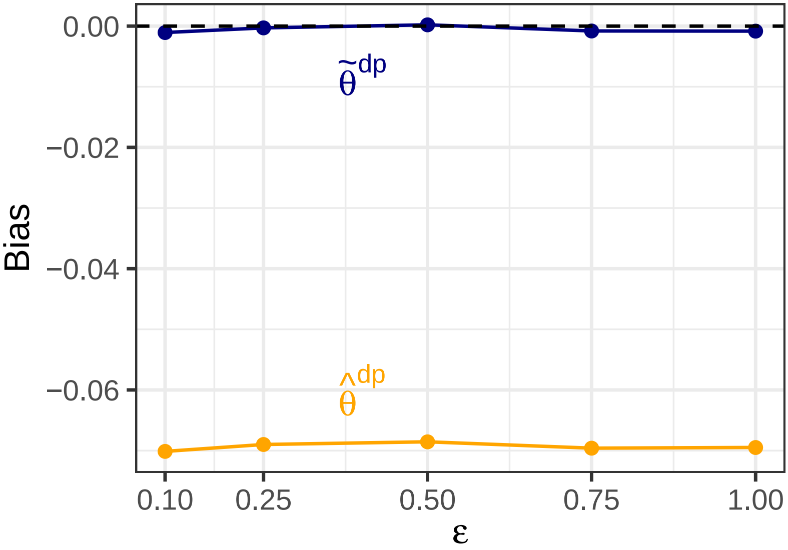

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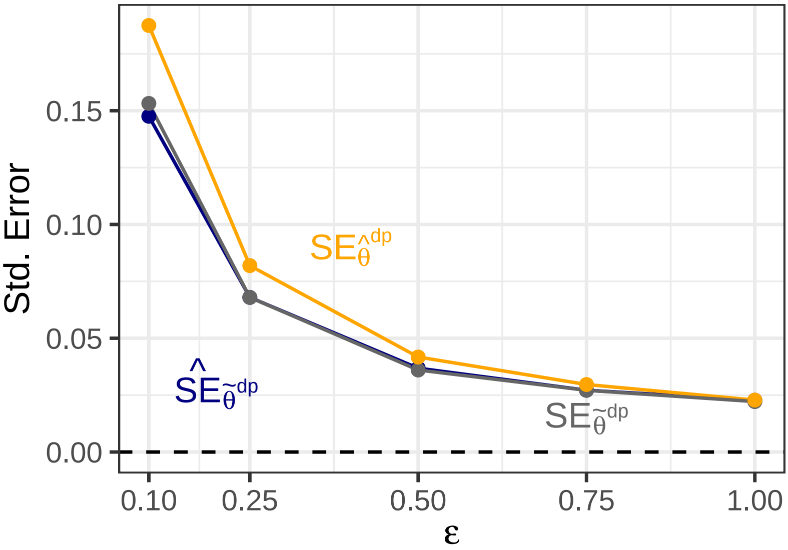

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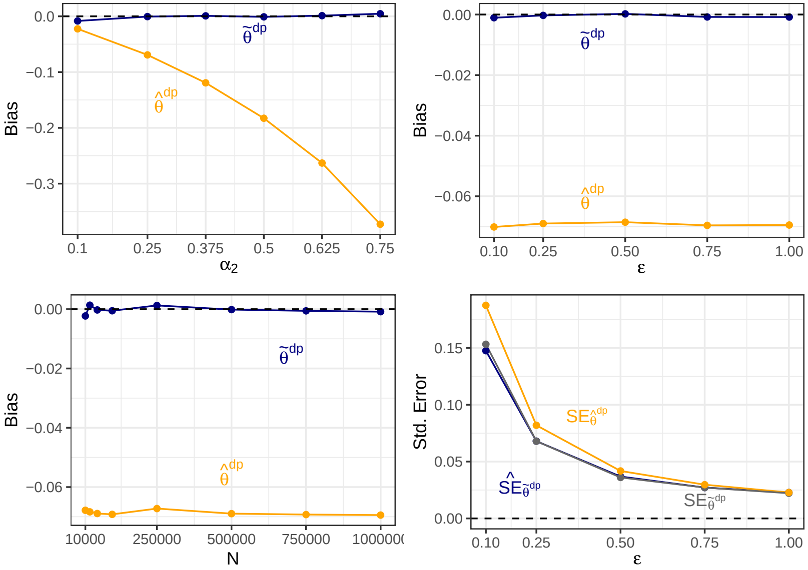

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