

Statistically Valid Inferences from Privacy Protected Data¹

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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**

Data Sharing Regime \rightsquigarrow Data Access Regime

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Theories of Inference: Statistics vs. CS

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Population

⋮

John

Heather

Georgie

Gary

Meg

Abhradeep

Ella

Anya

Greg

Juan

Mean
income:

\$48

Quantity
of Interest

Theories of Inference: Statistics vs. CS

	Population	Sample
	:	X
	John	✓
	Heather	✓
	Georgie	✓
	Gary	✓
	Meg	✓
	Abhradeep	✓
	Ella	✓
	Anya	✓
	Greg	✓
	Juan	✓
Mean income:	\$48	

Quantity
of Interest

Theories of Inference: Statistics vs. CS

Population	Sample	\$
:	X	
John	✓	76
Heather	✓	96
Georgie	✓	145
Gary	✓	122
Meg	✓	86
Abhradeep	✓	127
Ella	✓	72
Anya	✓	132
Greg	✓	95
Juan	✓	134

Mean
income:

\$48

Classical
Inference

\$108

Quantity
of Interest

Usually
no direct
relevance

Theories of Inference: Statistics vs. CS

Population	Sample	\$
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John	✓	76
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Mean
income:

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Quantity
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Usually
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Theories of Inference: Statistics vs. CS

Population	Sample	\$	+Privacy
:	X		
John	✓	76	Noise & Censoring
Heather	✓	96	
Georgie	✓	145	
Gary	✓	122	
Meg	✓	86	
Abhradeep	✓	127	
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Gary	✓	122		113
Meg	✓	86		125
Abhradeep	✓	127		97
Ella	✓	72		101
Anya	✓	132		128
Greg	✓	95		83
Juan	✓	134		201

Mean income:

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Classical Inference

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Query-Response

\$111

Quantity of Interest

Usually no direct relevance

No direct relevance

Theories of Inference: Statistics vs. CS

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Mean income:



Differential Privacy and its Inferential Challenges

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- Estimators

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 - Classical Statistics: Apply statistic s to dataset D , $s(D)$

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**

Differential Privacy and its Inferential Challenges

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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

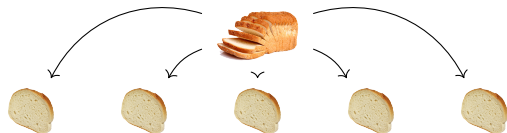
A Differentially Private Estimator

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Private data

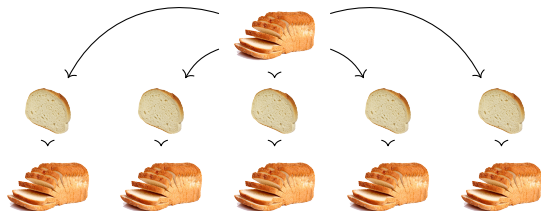
A Differentially Private Estimator



Private data

Partition

A Differentially Private Estimator

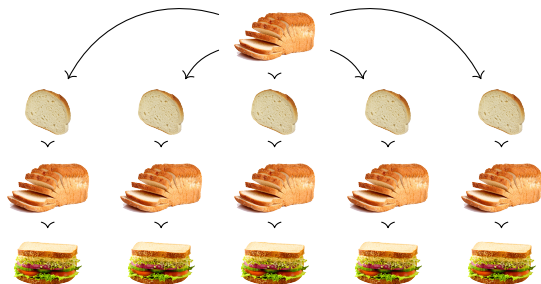


Private data

Partition

Bag of little bootstraps

A Differentially Private Estimator



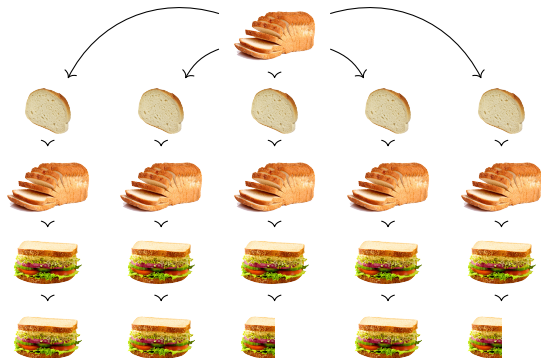
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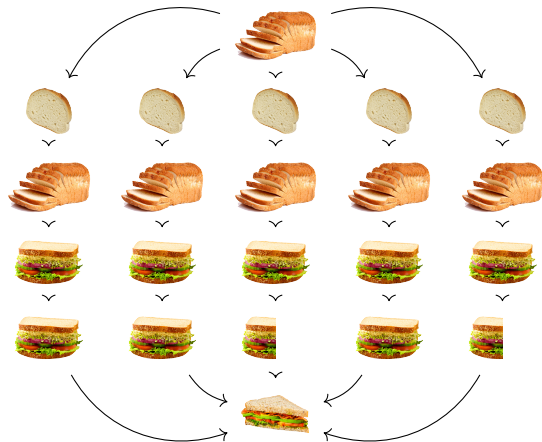
Partition

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Estimator

Censor

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Private data

Partition

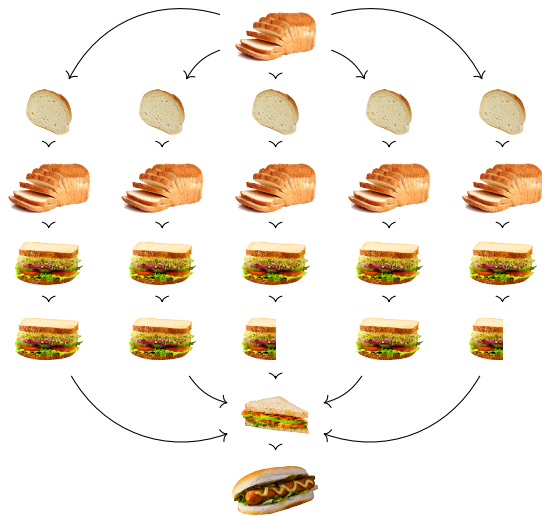
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Estimator

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Private data

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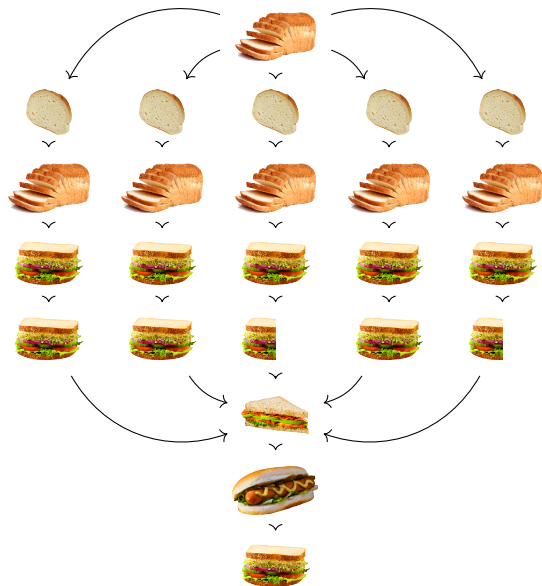
Estimator

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Noise

A Differentially Private Estimator



Private data

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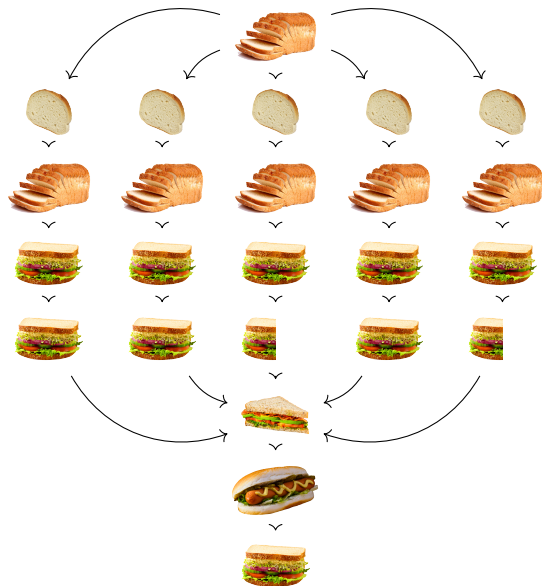
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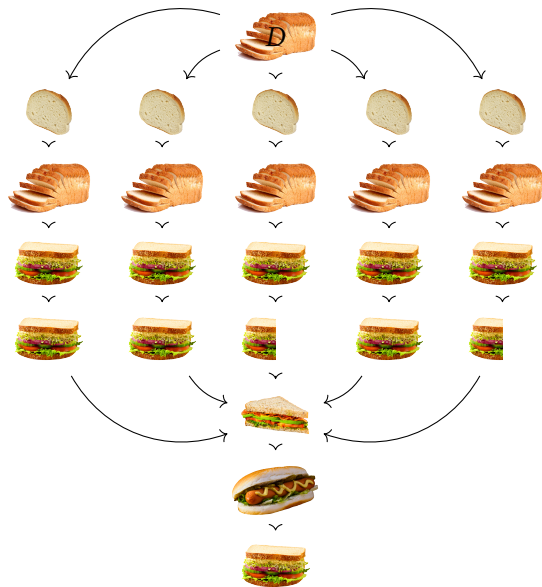
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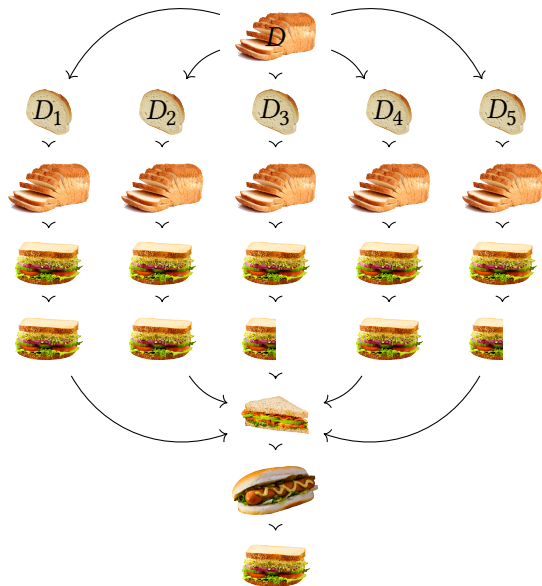
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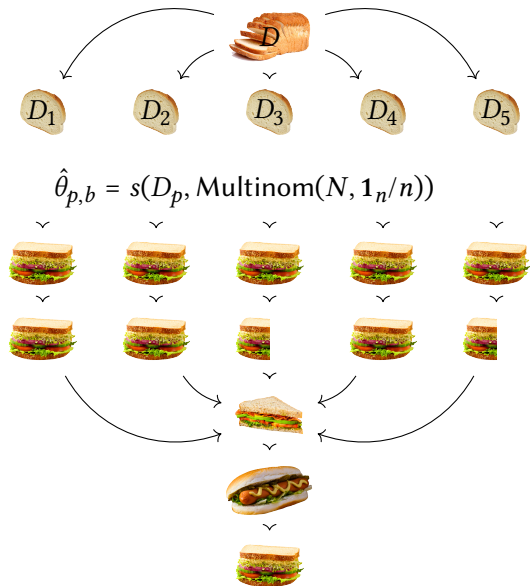
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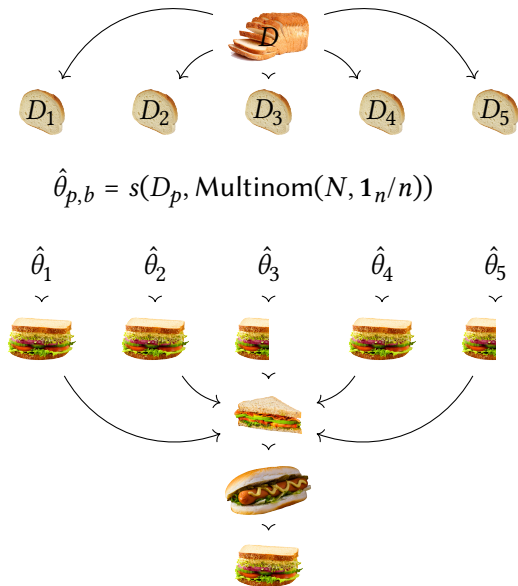
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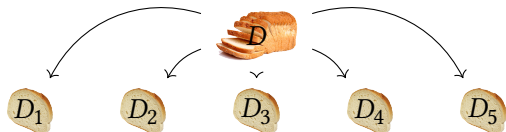
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Partition

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

Bag of little bootstraps

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

Estimator

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

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Average

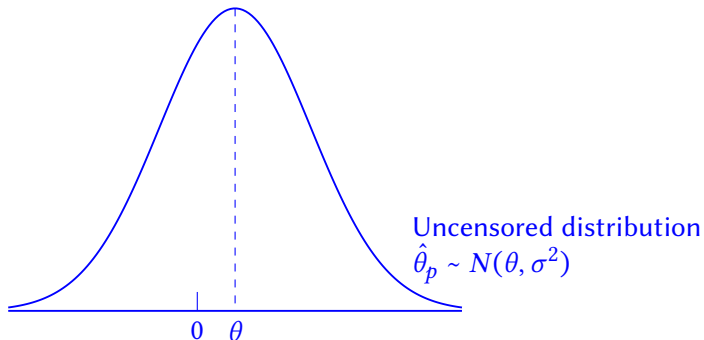
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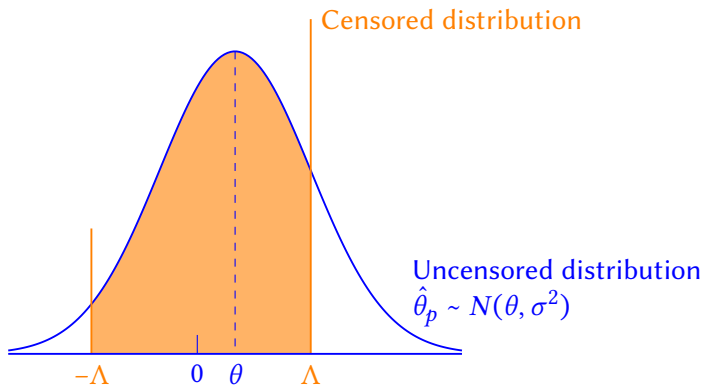
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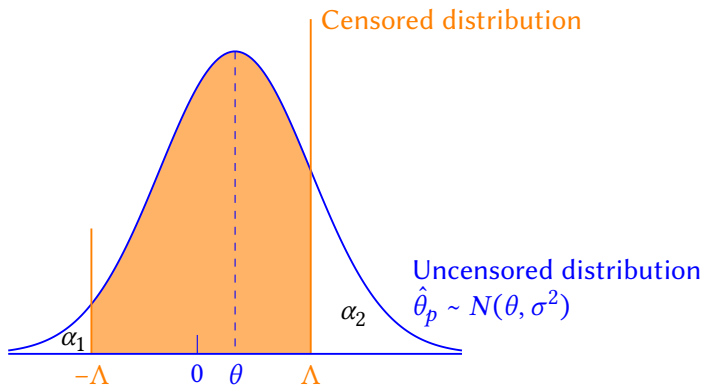
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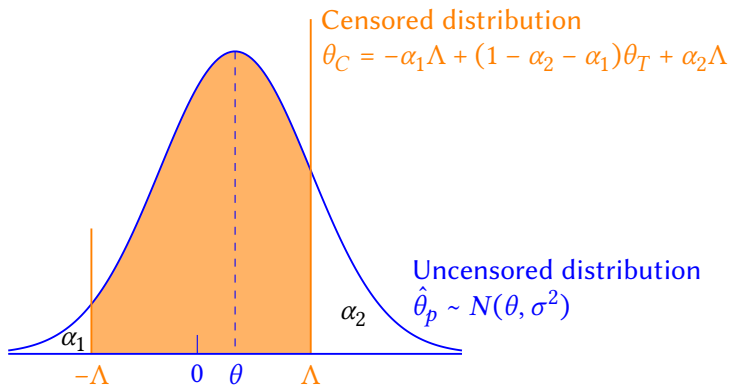
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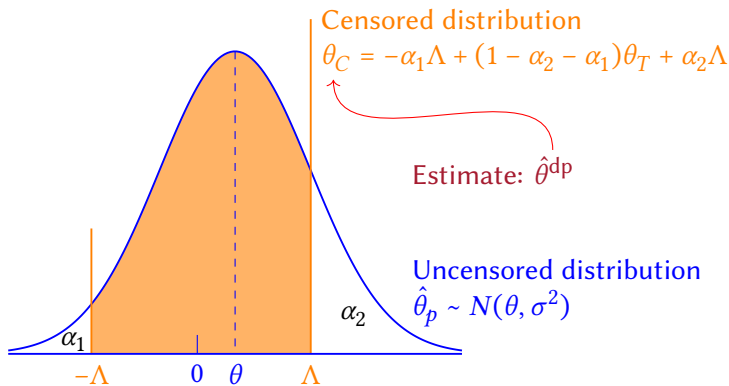
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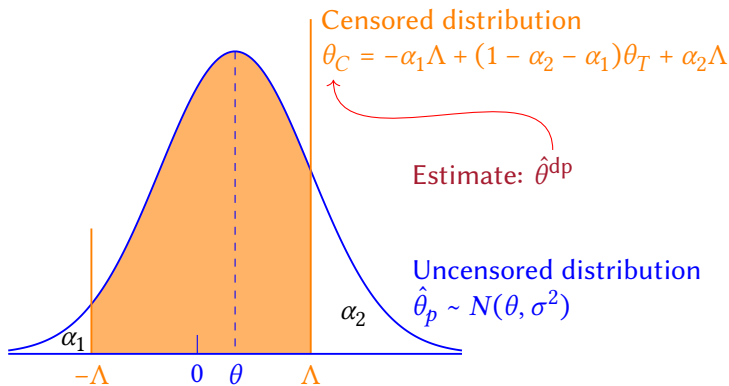
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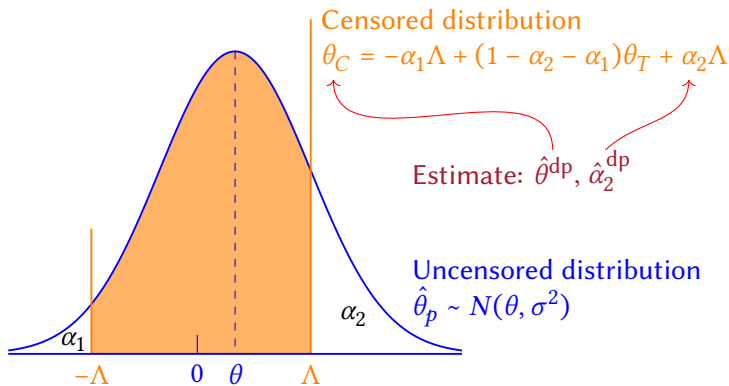


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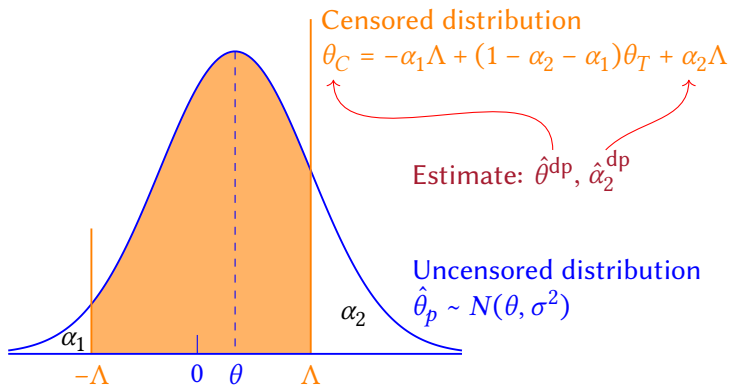


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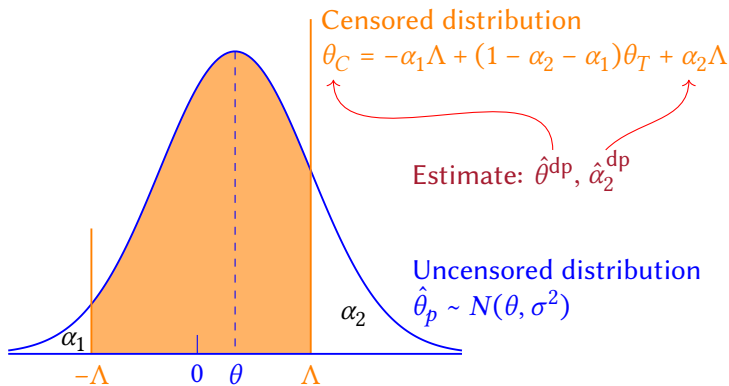


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~~3 eqns, 4 unknowns $\theta, \sigma^2, \alpha_1, \alpha_2$~~
 Solve for θ (and σ^2, α_1)

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

Solving Political Problems Technologically

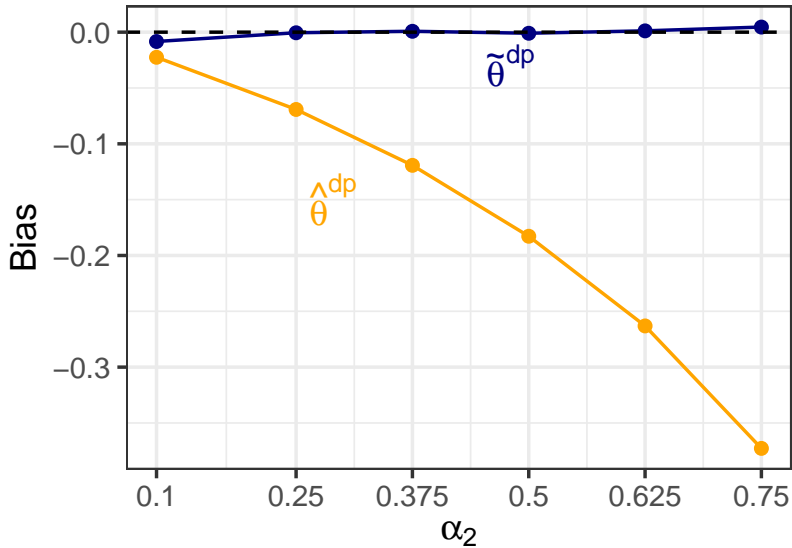
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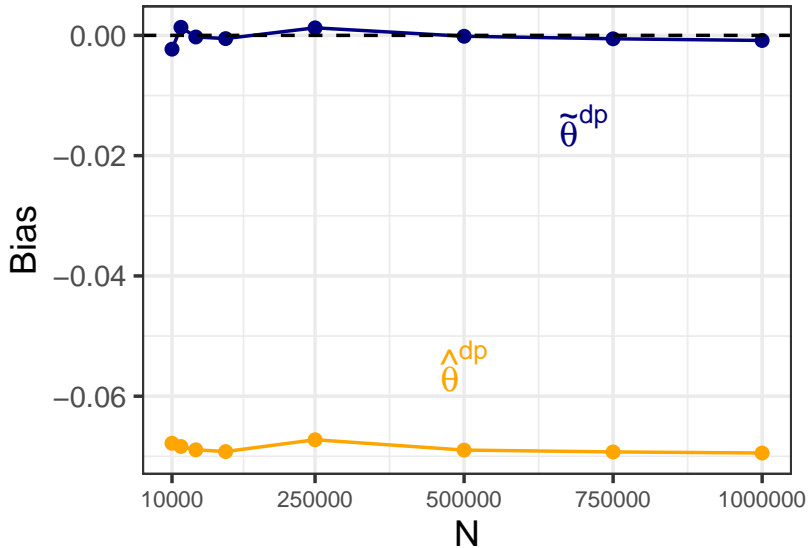
The Algorithm in Practice

Simulations: Finite Sample Evaluation

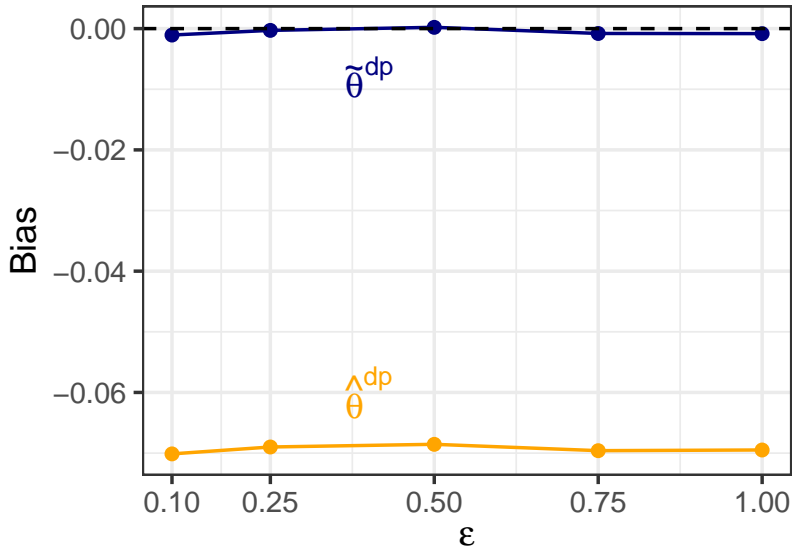
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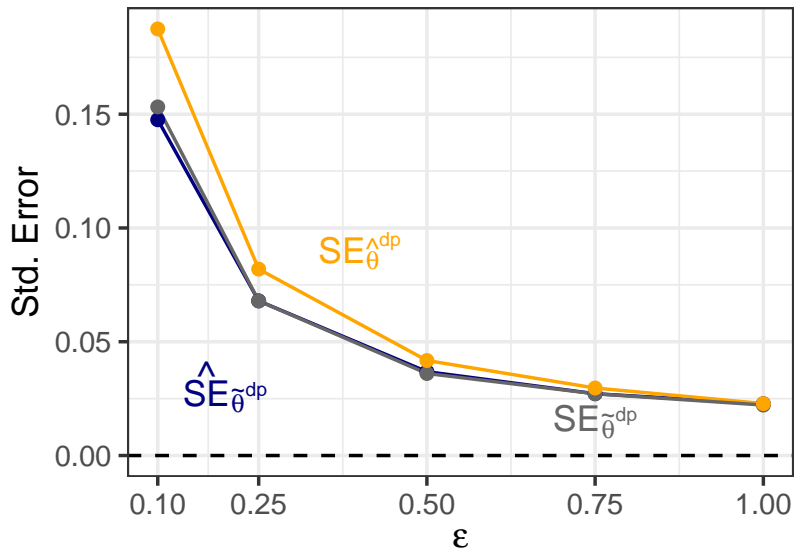
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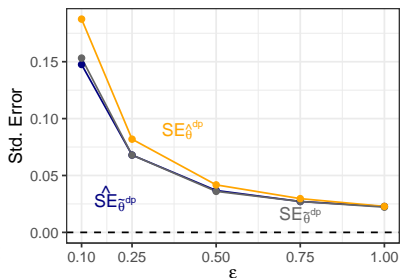
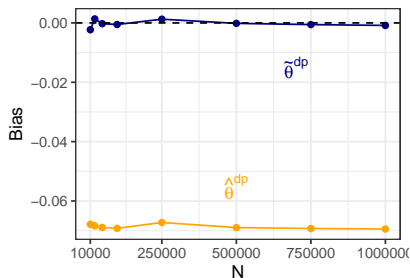
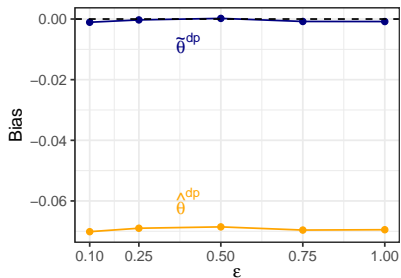
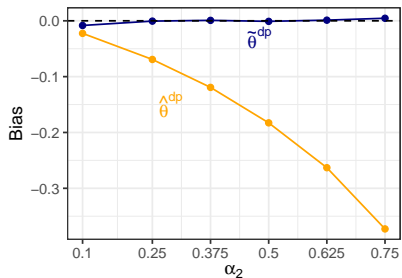
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 - **Easy to implement**

For more information



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Paper, software, slides: GaryKing.org/dp