Statistically Valid Inferences from Privacy Protected Data

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Deloitte Data Science Seminar, 7/14/2022

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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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- Just one issue: Facebook's implementation plan was illegal!
- New Problem: Sharing data without it leaving Facebook

Who Needs to Share Data (Safely)?

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- One division of a company $\rightsquigarrow$ another division

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- A Company or Government $\rightsquigarrow$ Academic Researchers

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The Algorithm in Practice

Theories of Inference: Statistics vs. CS

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Population
⋮
James
Mohammad
Tysen
Heather
Georgie
Gary
Meg
Abhradeep
Tim
Cathy

Mean income: $48

Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample
⋮	✗
James	✓
Mohammad	✓
Tysen	✓
Heather	✓
Georgie	✓
Gary	✓
Meg	✓
Abhradeep	✓
Tim	✓
Cathy	✓
$48	

Mean income:

Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample	$
⋮	✗	?
James	✓	122
Mohammad	✓	76
Tysen	✓	145
Heather	✓	96
Georgie	✓	86
Gary	✓	127
Meg	✓	72
Abhradeep	✓	132
Tim	✓	95
Cathy	✓	134
Mean income: $48		$108

Classical Inference

Quantity of Interest

Usually no direct relevance

Theories of Inference: Statistics vs. CS

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⋮	✗	?
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Tysen	✓	145
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Classical Inference

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Usually no direct relevance

Theories of Inference: Statistics vs. CS

Population	Sample	$	+Privacy
⋮	✗	?	
James	✓	122	Noise & Censoring
Mohammad	✓	76	
Tysen	✓	145	
Heather	✓	96	
Georgie	✓	86	
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Theories of Inference: Statistics vs. CS

	Population	Sample	$	+Privacy	=dp$
	⋮	✗	?		
	James	✓	122		85
	Mohammad	✓	76		103
	Tysen	✓	145		75
	Heather	✓	96		113
	Georgie	✓	86	Noise & Censoring	125
	Gary	✓	127		97
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Mean income:	$48	Classical Inference	$108	Query-Response	$111
	Quantity of Interest		**Usually no direct relevance**		**No direct relevance**

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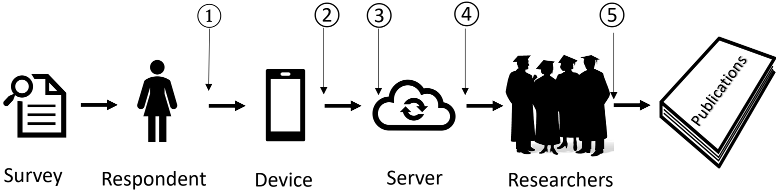
Classical Inference

Query-Response

Statistically Valid Inferences from Privacy Protected Data

Protecting Survey Data



Differential Privacy and its Inferential Challenges

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A Differentially Private Estimator

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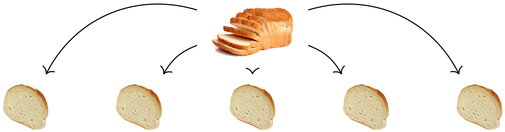
Private data

A Differentially Private Estimator



Private data

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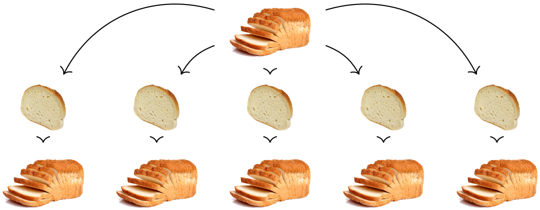
A Differentially Private Estimator



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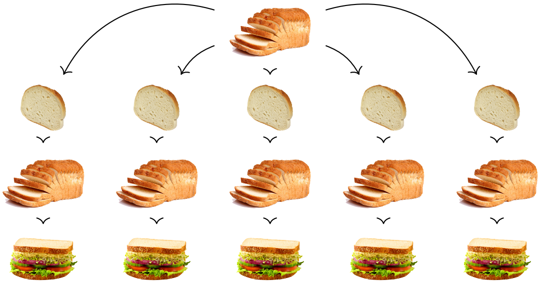

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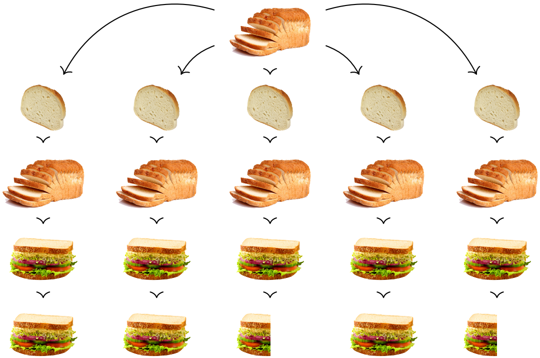

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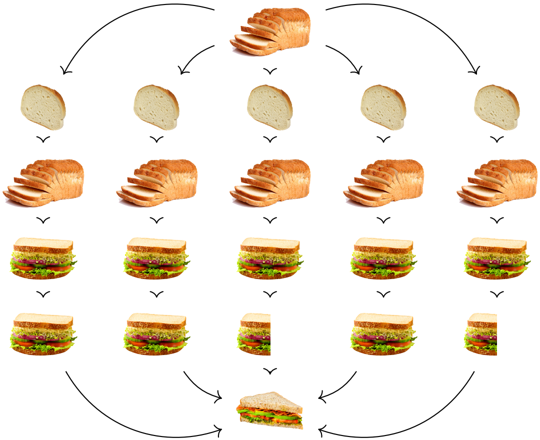

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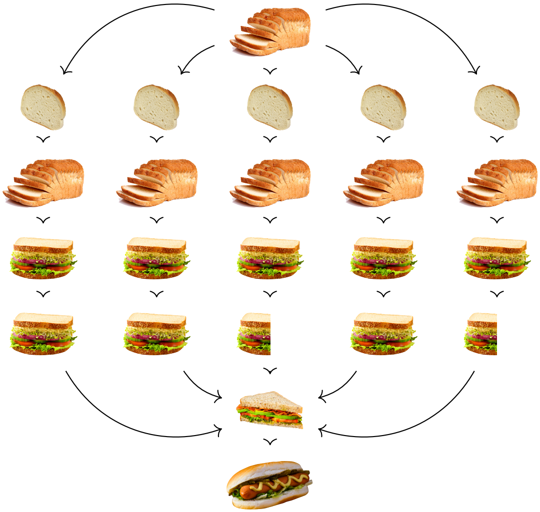

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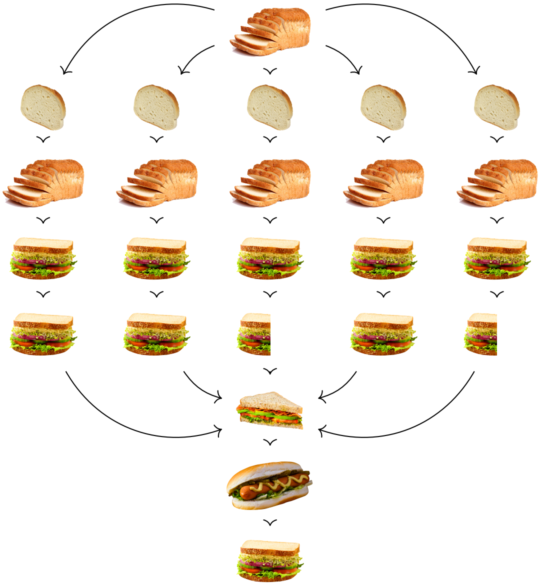

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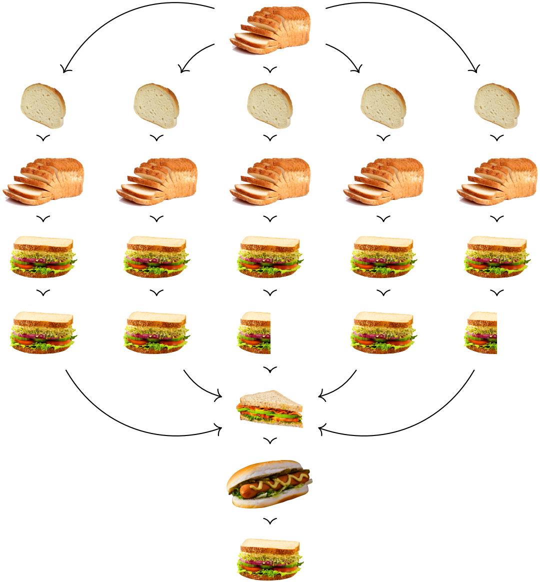

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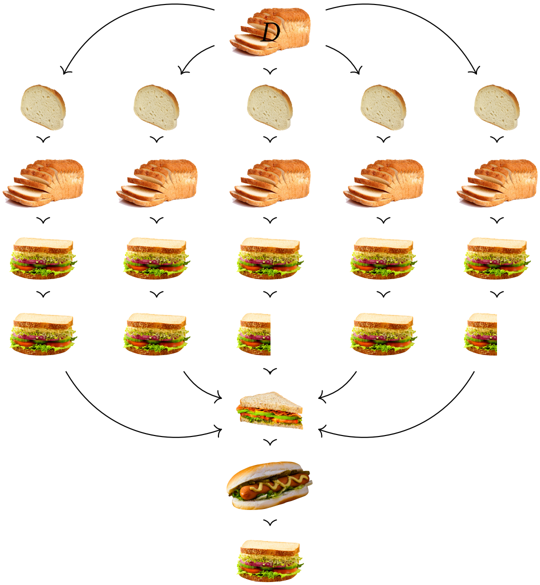

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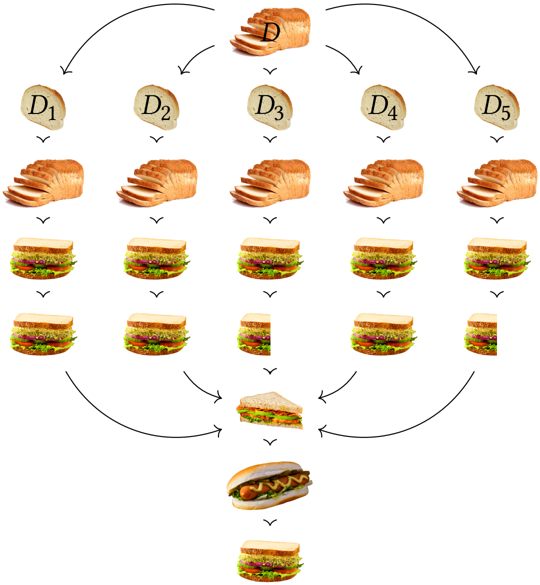

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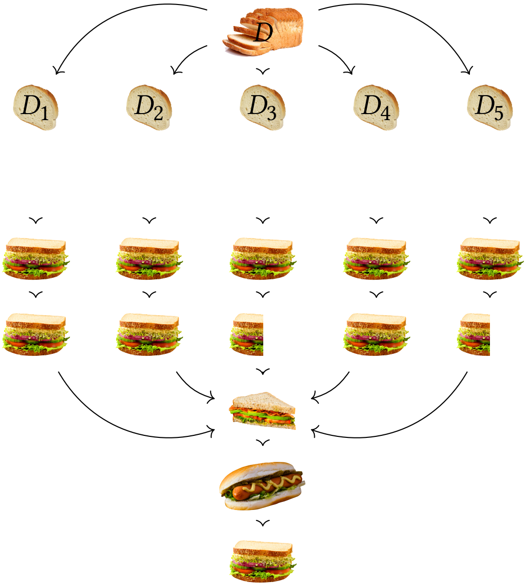

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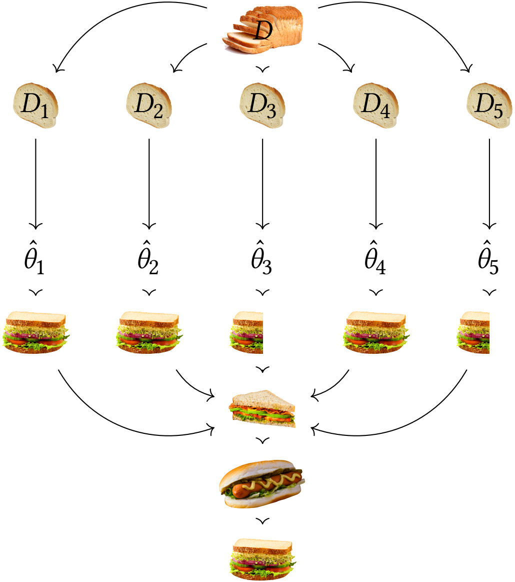

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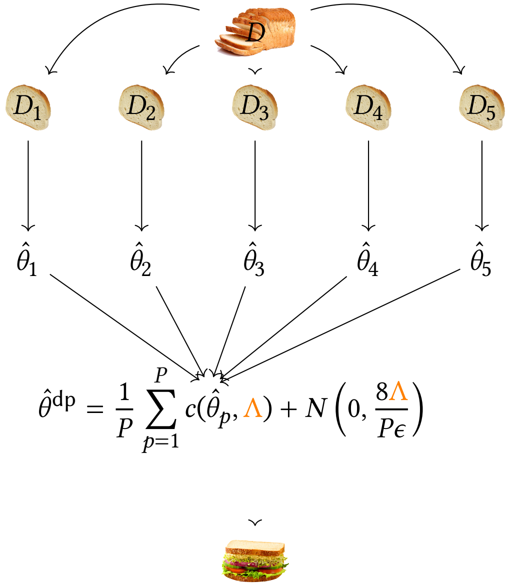

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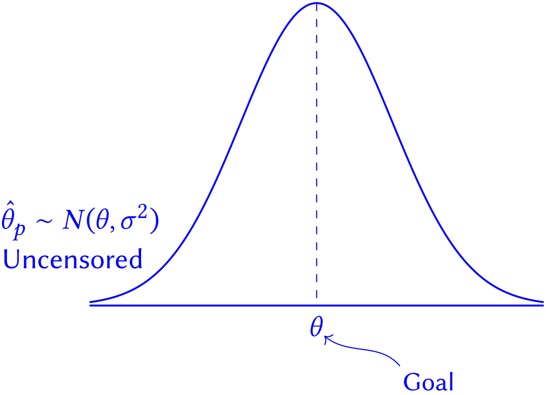

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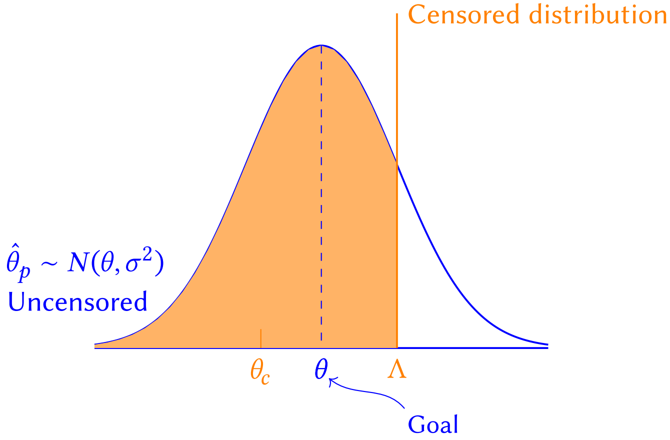

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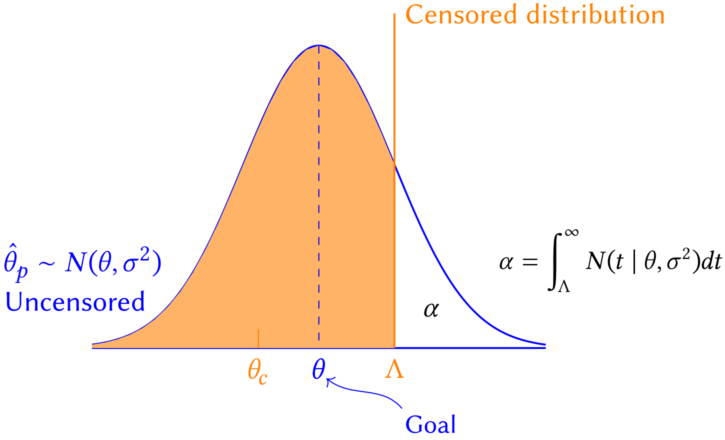

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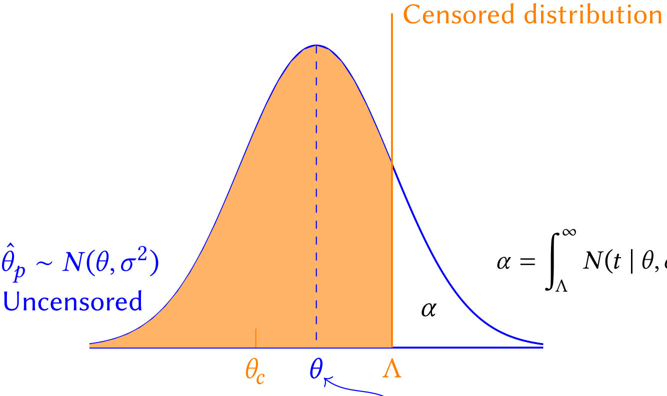

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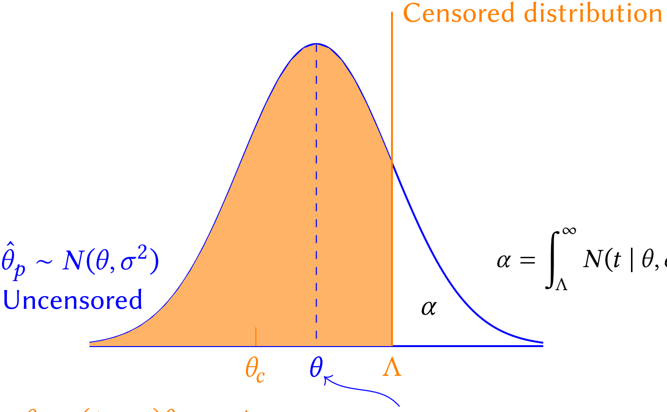

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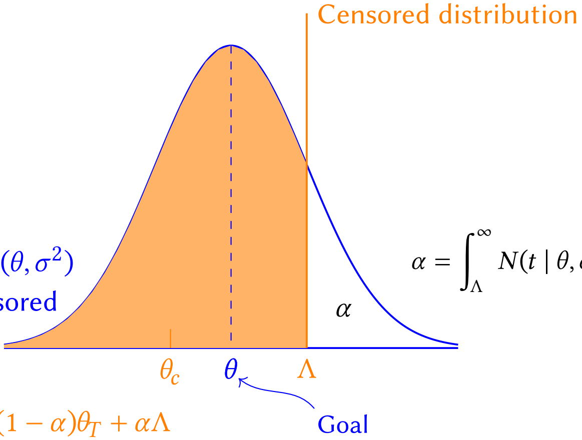
Uncensored



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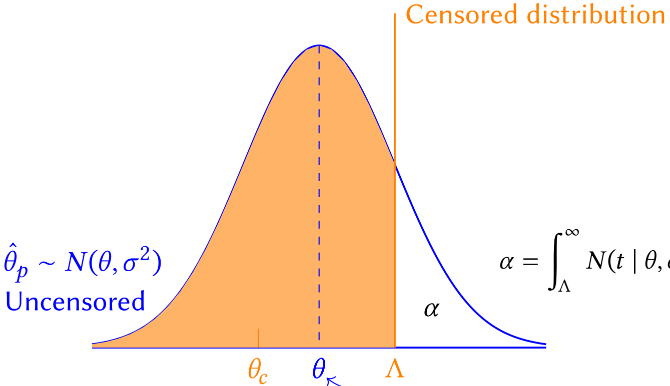

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Goal

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

Equations: 2

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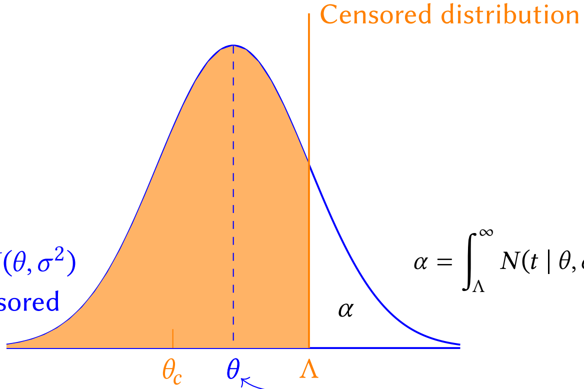

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- Simulate estimates via standard (Clarify) procedures:

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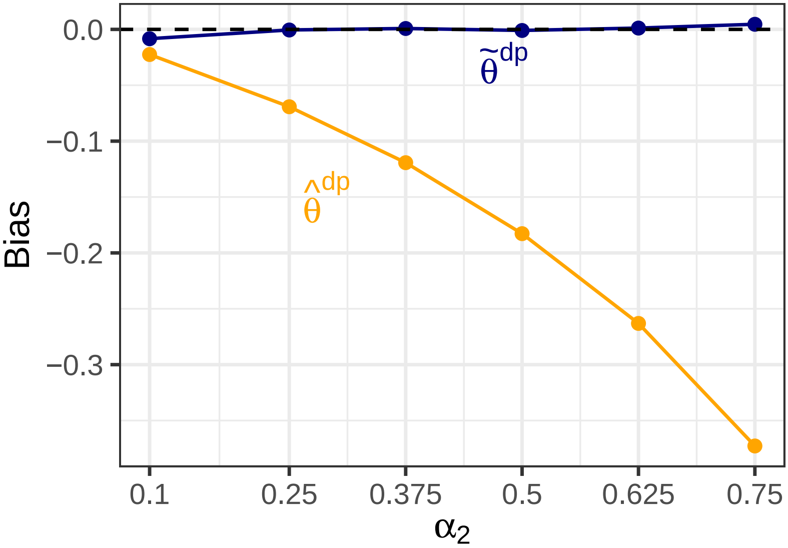

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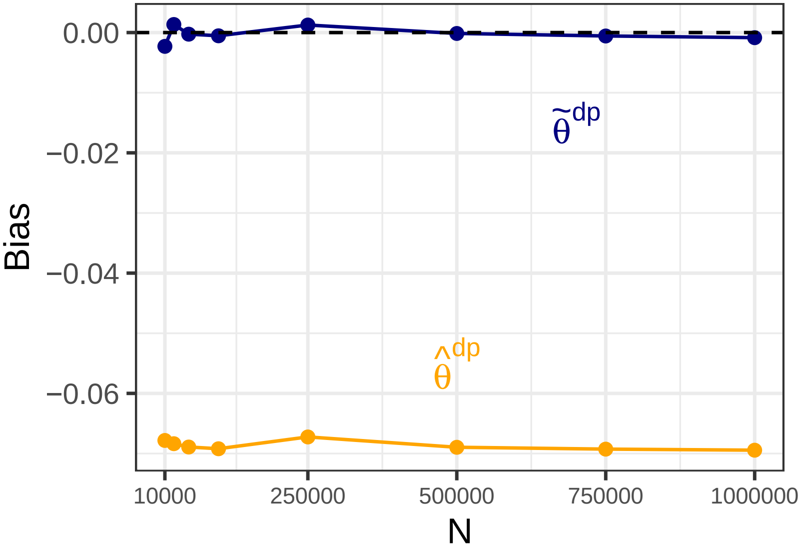

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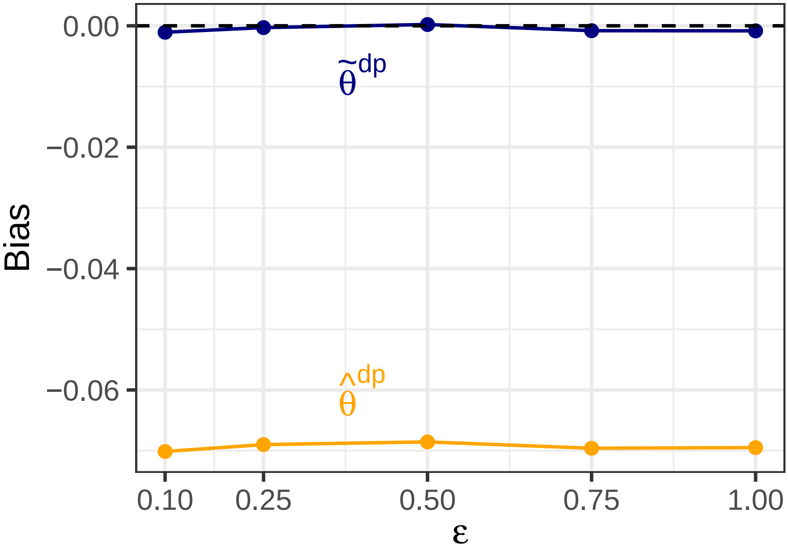

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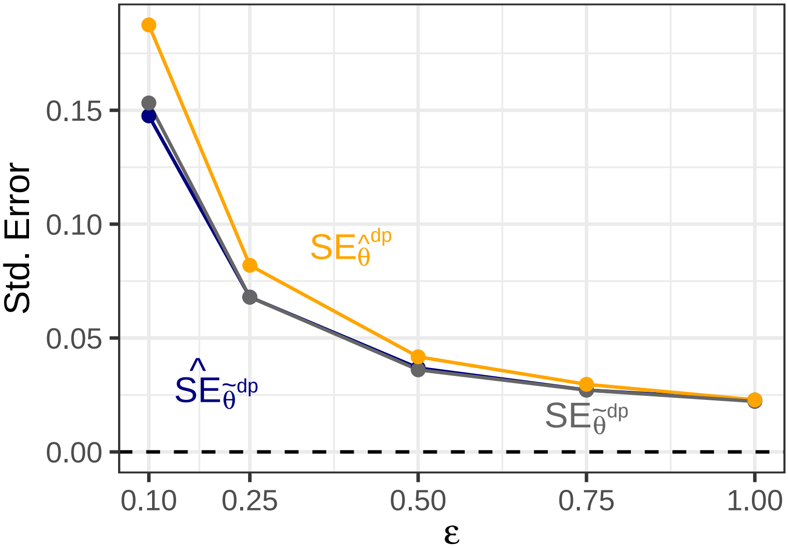

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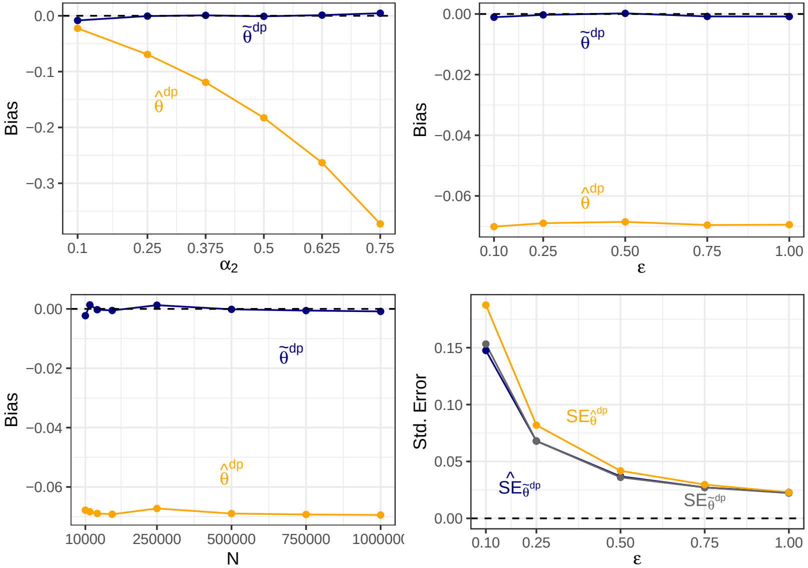
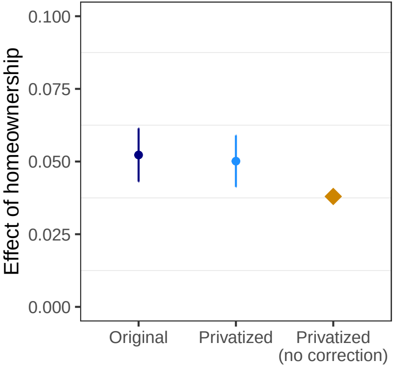
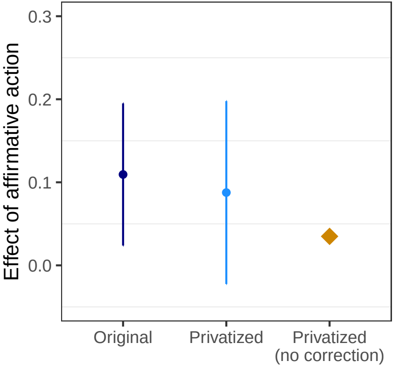


Similar Empirical Results, Larger CIs



(a) Yoder (2020)



(b) Bhavnani and Lee (2019)

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- Community based, Open Source Software: OpenDP.org

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Appendix

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