Statistically Valid Inferences from Privacy Protected Data[1]

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Interagency Arctic Research Policy Committee, 11/19/2020

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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

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    - *no* uncertainty estimates

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A General Purpose, Statistically Valid DP Algorithm

The Algorithm in Practice

Theories of Inference: Statistics vs. CS

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	Population
	⋮
	Lindsay
	Salil
	Georgie
	Gary
	Meg
	Abhradeep
	Joshua
	Annie
	Bob
	Ellen
Mean income:	$48

Quantity of Interest

Theories of Inference: Statistics vs. CS

	Population	Sample
	⋮	✗
	Lindsay	✓
	Salil	✓
	Georgie	✓
	Gary	✓
	Meg	✓
	Abhradeep	✓
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Mean income:	\$48	

Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample	$
⋮	✗	?
Lindsay	✓	122
Salil	✓	76
Georgie	✓	145
Gary	✓	96
Meg	✓	86
Abhradeep	✓	127
Joshua	✓	72
Annie	✓	132
Bob	✓	95
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Mean income: \$48 Classical Inference \$108

Quantity of Interest

Usually no direct relevance

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$48		$108

Mean income: $48 ← Classical Inference — $108

Quantity of Interest ($48)

Usually no direct relevance ($108)

Theories of Inference: Statistics vs. CS

Population	Sample	$	+Privacy
⋮	✗	?	
Lindsay	✓	122	Noise & Censoring
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Georgie	✓	145	
Gary	✓	96	
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Mean income: $48		$108	

Classical Inference

Quantity of Interest

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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

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Differential Privacy and its Inferential Challenges

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- Estimators

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  - DP Mechanism: $M(s, D)$, with noise & censoring

Differential Privacy and its Inferential Challenges

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

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

Differential Privacy and its Inferential Challenges

- Estimators
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A Differentially Private Estimator

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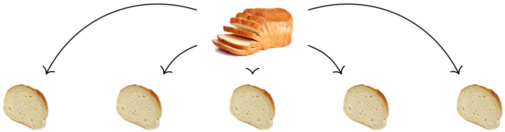
Private data

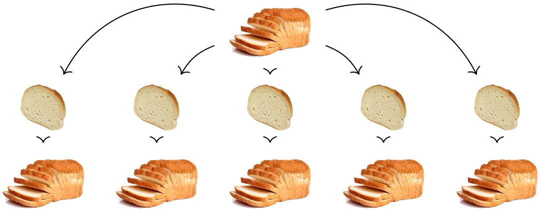
A Differentially Private Estimator



Private data

Partition

A Differentially Private Estimator



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Bag of little bootstraps

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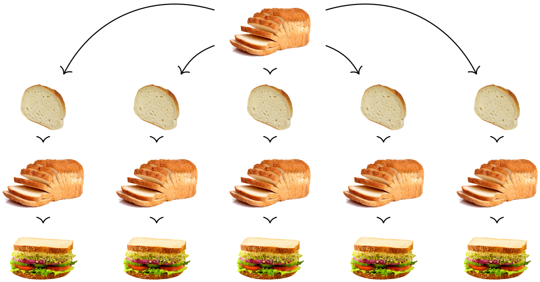

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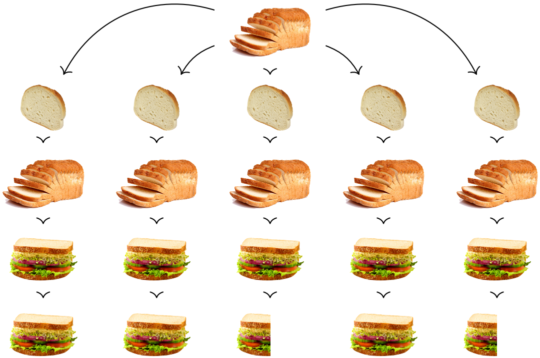

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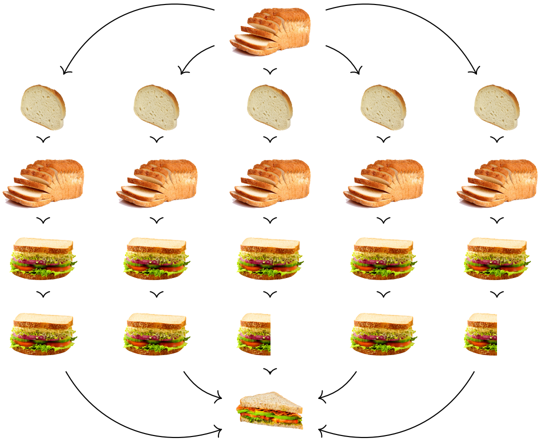

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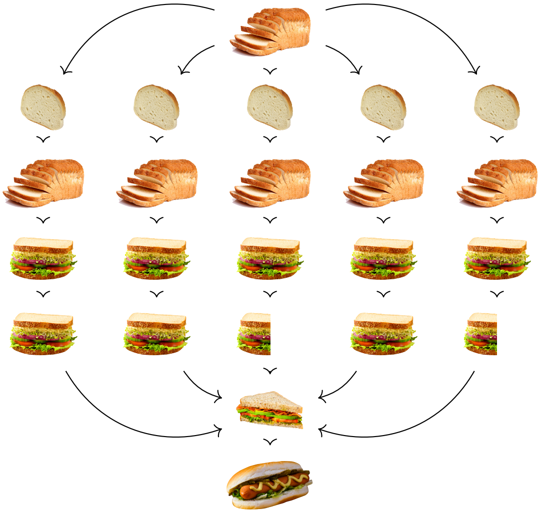

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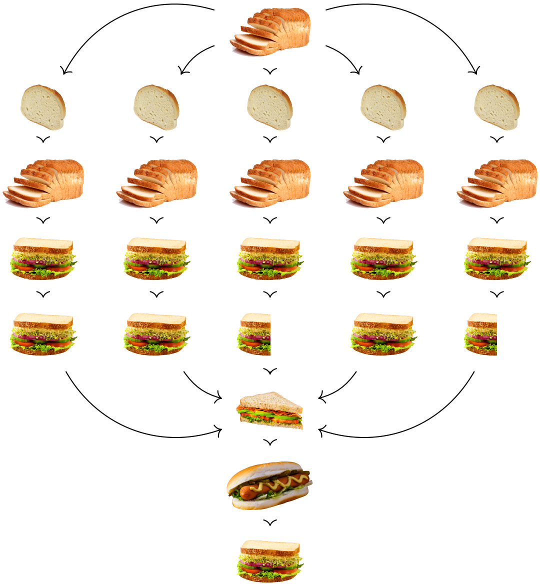

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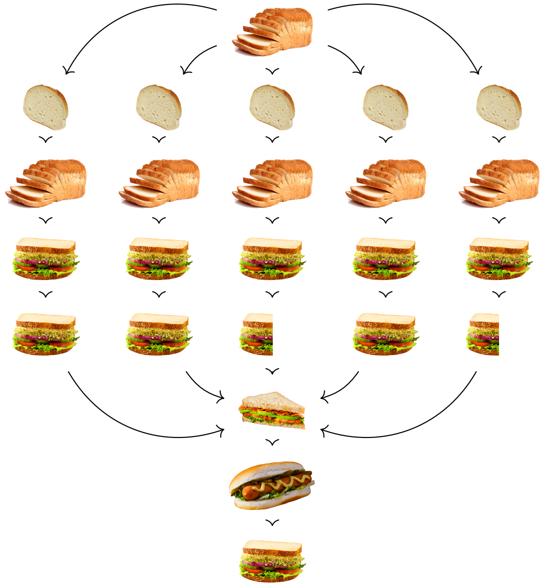

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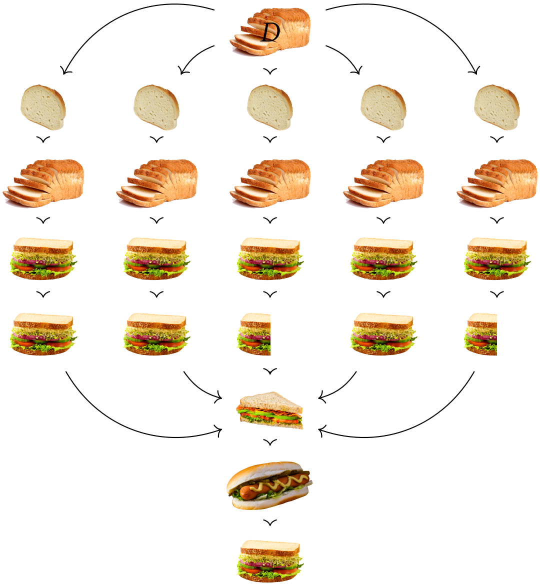

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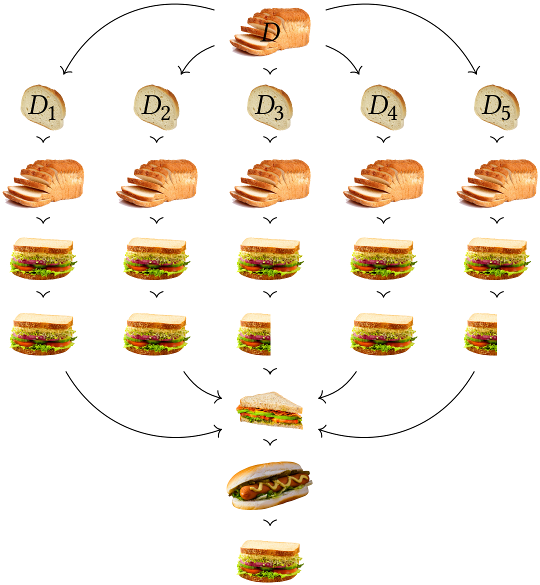

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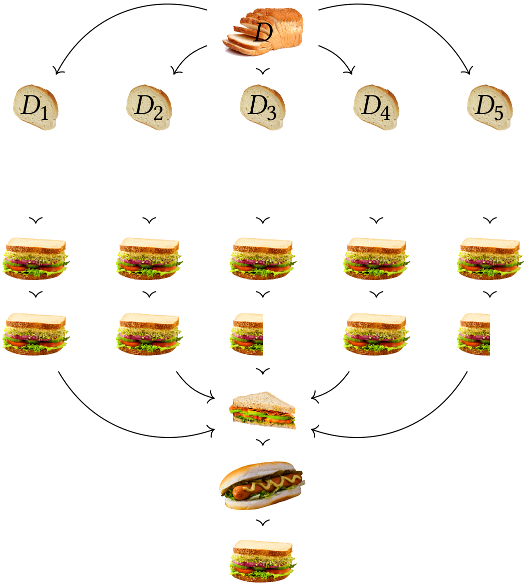

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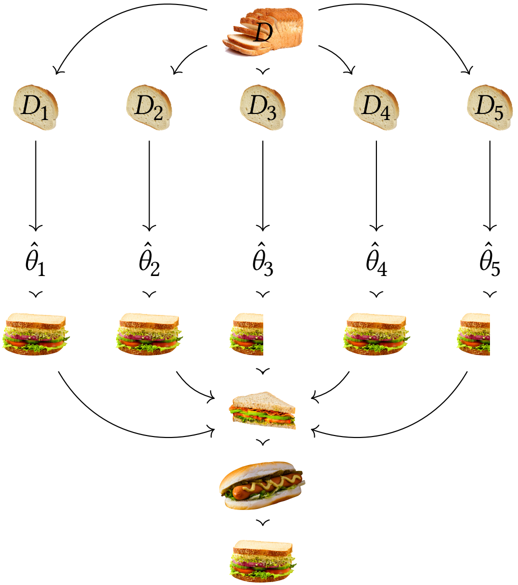

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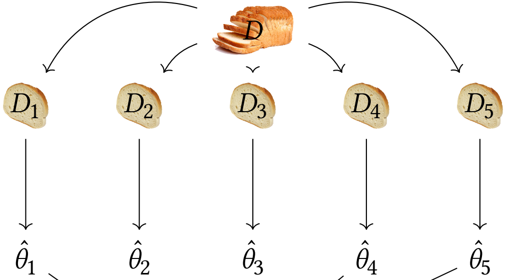

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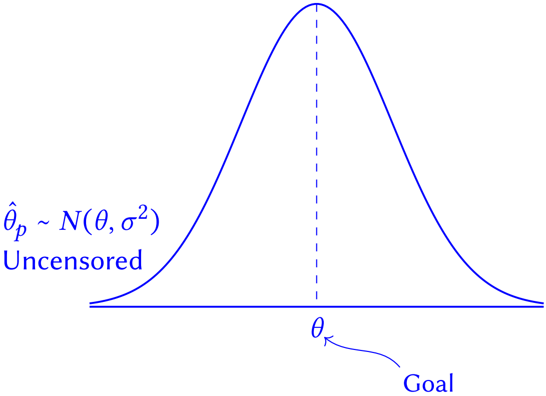

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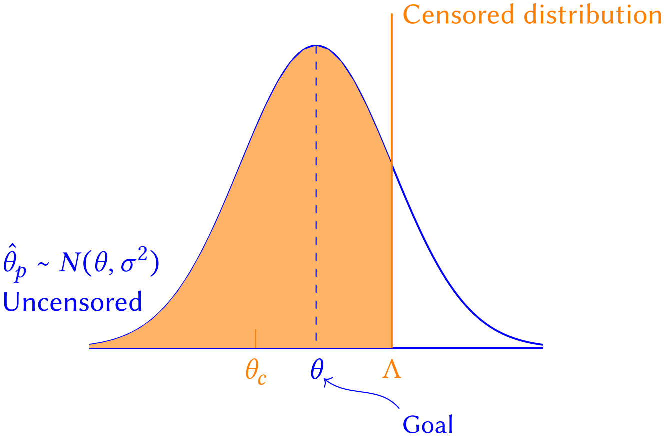

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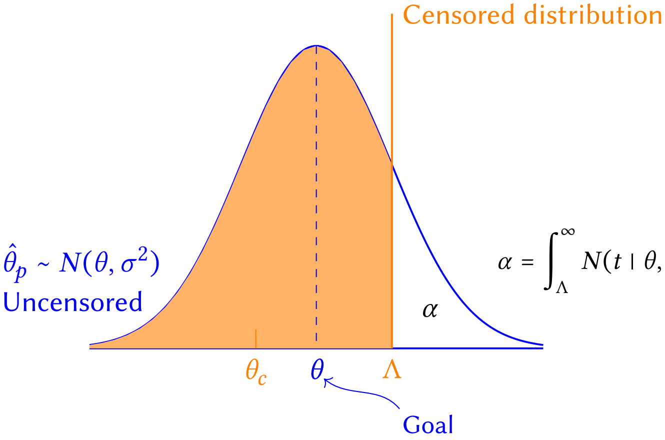

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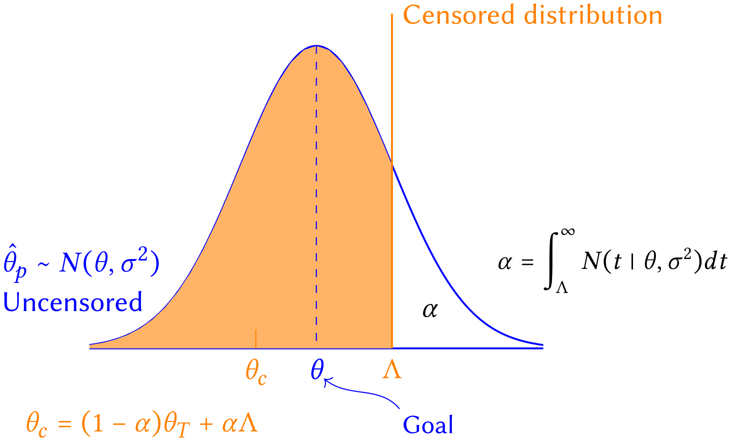

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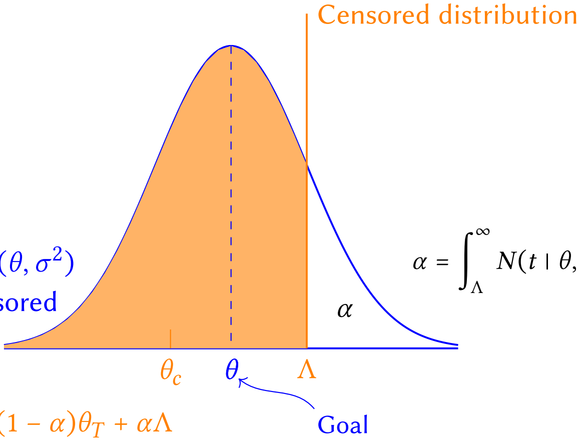

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Uncensored

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Equations: 2

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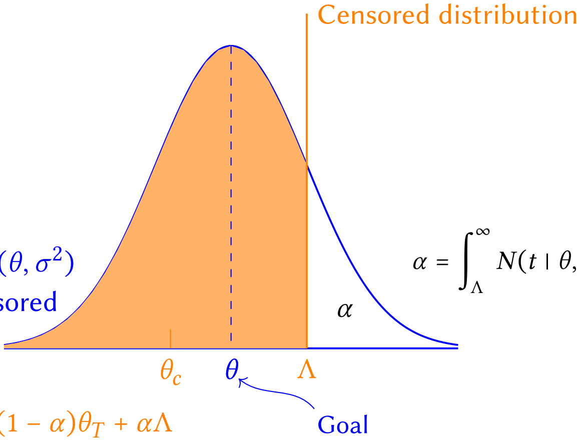

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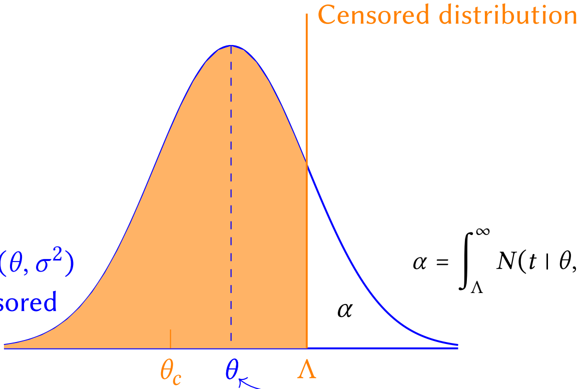

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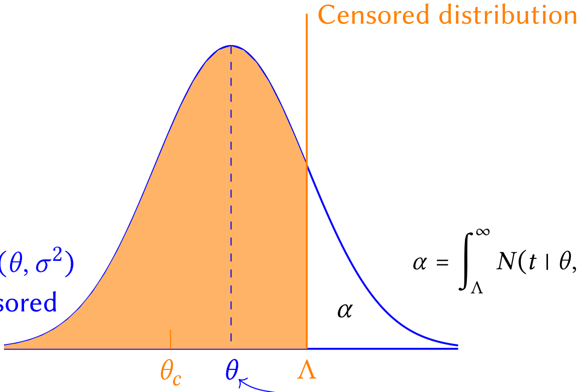

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- Simulate estimates via standard (Clarify) procedures:

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Simulations: Finite Sample Evaluation

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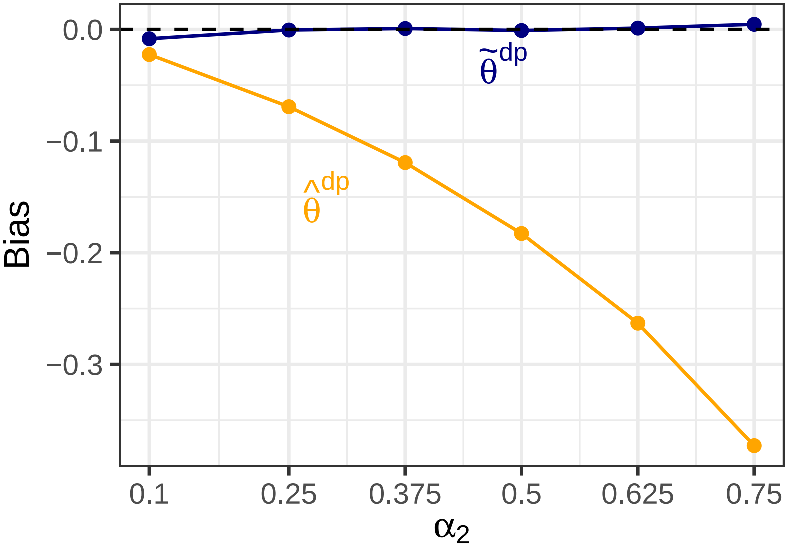

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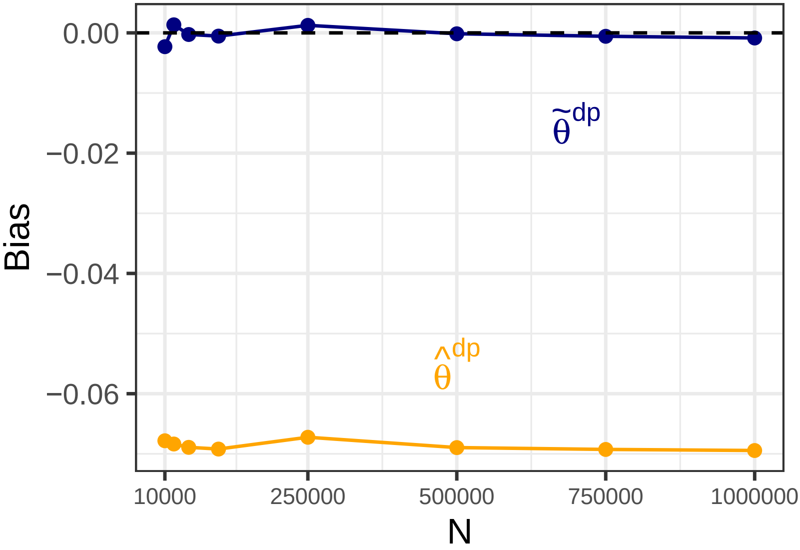

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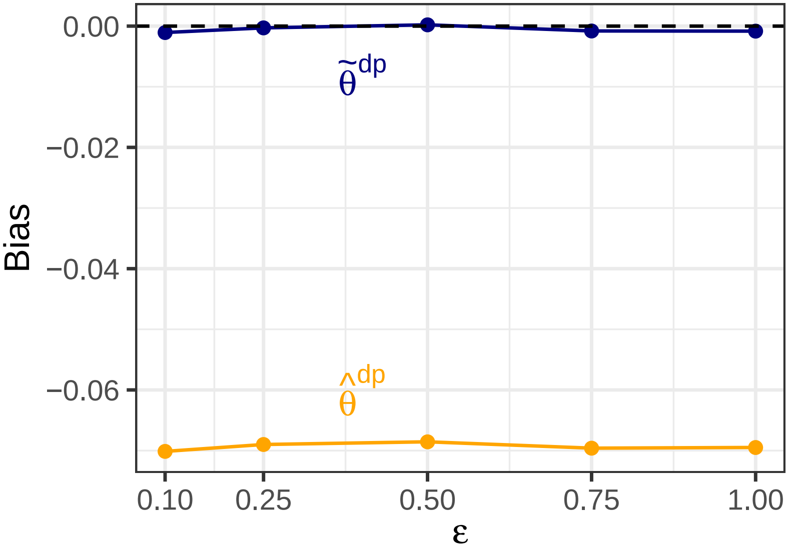

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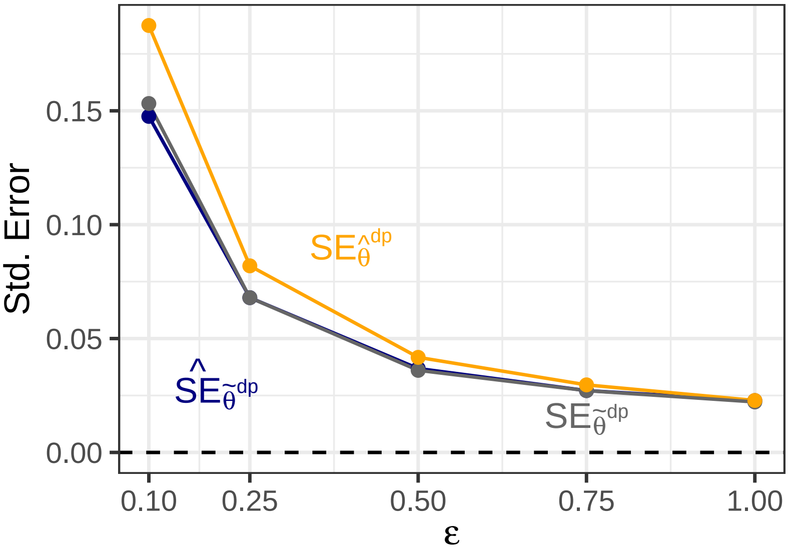

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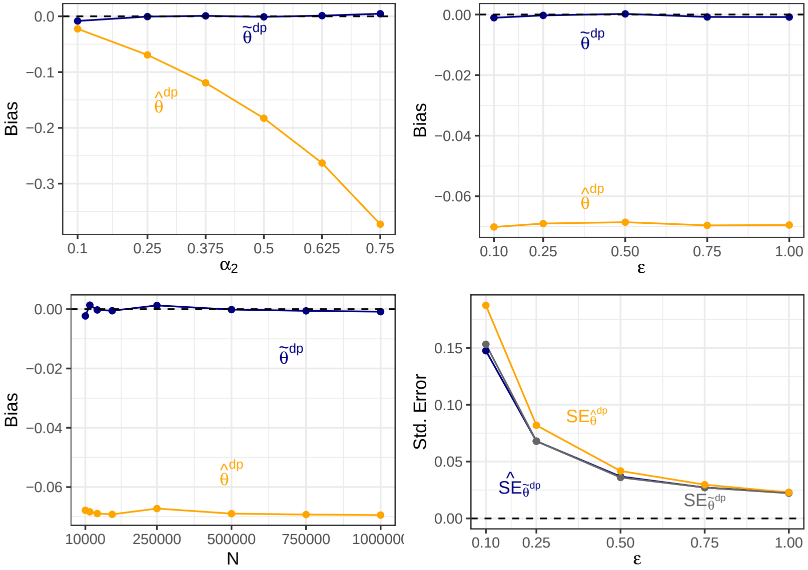

Concluding Remarks

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  - Implementations in progress:

Concluding Remarks

- Data sharing $\rightsquigarrow$ data access
  - DP protects individual privacy
  - Enables inference to private database, not population
  - Usually biased, no uncertainty estimates
  - Fails to protect society from fallacious scientific conclusions
- Inferential validity
  - A scientific statement: not necessarily correct, but must have:
  - known statistical properties & valid uncertainty estimates
- Proposed algorithm
  - Generic: almost any statistical method or quantity of interest
  - Statistically unbiased, lower variance
  - Valid uncertainty estimates
  - Computationally efficient
  - Solves political problems technologically
  - Implementations in progress:
    - Facebook, Microsoft+Harvard/IQSS, OpenDP

For more information

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Paper, software, slides, video: GaryKing.org/dp

Appendix

Properties of Differential Privacy

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