Statistically Valid Inferences from Privacy Protected Data

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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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The Algorithm in Practice

Theories of Inference: Statistics vs. CS

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Population
⋮
Maria
Adel
Károly
Connor
Georgie
Gary
Meg
Abhradeep
Tim
John

Mean income: $48

Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample
⋮	✗
Maria	✓
Adel	✓
Károly	✓
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Abhradeep	✓
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John	✓

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Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample	$
⋮	✗	?
Maria	✓	122
Adel	✓	76
Károly	✓	145
Connor	✓	96
Georgie	✓	86
Gary	✓	127
Meg	✓	72
Abhradeep	✓	132
Tim	✓	95
John	✓	134

Mean income: $48 Classical Inference $108

Quantity of Interest

Usually no direct relevance

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Mean income: \$48		\$108

Classical Inference

Quantity of Interest

Usually no direct relevance

Theories of Inference: Statistics vs. CS

Population	Sample	$	+Privacy
⋮	✗	?	
Maria	✓	122	Noise & Censoring
Adel	✓	76	
Károly	✓	145	
Connor	✓	96	
Georgie	✓	86	
Gary	✓	127	
Meg	✓	72	
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Mean income: $48 Classical Inference $108 Query-Response $111

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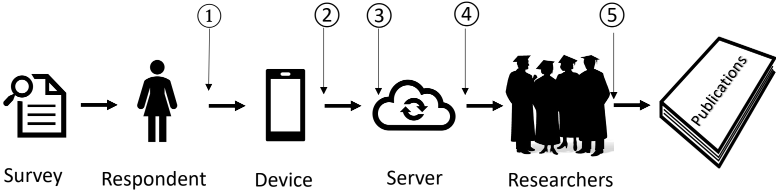
Mean income: $48		$108		$111

Classical Inference

Query-Response

Statistically Valid Inferences from Privacy Protected Data

ProtectingSurvey Data



Differential Privacy and its Inferential Challenges

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    - 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

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A Differentially Private Estimator

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Private data

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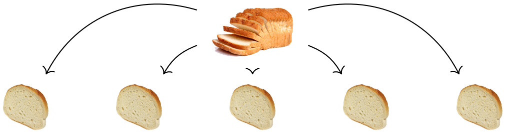
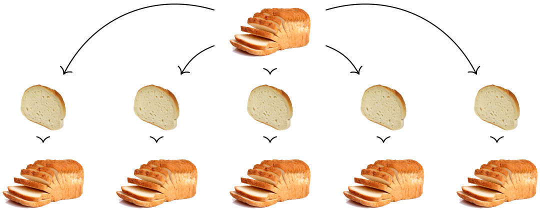


Private data

Partition

A Differentially Private Estimator



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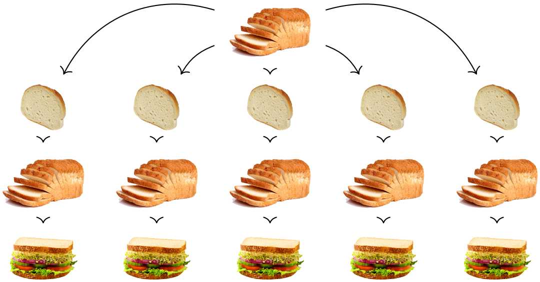

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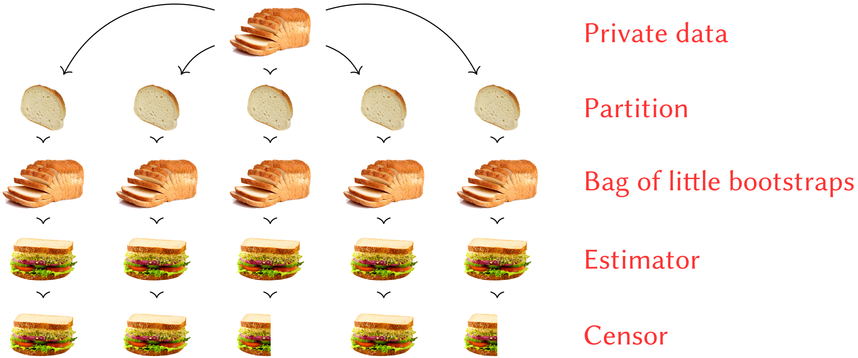

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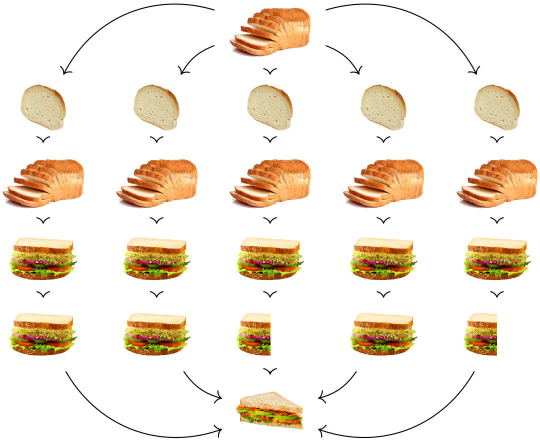

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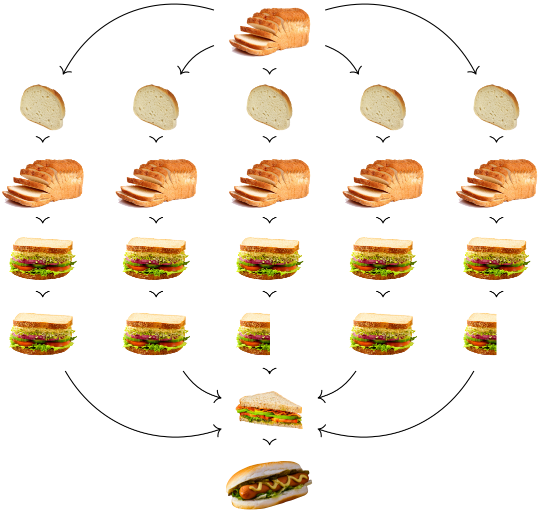

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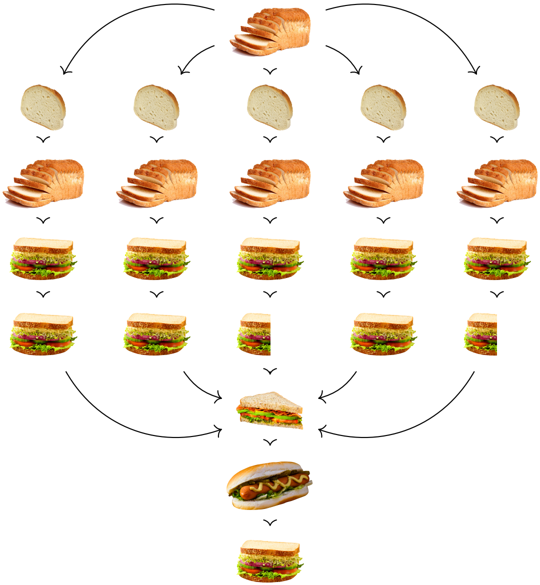

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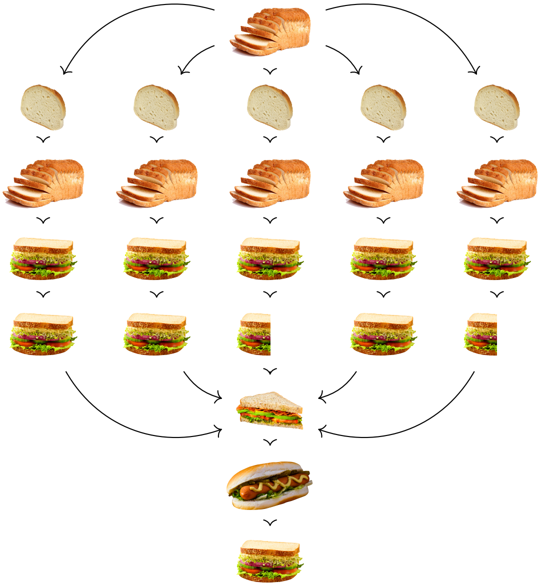

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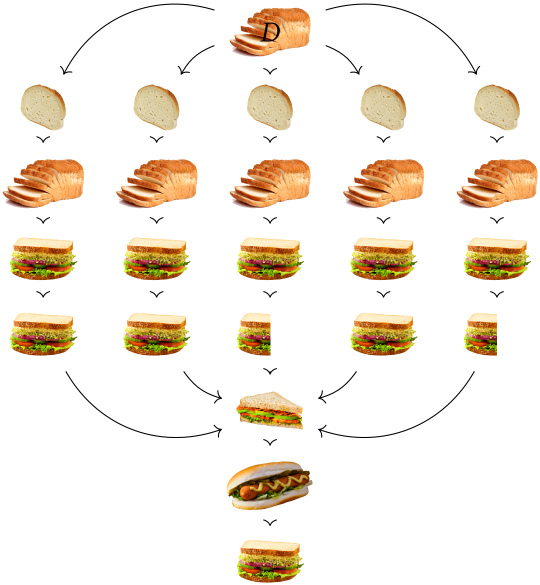

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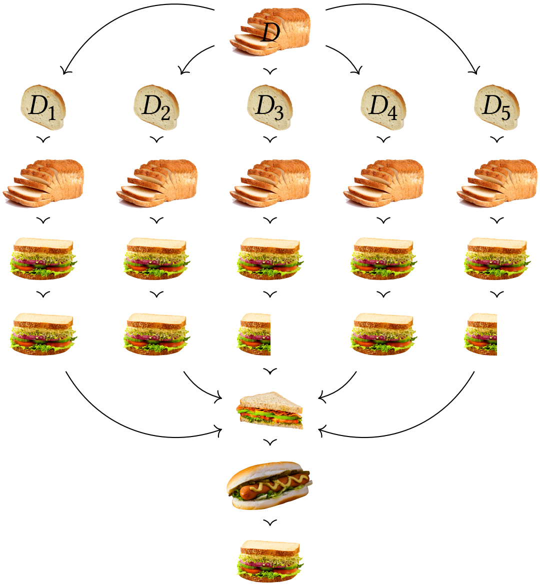

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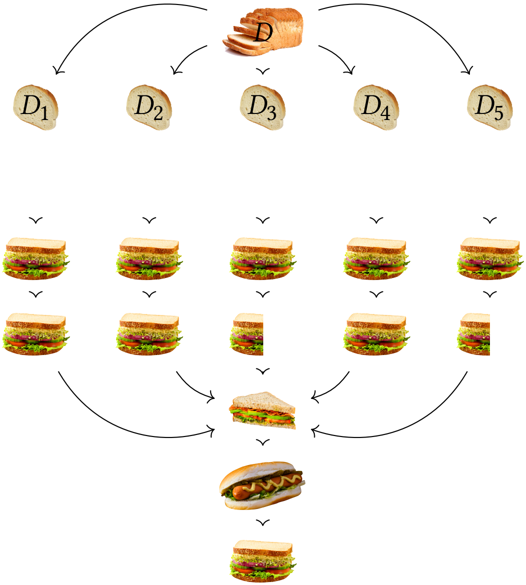

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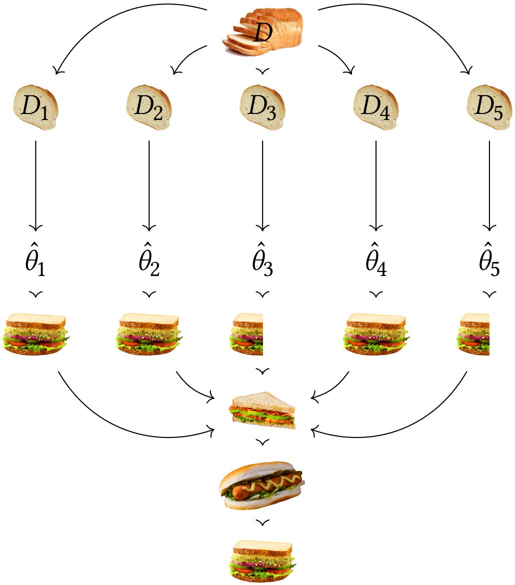

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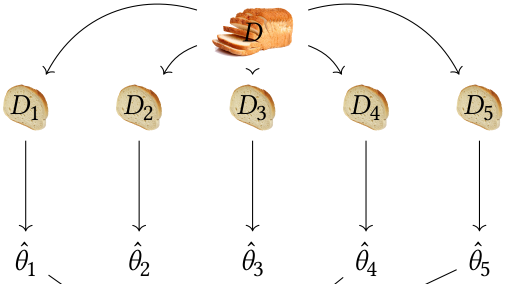

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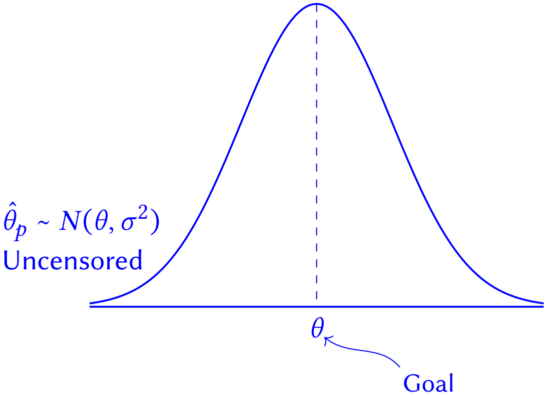

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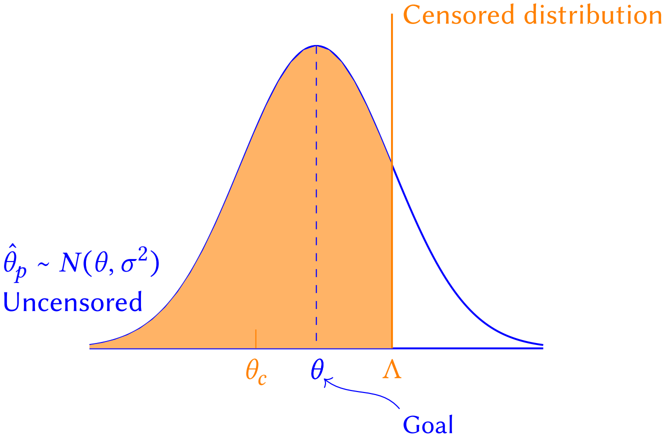

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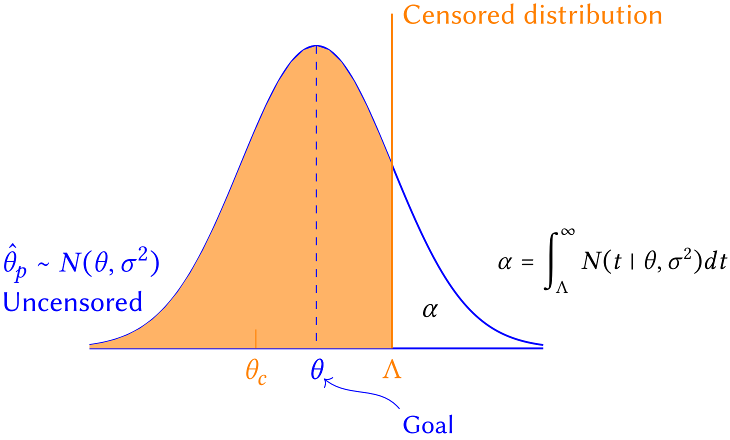

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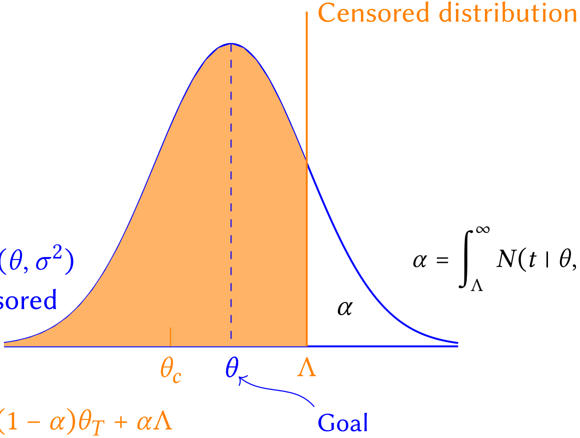
Uncensored



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

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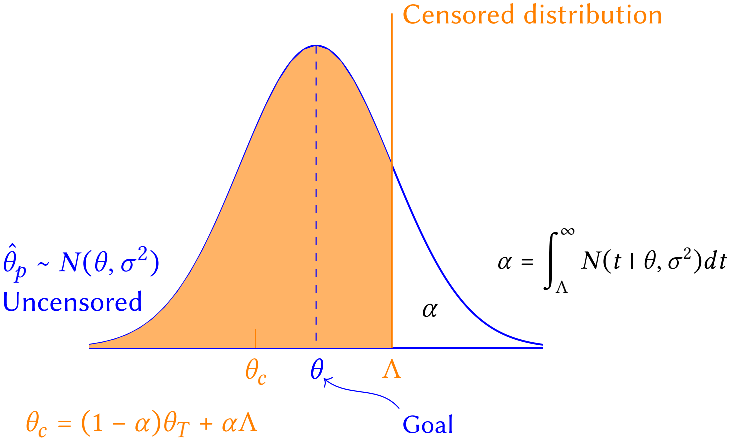

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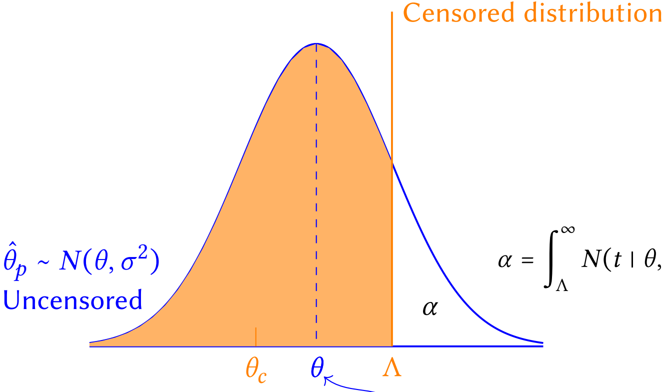

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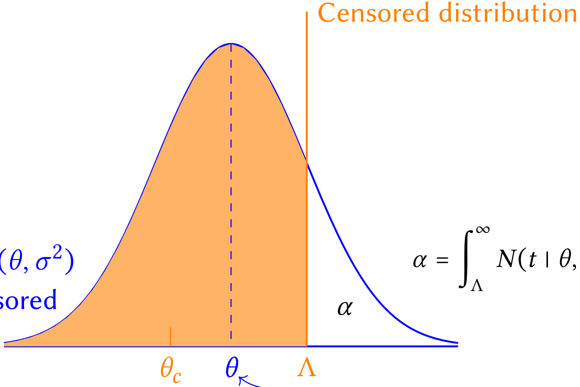

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Goal

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

Equations: 2

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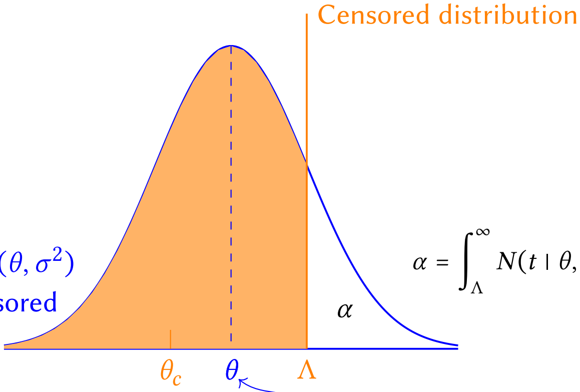

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- Simulate estimates via standard (Clarify) procedures:

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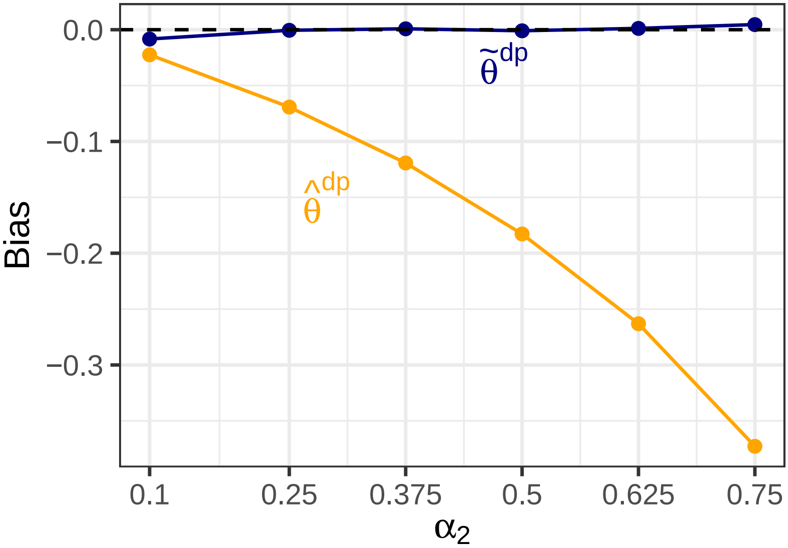

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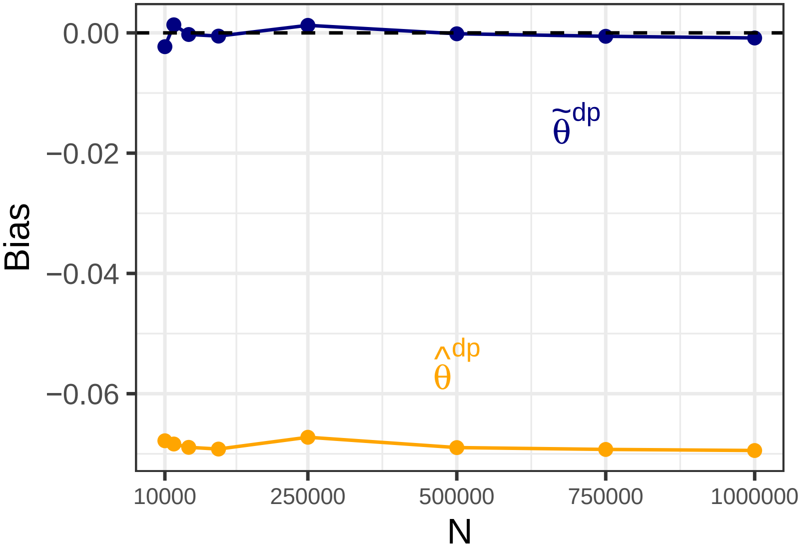

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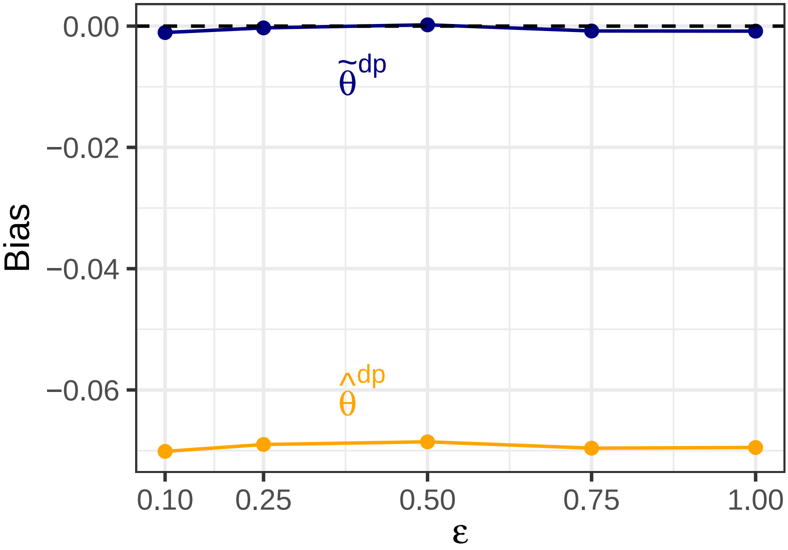

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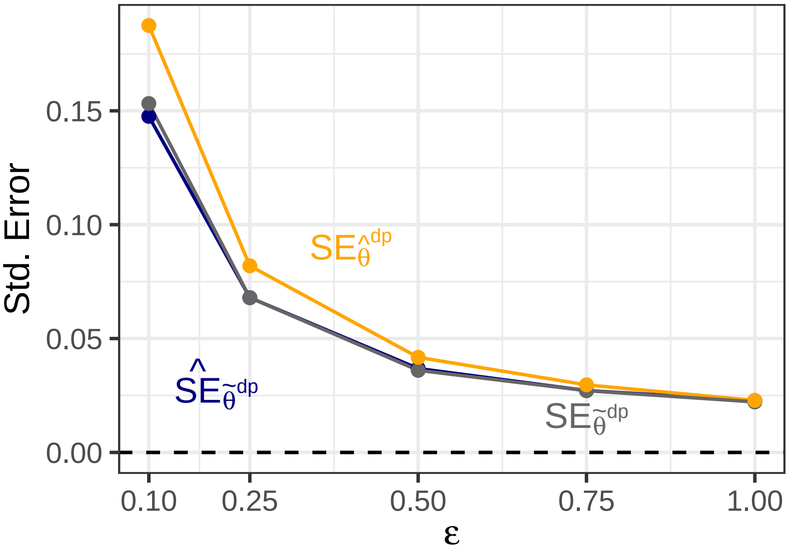

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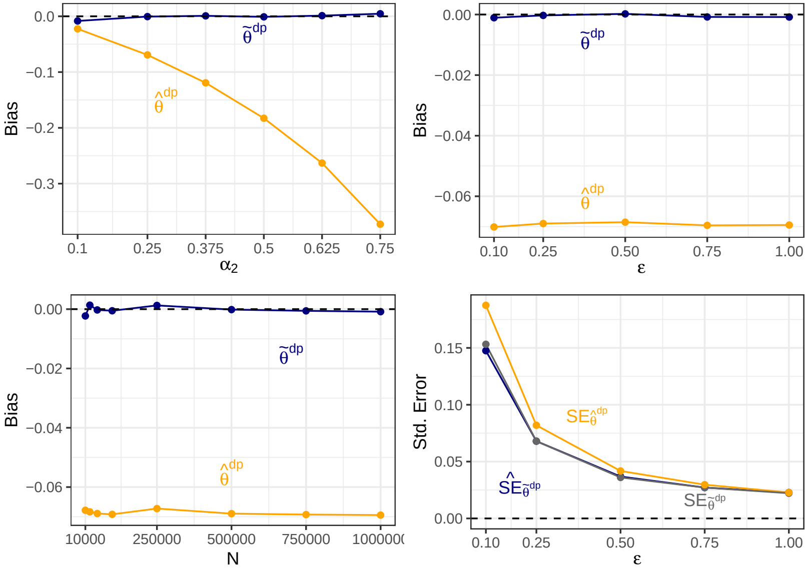

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  - Enables inference to private database, not population
  - Usually biased, no uncertainty estimates
  - Fails to protect society from fallacious scientific conclusions
- Inferential validity
  - A scientific statement: not necessarily correct, but 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

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Appendix

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