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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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
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$48	

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Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample	$
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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

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Mean income: $48		$108

Classical Inference

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Theories of Inference: Statistics vs. CS

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Maria	✓	122	
Adel	✓	76	
Károly	✓	145	Noise & Censoring
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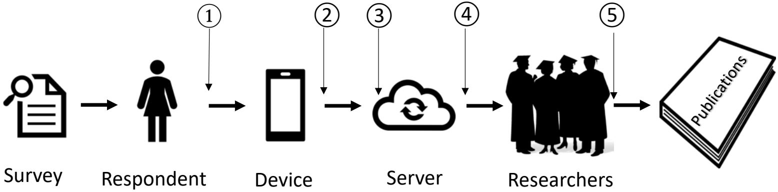
Classical Inference

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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    - Fundamental problems for statistical inference
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- Statistical properties: usually biased, no uncertainty estimates

Solving Political Problems Technologically

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The Algorithm in Practice

A Differentially Private Estimator

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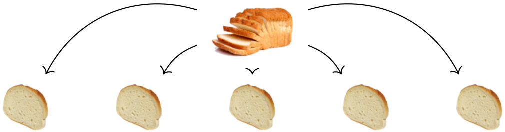
Private data

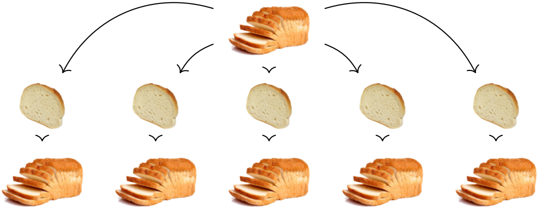
A Differentially Private Estimator



Private data

Partition

A Differentially Private Estimator



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Bag of little bootstraps

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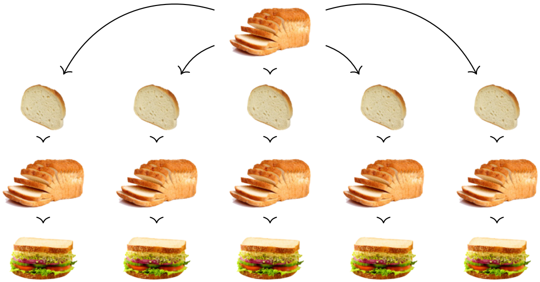

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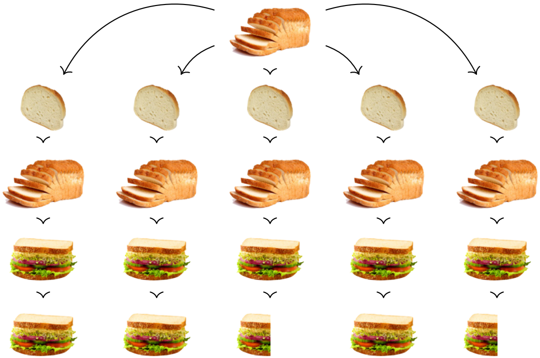

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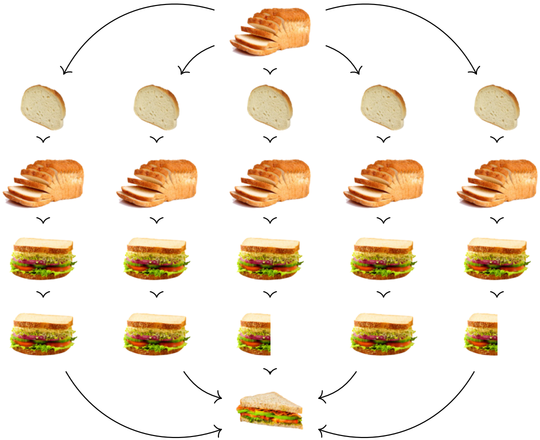

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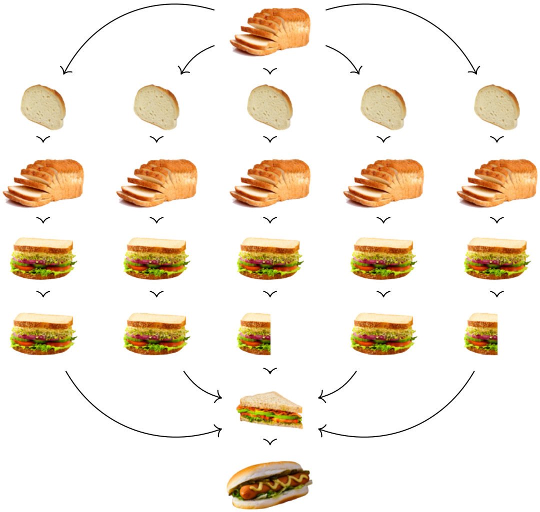

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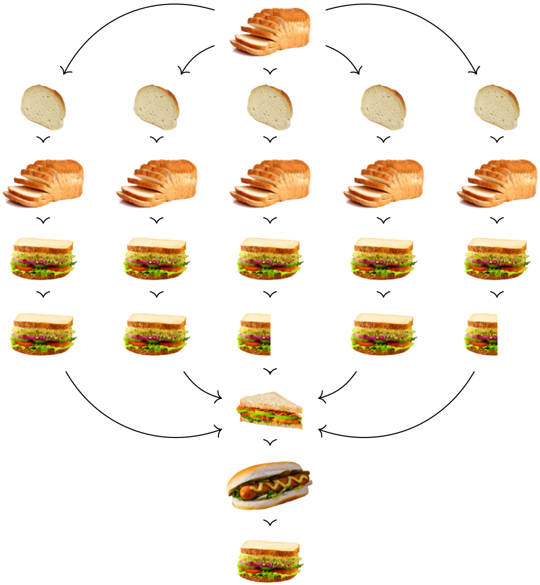

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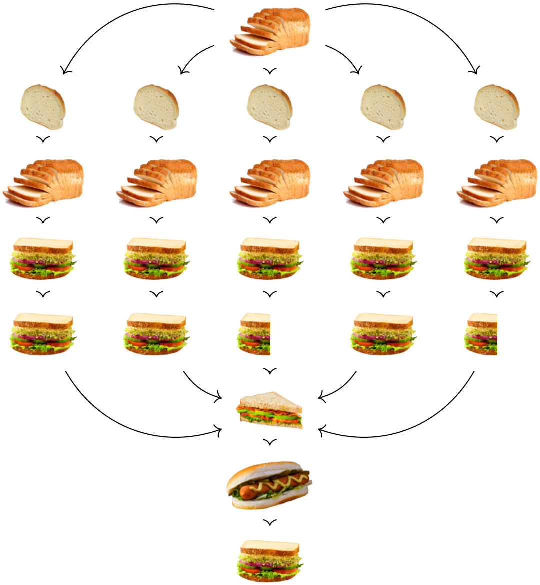

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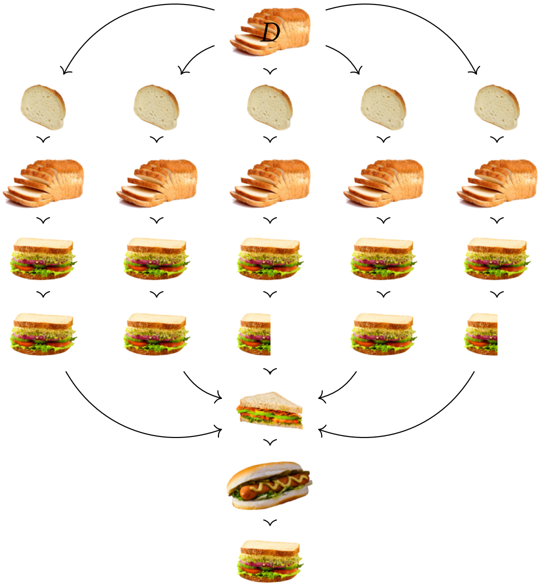

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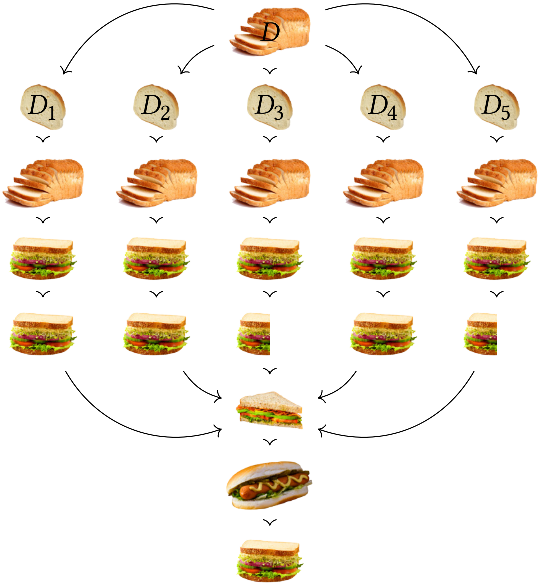

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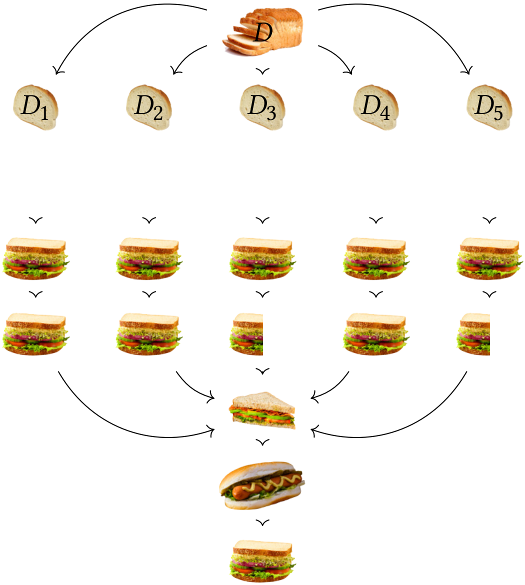

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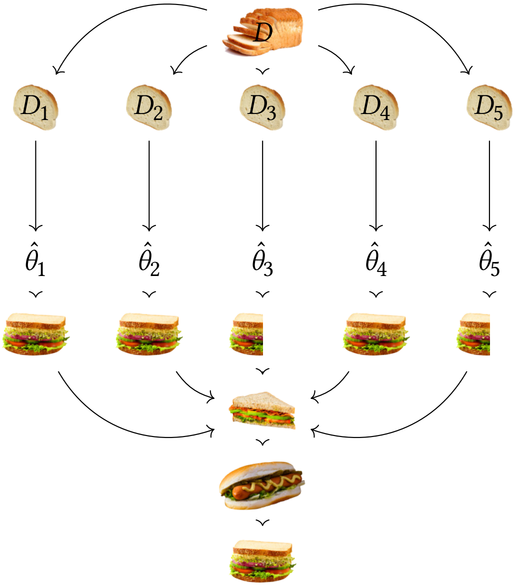

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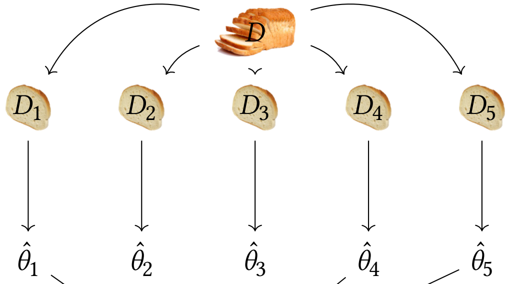

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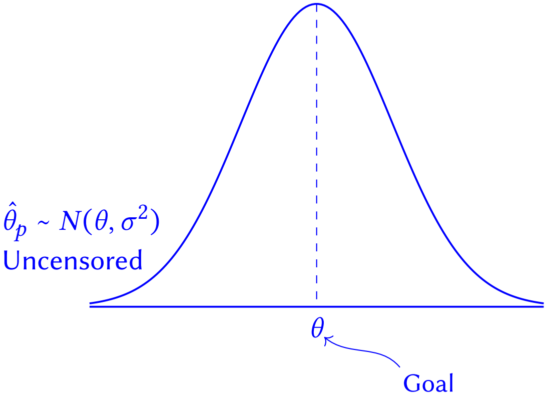

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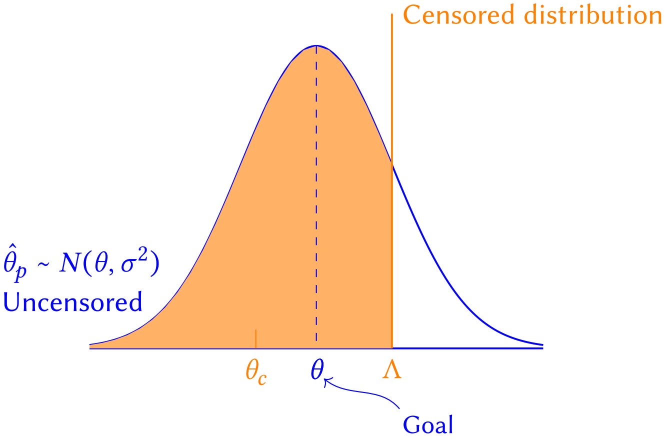

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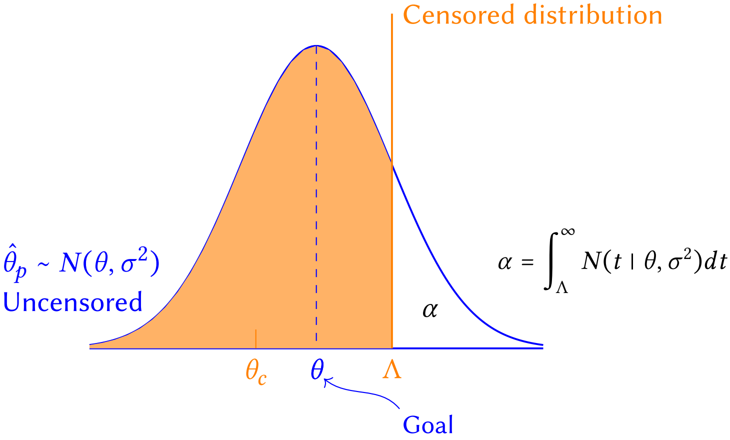

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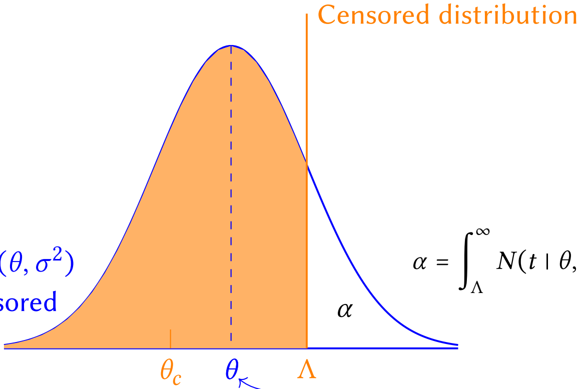
Uncensored



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

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Goal

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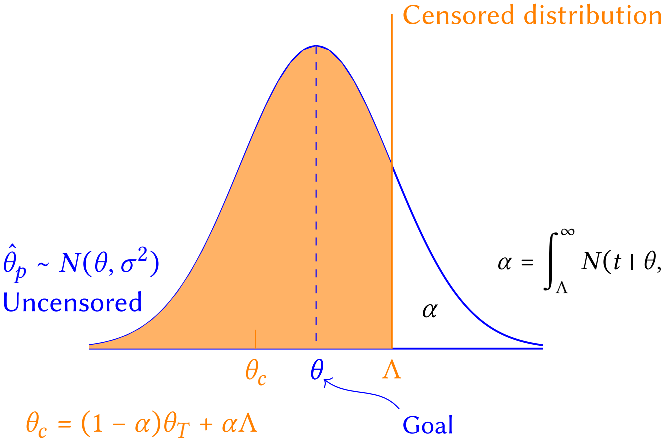

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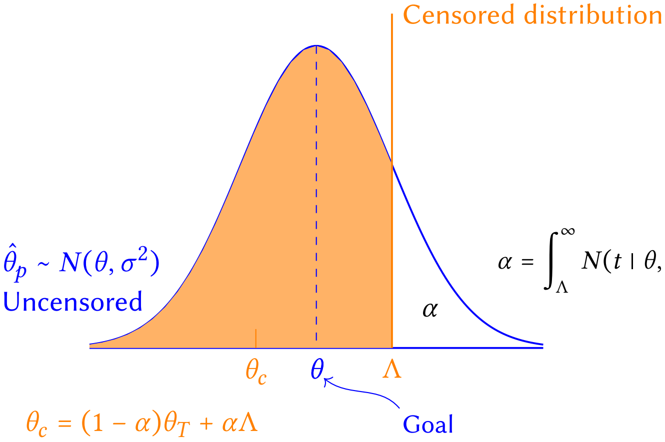

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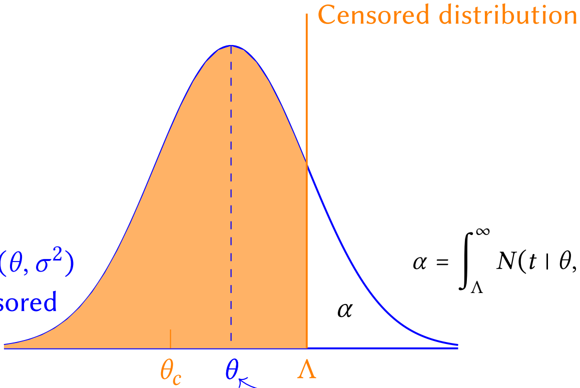

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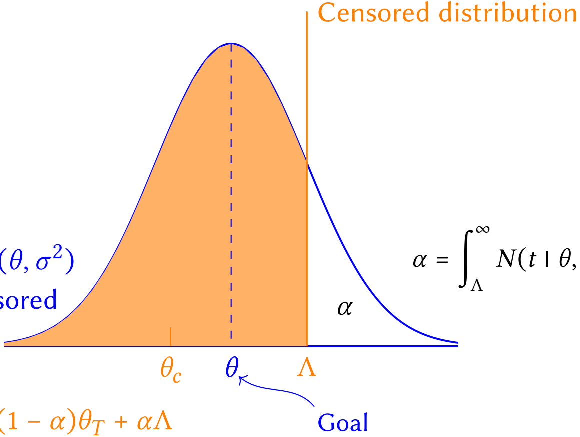

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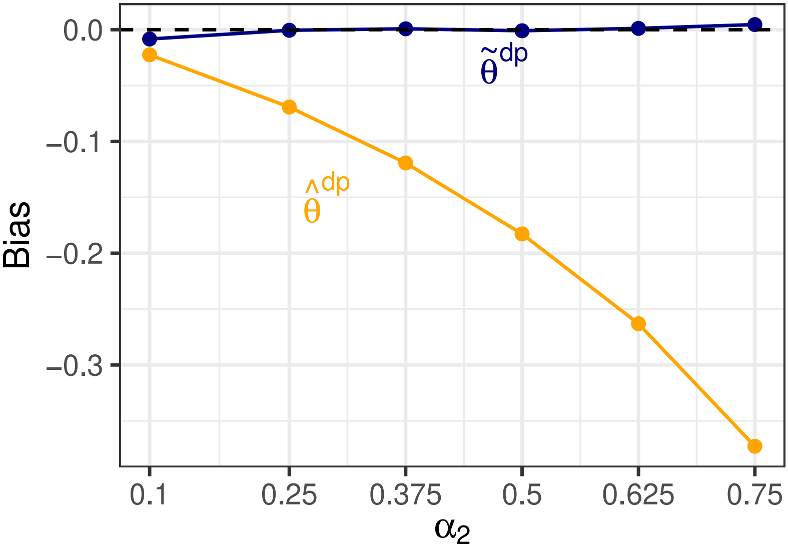

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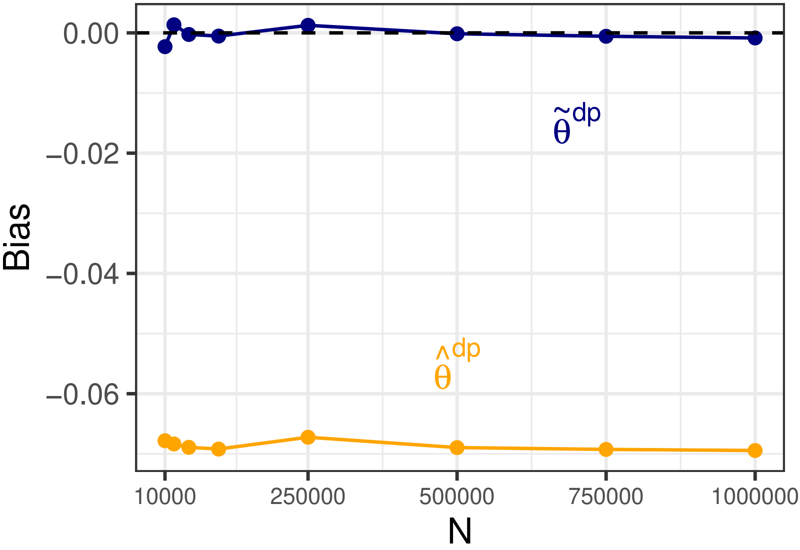

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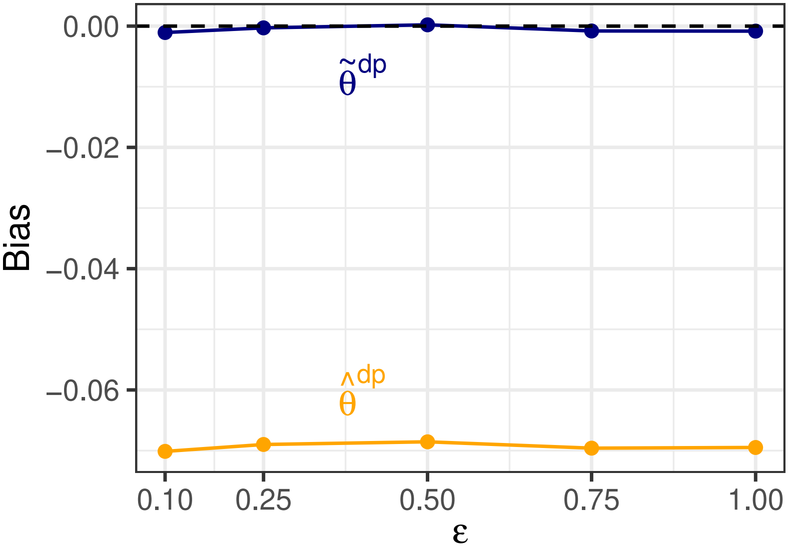

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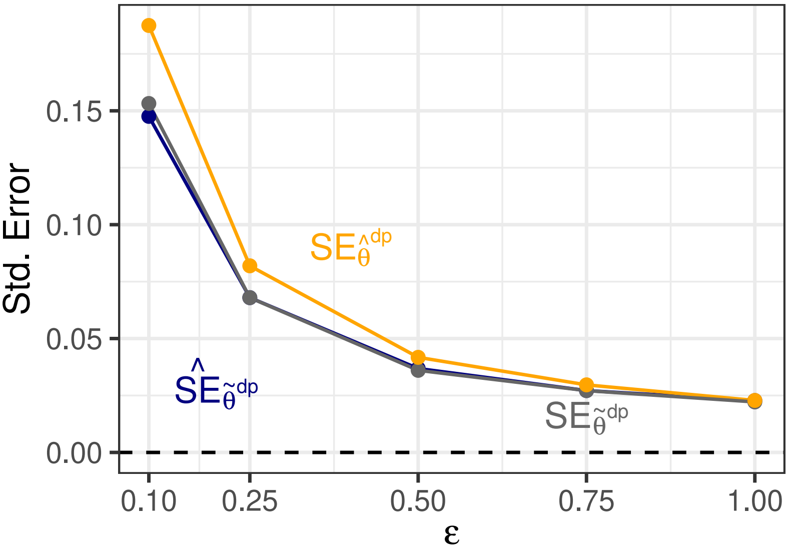

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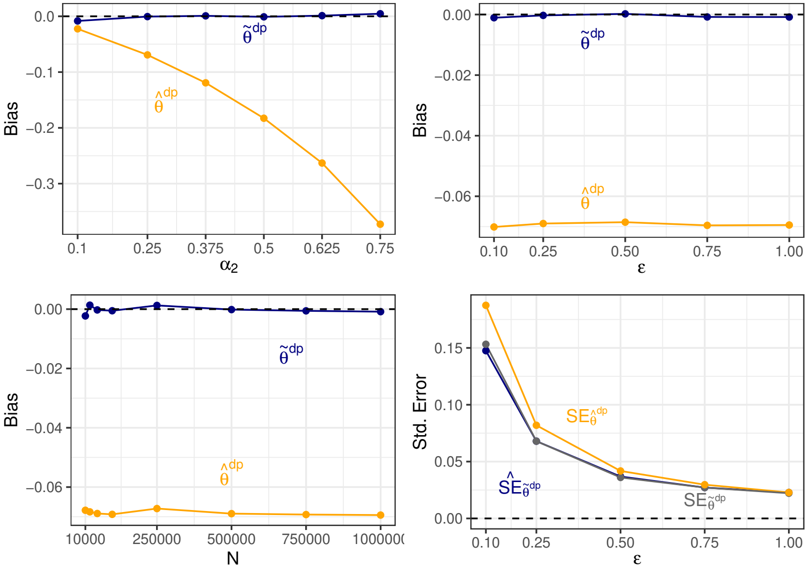

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Concluding Remarks

- 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

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- Georgina Evans and Gary King. Forthcoming. "Statistically Valid Inferences from Differentially Private Data Releases, with Application to the Facebook URLs Dataset" *Political Analysis*

Appendix

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  - With DP: ~~P-hacking~~, surveys treated like the Mars lander