Statistically Valid Inferences from Privacy Protected Data

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Pew Research Center, 4/24/2025

[1] GaryKing.org/privacy. Based on APSR/AJPS/PA articles with subsets of {Georgie Evans, Meg Schwenzfeier, Adam D. Smith, Abhradeep Thakurta}

Progress in Social Science

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  - I.e., everyone gets what they want, without balancing.

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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- New Problem: Sharing data without it leaving Facebook

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Population
⋮
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Claudia
Michelle
Courtney
Neha
Monica
Alan
Mark Hugo
Katerina Eva
Kim

Mean income: $48

Quantity of Interest

Theories of Inference: Statistics vs. CS

Population	Sample
⋮	✗
Michael	✓
Claudia	✓
Michelle	✓
Courtney	✓
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Population	Sample	$
⋮	✗	?
Michael	✓	122
Claudia	✓	76
Michelle	✓	145
Courtney	✓	96
Neha	✓	86
Monica	✓	127
Alan	✓	72
Mark Hugo	✓	132
Katerina Eva	✓	95
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Population	Sample	$	+Privacy
⋮	✗	?	
Michael	✓	122	
Claudia	✓	76	
Michelle	✓	145	Noise & Censoring
Courtney	✓	96	
Neha	✓	86	
Monica	✓	127	
Alan	✓	72	
Mark Hugo	✓	132	
Katerina Eva	✓	95	
Kim	✓	134	
Mean income:	$48	$108	

Classical Inference

Quantity of Interest

Usually no direct relevance

Theories of Inference: Statistics vs. CS

Population	Sample	$	+Privacy	=dp$
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Michael	✓	122		85
Claudia	✓	76		103
Michelle	✓	145		75
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Neha	✓	86		125
Monica	✓	127		97
Alan	✓	72		101
Mark Hugo	✓	132		128
Katerina Eva	✓	95		83
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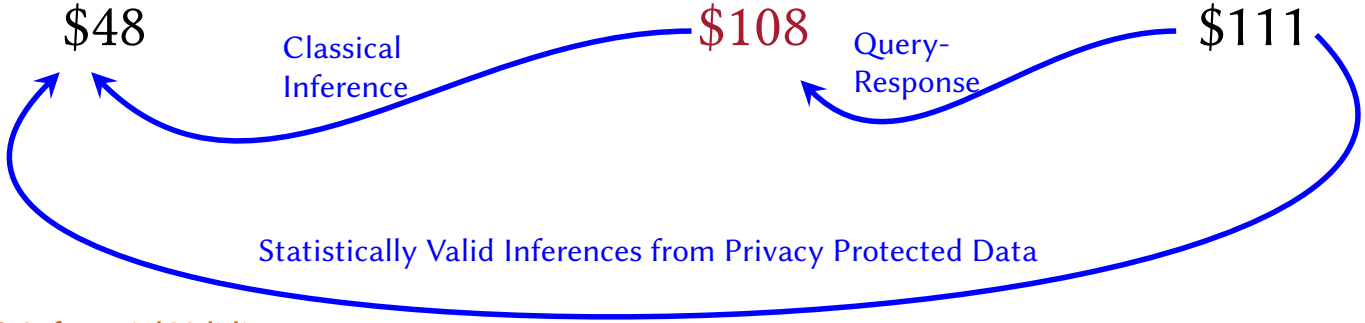
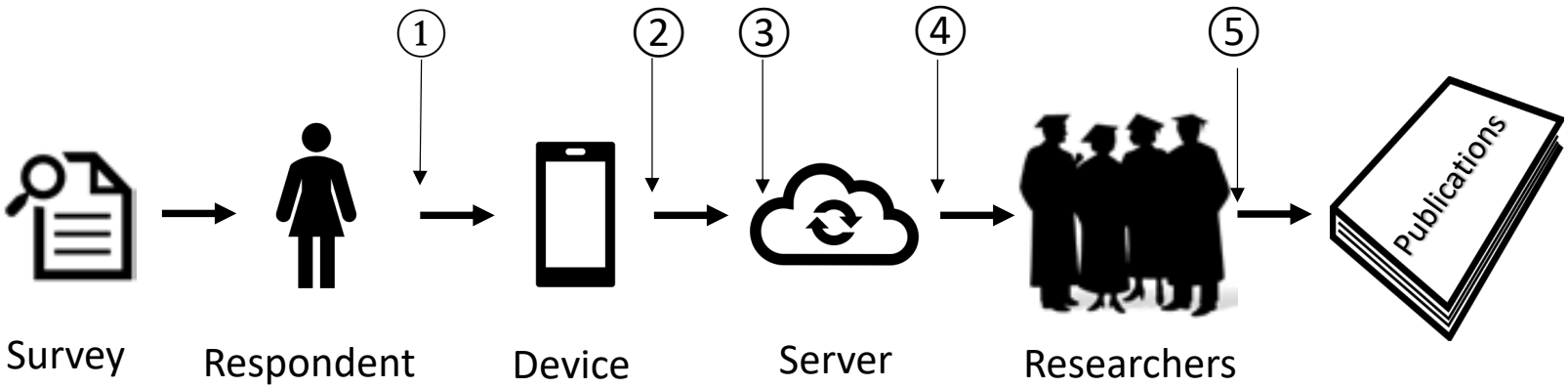
Noise & Censoring



Protecting Survey Data



Differential Privacy and its Inferential Challenges

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- Estimators

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  - Or: mess with gradients, $X_i' X_i$, data, QOIs, etc.
- Statistical properties: usually biased, no uncertainty estimates

Solving Political Problems Technologically

Differential Privacy & Inferential Validity

A General Purpose, Statistically Valid DP Algorithm

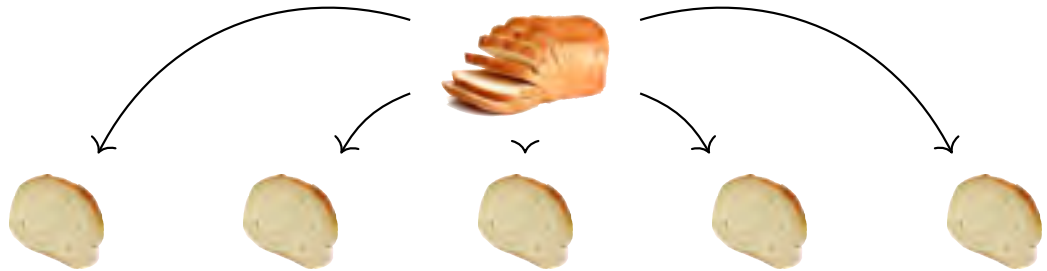
The Algorithm in Practice

A *Generic* Differentially Private Estimator

A *Generic* Differentially Private Estimator

Private data

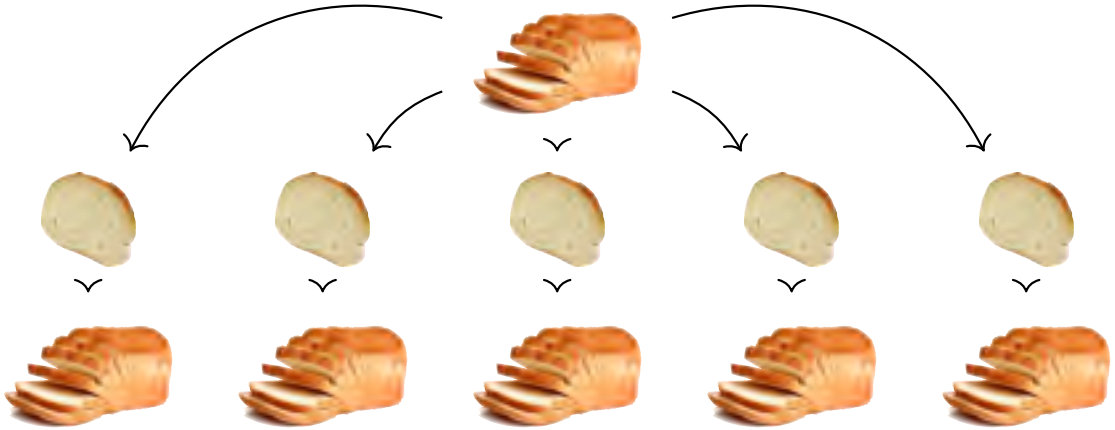
A *Generic* Differentially Private Estimator



Private data

Partition

A *Generic* Differentially Private Estimator

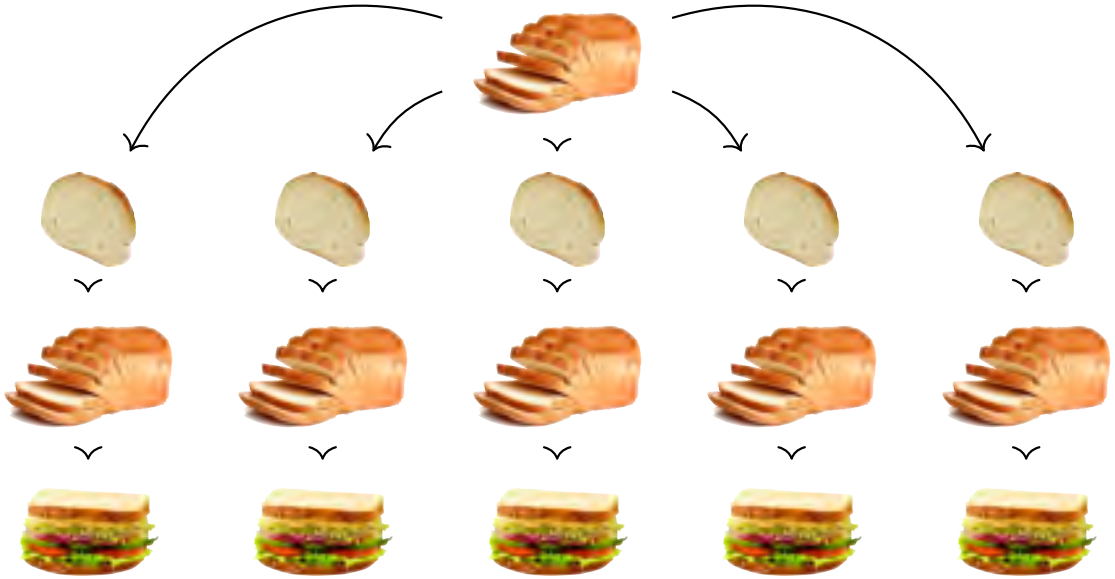


Private data

Partition

Bag of little bootstraps

A *Generic* Differentially Private Estimator



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Estimator

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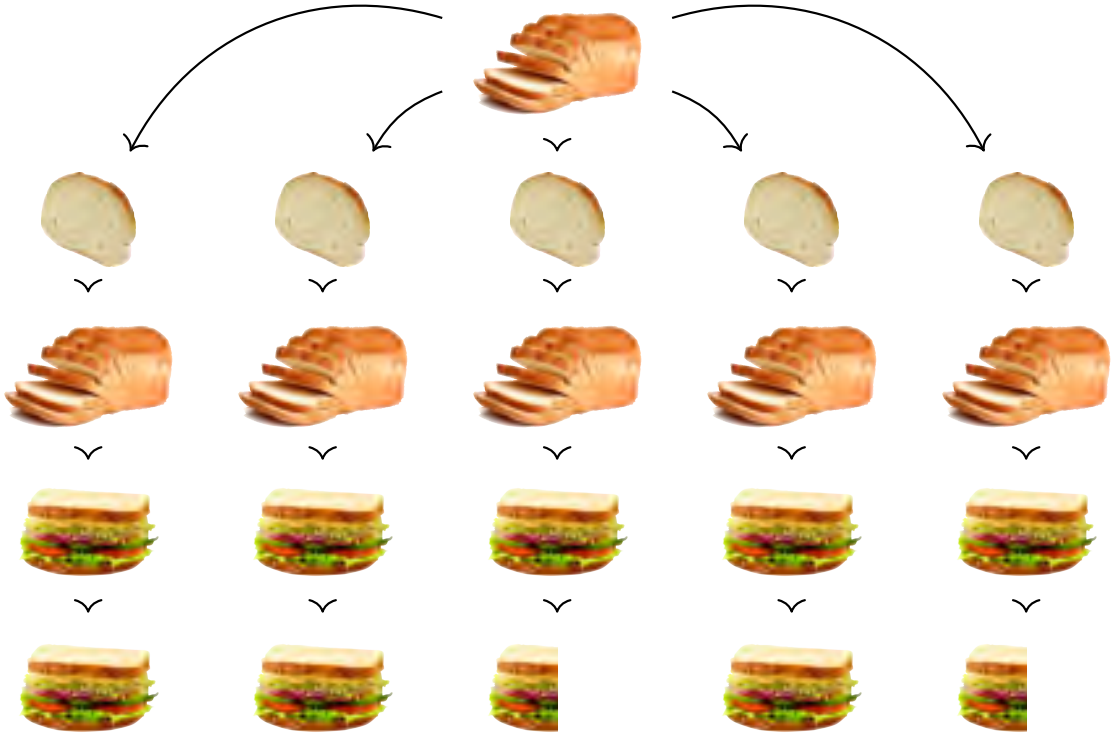

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Estimator

Censor

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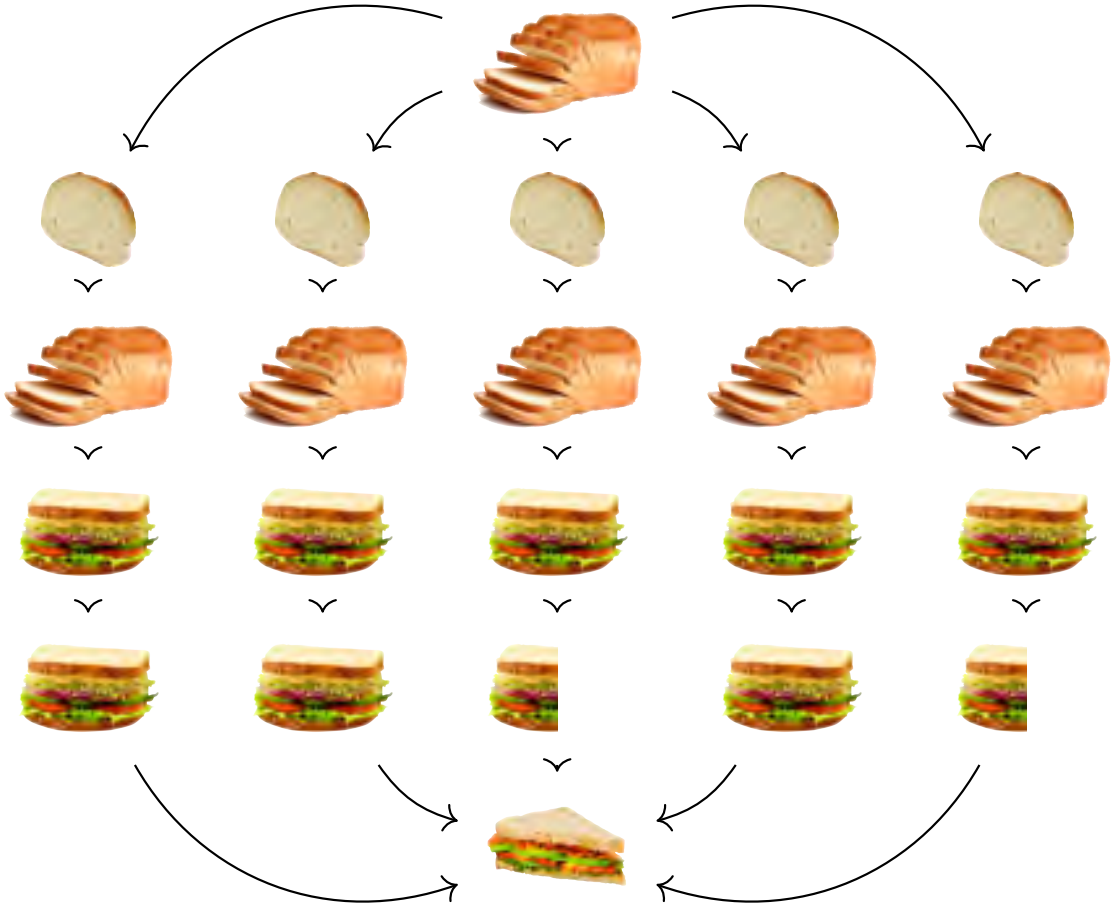

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Estimator

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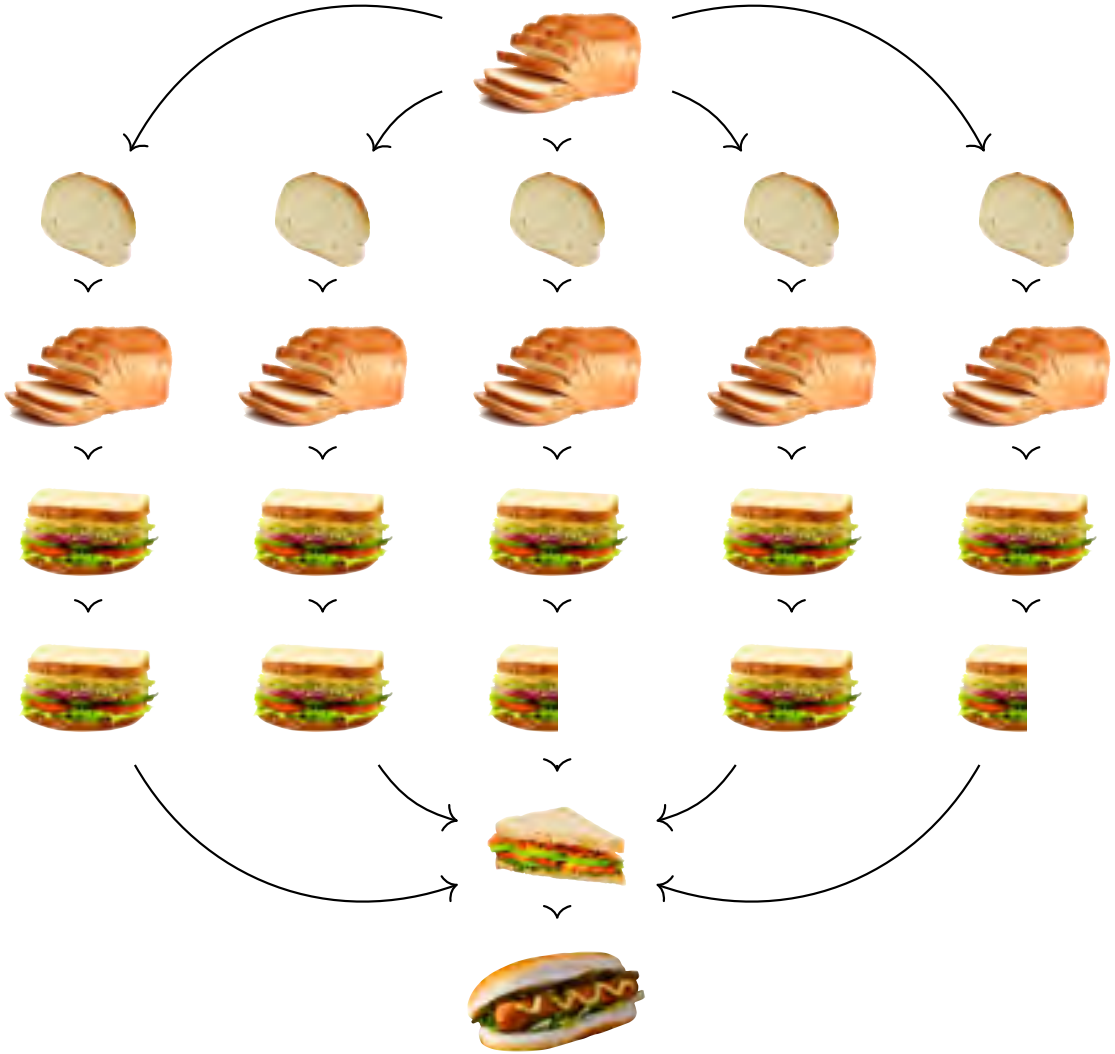

Private data

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Noise

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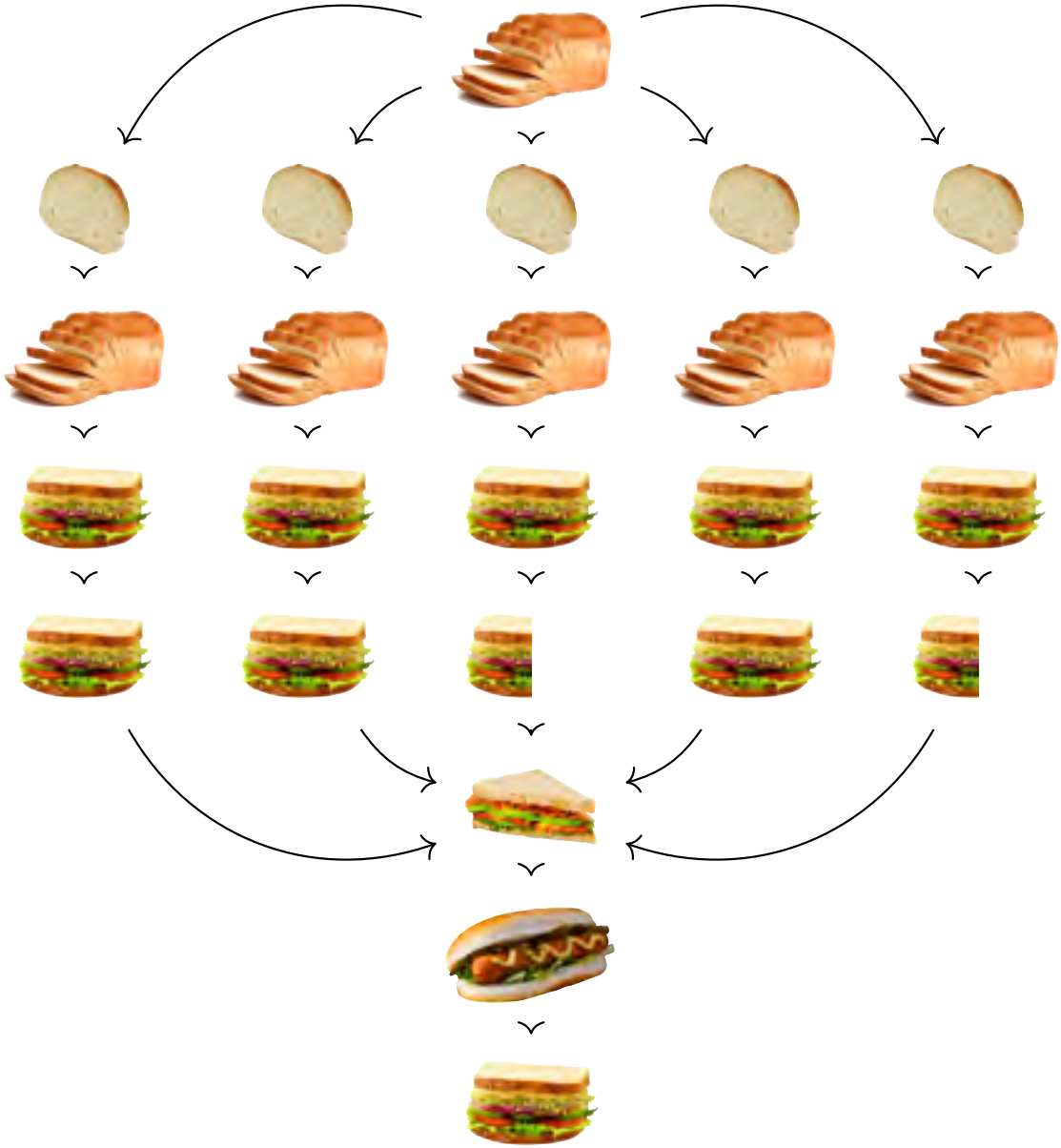

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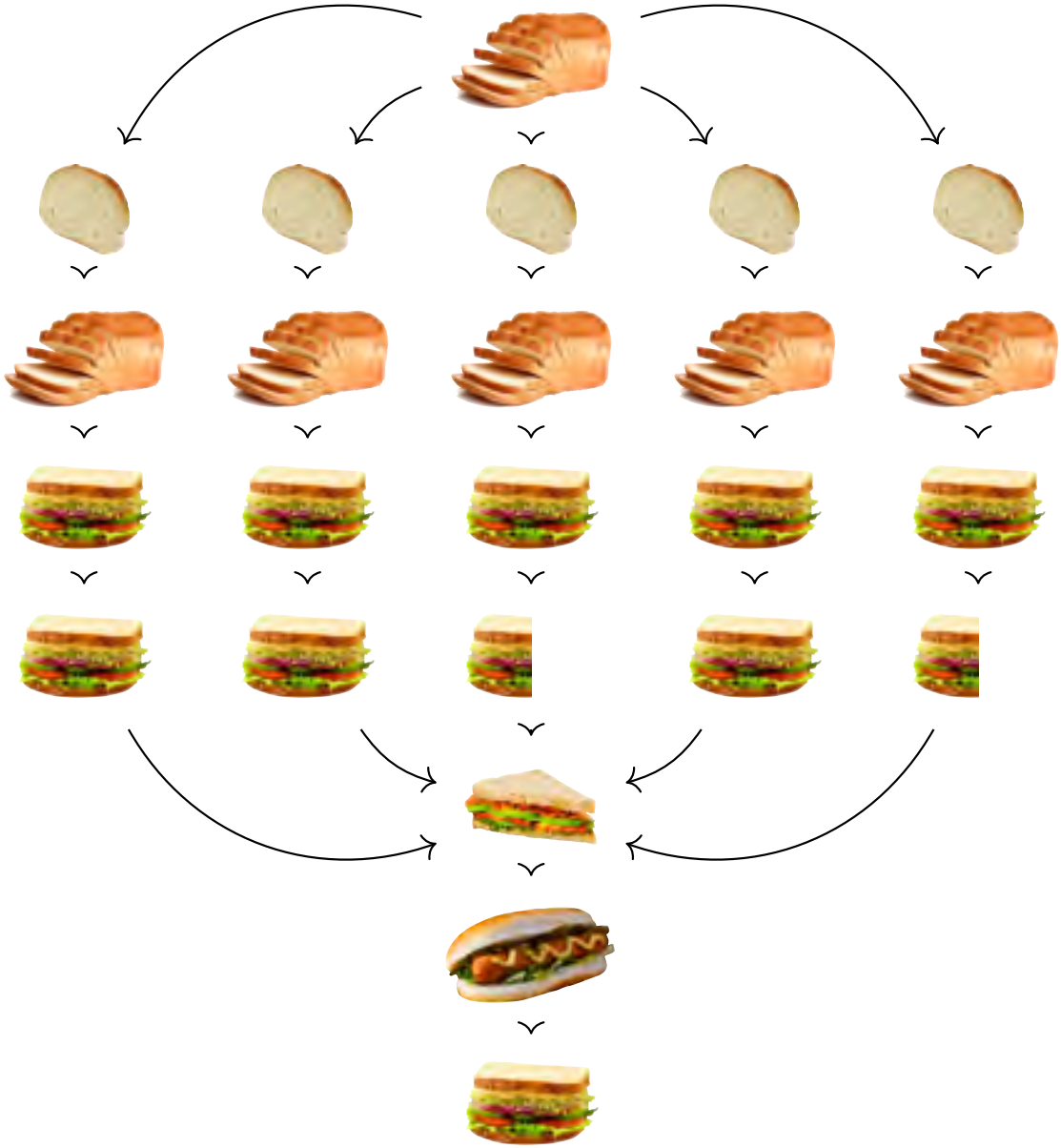

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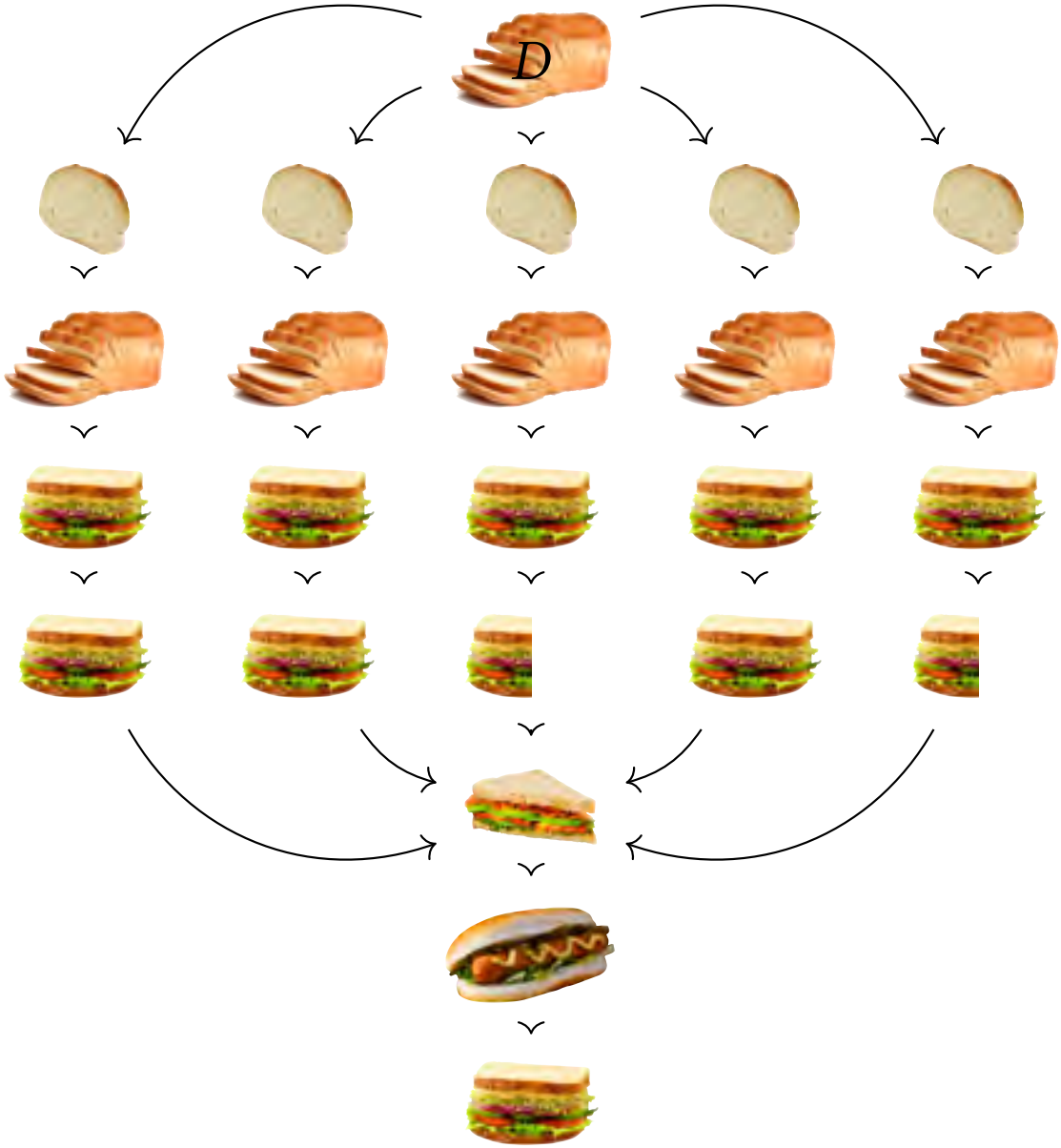

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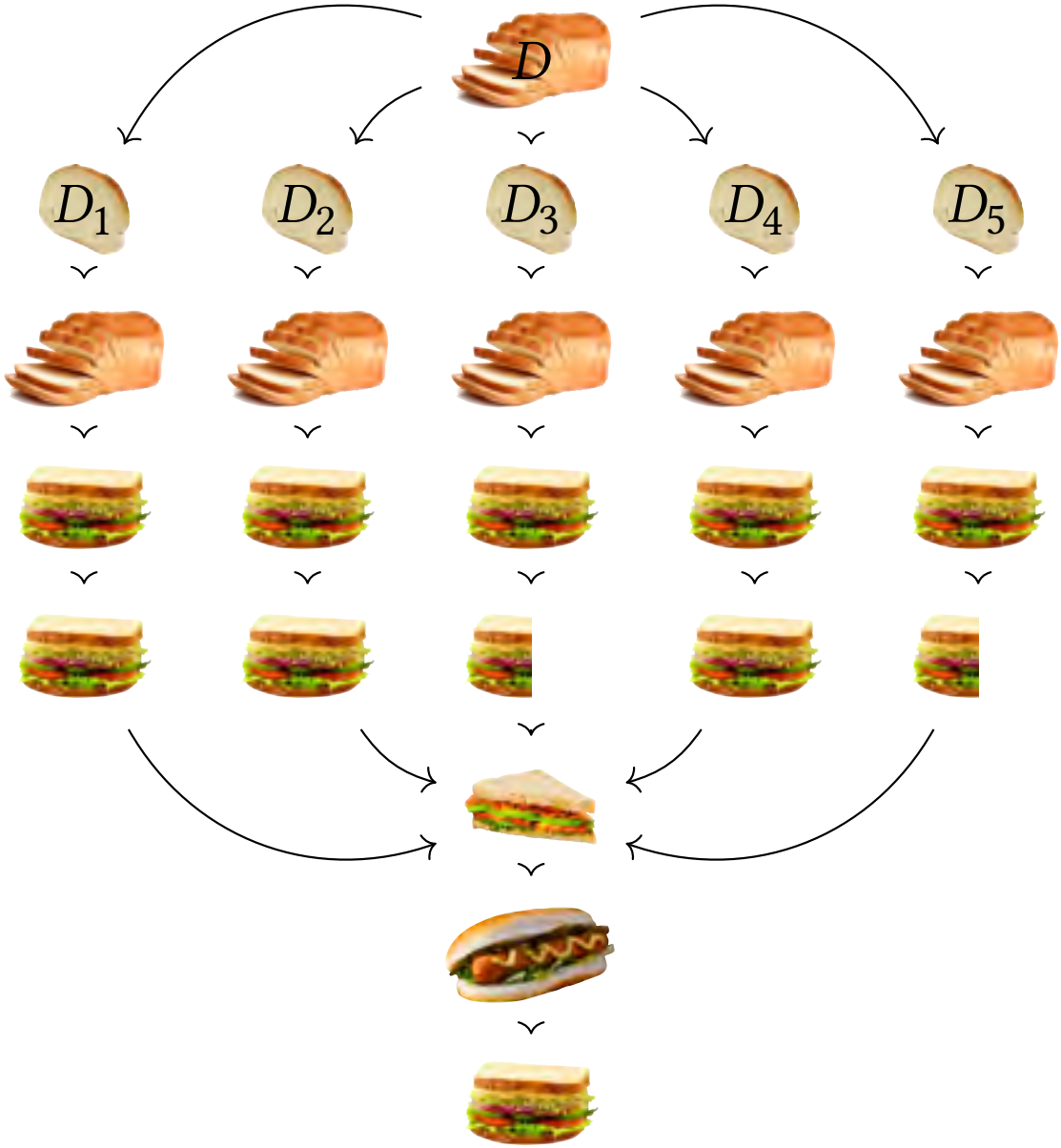

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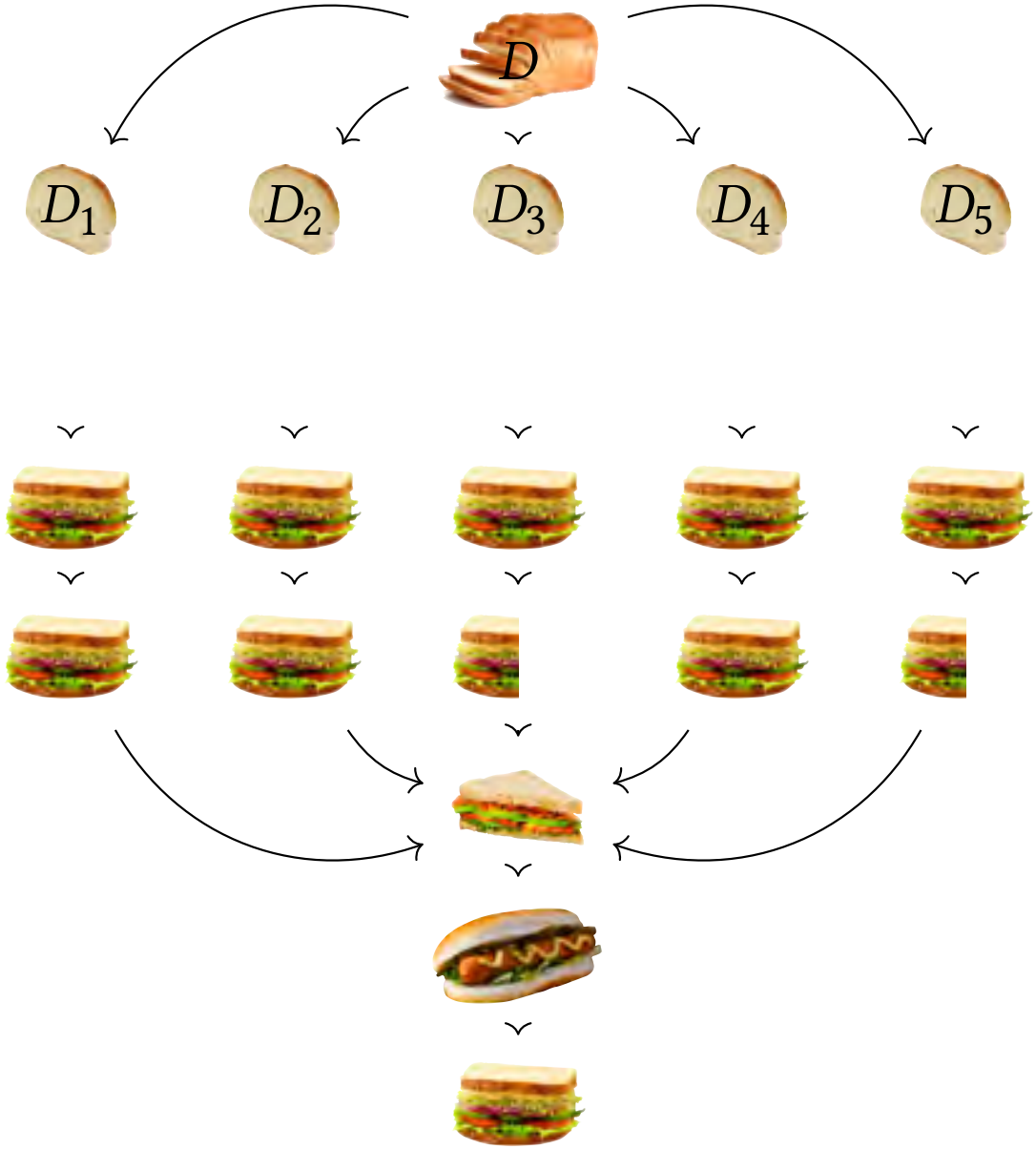

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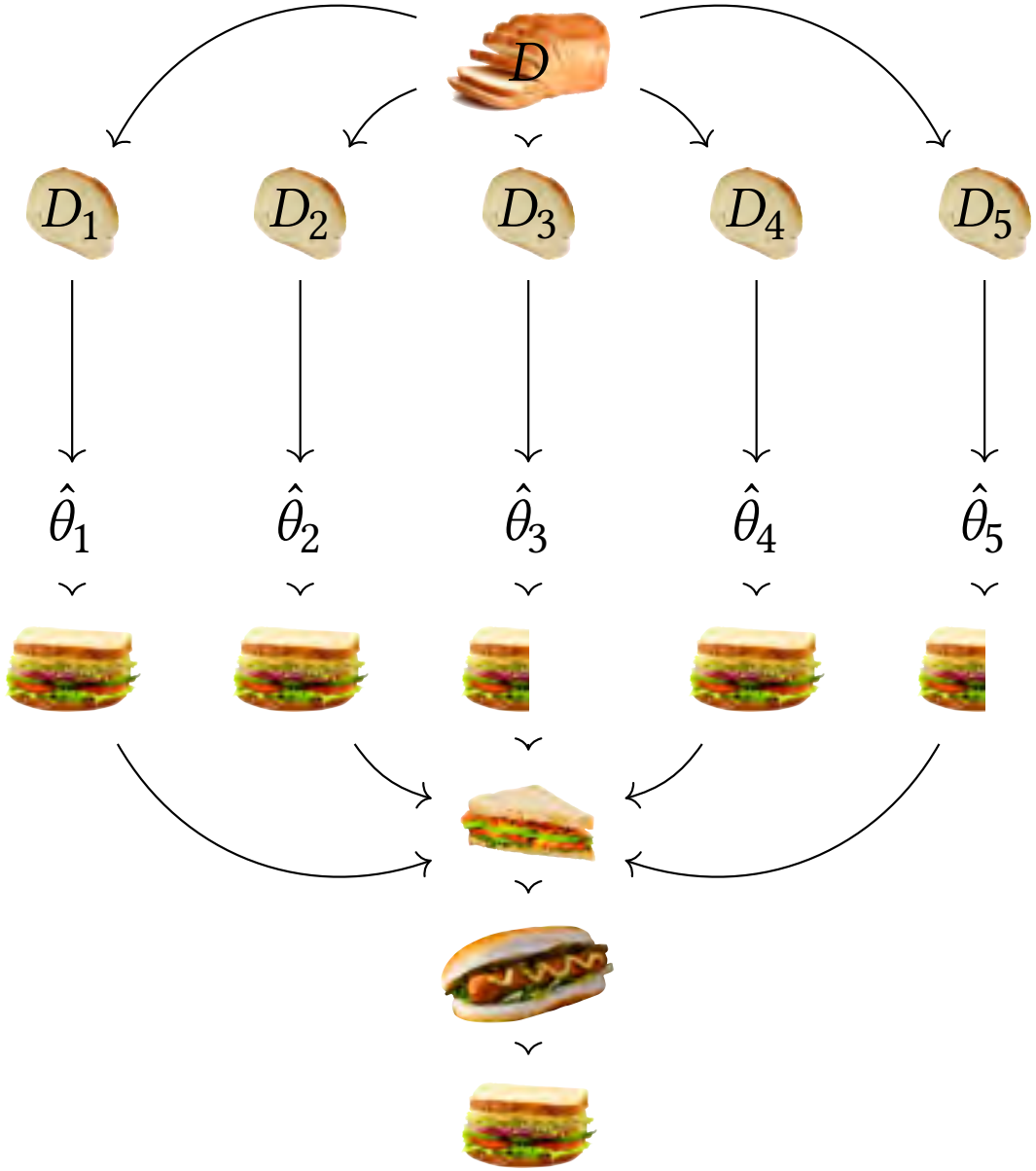

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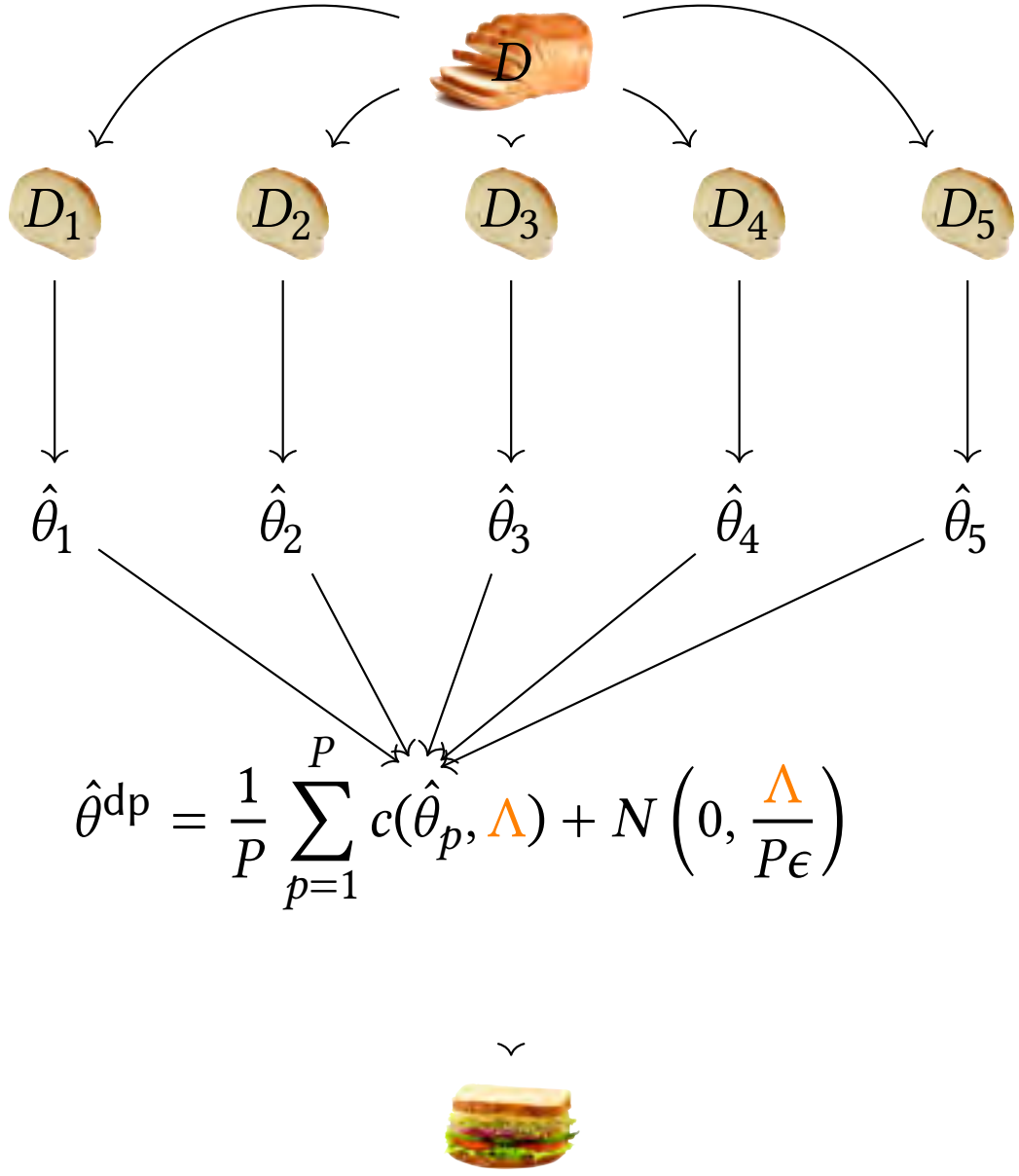

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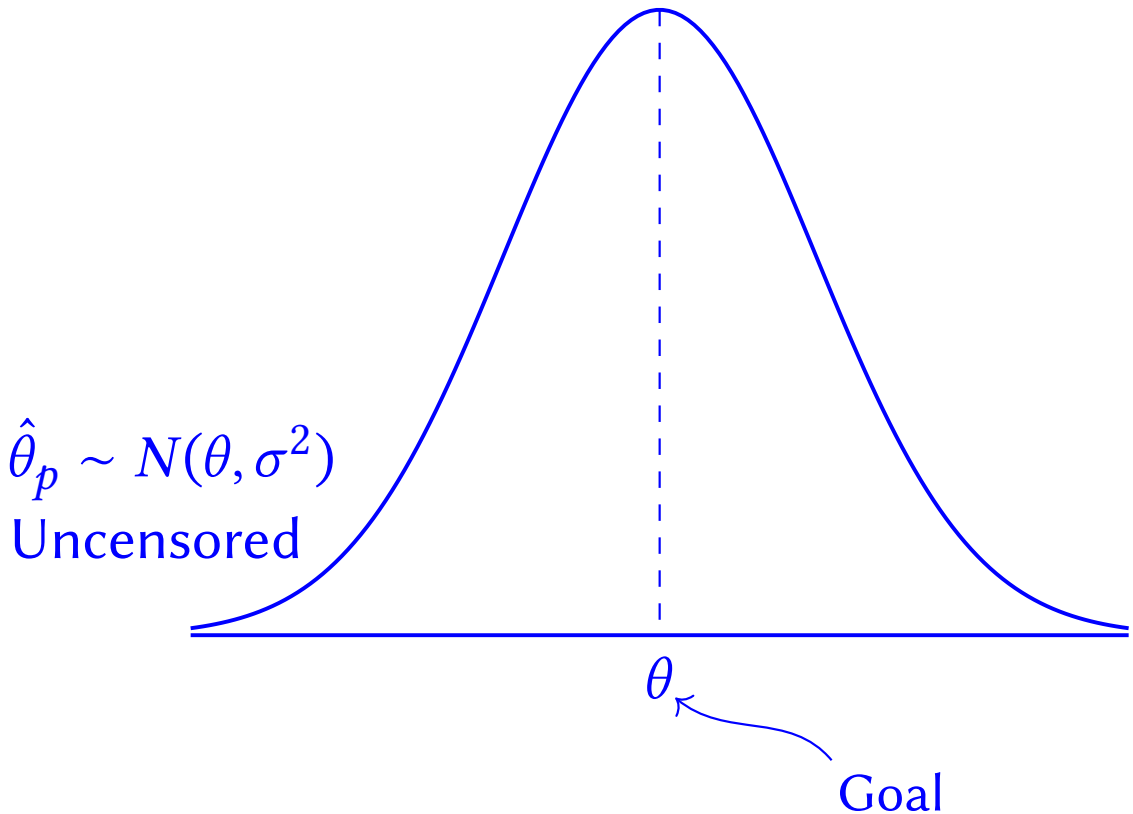

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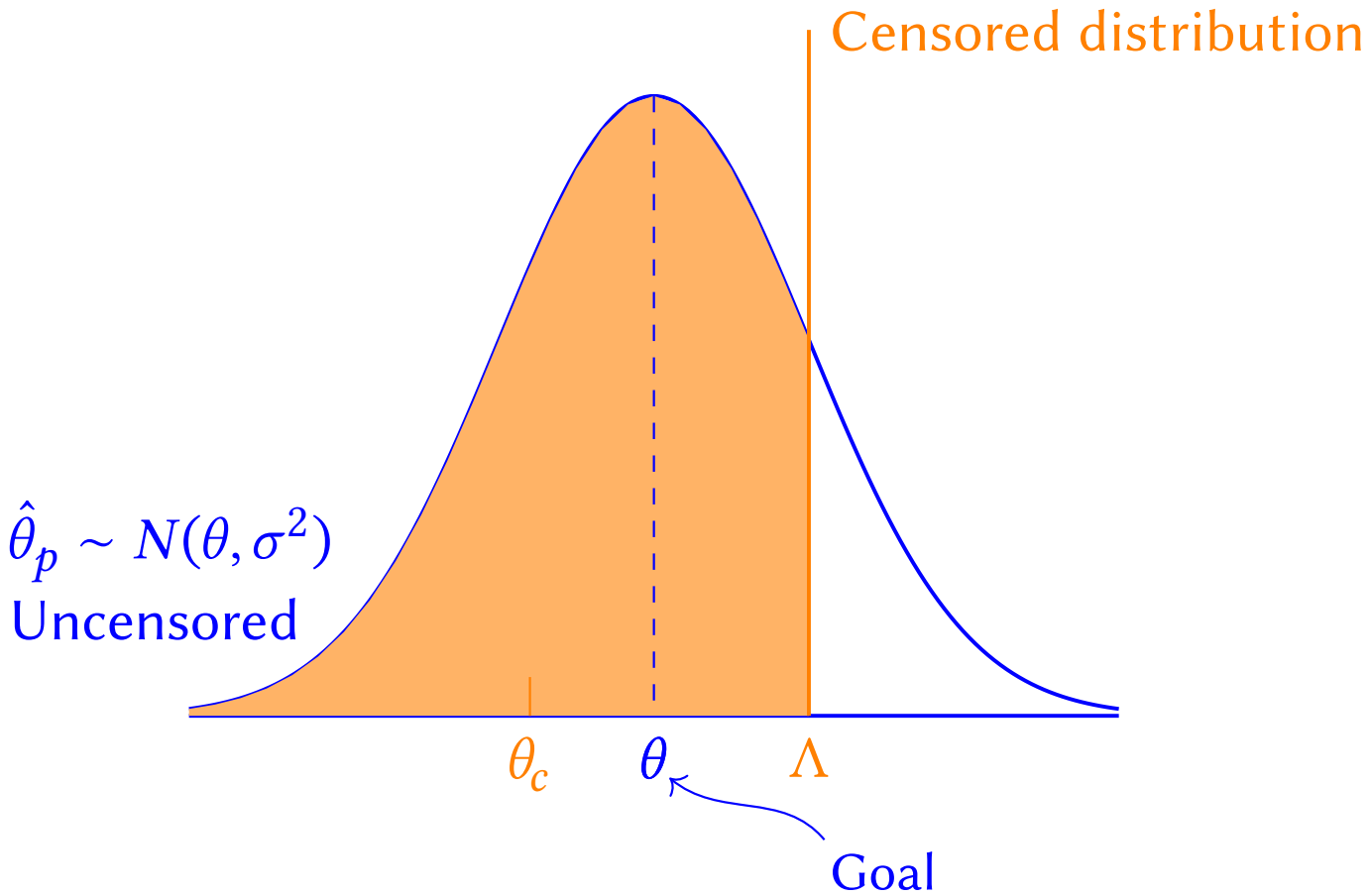

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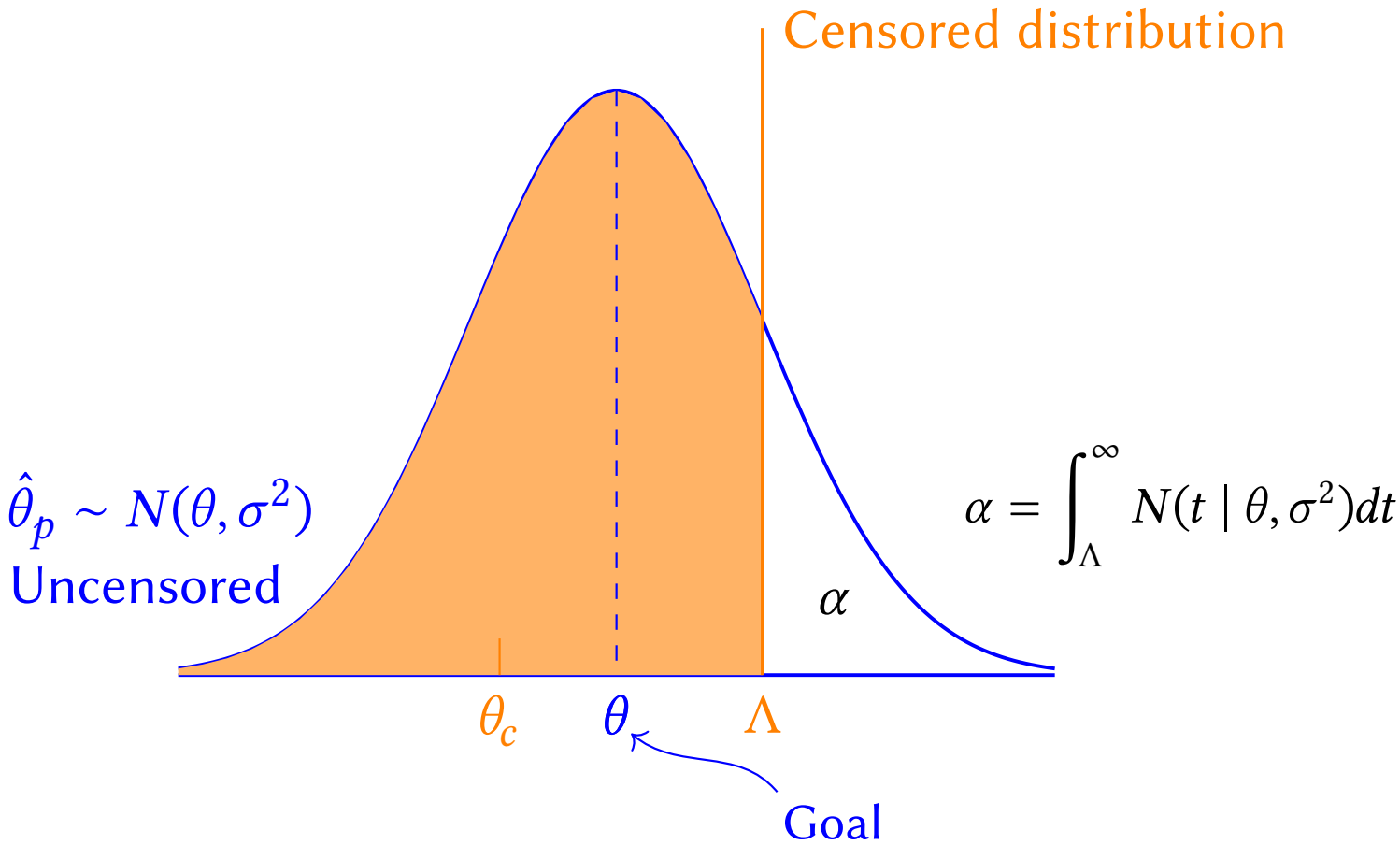

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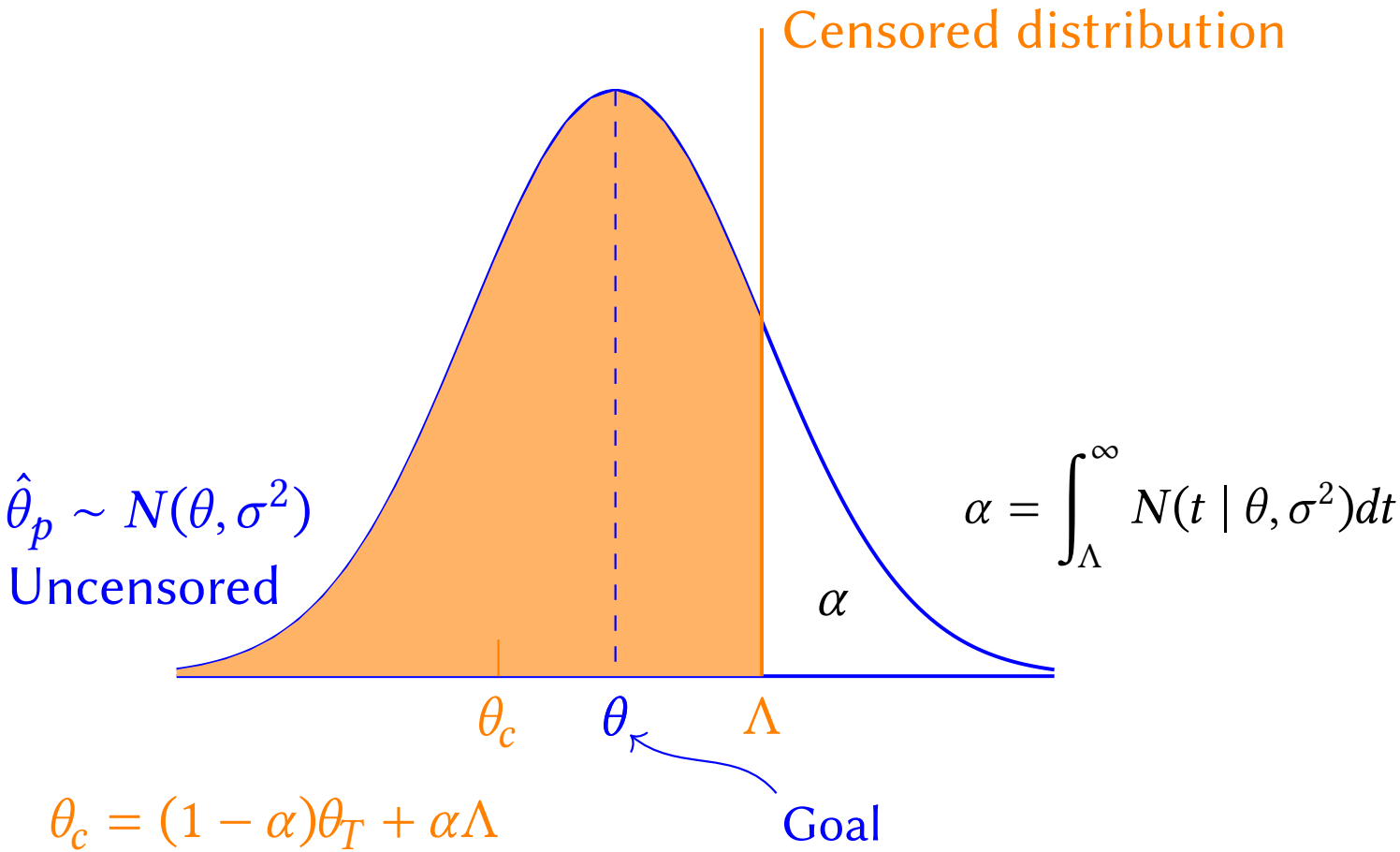

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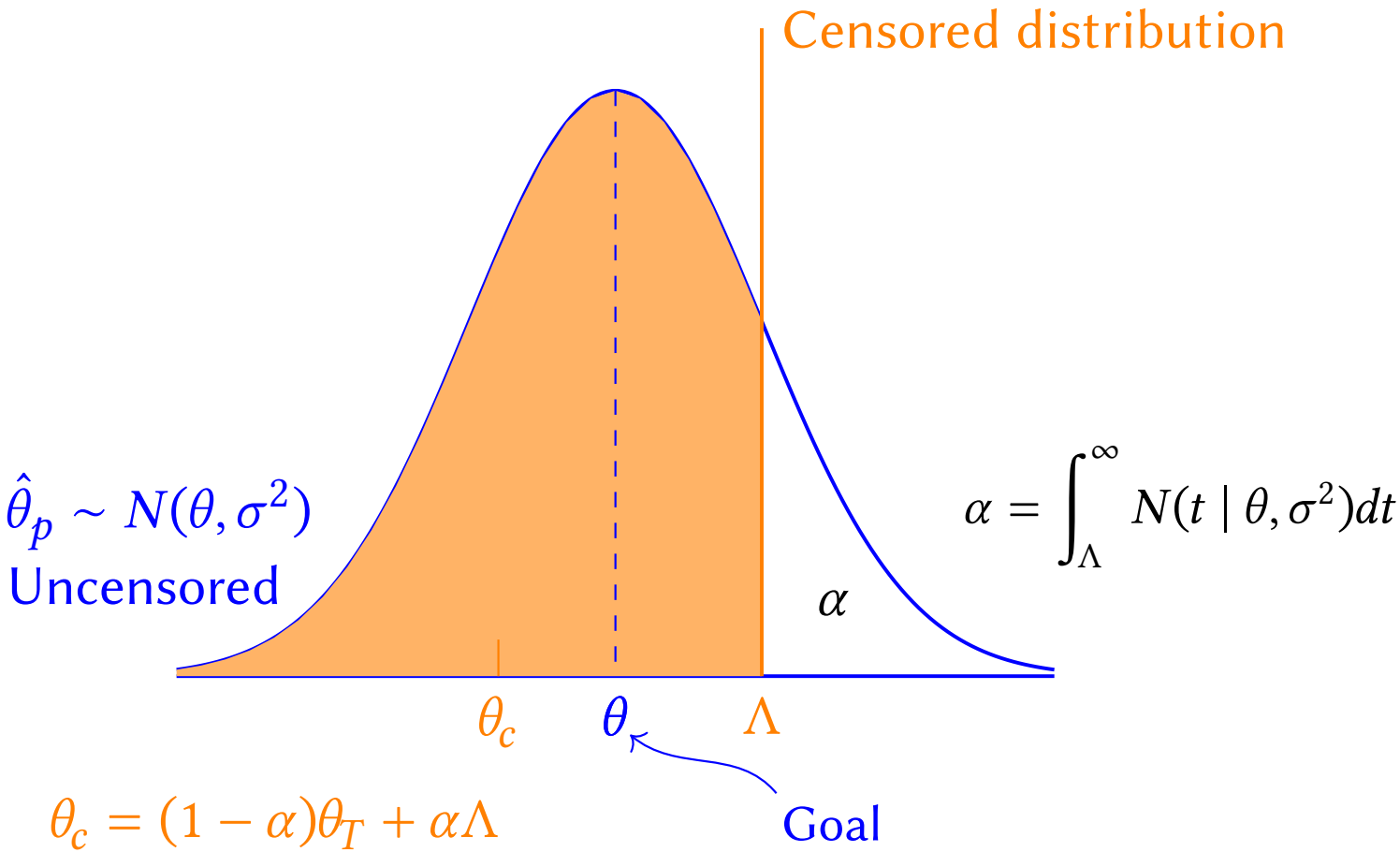

Equations: 2

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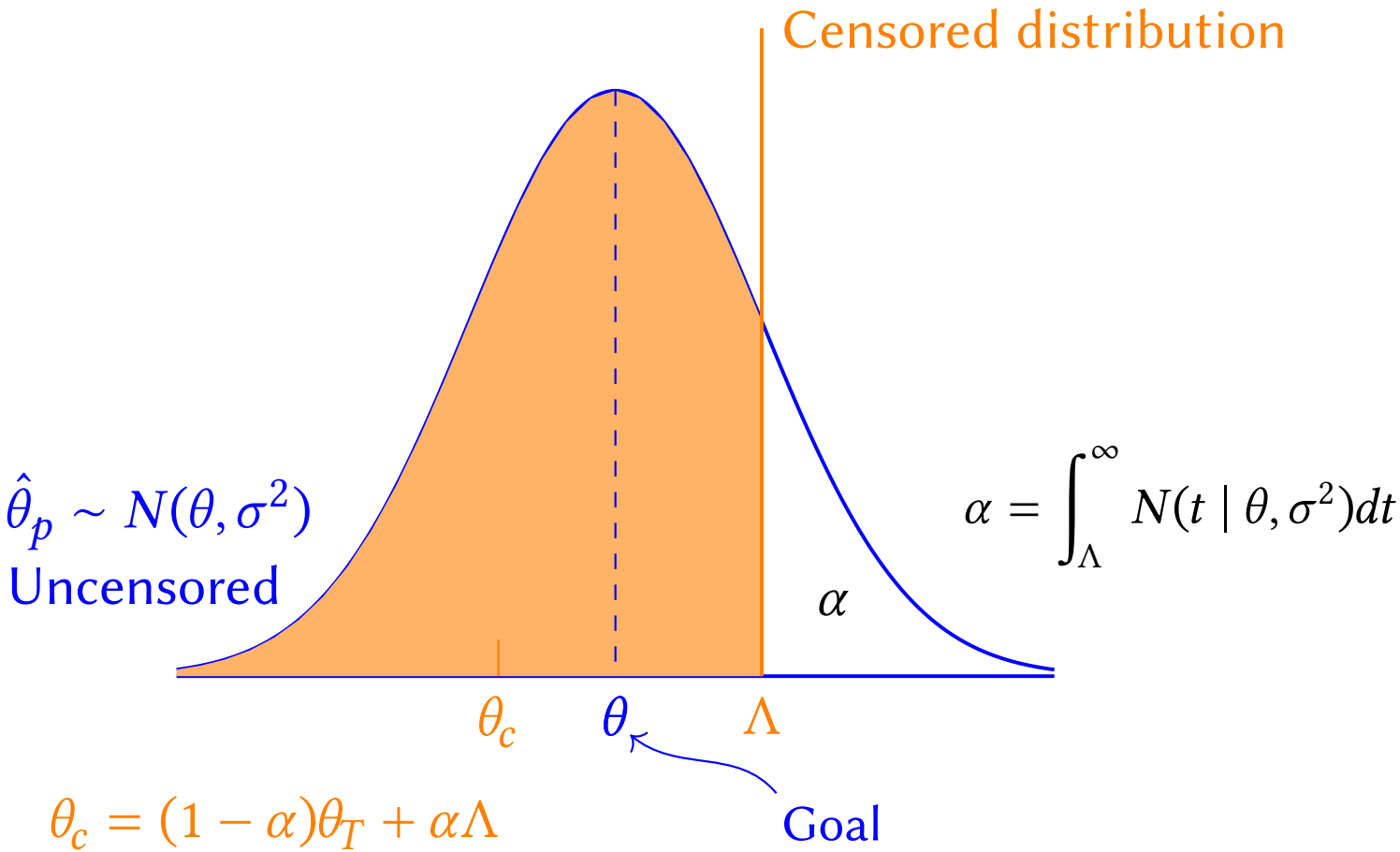

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Unknowns: θ, σ^2, α, θ_c

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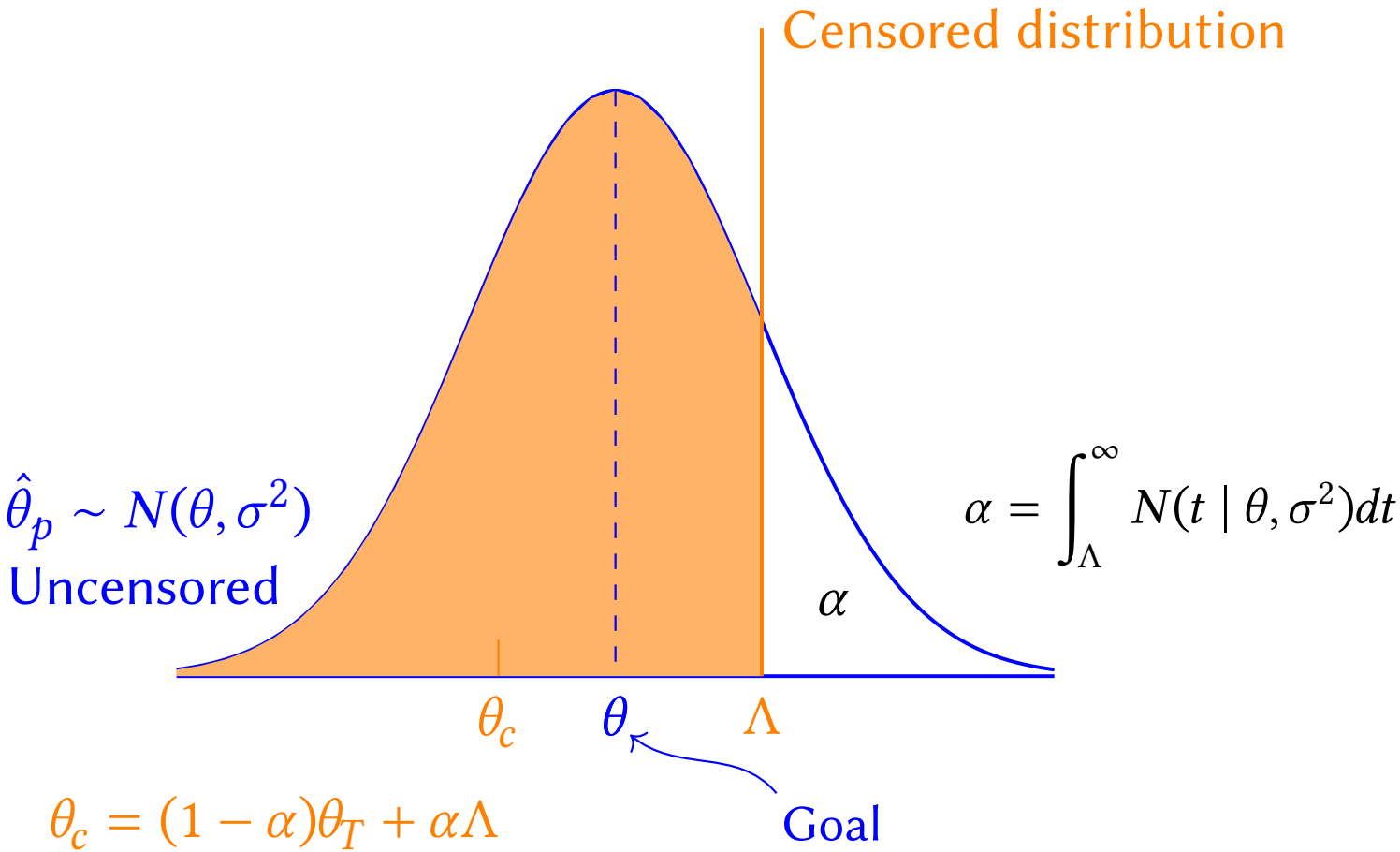

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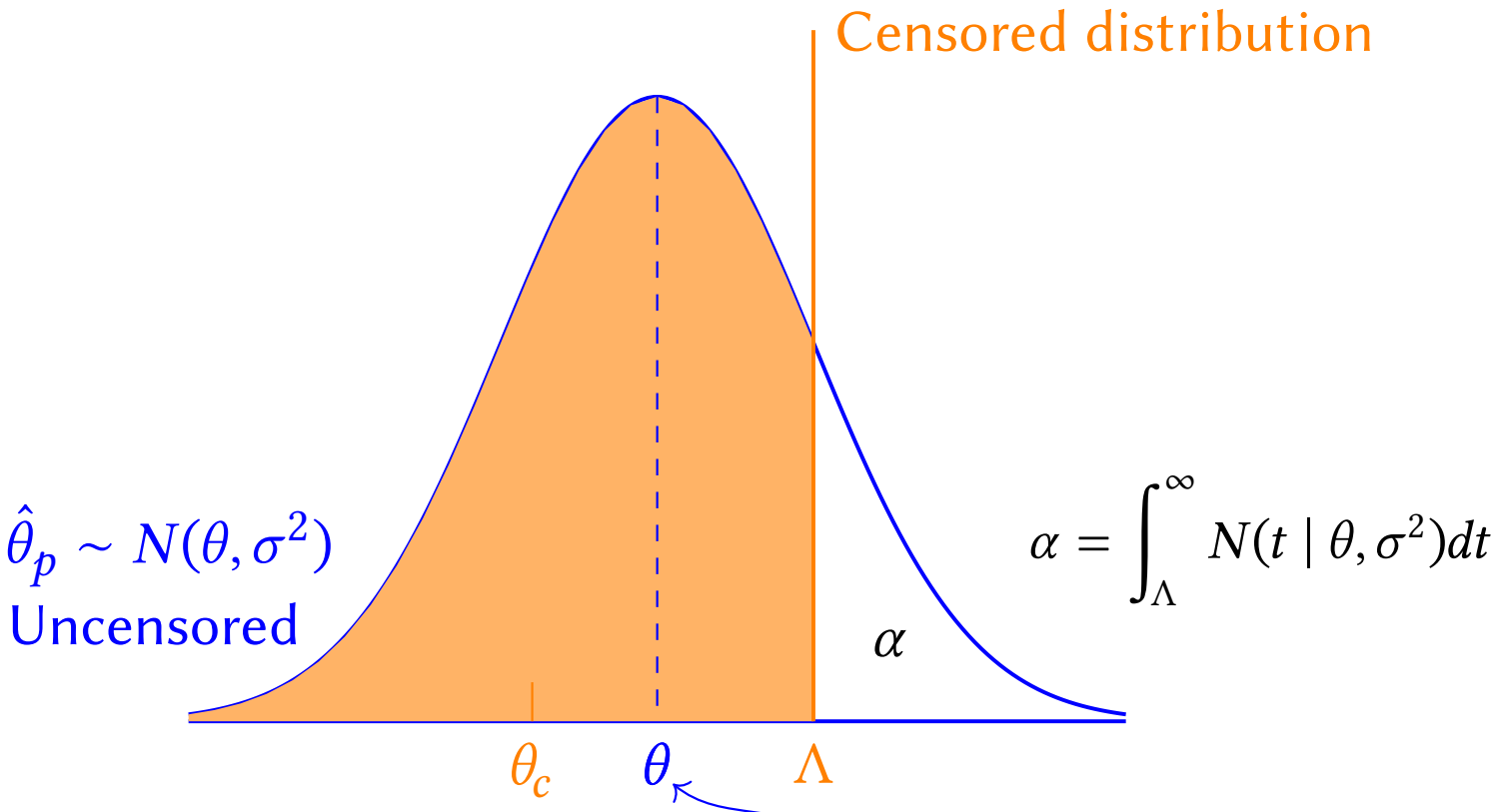

$$\alpha = \int_{\Lambda}^{\infty} N(t \mid \theta, \sigma^2)dt$$

$\theta_c = (1-\alpha)\theta_T + \alpha\Lambda$

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

Equations: 2

Unknowns: θ, σ^2, ~~α~~, ~~θ_c~~ ✗ ✗

Variance Estimation

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- Simulate estimates via standard (Clarify) procedures:

$$\hat{\theta}^{\text{dp}}, \hat{\alpha}^{\text{dp}} \sim N\left(\begin{bmatrix} \hat{\theta}^{\text{dp}} \\ \hat{\alpha}^{\text{dp}} \end{bmatrix}, \begin{bmatrix} \hat{V}(\hat{\theta}^{\text{dp}}) & \widehat{\text{Cov}}(\hat{\alpha}^{\text{dp}}, \hat{\theta}^{\text{dp}}) \\ \widehat{\text{Cov}}(\hat{\alpha}^{\text{dp}}, \hat{\theta}^{\text{dp}}) & \hat{V}(\hat{\alpha}^{\text{dp}}) \end{bmatrix}\right)$$

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Functions of disclosed params

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Simulations: Finite Sample Evaluation

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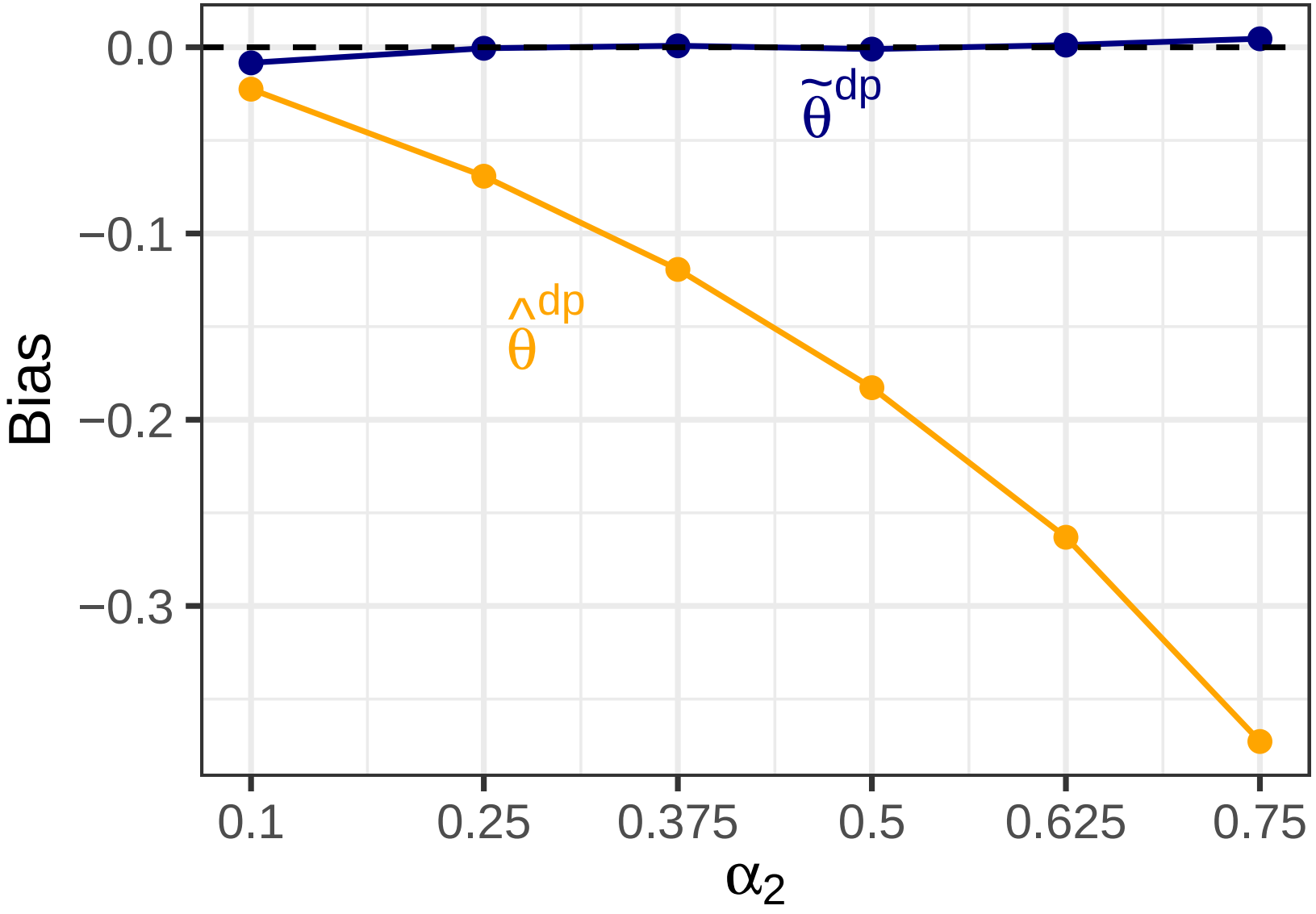

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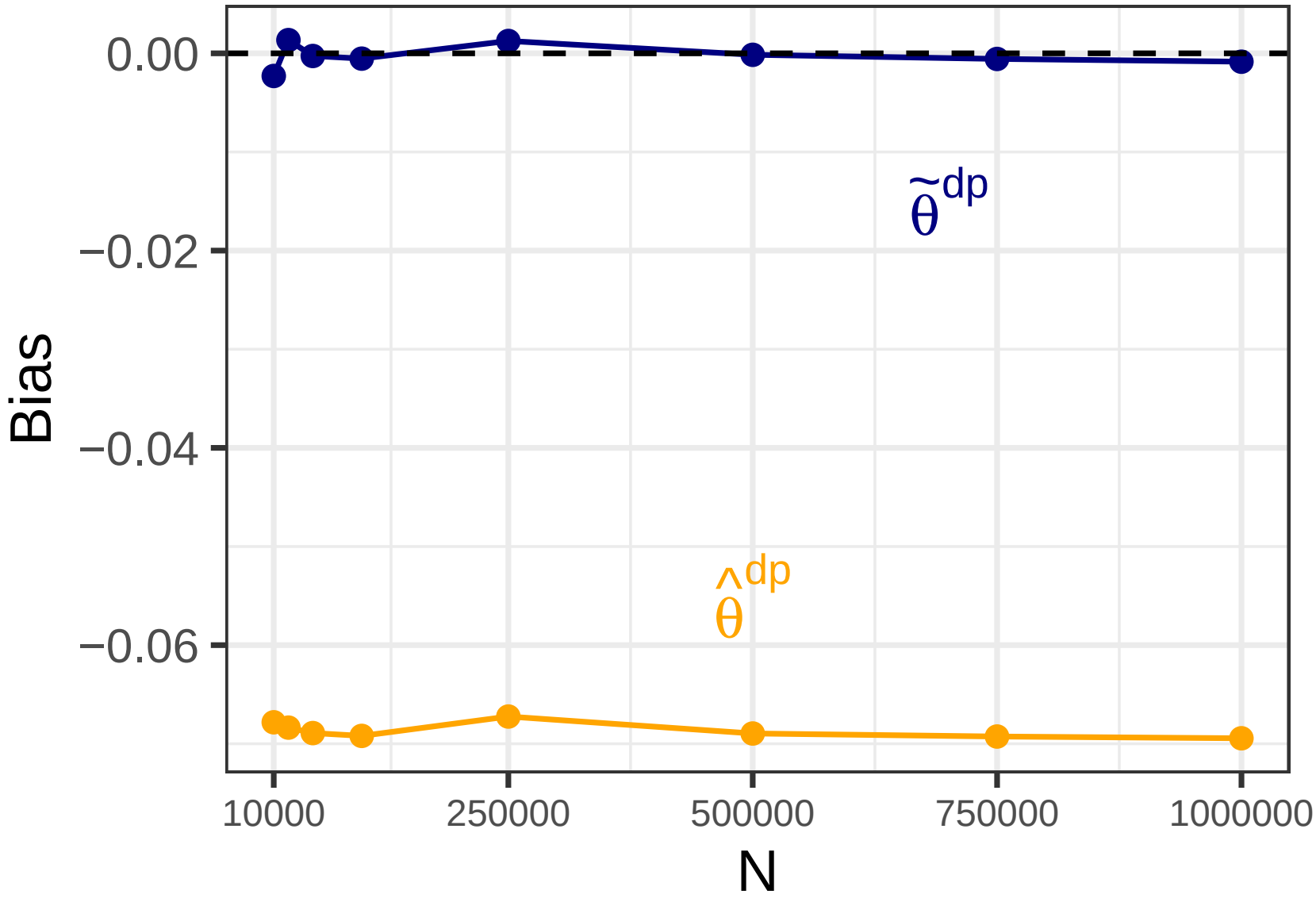

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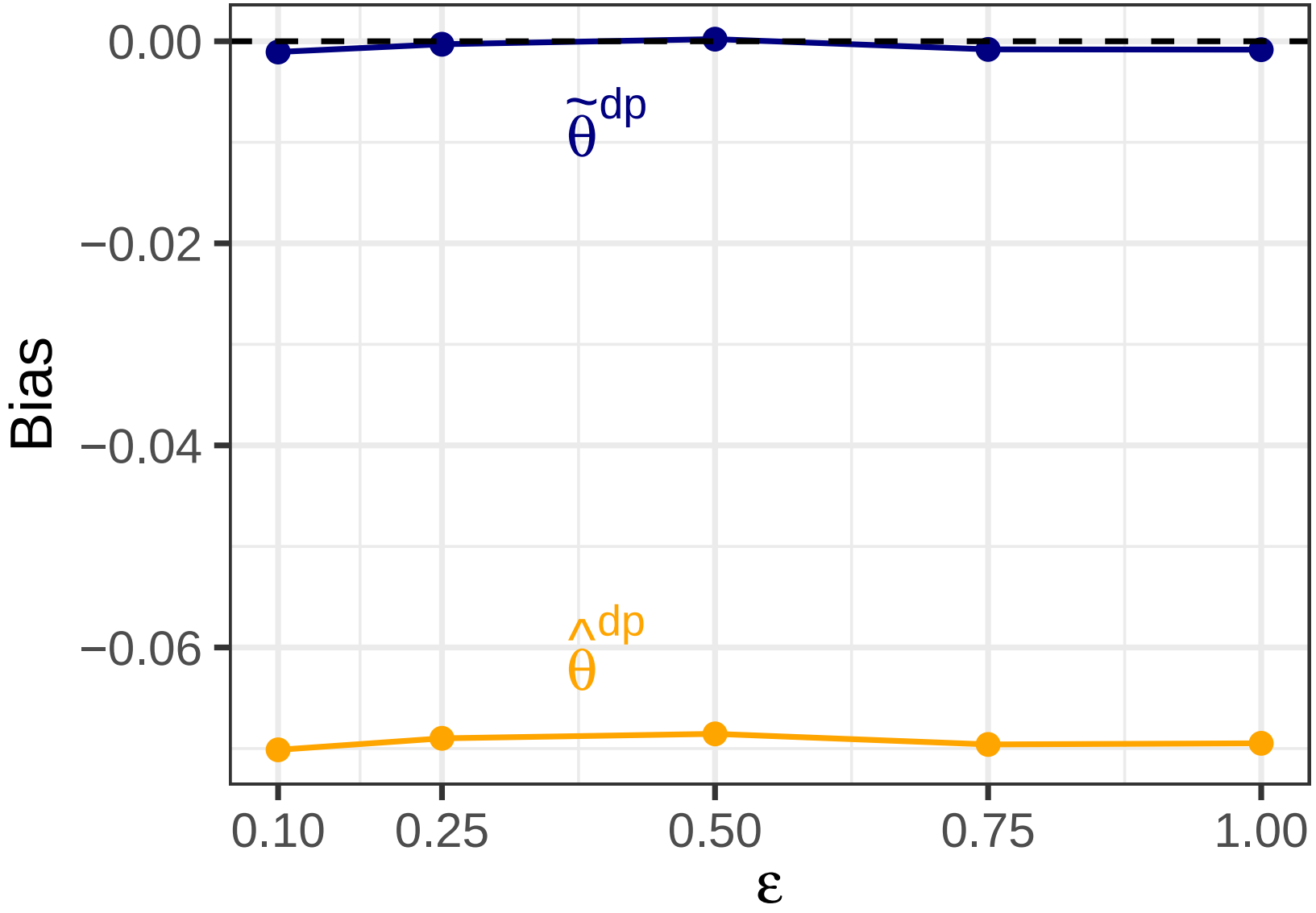
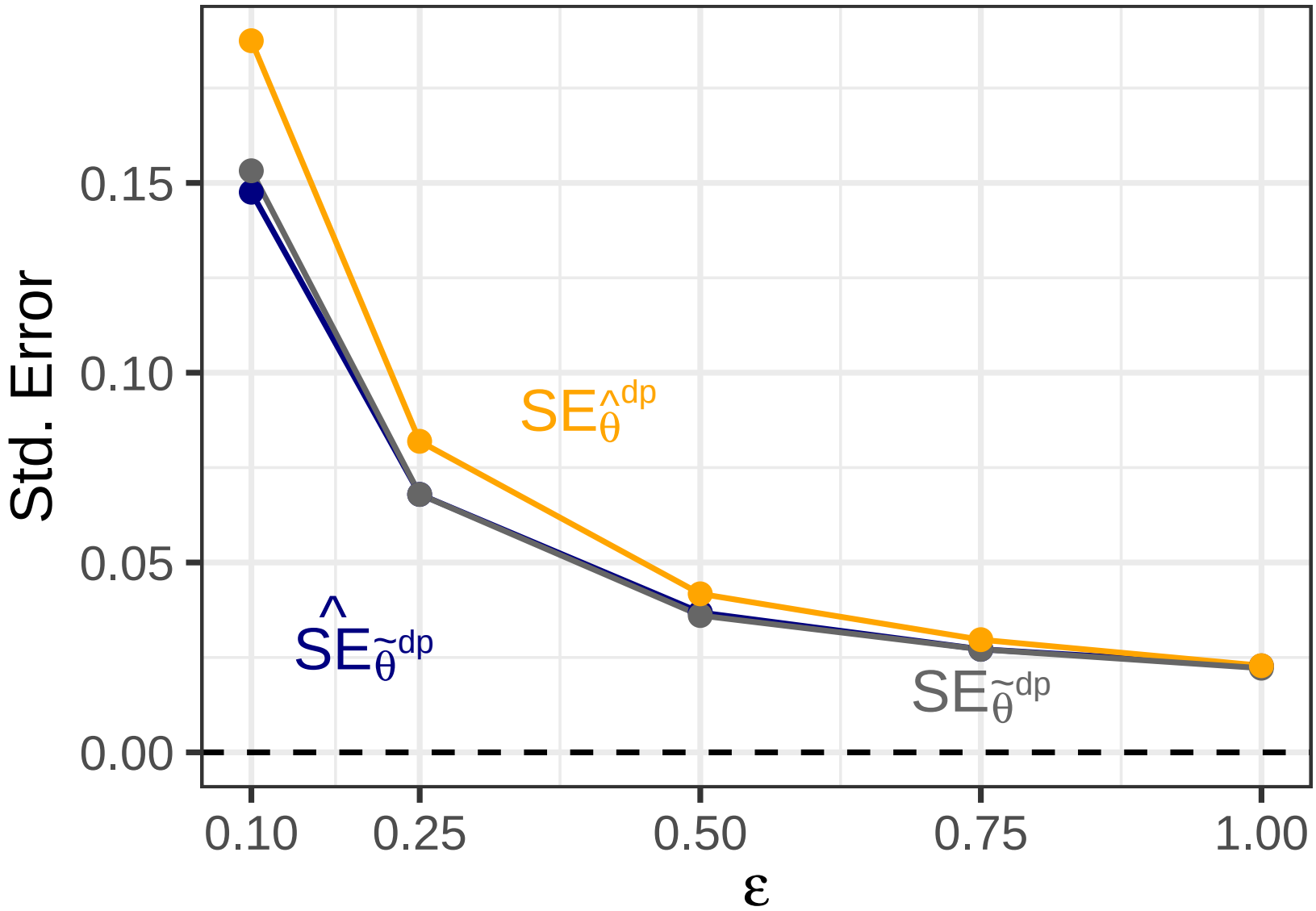


Simulations: Finite Sample Evaluation



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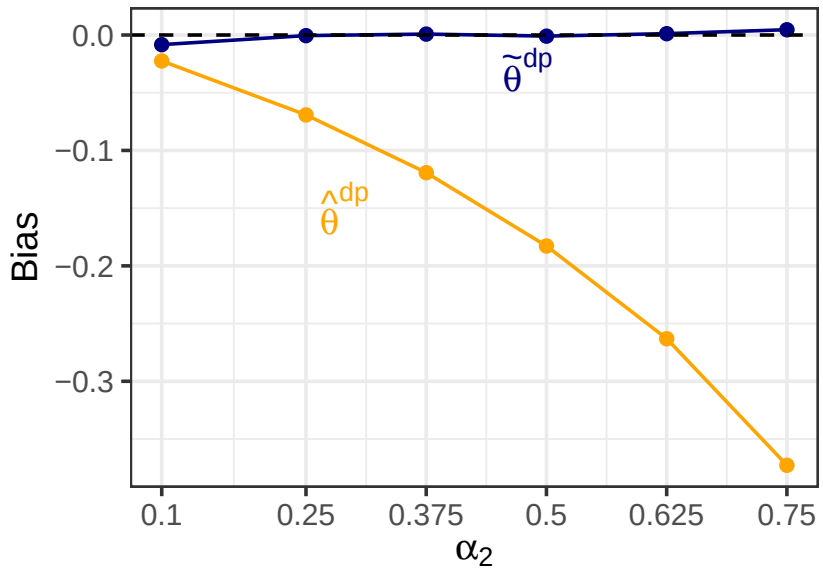
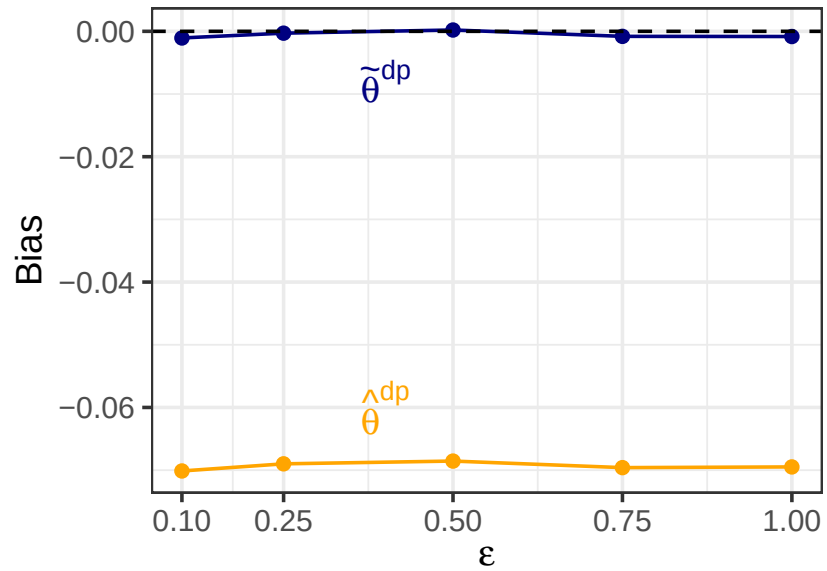
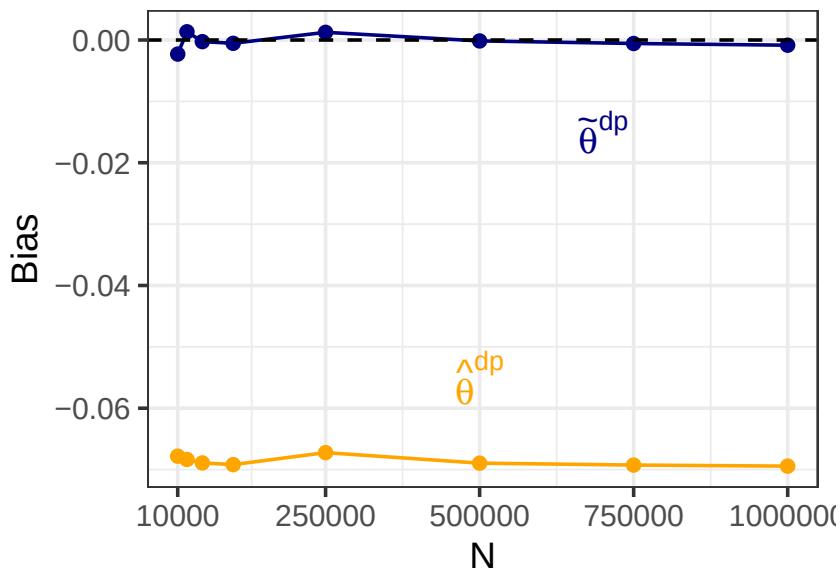
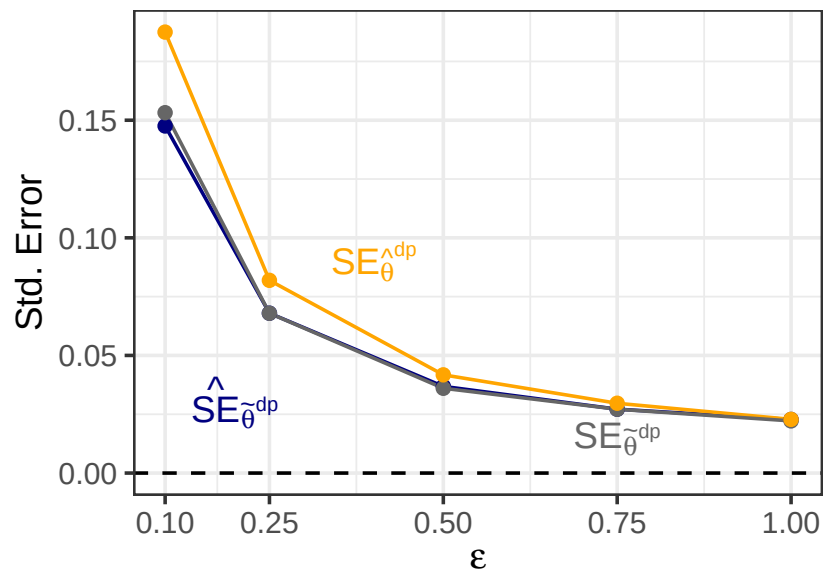
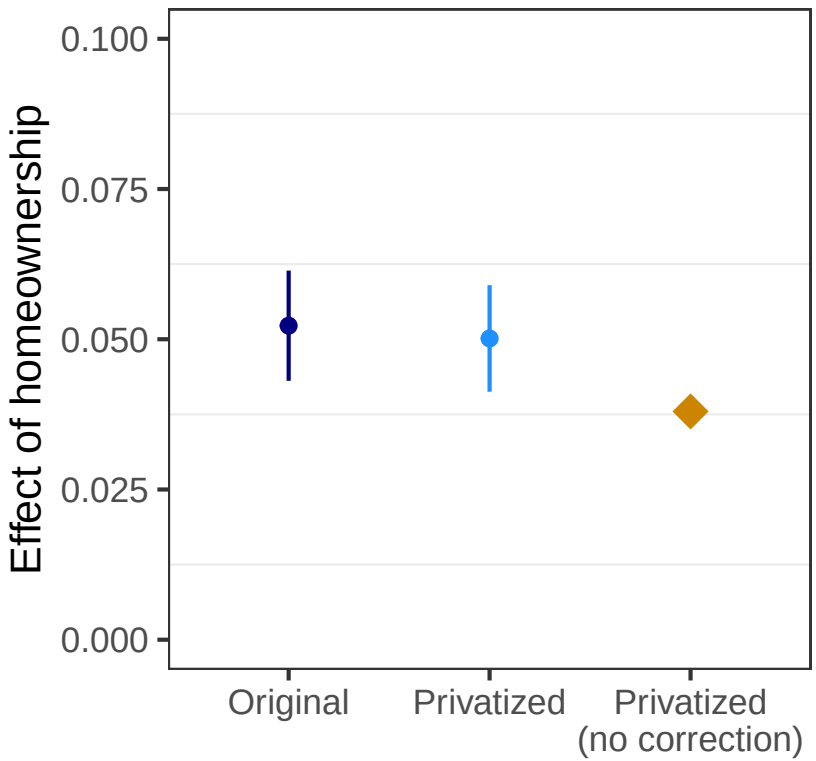




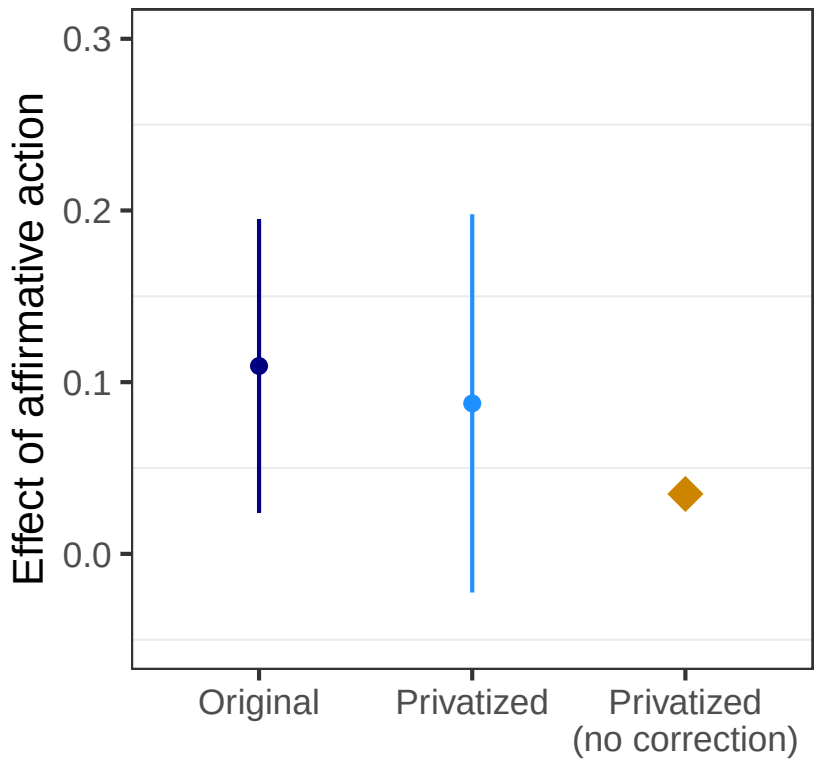




Similar Empirical Results, Larger CIs



(a) Yoder (APSR, 2020)



(b) Bhavnani and Lee (AJPS, 2019)

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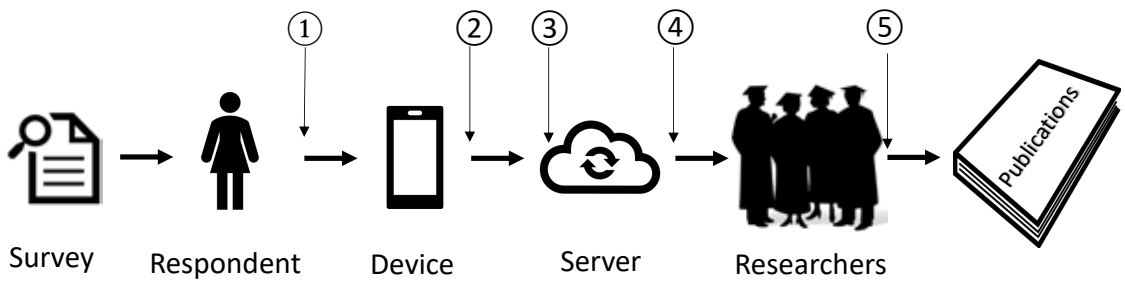

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Appendix

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