General-purpose Statistical Inference with Differential Privacy Guarantees

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PURDUE UNIVERSITY

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Table of Contents

Does Anonymization Guarantee Privacy?

Data Considered for Sharing

Age	Zip Code	Gender	Diagnosis
15	00000	Male	Diabetes
21	00001	Female	Influenza
36	10000	Male	Broken Arm
91	10001	Female	Acid Reflux

Voter Registration Records (Identified Resource)

Birthdate	Zip Code	Gender	Name
2/2/1989	00001	Female	Alice Smith
3/3/1974	10000	Male	Bob Jones
4/4/1919	10001	Female	Charlie Doe

Linking two data sources to identity diagnoses.

Figure: (Department of Health & Human Services) De-identification of sensitive information[1]. Dataset on the left is released without Name. Using another public dataset on the right, we can recover the names in the anonymized dataset.

[1] https://www.hhs.gov/hipaa/for-professionals/privacy/special-topics/de-identification/index.html

Does intuitive technique work? Not for the 2010 Census

Table: Percentage of reconstructed records that exactly agree with the original Census Edited File on location, sex, age, race, and ethnicity[2].

	Agreement Rates
Published 2010 Census Tables (swapping)	46.5%
Disclosure Avoidance System (differential privacy)	15.7%

[2] https://www2.census.gov/about/partners/cac/sac/meetings/2022-03/presentation-reconstruction-and-reidentification-of-the-dhc.pdf

How to Release a Model Safely?

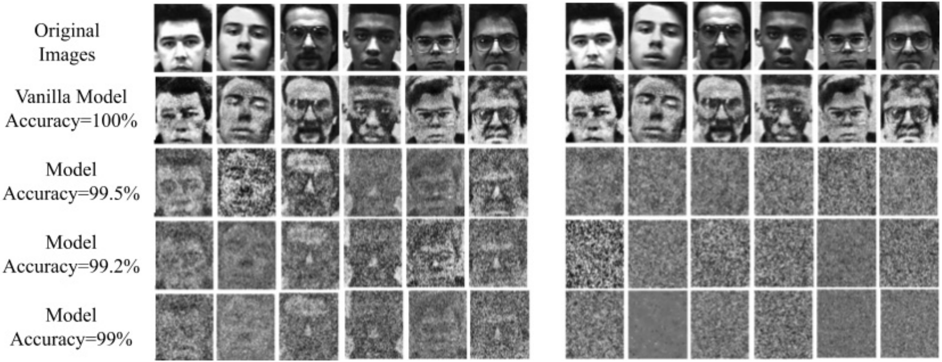

Figure: Model inversion attack (MIA) results on non-private model trained on Faces94 dataset and differentially privately (DP) trained models (left is record-DP, and right is class-DP)[3].

[3]Zhang, Qiuchen, et al. "Broadening differential privacy for deep learning against model inversion attacks." 2020 IEEE International Conference on Big Data (Big Data). IEEE, 2020.

Who Uses Differential Privacy (DP)?

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Statisticians!

Awesome-Differential-Privacy-for-Statisticians

(my GitHub repo collecting papers on DP+STAT.)

DP: a Probabilistic Measure for Privacy Protection

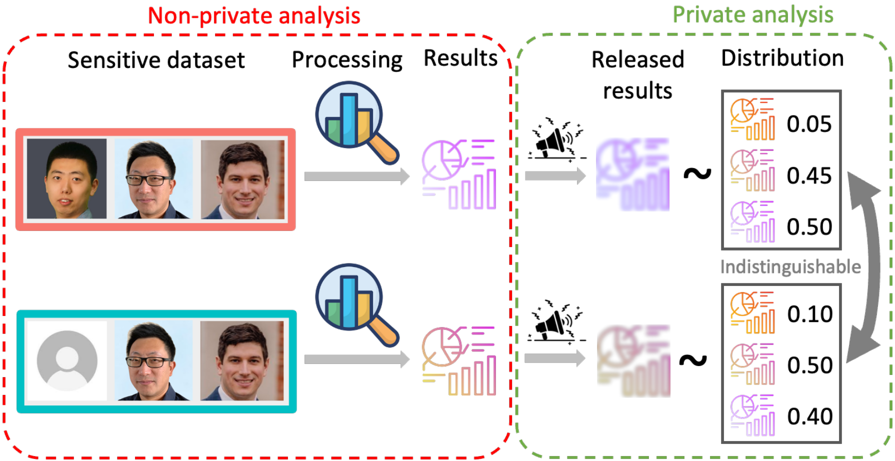
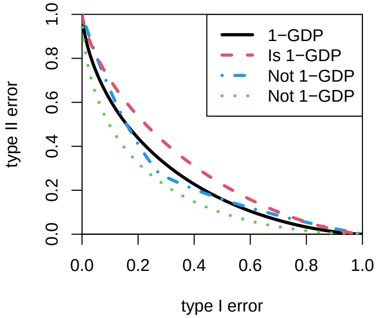


Figure: The output of the mechanism is roughly the same (approximately indistinguishable) when the input data is slightly changed. This is required for all datasets as input.

DP: Formal Definition

- A mechanism M is μ-Gaussian DP (Dong, Roth, and Su, 2022, μ-GDP) if for any two datasets D, D' differing in one entry, the hypothesis test, using output of M, $H_0 : Z \sim M(D), H_1 : Z \sim M(D')$ is never easier than $H_0 : Z \sim N(0, 1), H_1 : Z \sim N(\mu, 1)$. (Given type I error, type II is lower bounded.)



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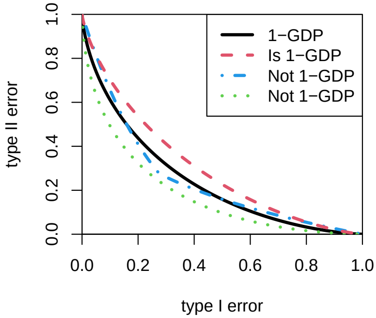

- (Our methods also apply to other DP notions like (ε, δ)-DP or Rényi DP, etc.)

GDP: Mechanism, Composition, and Post-processing

- Sensitivity: (largest impact from one individual) The sensitivity of $g(\cdot)$ is

$$\Delta(g) \geq \sup \left\| g(D) - g(D') \right\|_2 ,$$

where the supremum is over D, D' differing in one entry.

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- Gaussian Mechanism: (add noise to protect privacy) If g has sensitivity $\Delta(g)$, then

$$M(D) = g(D) + \xi_{\mathrm{DP}}, \ \xi_{\mathrm{DP}} \sim N\left(0, \left(\frac{\Delta(g)}{\mu}\right)^2\right)$$

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- Composition: (more release $\rightarrow$ less privacy) If M_1 and M_2 are μ_1-GDP and μ_2-GDP, respectively, then the joint release (M_1, M_2) is $\sqrt{\mu_1^2 + \mu_2^2}$-GDP.

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- Post-processing: (forestall all attackers) If $M(\cdot)$ is μ-GDP, then $\psi(M(\cdot))$ is μ-GDP.

Can We Naïvely Trust the Output of DP Mechanisms?

SCIENCE ADVANCES | RESEARCH ARTICLE

SOCIAL SCIENCES

The use of differential privacy for census data and its impact on redistricting: The case of the 2020 U.S. Census

Christopher T. Kenny[1], Shiro Kuriwaki[2], Cory McCartan[3], Evan T. R. Rosenman[4], Tyler Simko[1], Kosuke Imai[1,3]*

"We find that the [Disclosure Avoidance System] DAS systematically undercounts the population in mixed-race and mixed-partisan precincts, yielding unpredictable racial and partisan biases."

Can We Naïvely Trust the Output of DP Mechanisms? (cont.)

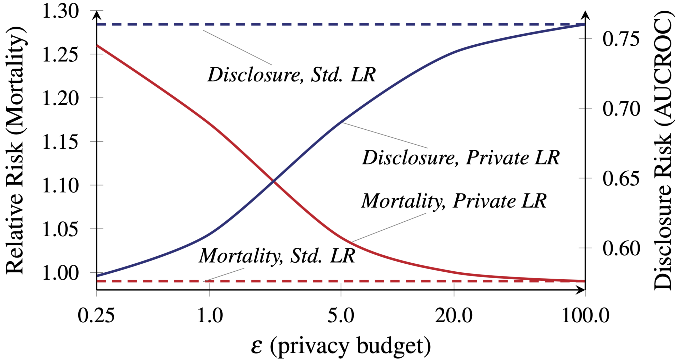

Figure: Mortality risk (relative to current clinical practice) and VKORC1 genotype disclosure risk of DP linear regression used for Warfarin dosing[4].

[4] Fredrikson, Matthew, et al. "Privacy in pharmacogenetics: An End-to-End case study of personalized warfarin dosing." 23rd USENIX security symposium. 2014.

Motivation

Quantify the uncertainty of the DP output by its sampling distribution.

Estimate the sampling distribution under DP $\rightarrow$ DP statistical inference.

Focus on frequentist approaches.

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Quantify the uncertainty of the DP output by its sampling distribution.

Estimate the sampling distribution under DP $\rightarrow$ DP statistical inference.

Focus on frequentist approaches.

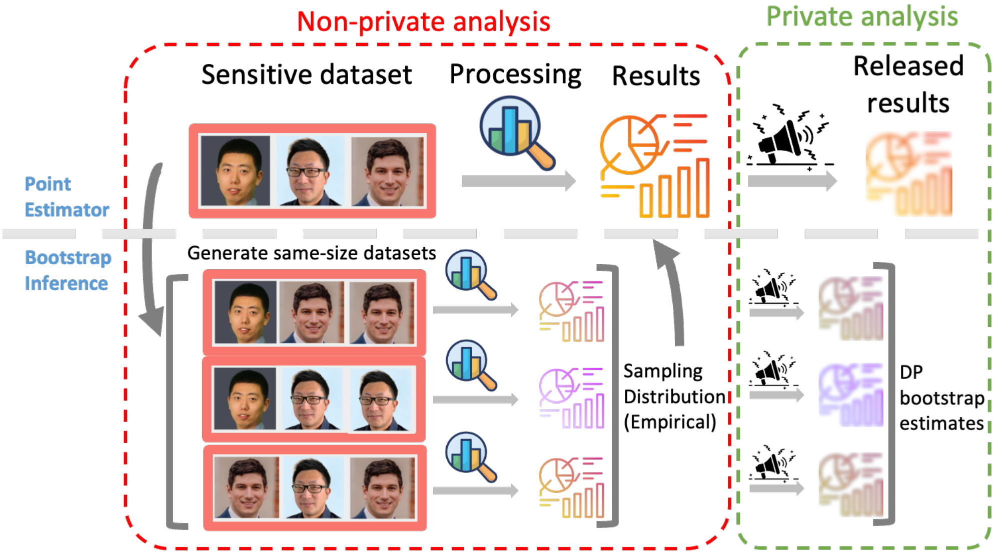
- Model-free. (Part I)
- Finite-sample valid. (Part II)
- Optimal. (Part III)
- Usable when we cannot choose the DP mechanism. (Part II & III)
  - E.g., post-process the release census data.

Motivations:

- Develop a DP mechanism for non-parametric inference.
  - Build a DP mechanism to enable bootstrap.
- Perform private inference for quantile regression.

[5] Wang, Zhanyu, Guang Cheng, and Jordan Awan. "Differentially Private Bootstrap: New Privacy Analysis and Inference Strategies." arXiv:2210.06140 (2022). This work is under review by JMLR.

DP Bootstrap for Private Uncertainty Quantification



Related Work

Existing privacy guarantees for DP Bootstrap are incorrect, and their confidence intervals have under-coverage.

DP Bootstrap

- Brawner and Honaker (2018); Koskela et al. (2020)
- Balle et al. (2018)

DP Parametric Bootstrap

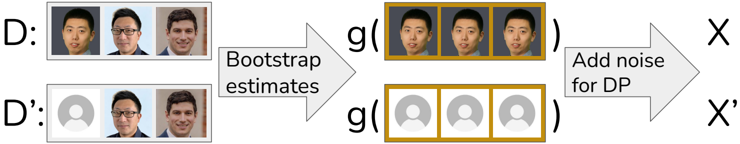
- Du et al. (2020); Ferrando et al. (2022); Alabi and Vadhan (2022)

Bag-of-little bootstrap

- Evans et al. (2023); Covington et al. (2021)

DP Bootstrap Privacy Analysis

- The naïve sensitivity is very large $\Rightarrow$ Need to add very large noise for DP.



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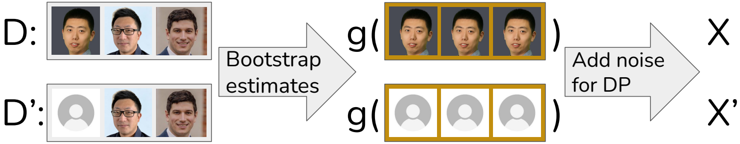

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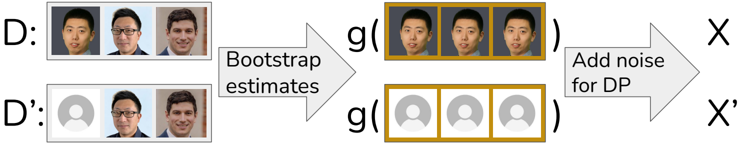

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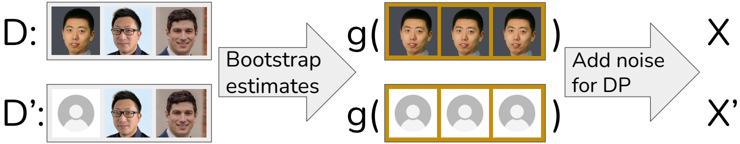

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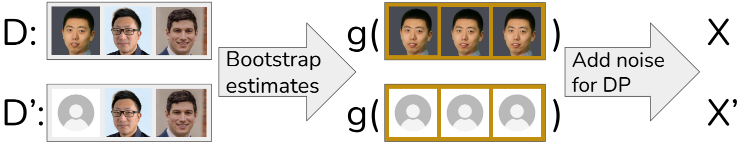

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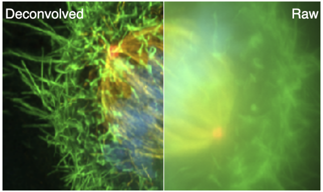
- By composition, running B times for B estimates is $\left(\sqrt{(2 - 2/\mathrm{e})B}\right)\mu$-GDP.

Deconvolution for Estimating Sampling Distribution

- Sampling distribution is affected by the added noises for DP.

$$M \circ \texttt{boot}(D) = g(\texttt{boot}(D)) + \xi_{\text{DP}}$$



- Use deconvolution to recover the distribution of bootstrap estimates from B DP bootstrap estimates and the distribution of added noises.

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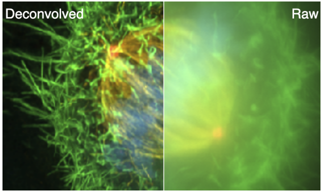

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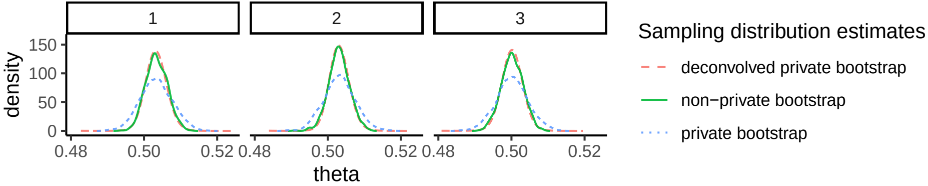

$g(D) = \frac{1}{n}\sum_{i=1}^{n} x_i$, $x_i \sim \mathrm{Unif}(0,1)$, $n = 10000$, $B = 1000$, $(\sqrt{2-2/e})$-GDP.

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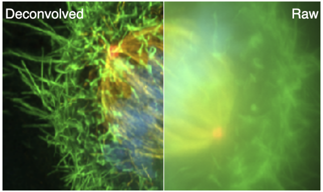

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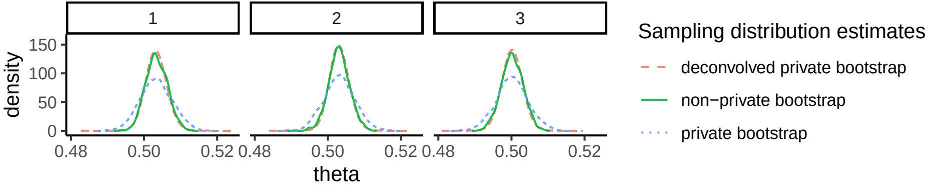

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- Construct DP confidence intervals using quantiles of deconvolved distribution.

Private Confidence Intervals (CIs) for Quantile Regression

- Using the 2016 Canada Census Public Use Microdata, we build 90% CIs for the slope in the quantile regression between market income 💰 & shelter cost 🏠.

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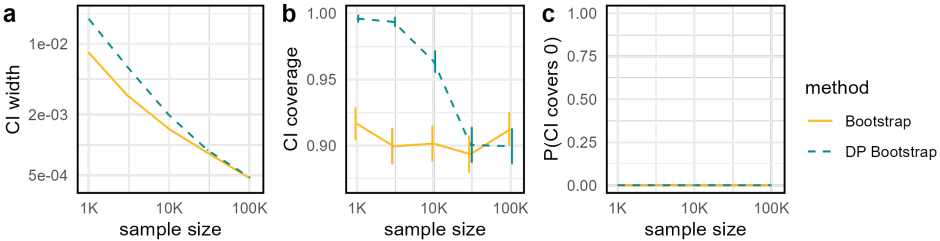

$\tilde{\theta} = \hat{\theta} + \xi$, $\hat{\theta} = \arg\min_\theta \left(R(\theta) + c\|\theta\|_2^2\right)$, $R(\theta) = \frac{1}{n}\sum_{i=1}^n (0.5 - \mathbb{1}(z_i \leq 0))z_i$ where $z_i = y_i - x_i\theta$,

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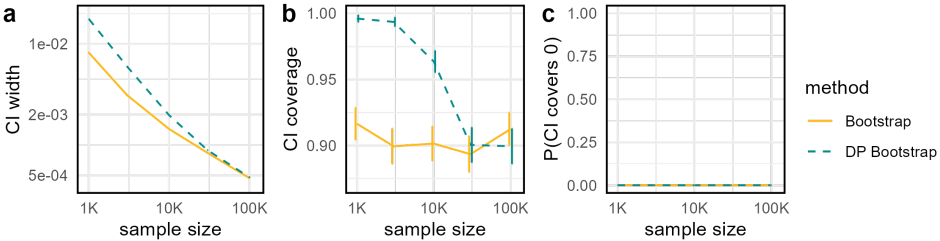
  - CIs never contain 0 $\rightarrow$ significant dependence between 💰 & 🏠.



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Contributions:

1. Propose and analyze a non-parametric DP bootstrap framework.
2. The first to perform private inference in quantile regression.

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3. Deconvolution is limited to additive noise mechanism (e.g., Gaussian Mechanism).

Part II: Simulation-based, Finite-sample Inference for Privatized Data[6]

Motivations:

- Finite-sample valid coverage/type I errors.

[6] Awan, Jordan, and Zhanyu Wang. "Simulation-based, Finite-sample Inference for Privatized Data." arXiv:2303.05328 (2023). This work is under major revision by JASA.

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Motivations:

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- A general framework that can be used without altering DP mechanisms.
- The privacy mechanism and data generating model are often easy to sample from, enabling simulation-based inference. Our method is inspired by Xie and Wang (2022).

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DP Statistics with Complex Sampling Distributions

Example: location-scale normal. Observe $D := (x_1, \ldots, x_n) \overset{\text{iid}}{\sim} N(\mu^*, \sigma^{*2})$.

- Non-private statistic: $\left(m(D) := \frac{1}{n} \sum_{i=1}^n x_i,\ \eta^2(D) := \frac{1}{n-1} \sum_{i=1}^n \left(x_i - \bar{X} \right)^2 \right)$.

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$$\left(\widetilde{m}(D) := m\left(\mathrm{clamp}_L^U(D)\right) + \frac{U-L}{n\varepsilon}N_1,\ \widetilde{\eta^2}(D) := \eta^2\left(\mathrm{clamp}_L^U(D)\right) + \frac{(U-L)^2}{n\varepsilon}N_2\right).$$

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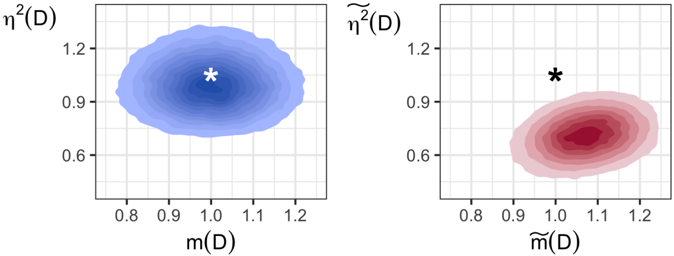

$\mu^* = 1,\ \sigma^* = 1,\ L = 0,\ U = 3,\ (\sqrt{2})$-GDP.

Related Work

Standard techniques are inapplicable or give poor results.

- Likelihood-based inference (Williams and McSherry, 2010)
- Asymptotics (Wang et al., 2018)

Promising directions:

- **Parametric bootstrap**
  - Du et al. (2020); Ferrando et al. (2022); Alabi and Vadhan (2022)
- **New asymptotics**
  - Wang et al. (2018, 2019)
- **Bayesian inference via data augmentation MCMC**
  - Ju et al. (2022)

Repro sample (Xie and Wang, 2022) is for likelihood-free simulation-based inference.

Failure of Naïve Usage of PB under DP

Privacy guarantee	1-GDP	0.5-GDP	0.3-GDP	0.1-GDP
Coverage	0.803	0.806	0.804	0.819

Table: Private 90% confidence intervals by `NOISYVAR+SIM` (Du, Foot, Moniot, Bray, and Groce, 2020) for the population mean of $N(0.5, 1)$. The sample size is 10000.

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Sample size	100	200	500	1000	2000	5000
Type I error	0.017	0.045	0.118	0.186	0.361	0.674

Table: Private hypothesis testings (level 0.05) using DP Monte Carlo tests (Alabi and Vadhan, 2022) on $H_0 : \beta_1^* = 0$ and $H_1 : \beta_1^* \neq 0$ with a regression model $Y = \beta_0^* + X\beta_1^* + \epsilon$ under 1-GDP.

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- A $(1-\alpha)$-prediction interval for s^* is $B_\alpha(\theta^*) = \left[\theta^* - \frac{z_{1-\alpha/2}}{\sqrt{n}},\ \theta^* + \frac{z_{1-\alpha/2}}{\sqrt{n}}\right]$.

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- The confidence interval is

$$\begin{aligned}\Gamma_\alpha(s^*) &= \{\theta \mid s^* \in B_\alpha(\theta)\} \\ &= \left[\overline{x} - \frac{z_{1-\alpha/2}}{\sqrt{n}},\ \overline{x} + \frac{z_{1-\alpha/2}}{\sqrt{n}}\right].\end{aligned}$$

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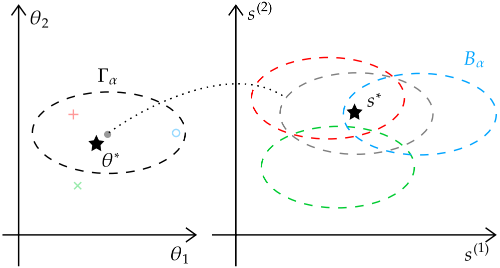

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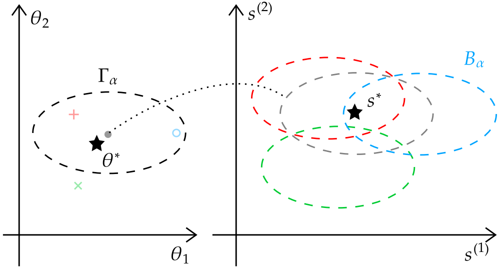

A confidence set $\Gamma_\alpha(s^*)$ can be constructed by inverting a prediction set $B_\alpha(\theta)$.

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Data-generating model:

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This setup (and our method) applies to all settings with low-d summary statistics s^*.

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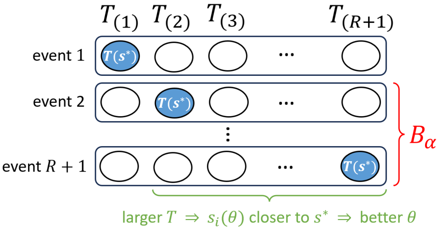

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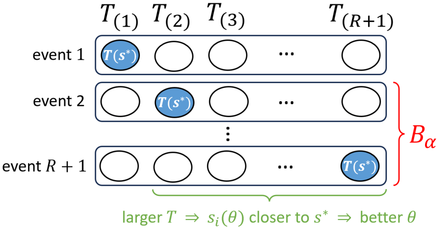

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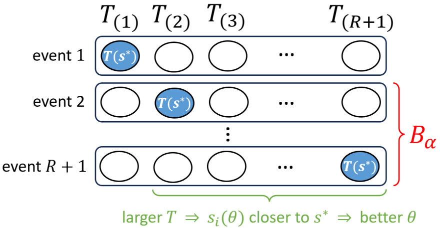
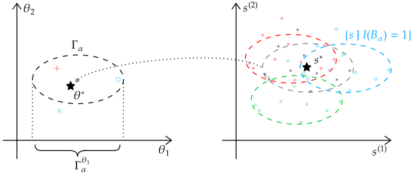
- $\Gamma_\alpha := \{\theta \mid \mathbb{1}(B_\alpha(\theta)) = 1\}$ is a $(1-\alpha)$-confidence set for θ^*.





Theorem: Confidence set from simulated (repro) samples

Set $\mathbf{S} = (s^*, s_1(\theta), \ldots, s_R(\theta))$ and $\left\{T^{\theta}_{(i)}\right\}_{i=1}^{R+1}$ be order statistics of

$$T(s^*; \mathbf{S}),\, T(s_1(\theta); \mathbf{S}), \ldots, T(s_R(\theta); \mathbf{S}),$$

where T is permutation-invariant in $\mathbf{S}$. Then $\left\{T^{\theta^*}_{(i)}\right\}_{i=1}^{R+1}$ are exchangeable. If lower values of T indicate unusual data points, then, a $(1-\alpha)$-confidence set is

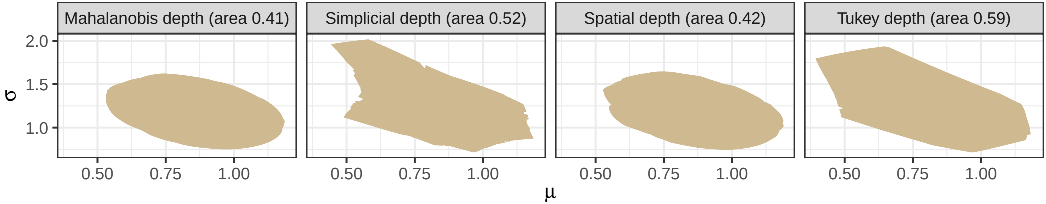
$$\Gamma_\alpha(s^*, u) := \left\{\theta \,\middle|\, T(s^*; \mathbf{S}) \in \left[T^{\theta}_{(\lfloor \alpha(R+1) \rfloor + 1)}, T^{\theta}_{(R+1)}\right]\right\}.$$

Key insights:

1. Include s^* in $\mathbf{S}$ to ensure exchangeability from permutation-invariance.
2. Prediction set from order statistics, like conformal prediction (Vovk et al., 2005).

Simulation-Based Confidence Sets by Repro Samples (cont.)

- Most statistical depths are permutation-invariant, and unusual points have lower depth, e.g., Mahalanobis depth: $T(s; \mathbf{S}) = \left[1 + (s - \mu_{\mathbf{S}})^\intercal \Sigma_{\mathbf{S}}^{-1}(s - \mu_{\mathbf{S}})\right]^{-1}$, where $(\mu_{\mathbf{S}}, \Sigma_{\mathbf{S}})$ is sample (mean, covariance) of $\mathbf{S}$.
- Comparing different depths with $s^* := \left(\widetilde{m}(D), \widetilde{\eta^2}(D)\right) = (1, 0.75)$.



Simulation-Based Hypothesis Testing (HT)

- We can leverage exchangeability to derive p-values as well.

Theorem: Hypothesis testing p-value

If T is a depth function taking value in $(0,1)$, then

$$p = \frac{1}{R+1}\left\lfloor \sup_{\theta\in\Theta_0}\left[\#\left\{i \mid T^{\theta}_{(i)} \leq T(s^*;\mathbf{S})\right\} + T(s^*;\mathbf{S})\right]\right\rfloor$$

is a valid p-value for $H_0 : \theta^* \in \Theta_0$.

Compared to Parametric Bootstrap

The main competitor for general frequentist inference for privatized data is the parametric bootstrap (PB).[7]

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Location-Scale Normal

- Suppose that $D := (x_1, \ldots, x_n)$, $x_i \overset{\text{iid}}{\sim} N(\mu^*, \sigma^*)$. Build CIs for μ^* and σ^*.
- True parameter $\theta^* := (\mu^*, \sigma^*)$.
- DP statistic $s := \left(\widetilde{m}, \widetilde{\eta^2}\right)$ satisfies $(\sqrt{2}\varepsilon)$-GDP.

$\widetilde{m}(D) := m\left(\text{clamp}_L^U(D)\right) + \frac{U-L}{n\varepsilon} N_1$, $\widetilde{\eta^2}(D) := \eta^2\left(\text{clamp}_L^U(D)\right) + \frac{(U-L)^2}{n\varepsilon} N_2$, where $N_1, N_2 \overset{\text{iid}}{\sim} N(0,1)$, $\text{clamp}_L^U(x) := \max(\min(x, U), L)$.

Method (95% CI)	**Coverage**		**Average width**	
	μ^*	σ^*	μ^*	σ^*
Repro Sample	0.989 (0.003)	0.998 (0.001)	0.599 (0.003)	0.758 (0.005)
Parametric Bootstrap	0.688 (0.015)	0.003 (0.001)	0.311 (0.001)	0.291 (0.001)

$\mu^* = 1$, $\sigma^* = 1$, $L = 0$, $U = 3$, $R = 200$, $(\sqrt{2})$-GDP.

Hypothesis Testing for Linear Regression

- This problem setting is used by (Alabi and Vadhan, 2022).
- Test $H_0 : \beta_1^* = 0$ and $H_1 : \beta_1^* \neq 0$ with $Y = \beta_0^* + X\beta_1^* + \epsilon$.

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- Test $H_0 : \beta_1^* = 0$ and $H_1 : \beta_1^* \neq 0$ with $Y = \beta_0^* + X\beta_1^* + \epsilon$.
- True parameter $\theta^* := (\beta_1^*, \beta_0^*, \mathbb{E}[X], \mathrm{Var}(X), \mathrm{Var}(\varepsilon))$.
- DP statistic $s := \left(\tilde{\bar{x}}, \widetilde{\overline{x^2}}, \tilde{\bar{y}}, \widetilde{\overline{xy}}, \widetilde{\overline{y^2}}\right)$ satisfies μ-GDP:

  Set clamp parameter to be Δ, $[x_i]_{-\Delta}^{\Delta} := \max(\min(x, \Delta), -\Delta)$.

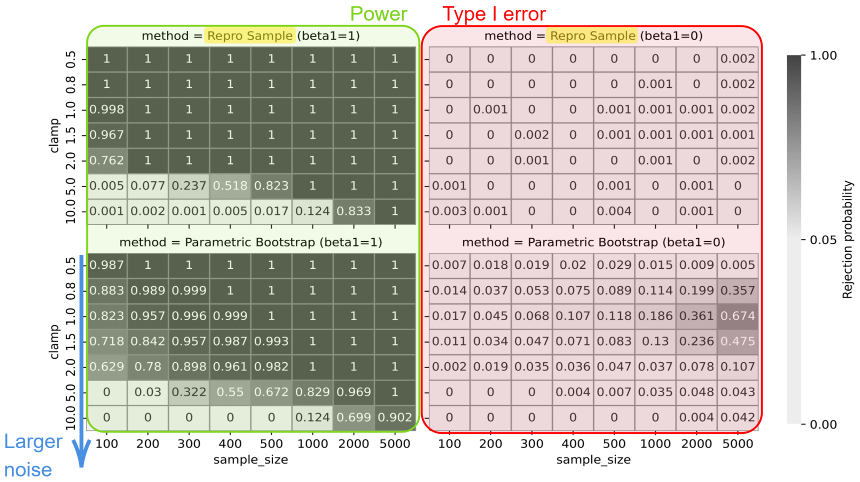
$$\tilde{\bar{x}} := \frac{1}{n}\sum_{i=1}^{n}[x_i]_{-\Delta}^{\Delta} + \frac{2\Delta}{(\mu/\sqrt{5})n}N_1, \qquad \widetilde{\overline{x^2}} := \frac{1}{n}\sum_{i=1}^{n}\left[x_i^2\right]_0^{\Delta^2} + \frac{\Delta^2}{(\mu/\sqrt{5})n}N_2,$$

$$\tilde{\bar{y}} := \frac{1}{n}\sum_{i=1}^{n}[y_i]_{-\Delta}^{\Delta} + \frac{2\Delta}{(\mu/\sqrt{5})n}N_3, \qquad \widetilde{\overline{xy}} := \frac{1}{n}\sum_{i=1}^{n}[x_i y_i]_{-\Delta^2}^{\Delta^2} + \frac{2\Delta^2}{(\mu/\sqrt{5})n}N_4,$$

$$\widetilde{\overline{y^2}} := \frac{1}{n}\sum_{i=1}^{n}\left[y_i^2\right]_0^{\Delta^2} + \frac{\Delta^2}{(\mu/\sqrt{5})n}N_5, \qquad \text{where} \quad N_i \overset{\text{iid}}{\sim} N(0,1).$$

Hypothesis Testing for Linear Regression (cont.)

- Compare rejection probabilities (level 0.05) to PB (Alabi and Vadhan, 2022).



$\beta_1^* = 0$ and 1, $\beta_0^* = -0.5$, $x_i \sim N(0.5, 1)$, $\varepsilon_i \sim N(0, 0.25)$, $R = 200$, 1-GDP.

Part II: Simulation-based, Finite-sample Inference for Privatized Data

Contributions: Expand Repro for finite-sample inference for privatized data.

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3. Optimizing over the nuisance parameters is computationally expensive.

Part III: Debiased Parametric Bootstrap for Privatized Data[8]

Motivations:

- Repro method is over-conservative and has no optimality guarantee.
- Existing parametric bootstrap (PB) gives biased results due to clamping.
- Need an estimator for PB: consistent & achieving the optimal asymptotic variance.

[8] Wang, Zhanyu, and Jordan Awan. "Debiased Parametric Bootstrap Inference on Privatized Data." This work is presented in TPDP 2023 and under preparation for journal submission.

Bias in Naïve DP Estimates due to Clamping

Example: location-scale normal. Observe $D := (x_1, \dots, x_n) \overset{\text{iid}}{\sim} N(\mu^*, \sigma^{*2})$.

- Non-private statistic: $\left(m(D) := \frac{1}{n} \sum_{i=1}^{n} x_i,\ \eta^2(D) := \frac{1}{n-1} \sum_{i=1}^{n} \left(x_i - \bar{X} \right)^2 \right)$.
- Private statistic, $(\sqrt{2}\varepsilon)$-GDP. $N_1, N_2 \overset{\text{iid}}{\sim} N(0,1)$, $\mathrm{clamp}_L^U(x) := \max(\min(x, U), L)$.

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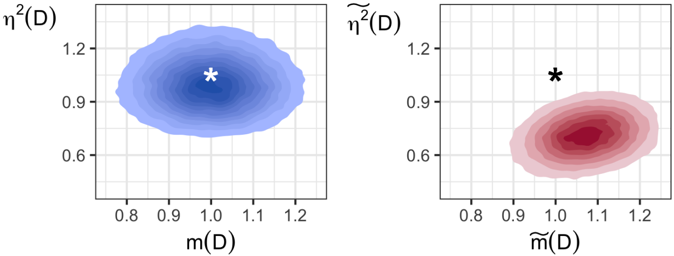
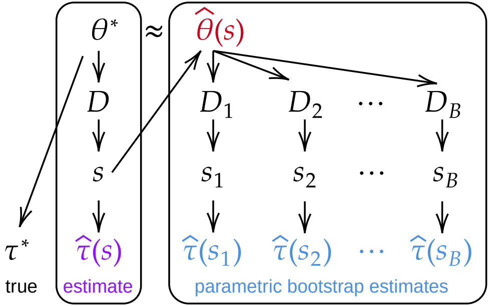


$\mu^* = 1,\ \sigma^* = 1,\ L = 0,\ U = 3,\ (\sqrt{2})$-GDP.

Parametric Bootstrap (PB)

- $D \sim F(x|\theta^*)$ with distribution F, true parameter θ^*.
  Compute summary statistic $s(D)$.



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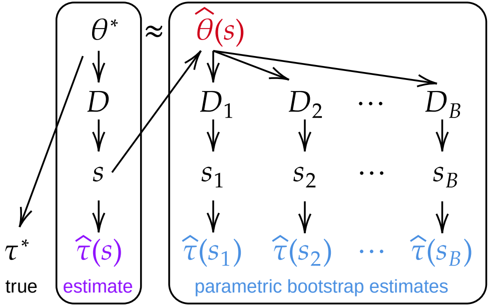

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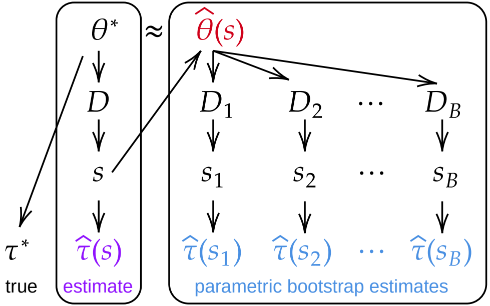

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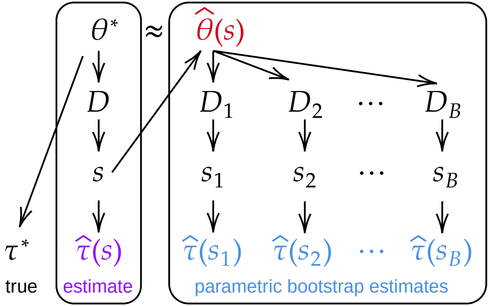

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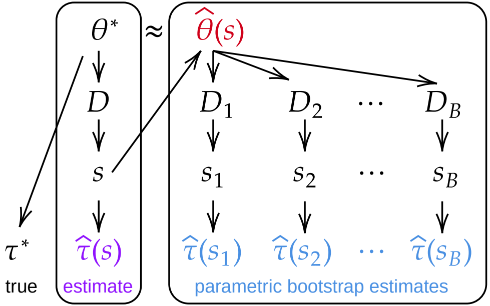

- Distributions of $\sqrt{n}(\hat{\tau}(D) - \tau^*)$ and $\sqrt{n}(\hat{\tau}(D_b) - \hat{\tau}(D))$ are $H_n(\theta^*)$ and $H_n(\hat{\theta}(D))$.

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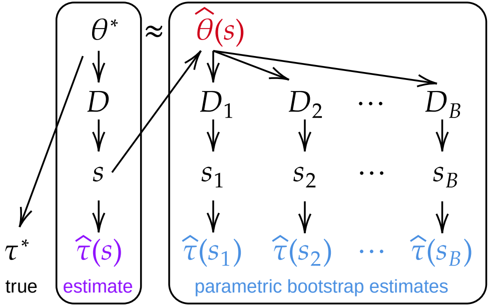
- Parameter of interest $\tau^* := \tau(\theta^*)$.
- Estimate θ^*, τ^* by $\hat{\theta}(s)$, $\hat{\tau}(s)$.
- Let $D_b \sim F(x|\hat{\theta}(s))$, $s_b = s(D_b)$. The PB estimator of τ^* is $\hat{\tau}(s_b)$.



- Distributions of $\sqrt{n}(\hat{\tau}(D) - \tau^*)$ and $\sqrt{n}(\hat{\tau}(D_b) - \hat{\tau}(D))$ are $H_n(\theta^*)$ and $H_n(\hat{\theta}(D))$.
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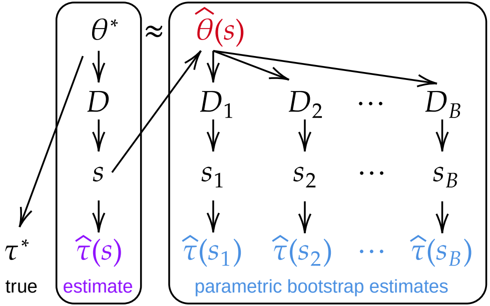

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When $\hat{\theta}(D)$ in PB is biased, the consistency may not hold.

Related Work

Naïve usage of PB under DP gives biased results.

Parametric bootstrap

- Du et al. (2020); Ferrando et al. (2022); Alabi and Vadhan (2022)

Bag-of-little bootstrap

- Evans et al. (2023); Covington et al. (2021)

Indirect inference for bias correction

- Gourieroux et al. (1993); Jiang and Turnbull (2004); Guerrier et al. (2019)

Indirect Estimator (Gourieroux, Monfort, and Renault, 1993)

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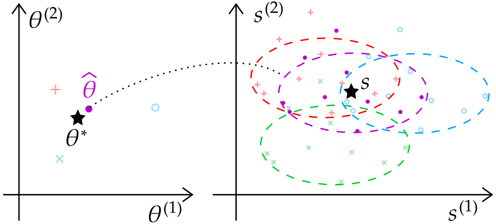

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Definition (Indirect estimator)

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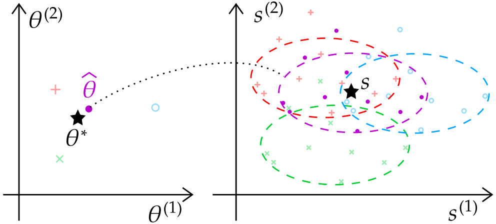

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Theorem: Indirect Estimator Consistency

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  1. $s_i(\theta)$ used in $\hat{\theta}_{\mathrm{IND}}$
  2. $s_b(\hat{\theta}_{\mathrm{IND}})$ used in PB
- The choice of Ω determines the asymptotic variance of $\hat{\theta}_{\mathrm{IND}}$.

(Novel) Adaptive Indirect Estimator

Definition (Adaptive indirect estimator)

Let $\Omega = (S(\theta))^{-1}$. $S(\theta)$: sample covariance matrix of $\{s_i(\theta)\}_{i=1}^{R}$.
(Intuition: tolerate more difference in more uncertain directions.)

$$\hat{\theta}_{\mathrm{ADI}} := \operatorname*{arg\,min}_{\theta \in \Theta} \left\| s^* - \frac{1}{R} \sum_{i=1}^{R} s_i(\theta) \right\|_{(S(\theta))^{-1}}.$$

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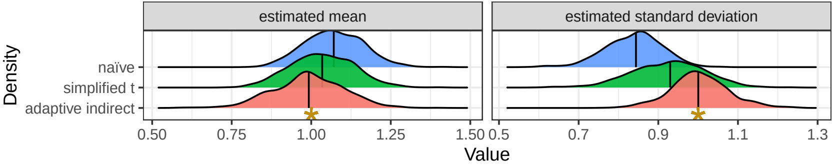
Theorem: Consistency and asymptotic variance ($R \to \infty$)

1. $\hat{\theta}_{\mathrm{ADI}}$ is a consistent estimator of θ^*, $\sqrt{n}\left(\hat{\theta}_{\mathrm{ADI}} - \theta^*\right)$ converges to a dist;
2. The parametric bootstrap CIs and HTs based on $\hat{\theta}_{\mathrm{ADI}}$ are consistent;
3. (Optimal asymptotic variance) For any well-behaved consistent estimator $\psi(s)$, we have $\mathrm{Var}\left(\lim_{n\to\infty}\sqrt{n}\left(\psi(s) - \theta^*\right)\right) \succeq \mathrm{Var}\left(\lim_{n\to\infty}\sqrt{n}\left(\hat{\theta}_{\mathrm{ADI}} - \theta^*\right)\right)$.

Inference of Parameters (μ^*, σ^*) of Normal

Figure: Sampling distributions of different estimates. Vertical line is median, '$*$' is true value.



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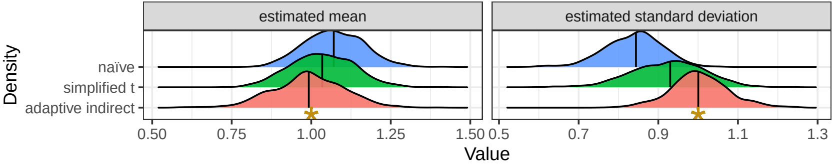
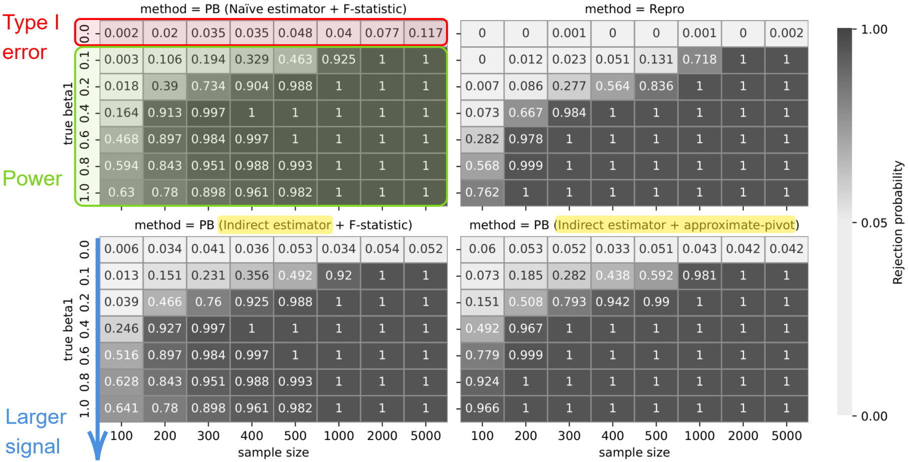


Method (95% CI)	Coverage		Average width	
	μ^*	σ^*	μ^*	σ^*
PB (adaptive indirect)	0.959 (0.006)	0.951 (0.007)	0.463 (0.003)	0.580 (0.003)
PB (naïve percentile)	0.697 (0.015)	0.006 (0.002)	0.311 (0.001)	0.293 (0.001)
PB (simplified t)	0.869 (0.011)	0.817 (0.012)	0.311 (0.001)	0.293 (0.001)
PB (Ferrando et al., 2022)	0.808 (0.012)	0.371 (0.015)	0.311 (0.001)	0.293 (0.001)
PB (Efron's BC)	0.854 (0.011)	0.042 (0.006)	0.298 (0.001)	0.139 (0.002)
PB (automatic percentile)	0.865 (0.011)	0.126 (0.010)	0.314 (0.001)	0.261 (0.001)
Repro (Awan and Wang, 2023)	0.989 (0.003)	0.998 (0.001)	0.599 (0.003)	0.758 (0.005)

$\mu^* = 1,\ \sigma^* = 1,\ L = 0,\ U = 3,\ R = 50,\ B = 200,\ (\sqrt{2})$-GDP.

Hypothesis Testing for Linear Regression

- Compare rejection probabilities (level 0.05) to (Alabi and Vadhan, 2022) & Repro.



$\Delta = 2,\ \beta_0^* = -0.5,\ x_i \sim N(0.5, 1),\ \varepsilon_i \sim N(0, 0.25),\ R = 50,\ B = 200,$ 1-GDP.

Part III: Debiased Parametric Bootstrap for Privatized Data

Contributions:

1. Prove consistency of PB (indirect estimator).
2. Propose an adaptive indirect estimator (ADI): consistent (PB), optimal asymp var.
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Compare ADI to Repro: (both simulation-based)

1. Repro is finite-sample valid with almost no assumptions while conservative.
2. ADI is an estimator, asymptotically optimal w/ more assumptions.
3. PB+ADI and Repro are state-of-the-art in different scenarios.

Summary

- DP bootstrap: non-parametric; difficult DP analysis; but restricted in mechanisms;
- Repro: accepts all mechanisms; finite-sample valid; but conservative;
- PB+ADI: accepts all mechanisms; asymp valid & efficient; but needs smoothness.

Repro and PB+ADI are general-purpose methods that solve the clamping problem and outperform (Alabi and Vadhan, 2022) which only focused on linear regression.

	DP bootstrap	Repro	PB+ADI
Data generating equation	Not needed	Needed	Needed & Smooth
DP mechanisms	All (for DP guarantee); Additive-noise (for inference)	Easily sampled	Easily sampled & Smooth
Inference	Asymptotic; often conservative; requires a point estimator	Finite-sample; often conservative; no estimator	Asymptotic; efficient; provides an estimator

Future Work

Future work

- For Repro and PB+ADI, find an appropriate data generating equation?
  - If there is none, consider non-parametric or semi-parametric models.
- Find the DP mechanism giving the optimal summary statistic s for inference?
- For DP Bootstrap, we need more post-processing in addition to deconvolution if the original mechanism gives a biased estimator.

References I

Daniel Alabi and Salil Vadhan. Hypothesis testing for differentially private linear regression. Advances in Neural Information Processing Systems, 35:14196–14209, 2022.

Jordan Awan and Zhanyu Wang. Simulation-based, finite-sample inference for privatized data. arXiv preprint arXiv:2303.05328, 2023.

Borja Balle, Gilles Barthe, and Marco Gaboardi. Privacy amplification by subsampling: Tight analyses via couplings and divergences. In Advances in Neural Information Processing Systems, volume 31, 2018.

Thomas Brawner and James Honaker. Bootstrap inference and differential privacy: Standard errors for free. Unpublished Manuscript, 2018.

Christian Covington, Xi He, James Honaker, and Gautam Kamath. Unbiased statistical estimation and valid confidence intervals under differential privacy. arXiv preprint arXiv:2110.14465, 2021.

Jinshuo Dong, Aaron Roth, and Weijie J. Su. Gaussian differential privacy. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 84(1):3–37, 2022.

Wenxin Du, Canyon Foot, Monica Moniot, Andrew Bray, and Adam Groce. Differentially private confidence intervals. arXiv preprint arXiv:2001.02285, 2020.

Bradley Efron. Empirical Bayes deconvolution estimates. Biometrika, 103(1):1–20, 2016.

Georgina Evans, Gary King, Margaret Schwenzfeier, and Abhradeep Thakurta. Statistically valid inferences from privacy-protected data. American Political Science Review, 117(4):12751290, 2023.

References II

Cecilia Ferrando, Shufan Wang, and Daniel Sheldon. Parametric bootstrap for differentially private confidence intervals. In International Conference on Artificial Intelligence and Statistics, pages 1598–1618. PMLR, 2022.

Christian Gourieroux, Alain Monfort, and Eric Renault. Indirect inference. Journal of applied econometrics, 8 (S1):S85–S118, 1993.

Stéphane Guerrier, Elise Dupuis-Lozeron, Yanyuan Ma, and Maria-Pia Victoria-Feser. Simulation-based bias correction methods for complex models. Journal of the American Statistical Association, 114(525):146–157, 2019.

Wenxin Jiang and Bruce Turnbull. The Indirect Method: Inference Based on Intermediate Statistics – A Synthesis and Examples. Statistical Science, 19(2):239 – 263, 2004.

Nianqiao Ju, Jordan Awan, Ruobin Gong, and Vinayak Rao. Data augmentation MCMC for Bayesian inference from privatized data. In Advances in Neural Information Processing Systems, volume 36, 2022.

Antti Koskela, Joonas Jälkö, and Antti Honkela. Computing tight differential privacy guarantees using fft. In Proceedings of the 23rd International Conference on Artificial Intelligence and Statistics, volume 108, pages 2560–2569. PMLR, 2020.

Vladimir Vovk, Alexander Gammerman, and Glenn Shafer. Algorithmic learning in a random world, volume 29. Springer, 2005.

Yue Wang, Daniel Kifer, Jaewoo Lee, and Vishesh Karwa. Statistical approximating distributions under differential privacy. Journal of Privacy and Confidentiality, 8(1), 2018.

References III

Yue Wang, Daniel Kifer, and Jaewoo Lee. Differentially private confidence intervals for empirical risk minimization. Journal of Privacy and Confidentiality, 9(1), 2019.

Oliver Williams and Frank McSherry. Probabilistic inference and differential privacy. Advances in Neural Information Processing Systems, 23:2451–2459, 2010.

Min-ge Xie and Peng Wang. Repro samples method for finite-and large-sample inferences. arXiv preprint arXiv:2206.06421, 2022.

f-DP and (ε, δ)-DP

Definition ((ε, δ)-DP)

A mechanism $M : \mathcal{X}^n \to \mathcal{Y}$ is (ε, δ)-DP if for any neighboring datasets $D \simeq D' \in \mathcal{X}^n$, and any measurable set $S \subseteq \mathcal{Y}$, the following inequality holds:

$$\Pr[M(D) \in S] \leq \mathrm{e}^{\varepsilon}\Pr[M(D') \in S] + \delta.$$

Definition (tradeoff function & f-DP)

Consider the hypothesis test $H_0 : Y \sim P$ versus $H_1 : Y \sim Q$. For any rejection rule $\phi(Y)$, α_ϕ is the type I error and β_ϕ is the type II error. The tradeoff function is

$$T_{P,Q}(\alpha) := \inf_{\phi}\{\beta_\phi \mid \alpha_\phi \leq \alpha\}.$$

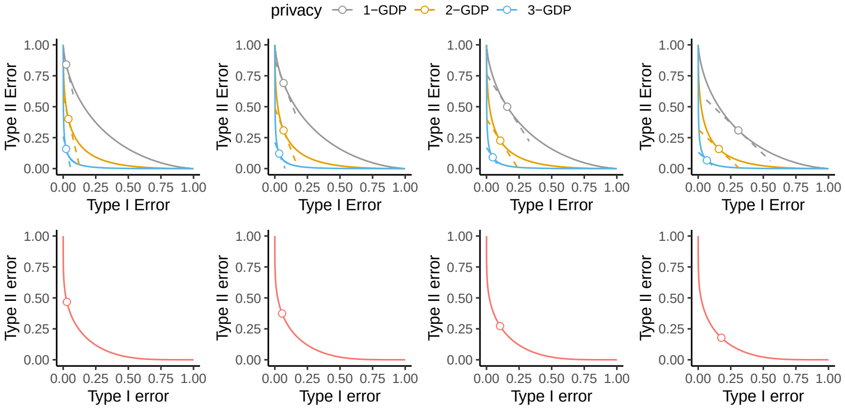
M is f-DP if $T_{M(D),M(D')}(\alpha) \geq f(\alpha)$ for any α and datasets D, D' with $D \simeq D'$.

Primal-dual conversion f-DP $\Leftrightarrow$ (ε, δ)-DP $\forall \varepsilon \geq 0$ with $\delta(\varepsilon) = 1 + f^*(-\mathrm{e}^{\varepsilon})$.

- $f_{\varepsilon,\delta}(\alpha) := \max\{0,\ 1 - \delta - \mathrm{e}^{\varepsilon}\alpha,\ \mathrm{e}^{-\varepsilon}(1 - \delta - \alpha)\}$-DP is equivalent to (ε, δ)-DP.

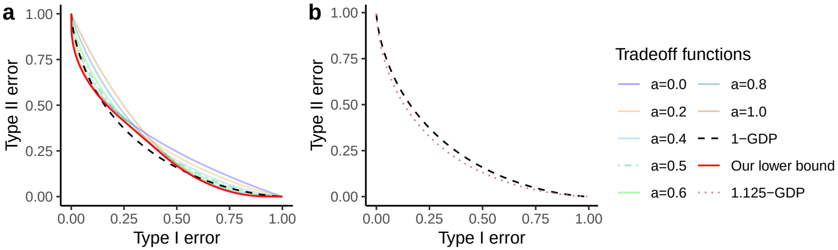
Privacy Guarantees for Mixture Mechanism

- If M randomly releases the output of M_i with probability p_i, and M_i is f_i-DP for $i \in [k]$, then M is f_{mix}-DP. $f_{\text{mix}} = \left(\sum_{i=1}^{k} \left(p_i f_i \circ (f_i')^{-1}\right)\right) \circ \left(\sum_{i=1}^{k} p_i (f_i')^{-1}\right)^{-1}$
- $\underline{p} = (p_1, p_2, p_3) = (\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$. f_1, f_2, f_3 correspond to 1-GDP, 2-GDP, and 3-GDP.



Privacy Analysis of DP Bootstrap: An Example

- Consider the Gaussian mechanism M with 1-GDP (dashed curve). $M \circ \texttt{boot}$ satisfies $f_{\texttt{boot}}$-DP (solid opaque curve). The transparent curves are for testing $M(D)$ vs $M(D')$ where $D = (a, 0, \ldots, 0)$, $D' = (a-1, 0, \ldots, 0)$, $M(D) = \frac{1}{n}\sum_{i=1}^{n} x_i + \xi$, $D = (x_1, x_2, \ldots, x_n)$, $\xi \sim \mathcal{N}(0, \frac{1}{n^2})$.
- The dashed and dotted dashed lines are misused as lower bounds in Brawner and Honaker (2018) and Koskela et al. (2020).



Accuracy of DP Bootstrap with Gaussian Mechanism

Unbiased estimate of θ	**Variance of the estimate**
Sample mean (non-private): $\hat{\theta}_1 = \bar{X}$	$\mathrm{Var}(\hat{\theta}_1) = \frac{\sigma_x^2}{n}$
Sample mean (Gaussian mechanism): $\hat{\theta}_2 = \bar{X} + \xi$ where $\xi \sim \mathcal{N}(0, \frac{1}{\mu^2 n^2})$	$\mathrm{Var}(\hat{\theta}_2) = \frac{\sigma_x^2}{n} + \frac{1}{\mu^2 n^2}$
Bootstrap (non-private): $\hat{\theta}_3 = \bar{X}$	$\mathrm{Var}(\hat{\theta}_3) = \frac{\sigma_x^2}{n}$
DP bootstrap (Gaussian mechanism): $\hat{\theta}_4 = \tilde{X}'$ where $\xi_b \sim \mathcal{N}(0, \frac{(2-2/e)B}{\mu^2 n^2})$	$\mathrm{Var}(\hat{\theta}_4) = \frac{1+1/B-1/(nB)}{n}\sigma_x^2 + \frac{(2-2/e)}{\mu^2 n^2}$

Unbiased estimate of $\mathrm{Var}(\hat{\theta}_i)$	**Variance of the estimate**
$\widehat{\mathrm{Var}}(\hat{\theta}_1) = \frac{s_X^2}{n}$	$\mathrm{Var}(\widehat{\mathrm{Var}}(\hat{\theta}_1)) \in O(\frac{1}{n^3})$
$\widehat{\mathrm{Var}}(\hat{\theta}_2) = \frac{s_X^2+\xi}{n} + \frac{1}{\mu^2 n^2}$ where $\xi \sim \mathcal{N}(0, \frac{1}{\mu^2 n^2})$	$\mathrm{Var}(\widehat{\mathrm{Var}}(\hat{\theta}_2)) \in O(\frac{1}{n^3} + \frac{1}{\mu^2 n^4})$
$\widehat{\mathrm{Var}}(\hat{\theta}_3) = \frac{n}{n-1}\hat{s}_B^2$	$\mathrm{Var}(\widehat{\mathrm{Var}}(\hat{\theta}_3)) \in O(\frac{1}{n^2 B} + \frac{1}{n^3})$
$\widehat{\mathrm{Var}}(\hat{\theta}_4) = \frac{nB+n-1}{B(n-1)}\tilde{s}_B^2 - \frac{(2-2/e)B}{n(n-1)\mu^2}$	$\mathrm{Var}(\widehat{\mathrm{Var}}(\hat{\theta}_4)) \in O(\frac{1}{n^2 B} + \frac{1}{n^3 \mu^2} + \frac{B}{n^4 \mu^4} + \frac{1}{n^3})$

DP Bootstrap: Deconvolution

- We choose to use `deconvolveR` (Efron, 2016) based on Empirical Bayes since it performs the best in our settings without tuning its hyper-parameters.
- For the model $Y = X + e$, `deconvolveR` assumes that Y and X are distributed discretely with the sizes of their supports $|\mathcal{Y}| = k$ and $|\mathcal{X}| = m$.
- It models the distribution of X by $f(\alpha) = \mathrm{e}^{Q\alpha}/c(\alpha)$ where Q is an $m \times p$ structure matrix with values from the natural spline basis with order p, $ns(\mathcal{X}, p)$, and α is the unknown p-dimensional parameter vector; $c(\alpha)$ is the divisor necessary to make f sum to 1.
- The estimation of the distribution of X is obtained through the estimation of α: It estimates α by maximizing a penalized log-likelihood $m(\alpha) = l(Y; \alpha) - s(\alpha)$ with respect to α where $s(\alpha)$ is the penalty term, and $l(Y; \alpha)$ is the log-likelihood function of Y derived from $f(\alpha)$ and the known distribution of e.

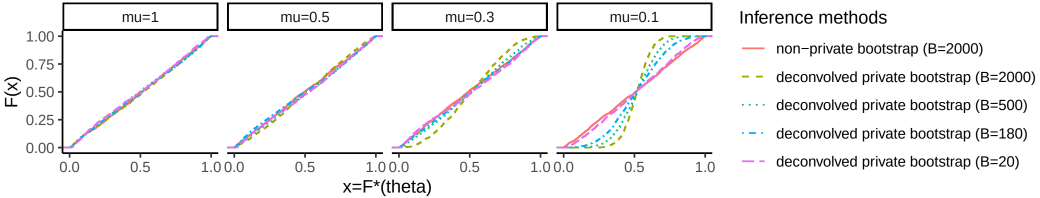
DP CIs for Normal: Compare DP Bootstrap to NoisyVar (Du et al., 2020)

Table: Coverage and width of CIs with different privacy guarantees. Confidence level is 90%. The standard error estimated from 2000 replicates is in parenthesis. $B \propto n\mu^2$.

Privacy	Method	Coverage	CI width
N/A	Bootstrap (B=2000)	0.905 (7e-3)	0.014 (6e-6)
1-GDP	DP bootstrap (B=2000)	0.896 (7e-3)	0.014 (1e-5)
	NoisyVar	0.803 (9e-3)	0.011 (7e-6)
0.5-GDP	DP bootstrap (B=500)	0.898 (7e-3)	0.014 (2e-5)
	NoisyVar	0.806 (9e-3)	0.011 (7e-6)
0.3-GDP	DP bootstrap (B=180)	0.901 (7e-3)	0.015 (3e-5)
	NoisyVar	0.804 (9e-3)	0.011 (7e-6)
0.1-GDP	DP bootstrap (B=20)	0.962 (4e-3)	0.020 (1e-4)
	NoisyVar	0.819 (9e-3)	0.012 (7e-6)

DP CIs for Normal

- Coverage check for all confidence levels.



Repro: Over-coverage

Table: Relative width due to over-coverage for the normal mean with known variance, when the nominal level is $1-\alpha = 0.95$, and the over-coverage level is $1-\alpha^* = (1-\alpha)^{1/d}$.

Dimension d	1	2	5	10	100	1000
Relative width	1	1.14	1.31	1.43	1.77	2.07

Table: 95% confidence intervals for private Bernoullis with unknown n. The first row uses Mahalanobis depth, and the second row uses an approximate pivot. For both intervals, an initial $(1-10^{-4})$-CI for n is used to reduce the nuisance parameter search. Parameters for the simulation are $n^* = 100$, $p^* = 0.2$, $\varepsilon = 1$, $R = 200$.

	Coverage	**Width**
Mahalanobis Depth	0.980 (0.004)	0.197 (0.001)
Approximate Pivot	0.949 (0.007)	0.163 (0.001)

Logistic Regression: Compare Repro to DP-CI-ERM (Wang et al., 2019)

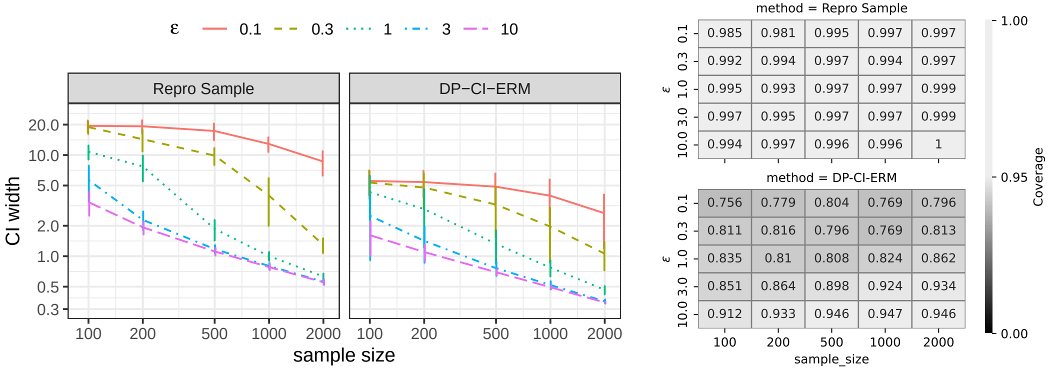


Figure: Width and coverage for the confidence intervals of β_1 in logistic regression with repro and DP-CI-ERM Wang et al. (2019). Parameters for this simulation are $a^* = b^* = 0.5$, $\beta_0^* = 0.5$, $\beta_1^* = 2$, $R = 200$, $\alpha = 0.05$, and the results were averaged over 1000 replicates.

$$\hat{\theta}_{\mathrm{DP}}(D; u) = \arg\min_{\theta \in \Theta} \left(\hat{\mathcal{L}}(\theta; D) + \frac{\gamma}{2n} \theta^\intercal \theta + \frac{u^\intercal \theta}{n} \right), \quad f(u; \varepsilon, \Delta) \propto \exp\left(-\frac{\varepsilon q}{\Delta} \|u\|_\infty \right).$$

Logistic Regression: Different Test Statistics in Repro

Table: Average width for the confidence intervals of β_1 in logistic regression using repro with the Mahalanobis depth on different summary statistics s. $T_{\text{pivot}} :=$
$\sqrt{n}\left(\hat{I}(\beta^*; D_{\theta^*}) + \text{Cov}(V)\right)^{-\frac{1}{2}}\left(\left(H^* + \frac{\gamma}{n}\right)\hat{\theta}_{\text{DP}} - H^*\beta^*\right)$, $H^* := \frac{1}{2}(\hat{I}(\hat{\theta}_{\text{DP}}; D_{\hat{\theta}^*_{\text{DP}}}) + \hat{I}(\beta^*; D_{\theta^*}))$.

$s = (\hat{\theta}_{\text{DP}}, \tilde{z}, \widetilde{z^2})$	$n = 100$	$n = 200$	$n = 500$	$n = 1000$	$n = 2000$
$\varepsilon = 0.1$	19.430 (0.089)	19.252 (0.099)	17.306 (0.109)	12.870 (0.072)	8.622 (0.077)
$\varepsilon = 0.3$	18.877 (0.091)	14.335 (0.114)	9.878 (0.064)	3.975 (0.064)	1.291 (0.007)
$\varepsilon = 1$	10.762 (0.057)	7.727 (0.073)	1.862 (0.014)	1.003 (0.004)	0.630 (0.002)
$\varepsilon = 3$	5.678 (0.071)	2.287 (0.016)	1.176 (0.004)	0.801 (0.002)	0.560 (0.001)
$\varepsilon = 10$	3.426 (0.030)	1.931 (0.010)	1.115 (0.004)	0.781 (0.002)	0.553 (0.001)
$s = (T_{\text{pivot}}, \tilde{z}, \widetilde{z^2})$	$n = 100$	$n = 200$	$n = 500$	$n = 1000$	$n = 2000$
$\varepsilon = 0.1$	19.240 (0.108)	19.337 (0.097)	18.487 (0.105)	14.789 (0.106)	7.000 (0.097)
$\varepsilon = 0.3$	19.243 (0.087)	15.533 (0.134)	8.234 (0.091)	2.577 (0.032)	1.148 (0.005)
$\varepsilon = 1$	9.939 (0.084)	4.613 (0.062)	1.594 (0.008)	0.955 (0.003)	0.617 (0.002)
$\varepsilon = 3$	3.309 (0.033)	1.905 (0.009)	1.118 (0.003)	0.782 (0.002)	0.553 (0.001)
$\varepsilon = 10$	2.381 (0.012)	1.665 (0.006)	1.058 (0.003)	0.762 (0.002)	0.545 (0.001)

Indirect Estimator (Gourieroux, Monfort, and Renault, 1993)

- Private statistics:

$$s := \arg\min_{\beta} \rho(\beta; D, u_{\mathrm{DP}}), \;\; D := G(\theta^*; u).$$

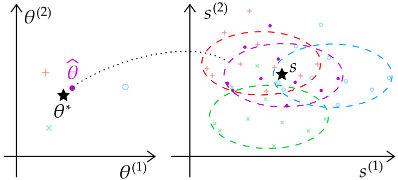
  - DP mechanism ρ contains extra uncertainty $u_{\mathrm{DP}} \sim F_{\mathrm{DP}}$,
  - e.g., Gaussian Mechanism, Objective perturbation.
- Fix the randomness (u^r, u^r_{DP}) in generating $D^r(\theta) := G(\theta, u^r)$ and

$$s^r(\theta) := \arg\min_{\beta} \rho(\beta; D^r(\theta), u^r_{\mathrm{DP}}).$$

- Find the θ generating $s^r(\theta)$ most similar to s.

Definition (Indirect estimator)

$$\hat{\theta}_{\mathrm{IND}} := \arg\min_{\theta \in \Theta} \left\| s - \frac{1}{R} \sum_{r=1}^{R} s^r(\theta) \right\|_{\Omega_n}.$$



Indirect Estimator: Asymptotic Distributions

- $\rho_n(\beta; D, u_{\mathrm{DP}}) \xrightarrow{\mathrm{P}} \rho_\infty(\beta; F_u, F_{\mathrm{DP}}, \theta^*)$,
- $b(\theta) := \mathrm{argmax}_{\beta \in \mathbb{B}} \rho_\infty(\beta; F_u, F_{\mathrm{DP}}, \theta)$, $\beta^* := b(\theta^*)$,
- $B^* := \frac{\partial b(\theta^*)}{\partial \theta}$, $J^* := -\frac{\partial^2 \rho_\infty(\beta^*; F_u, F_{\mathrm{DP}}, \theta^*)}{(\partial \beta)(\partial \beta^\intercal)}$,
- $\sqrt{n}(\frac{\partial \rho_n(\beta^*; D, u_{\mathrm{DP}})}{\partial \beta}) \xrightarrow{\mathrm{d}} F^*_{\rho,u,\mathrm{DP}}$, $\Omega_n \to \Omega$.

Let $v_i \overset{\text{iid}}{\sim} F^*_{\rho,u,\mathrm{DP}}$, $\Sigma^* := \mathrm{Var}[(J^*)^{-1} v_0] = \mathrm{Var}\left(\lim_{n\to\infty} \sqrt{n}(s - b(\theta^*))\right)$, $\Omega^* := (\Sigma^*)^{-1}$.

$$\sqrt{n}(\hat{\theta}_{\mathrm{IND}} - \theta^*) \xrightarrow{d} ((B^*)^\intercal \Omega B^*)^{-1} (B^*)^\intercal \Omega (J^*)^{-1} \left(v_0 - \frac{1}{R}\sum_{i=1}^{R} v_i\right).$$

$$\sqrt{n}(\hat{\theta}_{\mathrm{ADI}} - \theta^*) \xrightarrow{d} ((B^*)^\intercal \Omega^* B^*)^{-1} (B^*)^\intercal \Omega^* (J^*)^{-1} (v_0 - \mathbb{E}(v_0)).$$

$$\mathrm{Var}\left(\lim_{n\to\infty} \sqrt{n}(\hat{\theta}_{\mathrm{IND}} - \theta^*)\right) \succeq \mathrm{Var}\left(\lim_{n\to\infty} \sqrt{n}(\hat{\theta}_{\mathrm{ADI}} - \theta^*)\right) = \left((B^*)^\intercal (\Sigma^*)^{-1} B^*\right)^{-1}.$$

Indirect Estimator: Confidence Interval and Approximate Pivot

- Test statistic $\hat{\tau}$. Auxiliary scale of test statistic $\hat{\sigma}$.
- Let $\hat{\xi}_{(j)}$ be the jth order statistic of $\left\{ \frac{\hat{\tau}(s_b) - \tau(\hat{\theta})}{\hat{\sigma}(s_b)} \right\}_{b=1}^{B}$.
- CI for $\tau(\theta^*)$ is $\left[\hat{\tau}(s) + \hat{\xi}_{(\lfloor (B+1)\alpha/2 \rfloor)} \hat{\sigma}(s),\ \hat{\tau}(s) + \hat{\xi}_{(1+B-\lfloor (B+1)\alpha/2 \rfloor)} \hat{\sigma}(s)\right]$.

We want to choose $\hat{\tau}$ and $\hat{\sigma}$ such that $\frac{\hat{\tau}(s_b) - \tau(\hat{\theta})}{\hat{\sigma}(s_b)}$ has mean 0 and variance 1.

- Note that $b(\theta^*) = \lim_{n\to\infty} s^*$ and $\Sigma(\theta^*) = \mathrm{Var}\left(\lim_{n\to\infty} \sqrt{n}(s - b(\theta^*))\right)$.
- Let $\hat{\theta} := \hat{\theta}_{\mathrm{ADI}}$, $\hat{\theta}_b := \hat{\theta}(s_b)$. Set the test statistic as $\hat{\tau}(s_b) := \eta_1(\hat{\theta}(s_b))$. We use $\hat{\sigma}(s_b)$ to estimate the asymptotic standard deviation of $\hat{\tau}(s_b)$, where

$$\hat{\sigma}(s_b) := \frac{1}{\sqrt{n}} \left(\frac{\partial \eta_1}{\partial \theta}(\hat{\theta}_b) \left(\left(\frac{\partial b}{\partial \theta}(\hat{\theta}_b) \right)^{\intercal} \Sigma(\hat{\theta}_b)^{-1} \frac{\partial b}{\partial \theta}(\hat{\theta}_b) \right)^{-1} \left(\frac{\partial \eta_1}{\partial \theta}(\hat{\theta}_b) \right)^{\intercal} \right)^{\frac{1}{2}}.$$

Indirect Estimator with Different R

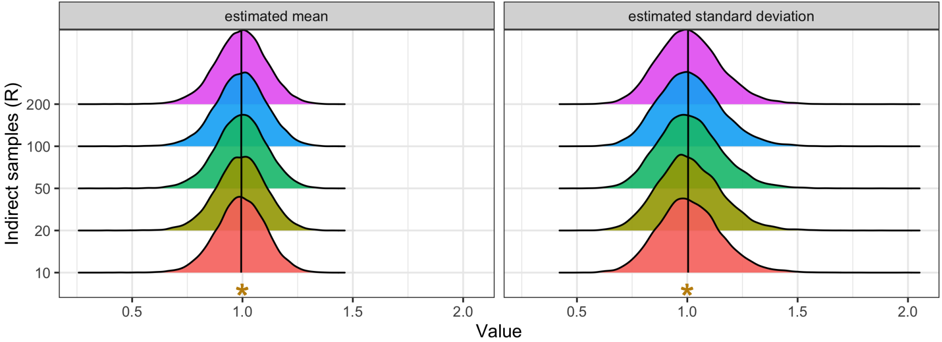


Figure: Comparison of the sampling distribution of the adaptive indirect estimates $\hat{\theta}_{\mathrm{ADI}}$ under different settings of the number of generated samples $R = 10, 20, 50, 100, 200$ in the normal distribution setting.

Indirect Estimator with Different Clamping Bounds

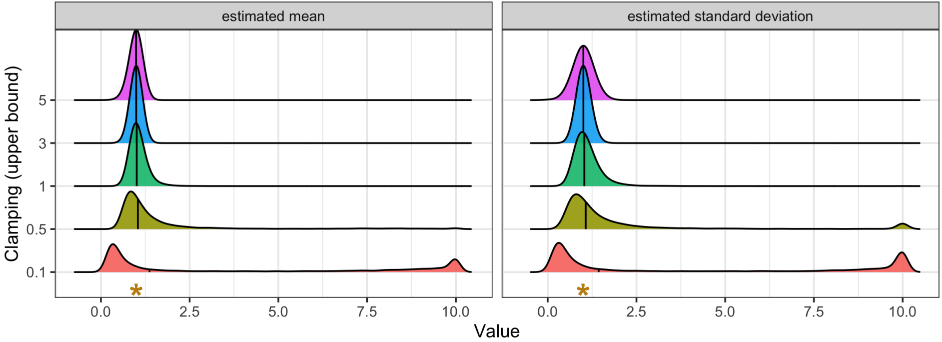


Figure: Comparison of the sampling distribution of the adaptive indirect estimates $\hat{\theta}_{\mathrm{ADI}}$ under different settings of the clamping parameter $U = 0.1, 0.5, 1, 3, 5$ in the normal distribution setting.