Efficient Inference on High-Dimensional Linear Models With Missing Outcomes

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Introduction

Consider a random sample $\{(Y_i, R_i, X_i)\}_{i=1}^n$ drawn from the joint distribution of (Y, R, X), where

- $Y \in \mathbb{R}$ is the outcome variable that could potentially be missing;
- $R \in \{0, 1\}$ is the indicator of Y being observed;
- $X \in \mathbb{R}^d$ is the high-dimensional covariate vector with $d \gg n$.

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▶ **Central Question of Interest:**

How can we conduct statistically and computationally efficient inference on $m_0(x) = \mathrm{E}(Y|X = x)$ despite missing outcomes?

Motivations: High-Dimensional Data

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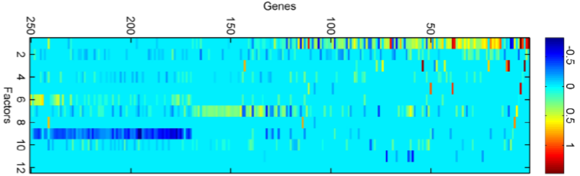

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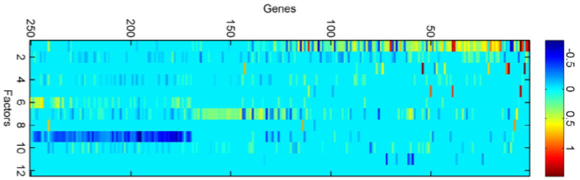

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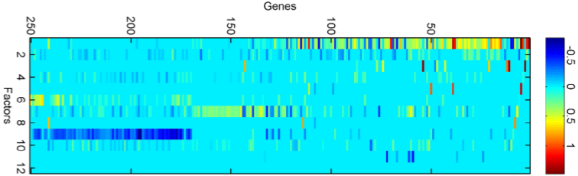

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2. Incorporating as many covariates as possible can control for potential confounders in causal inference (Wyss et al., 2022).

3. Generating high-dimensional covariates with interaction terms or spline features enables the simple parametric (e.g., linear) model to capture complex patterns (Belloni et al., 2019).

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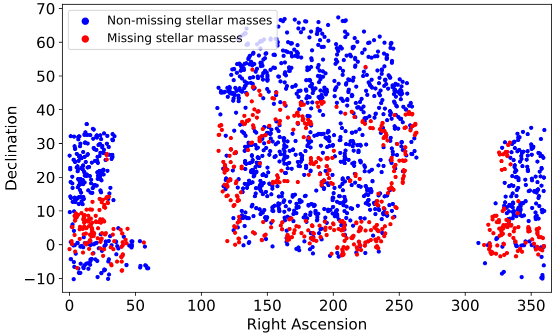
► **More Concrete Example:** Some (estimated) stellar masses of the observed galaxies in the Sloan Digital Sky Survey (SDSS-IV) are missing in the Firefly value-added catalog (Comparat et al., 2017).

Motivations: Stellar Mass Inference Problem

The missingness of (estimated) stellar masses is due to

- Limiting usage of the observational run in SDSS-IV for galaxy targets;
- Potential data contamination;
- Misclassification of galaxies as stars.



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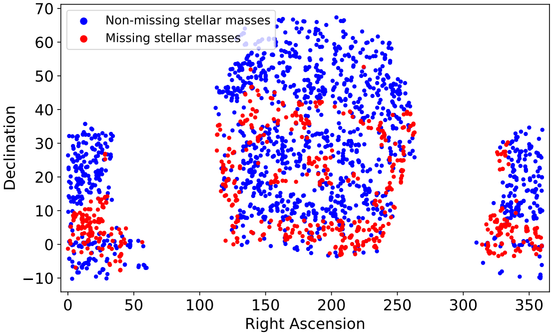

Figure 1: Galaxy distribution at a high redshift slice $0.4 \sim 0.401$.

► **Scientific Question:** *How can we conduct valid inference on the (estimated) stellar mass based on the spectroscopic and photometric properties?*

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1. *(Linearity)* The data $\{(Y_i, R_i, X_i)\}_{i=1}^n \subset \mathbb{R} \times \{0,1\} \times \mathbb{R}^d$ are i.i.d. observations from a sparse linear model

$$Y = X^T\beta_0 + \epsilon \quad \text{with} \quad \mathrm{E}\left(\epsilon \middle| X\right) = 0 \quad \text{and} \quad \mathrm{E}\left(\epsilon^2 \middle| X\right) = \sigma_\epsilon^2,$$

where $||\beta_0||_0 = \sum_{k=1}^d \mathbb{1}_{\{\beta_{0k} \neq 0\}} = s_\beta \ll d$.

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  - Sparse additive model (Ravikumar et al., 2009);
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1. (*Fully observed outcomes*) Debiased Lasso is applicable (Zhang and Zhang, 2014; van de Geer et al., 2014; Javanmard and Montanari, 2014):

$$\widehat{\beta}^{\text{debias}} = \widehat{\beta}_\lambda + \frac{1}{n}\widehat{\Theta}\sum_{i=1}^n X_i(Y_i - X_i^T\widehat{\beta}_\lambda),$$

- $\widehat{\beta}_\lambda = \underset{\beta\in\mathbb{R}^d}{\arg\min}\left[\frac{1}{2n}\sum_{i=1}^n (Y_i - X_i^T\beta)^2 + \lambda\left|\left|\beta\right|\right|_1\right]$ is a Lasso solution with the regularization parameter $\lambda > 0$;
- $\widehat{\Theta} \in \mathbb{R}^{d\times d}$ is an approximation to the matrix inverse $\left(\frac{1}{n}\sum_{i=1}^n X_i X_i^T\right)^{-1}$.

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2. (*MAR outcomes*) Chakrabortty et al. (2019) proposed an M-estimation framework with a Lasso-type debiased and doubly robust estimator.

- **Drawbacks of the Existing Approaches:**

1. (*Computational issue*) They require a good approximation to the $d \times d$ debiasing matrix $\widehat{\Theta}$.

2. (*Loss of statistical efficiency*) Sample splitting or cross-fitting is necessary for the M-estimation framework.

Drawback of Existing Works and Our Contributions

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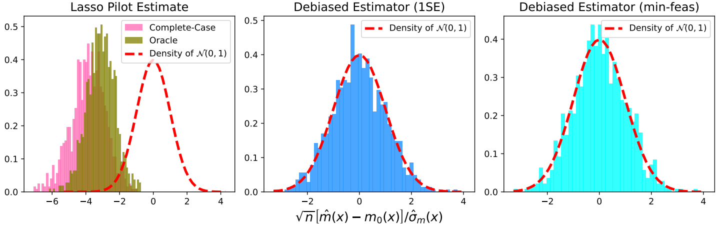
- **Our Contributions:**

- (*Computational efficiency*) Our core debiasing program is convex and only needs to solve for a n-dimensional weight vector.
- (*Statistical efficiency*) Our debiased estimator is semi-parametrically efficient among all asymptotically linear estimators.

Highlights of Today's Presentation



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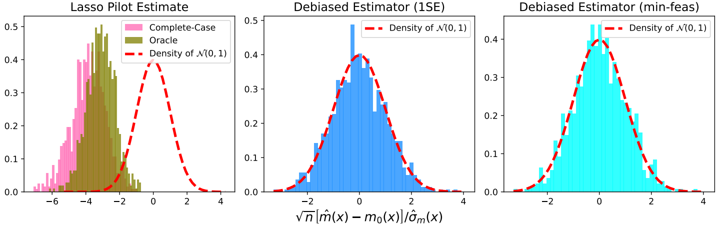

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   - Estimate $\pi(X) = \mathrm{P}(R = 1|X)$ via any machine learning methods.
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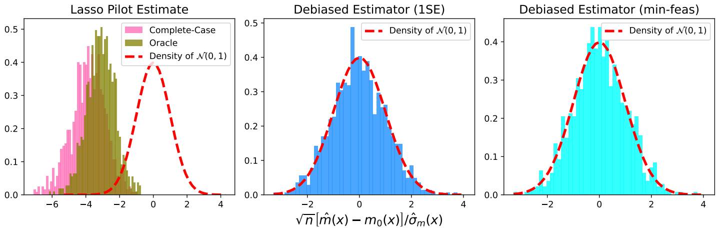

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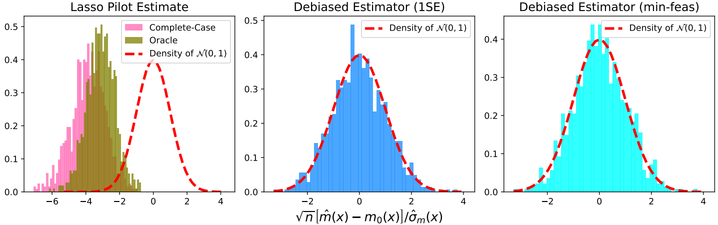

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2. Discuss the asymptotic normality and semi-parametric efficiency of our final debiased estimator.
3. Demonstrate the finite-sample performance via simulations and present an application to the stellar mass inference problem.

Methodology

Heuristics From Debiased Lasso

For any fixed $\lambda > 0$, the Lasso solution (on the complete-case data) is a biased estimator of $\beta_0 \in \mathbb{R}^d$:

$$\widehat{\beta}_\lambda = \arg\min_{\beta \in \mathbb{R}^d} \left[\frac{1}{2n} \sum_{i=1}^{n} R_i (Y_i - X_i^T \beta)^2 + \lambda \left|\left|\beta\right|\right|_1 \right].$$

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- Optimality/KKT condition reads

$$\frac{1}{n} \sum_{i=1}^{n} R_i X_i \left(Y_i - X_i^T \widehat{\beta}_\lambda \right) = \lambda \widehat{z} \quad \text{with} \quad \widehat{z} \in \partial \left|\left| \widehat{\beta}_\lambda \right|\right|_1 \in \mathbb{R}^d. \tag{1}$$

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- Linearity assumption $Y_i = X_i^T \beta_0 + \epsilon_i$ for $i = 1, ..., n$ implies that

$$\frac{1}{n} \sum_{i=1}^{n} R_i X_i \epsilon_i + \widehat{\Sigma} \left(\beta_0 - \widehat{\beta}_\lambda \right) = \lambda \widehat{z} \quad \text{with} \quad \widehat{\Sigma} = \frac{1}{n} \sum_{i=1}^{n} R_i X_i X_i^T.$$

Heuristics From Debiased Lasso

- Given an approximation $\widehat{\Theta} \in \mathbb{R}^{d\times d}$ to the gram matrix $\widehat{\Sigma}$, it becomes

$$\widehat{\beta}_\lambda - \beta_0 + \widehat{\Theta}\lambda\widehat{z} = \underbrace{\frac{1}{n}\sum_{i=1}^{n} R_i \widehat{\Theta} X_i \epsilon_i}_{\text{Stochastic error } \sim \mathcal{N}_d(0,\widetilde{\Sigma})} + \underbrace{\left(\widehat{\Theta}\widehat{\Sigma} - I_d\right)\left(\beta_0 - \widehat{\beta}_\lambda\right)}_{\text{Asymptotically negligible bias}}.$$

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- By KKT condition (1), the debiased Lasso estimate is thus given by

$$\begin{aligned}\widehat{\beta}^{\text{debias}} &= \widehat{\beta}_\lambda + \widehat{\Theta}\lambda\widehat{z} \\ &= \widehat{\beta}_\lambda + \frac{1}{n}\sum_{i=1}^{n} R_i \widehat{\Theta} X_i \left(Y_i - X_i^T \widehat{\beta}_\lambda\right).\end{aligned}$$

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- A candidate debiased estimator for $m_0(x) = x^T \beta_0$ is

$$\widehat{m}^{\text{debias}}(x) = x^T \widehat{\beta}^{\text{debias}} = x^T \widehat{\beta}_\lambda + \frac{1}{n} x^T \widehat{\Theta} \sum_{i=1}^n R_i X_i \left(Y_i - X_i^T \widehat{\beta}_\lambda\right).$$

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► **Issue:** Fitting the debiasing matrix $\widehat{\Theta} \in \mathbb{R}^{d \times d}$ is computationally inefficient; see, *e.g.*, the nodewise regression (Meinshausen and Bühlmann, 2006; van de Geer et al., 2014).

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- **Solution:** Introduce the weight vector $\widehat{\boldsymbol{w}} = (\widehat{w}_1, ..., \widehat{w}_n)^T \in \mathbb{R}^n$ with

$$\widehat{w}_i = \begin{cases} \frac{1}{\sqrt{n}} x^T \widehat{\Theta} X_i & R_i = 1, \\ 0 & R_i = 0, \end{cases}$$

for $i = 1, ..., n$ so that our final debiased estimator becomes

$$\widehat{m}^{\text{debias}}(x; \widehat{\boldsymbol{w}}) = x^T \widehat{\beta} + \frac{1}{\sqrt{n}} \sum_{i=1}^{n} \widehat{w}_i R_i \left(Y_i - X_i^T \widehat{\beta} \right). \tag{2}$$

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- **Question:** How do we estimate the weight vector $\widehat{\boldsymbol{w}} = (\widehat{w}_1, ..., \widehat{w}_n)^T$?

Optimize Over the Conditional Mean Square Error

Consider the generic debiased estimator $m^{\text{debias}}(x;\boldsymbol{w})$ from (2) as:

$$m^{\text{debias}}(x;\boldsymbol{w}) = x^T\beta + \frac{1}{\sqrt{n}}\sum_{i=1}^{n} w_i R_i \left(Y_i - X_i^T\beta\right). \tag{3}$$

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The conditional mean squared error of $\sqrt{n}\, m^{\text{debias}}(x;\boldsymbol{w})$ is given by

$$\begin{aligned}
&\mathrm{E}\left[\left(\sqrt{n}\, m^{\text{debias}}(x;\boldsymbol{w}) - \sqrt{n}\, m_0(x)\right)^2 \middle| X_1,\ldots,X_n\right] \\
&= \underbrace{\sigma_\epsilon^2 \sum_{i=1}^{n} w_i^2 \pi(X_i)}_{\text{Main Conditional Variance}} + \underbrace{\left[\left(\frac{1}{\sqrt{n}}\sum_{i=1}^{n} w_i \pi(X_i) X_i - x\right)^T \sqrt{n}\left(\beta_0 - \beta\right)\right]^2}_{\text{Conditional Bias}} \\
&\quad + \underbrace{(\beta_0 - \beta)^T \left[\sum_{i=1}^{n} w_i^2 \pi(X_i)\left(1 - \pi(X_i)\right) X_i X_i^T\right](\beta_0 - \beta)}_{\text{Asymptotically Negligible Conditional Variance}},
\end{aligned}$$

where $\pi(X) = \mathrm{P}(R = 1|X)$ is the propensity score under MAR condition.

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- By Hölder's inequality, the "Conditional Bias" is upper bounded by

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- We design our core debiasing program as:

$$\min_{\boldsymbol{w}\in\mathbb{R}^n} \sum_{i=1}^n \widehat{\pi}_i w_i^2 \quad \text{subject to} \quad \left\| x - \frac{1}{\sqrt{n}} \sum_{i=1}^n w_i \cdot \widehat{\pi}_i \cdot X_i \right\|_\infty \le \frac{\gamma}{n},$$

where $\gamma > 0$ is a tuning parameter and $\widehat{\pi}_i$ is a consistent estimate of the propensity score $\pi(X_i)$ for $i = 1, ..., n$.

Proposed Debiasing Inference Procedure

1. Compute the Lasso pilot estimate $\widehat{\beta}_\lambda$ on the complete-case data

$$\widehat{\beta}_\lambda = \arg\min_{\beta \in \mathbb{R}^d} \left[\frac{1}{2n} \sum_{i=1}^{n} R_i (Y_i - X_i^T \beta)^2 + \lambda \, ||\beta||_1 \right].$$

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$$\widehat{\beta}_\lambda = \operatorname*{arg\,min}_{\beta \in \mathbb{R}^d} \left[\frac{1}{2n} \sum_{i=1}^n R_i (Y_i - X_i^T \beta)^2 + \lambda \left|\left|\beta\right|\right|_1 \right].$$
2. Obtain consistent propensity score estimates $\widehat{\pi}_i, i = 1, ..., n$ by *any machine learning method* based on $\{(X_i, R_i)\}_{i=1}^n \subset \mathbb{R}^d \times \{0, 1\}$.

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4. Define the debiased estimator for $m_0(x)$ as:
$$\widehat{m}^{\text{debias}}(x; \widehat{\boldsymbol{w}}) = x^T \widehat{\beta} + \frac{1}{\sqrt{n}} \sum_{i=1}^{n} \widehat{w}_i R_i \left(Y_i - X_i^T \widehat{\beta} \right).$$

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5. Construct the asymptotic $(1-\tau)$-level confidence interval for $m_0(x)$ as:

$$\left[\widehat{m}^{\text{debias}}(x; \widehat{\boldsymbol{w}}) \pm \Phi^{-1}\left(1-\frac{\tau}{2}\right)\cdot\widehat{\sigma}_\epsilon\cdot\sqrt{\frac{1}{n}\sum_{i=1}^n \widehat{\pi}_i\widehat{w}_i^2}\right]$$ with $\Phi(\cdot)$ being the CDF of $\mathcal{N}(0,1)$.

There are two unanswered questions in our proposed debiasing inference procedure:

1. How can we select the tuning parameter $\gamma > 0$ for our debiasing program?

$$\min_{\boldsymbol{w} \in \mathbb{R}^n} \left\{ \sum_{i=1}^n \widehat{\pi}_i w_i^2 : \left|\left| x - \frac{1}{\sqrt{n}} \sum_{i=1}^n w_i \cdot \widehat{\pi}_i \cdot X_i \right|\right|_\infty \leq \frac{\gamma}{n} \right\}.$$

2. Why is the asymptotic $(1-\tau)$-level confidence interval for $m_0(x)$ valid?

$$\left[\widehat{m}^{\text{debias}}(x; \widehat{\boldsymbol{w}}) \pm \Phi^{-1}\left(1 - \frac{\tau}{2}\right) \cdot \widehat{\sigma}_\epsilon \cdot \sqrt{\frac{1}{n} \sum_{i=1}^n \widehat{\pi}_i \widehat{w}_i^2}\right] \quad \text{with } \Phi(\cdot) \text{ being the CDF of } \mathcal{N}(0,1).$$

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► **Answer:** The above two questions can be addressed by the *dual formulation/solution* of our debiasing program!

Dual Formulation of Our Debiasing Program

The primal form of our debiasing program is a quadratic programming problem with a box constraint:

$$\min_{\boldsymbol{w}\in\mathbb{R}^n}\left\{\sum_{i=1}^n \widehat{\pi}_i w_i^2 : \left\|x - \frac{1}{\sqrt{n}}\sum_{i=1}^n w_i \cdot \widehat{\pi}_i \cdot X_i\right\|_\infty \le \frac{\gamma}{n}\right\}.$$

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Proposition (Proposition 1 in Zhang et al. 2023)

The dual form of our debiasing program is given by

$$\min_{\ell\in\mathbb{R}^d}\left\{\frac{1}{4n}\sum_{i=1}^n \widehat{\pi}_i\left[X_i^T\ell\right]^2 + x^T\ell + \frac{\gamma}{n}\,||\ell||_1\right\}.$$

If the strong duality holds, we further have that

$$\widehat{w}_i = -\frac{1}{2\sqrt{n}}\cdot X_i^T\widehat{\ell} \quad \text{for} \quad i=1,\ldots,n,$$

where $\widehat{\boldsymbol{w}}\in\mathbb{R}^n$ and $\widehat{\ell}\in\mathbb{R}^d$ are the solutions to the primal and dual debiasing program, respectively.

Practical Implication of Our Dual Debiasing Program

The dual form of our debiasing program is an *unconstrained* quadratic programming problem:

$$\min_{\ell \in \mathbb{R}^d} \left\{ \frac{1}{4n} \sum_{i=1}^{n} \widehat{\pi}_i \left[X_i^T \ell \right]^2 + x^T \ell + \frac{\gamma}{n} ||\ell||_1 \right\}.$$

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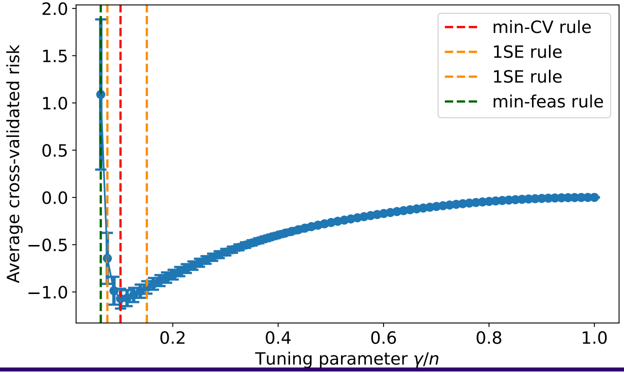
We can fine-tune $\gamma > 0$ by cross-validation.



Interpretations From Neyman Near-Orthogonalization

- Consider the regression function $m \equiv m(x) \in \mathbb{R}$ as the main parameter to be inferred and $\beta \in \mathbb{R}^d$ as the high-dimensional nuisance parameter.

- Our generic debiased estimator $m^{\text{debias}}(x, \boldsymbol{w})$ solves the sample-based estimating equation

$$\frac{1}{n}\sum_{i=1}^{n} \Xi_x(Y_i, R_i, X_i; m^{\text{debias}}, \beta) = m^{\text{debias}}(x; \boldsymbol{w}) - x^T\beta - \frac{1}{\sqrt{n}}\sum_{i=1}^{n} w_i \cdot R_i \left(Y_i - X_i^T\beta\right) = 0.$$

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- The Neyman near-orthogonalization condition (Chernozhukov et al., 2018) given $\boldsymbol{X} = (X_1, ..., X_n)^T \in \mathbb{R}^{n\times d}$ at $(m_0, \beta_0) = (x^T\beta_0, \beta_0)$ requires

$$\begin{aligned} &\mathrm{E}\left[\frac{1}{n}\sum_{i=1}^{n} \Xi_x(Y_i, R_i, X_i; m_0, \beta_0)\middle|\boldsymbol{X}\right] = 0, \\ &\sup_{\beta \in \mathcal{T}_n}\left|\left\{\frac{\partial}{\partial\beta}\mathrm{E}\left[\frac{1}{n}\sum_{i=1}^{n} \Xi_x(Y_i, R_i, X_i; m, \beta)\middle|\boldsymbol{X}\right]\Bigg|_{(m_0,\beta_0)}\right\}^T(\beta - \beta_0)\right| \leq \frac{\delta_n}{\sqrt{n}}, \end{aligned} \tag{4}$$

where $\mathcal{T}_n$ is a properly shrinking neighborhood of β_0 and $\delta_n = o(1)$.

- Both conditions in (4) hold true, because for any $\beta \in \mathcal{T}_n$ and some convex set $\mathcal{B}$ containing β_0, we have that

$$\begin{aligned}
&\left|\left\{\frac{1}{n}\sum_{i=1}^{n}\frac{\partial}{\partial\beta}\mathrm{E}\left[\Xi_x(Y_i,R_i,X_i;m,\beta)|X\right]\Big|_{(m_0,\beta_0)}\right\}^T(\beta-\beta_0)\right| \\
&=\left|\left[x-\frac{1}{\sqrt{n}}\sum_{i=1}^{n}w_i\cdot\pi(X_i)X_i\right]^T(\beta_0-\beta)\right| \\
&\text{“}\leq\text{”}\left|\left|x-\frac{1}{\sqrt{n}}\sum_{i=1}^{n}w_i\cdot\widehat{\pi}_i\cdot X_i\right|\right|_{\infty}||\beta-\beta_0||_1 \quad \text{by Hölder's inequality} \\
&\leq\frac{\gamma}{n}||\beta-\beta_0||_1 \quad \text{by the box constraint in our debiasing program} \\
&\leq\frac{\delta_n}{\sqrt{n}} \quad \text{by setting } \mathcal{T}_n=\left\{\beta\in\mathcal{B}\subset\mathbb{R}^d:||\beta-\beta_0||_1\leq\frac{\sqrt{n}\delta_n}{\gamma}\right\}.
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- Our debiasing program optimizes the (estimated) variance among all the estimators satisfying Neyman near-orthogonalization (4).

Interpretations From Neyman Near-Orthogonalization

- Both conditions in (4) hold true, because for any $\beta \in \mathcal{T}_n$ and some convex set $\mathcal{B}$ containing β_0, we have that

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$$= \left| \left[x - \frac{1}{\sqrt{n}} \sum_{i=1}^{n} w_i \cdot \pi(X_i) X_i \right]^T (\beta_0 - \beta) \right|$$

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- Our debiasing program optimizes the (estimated) variance among all the estimators satisfying Neyman near-orthogonalization (4).
- (4) also allows our debiasing program to *de-correlate* the Lasso pilot regression from propensity score estimation and weight optimization.

Asymptotic Theory

- **Goal:** Establish the asymptotic normality of our debiased estimator

$$\widehat{m}^{\text{debias}}(x;\widehat{\boldsymbol{w}}) = x^T\widehat{\beta} + \frac{1}{\sqrt{n}}\sum_{i=1}^{n}\widehat{w}_i R_i\left(Y_i - X_i^T\widehat{\beta}\right).$$

Linearity assumption $Y_i = X_i^T\beta_0 + \epsilon_i$ for $i = 1, ..., n$ implies that

$$\sqrt{n}\left[\widehat{m}^{\text{debias}}(x;\widehat{\boldsymbol{w}}) - m_0(x)\right] = \underbrace{\sum_{i=1}^{n}\widehat{w}_i R_i\epsilon_i}_{\text{Not an i.i.d. sum!}} + \left[x - \frac{1}{\sqrt{n}}\sum_{i=1}^{n}\widehat{w}_i R_i X_i\right]^T\sqrt{n}\left(\widehat{\beta} - \beta_0\right),$$

Theoretical Implication of Our Dual Debiasing Program

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- **Solution:** With the dual relation $\widehat{w}_i = -\frac{1}{2\sqrt{n}} \cdot X_i^T\widehat{\ell}, i = 1, ..., n$, we obtain

$$\begin{aligned}\sqrt{n}\left[\widehat{m}^{\text{debias}}(x;\widehat{\boldsymbol{w}}) - m_0(x)\right] &= -\frac{1}{2\sqrt{n}}\sum_{i=1}^n R_i\epsilon_i X_i^T\widehat{\ell} + \left[x + \frac{1}{2n}\sum_{i=1}^n R_i X_i X_i^T\widehat{\ell}\right]^T \sqrt{n}\left(\beta_0 - \widehat{\beta}\right)\\ &= \underbrace{-\frac{1}{2\sqrt{n}}\sum_{i=1}^n R_i\epsilon_i X_i^T \ell_0(x)}_{\text{i.i.d. sum!}} + \underbrace{\text{“Bias terms”}}_{o_P(1)}.\end{aligned}$$

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$$\inf_{x \in \mathbb{S}^{d-1}} \mathrm{E}\left[R(X^T v)^2\right] \geq \kappa_R^2 \quad \text{with} \quad \mathbb{S}^{d-1} = \left\{x \in \mathbb{R}^d : ||x||_2 = 1\right\}.$$

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4. Define the population dual program as:

$$\min_{\ell \in \mathbb{R}^d} \left\{\frac{1}{4}\mathrm{E}\left[R\left(X^T \ell\right)^2\right] + x^T \ell\right\},$$

whose exact solution is $\ell_0(x) = -2\left[\mathrm{E}\left(RXX^T\right)\right]^{-1} x$. We assume that the r_ℓ-approximation $\widetilde{\ell}(x)$ to $\ell_0(x)$ is sparse with $r_\ell \in \left[0, \frac{1}{2}\right]$, *i.e.*,

$$s_\ell(x) = \left|\left|\widetilde{\ell}(x)\right|\right|_0 \ll \min\{n,d\} \;\text{ with }\; \widetilde{\ell}(x) = \arg\min_{u \in \mathbb{R}^d} \left\{||u||_0 : ||u - \ell_0(x)||_2 \leq r_\ell \,||\ell_0(x)||_2\right\}.$$

1. **Consistency of Lasso pilot estimate:** If $\lambda \asymp \sigma_\epsilon \sqrt{\frac{\log d}{n}}$ with $\log d = o(n)$, then $\left|\left|\widehat{\beta} - \beta_0\right|\right|_2 = O_P\left(\frac{1}{\kappa_R^2}\sqrt{\frac{s_\beta \log d}{n}}\right)$.

2. **Consistency of the solution to the dual debiasing program:** If r_ℓ shrinks to 0 in a certain rate and $\frac{\gamma}{n} \asymp \frac{||x||_2}{\kappa_R}\sqrt{\frac{\log d}{n}} + \frac{||x||_2}{\kappa_R^2} \cdot r_\pi$, then

$$\left|\left|\widehat{\ell}(x) - \ell_0(x)\right|\right|_2 = O_P\left(\frac{1}{\kappa_R^3}\sqrt{\frac{s_\ell(x)\log d}{n}} + \frac{r_\ell}{\kappa_R^4} + \frac{r_\pi\sqrt{s_\ell(x)}}{\kappa_R^4}\right).$$

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Consistency and Asymptotic Normality

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Note: Under the same choice of $\gamma > 0$, the strong duality holds.

Theorem (Theorem 7 in Zhang et al. 2023)

If $\frac{(1+\kappa_R^2)s_{\max}\log(nd)}{\kappa_R^4} = o\left(\sqrt{n}\right)$, $\frac{(1+\kappa_R^4)\sqrt{s_{\max}\log(nd)}}{\kappa_R^6}\left(r_\ell + r_\pi\right) = o(1)$, *and* $||x||_2 = O(1)$, *then*

$$\frac{\sqrt{n}\left[\widehat{m}^{\text{debias}}(x;\widehat{\boldsymbol{w}}) - m_0(x)\right]}{\sigma_m(x)} \xrightarrow{d} \mathcal{N}(0,\, 1).$$

Discussions on Our Theoretical Results

1. Our growth requirement $s_{\max} = o\left(\frac{\sqrt{n}}{\log d}\right)$ on the sparsity level is a standard and *essentially necessary* condition for asymptotic normality; see Section 8.6 of Jankova and van de Geer (2018).

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2. Given any dimension $d > 0$, the asymptotic variance of our debiased estimator
$$\sigma_m^2(x) = \sigma_\epsilon^2 \cdot x^T \left[\mathrm{E}\left(RXX^T\right)\right]^{-1} x$$
attains the *semi-parametric efficiency bound* among all asymptotically linear estimators under MAR outcomes (Müller and Keilegom, 2012).

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Proposition (Proposition 8 in Zhang et al. 2023)

If $\frac{(1+\kappa_R^3)}{\kappa_R^5}\sqrt{\frac{s_\ell(x)\log(nd)}{n}} = o(1)$, $\frac{(1+\kappa_R^4)}{\kappa_R^6}\left[r_\ell + r_\pi\sqrt{s_\ell(x)}\right] = o(1)$, *and* $||x||_2 = O(1)$, *then*
$$\left|\sum_{i=1}^n \widehat{\pi}_i \widehat{w}_i^2 - x^T\left[\mathrm{E}\left(RXX^T\right)\right]^{-1} x\right| = o_P(1).$$

Overfitting the Propensity Scores

Our theoretical results also provide insightful answers to the following two questions:

- Why don't we need sample splitting or cross fitting?
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- Why don't we need sample splitting or cross fitting?
- Why can we estimate the propensity score by any machine learning methods without worrying about the overfitting issue?

► **Answer:** Our asymptotic normality result depends on the *in-sample* estimation error r_π of the propensity score; recall that

$$\mathrm{P}\left(\max_{1\leq i\leq n}|\widehat{\pi}_i - \pi_i| > r_\pi\right) < \delta \quad \text{with} \quad \pi_i = \pi(X_i), i = 1, ..., n.$$

- In other words, our debiased estimator performs even better when we overfit the propensity scores $\pi(X_i) = \mathrm{P}(R_i = 1|X_i), i = 1, ..., n$.

Overfitting the Propensity Scores

Our theoretical results also provide insightful answers to the following two questions:

- Why don't we need sample splitting or cross fitting?
- Why can we estimate the propensity score by any machine learning methods without worrying about the overfitting issue?

► **Answer:** Our asymptotic normality result depends on the *in-sample* estimation error r_π of the propensity score; recall that

$$\mathrm{P}\left(\max_{1\leq i\leq n} |\widehat{\pi}_i - \pi_i| > r_\pi\right) < \delta \quad \text{with} \quad \pi_i = \pi(X_i), i = 1, ..., n.$$

- In other words, our debiased estimator performs even better when we overfit the propensity scores $\pi(X_i) = \mathrm{P}(R_i = 1|X_i), i = 1, ..., n$.
- This coincides with *"benign overfitting"* in linear regression or neural networks (Bartlett et al., 2020; Li et al., 2021; Cao et al., 2022).

Comparative Simulations

Experimental Setups and Evaluation Metrics

We compare our debiasing method with L_1-penalized logistic regression for the propensity score estimation with several existing methods:

- **"DL-Jav":** The debiased Lasso by Javanmard and Montanari (2014).
- **"DL-vdG":** The debiased Lasso by van de Geer et al. (2014).
- **"Refit":** Run the regular least-square regression on the support set of the Lasso pilot estimate (Belloni and Chernozhukov, 2013).

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These methods to be compared are implemented on

- Complete-case (CC) data $\{(X_i, Y_i, R_i = 1)\}_{i=1}^n$;
- Inverse probability weighted (IPW) data $\left\{\left(\frac{X_i}{\sqrt{\widehat{\pi}_i}}, \frac{Y_i}{\sqrt{\widehat{\pi}_i}}, R_i = 1\right)\right\}_{i=1}^n$;
- Oracle fully observed data (X_i, Y_i) for $i = 1, ..., n$.

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Evaluation metrics on 1000 Monte Carlo experiments include

- Average absolute bias $\left|\widehat{m}^{\text{debias}}(x) - m_0(x)\right|$;
- Average coverage of the yielded 95% confidence intervals;
- Average length of the yielded 95% confidence intervals.

Simulation Results Under Gaussian Noises (I)

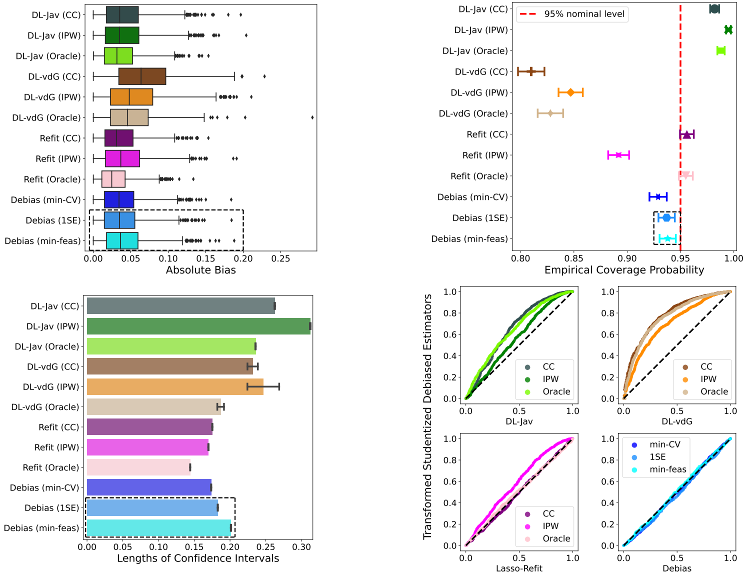

Figure 2: Sparse β_0^{sp} and sparse $x^{(2)}$ with $X_i \sim \mathcal{N}_d(\mathbf{0}, \Sigma^{\text{cs}}), i = 1, ..., n$.

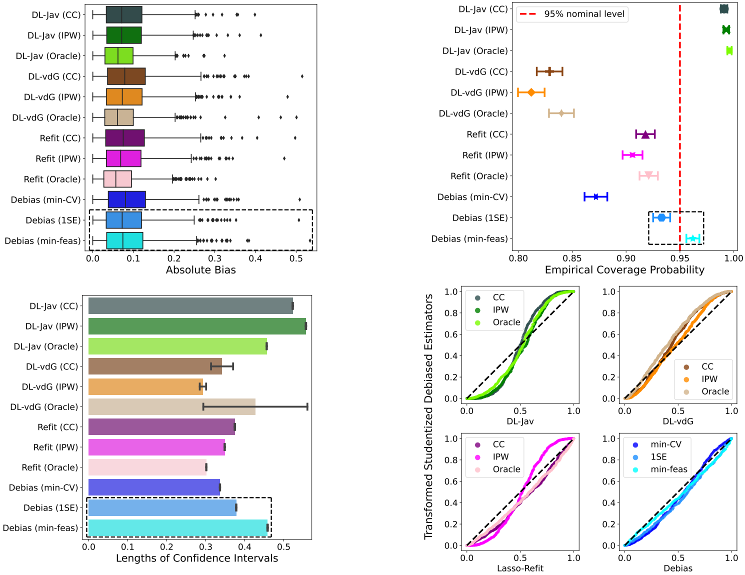

Figure 3: Pseudo-dense β_0^{pd} and sparse $x^{(2)}$ with $X_i \sim \mathcal{N}_d(\mathbf{0}, \Sigma^{\text{ar}}), i = 1, ..., n$.

Simulation Results Under Laplace$(0, 1/\sqrt{2})$ Noises

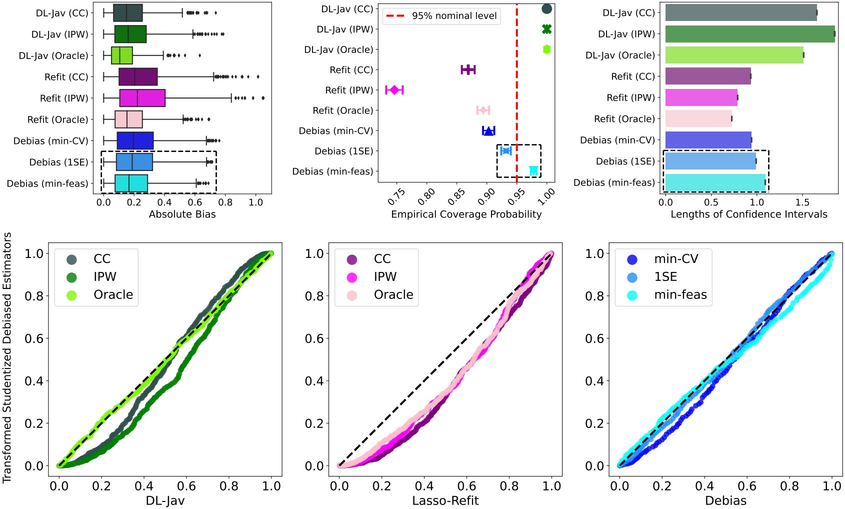

Figure 4: Dense β_0^{de} and sparse $x^{(4)}$ with $X_i \sim \mathcal{N}_d(\mathbf{0}, \Sigma^{\text{cs}}), i = 1, ..., n$.

Simulation Results Under t_2-Distributed Noises

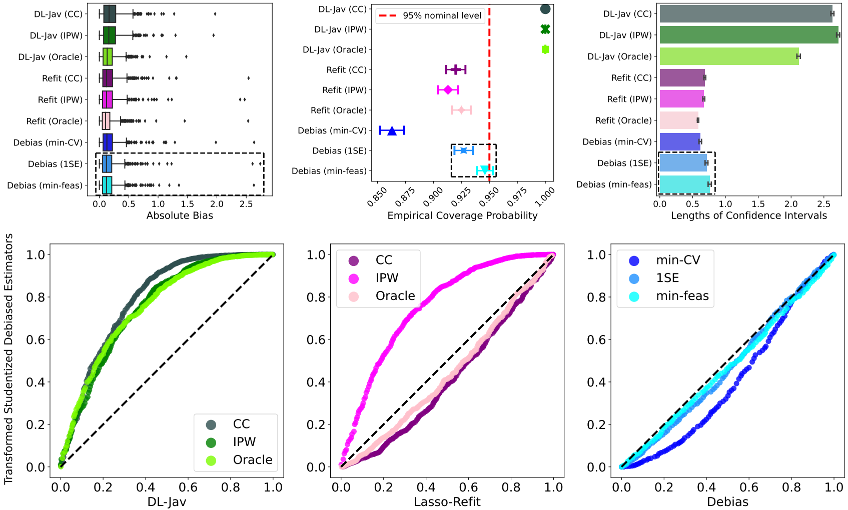

Figure 5: Pseudo-dense β_0^{pd} and dense $x^{(4)}$ with $X_i \sim \mathcal{N}_d(\mathbf{0}, \Sigma^{\text{ar}}), i = 1, ..., n$. Note that the mean-zero t_2 distribution has *infinite* variance.

1. True propensity score model: $\mathrm{P}(R_i = 1|X_i) = \Phi\left(-4 + \sum_{k=1}^{K} Z_{ik}\right)$, where $(Z_{i1}, ..., Z_{iK})$ contains all polynomial combinations of the first eight components $X_{i1}, ..., X_{i8}$ of $X_i \in \mathbb{R}^{1000}$ with degrees ≤ 2.

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2. Estimate the propensity scores $\pi(X_i), i = 1, ..., n$ by the following nonlinear/nonparametric machine learning methods:
   - **Gaussian Naive Bayes ("NB")**.
   - **Random Forest ("RF"):** 100 trees, bootstrapping samples, and the Gini impurity.
   - **Support Vector Machine ("SVM"):** Gaussian radial basis function.
   - **Neural Network ("NN"):** Two hidden layers of size 80×50 and ReLU $h(x) = \max\{x, 0\}$ as the activation function.

Proposed Method With Nonparametric Propensity Scores

1. True propensity score model: $\mathrm{P}(R_i = 1|X_i) = \Phi\left(-4 + \sum_{k=1}^{K} Z_{ik}\right)$, where $(Z_{i1}, ..., Z_{iK})$ contains all polynomial combinations of the first eight components $X_{i1}, ..., X_{i8}$ of $X_i \in \mathbb{R}^{1000}$ with degrees ≤ 2.

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3. Include an extra evaluation metric as the average mean absolute error ("Avg-MAE") for the estimated propensity scores.

Simulation Results With Nonparametric Propensity Scores

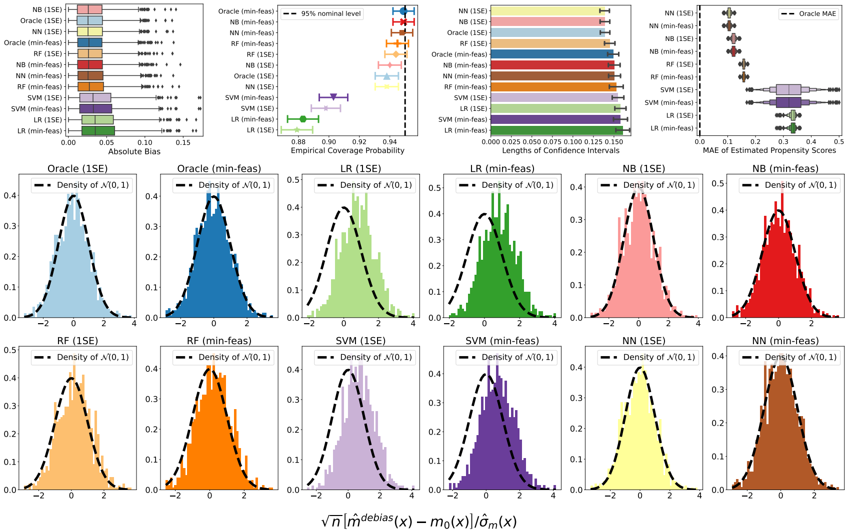
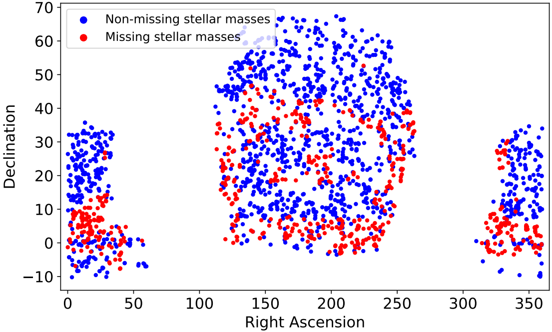


Figure 6: Sparse β_0^{sp} and (weakly) dense $x^{(4)}$.

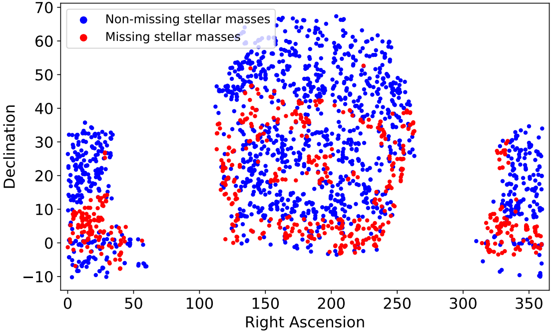
Real-World Applications

Recall that some estimated stellar masses of the observed galaxies in SDSS-IV are missing in the most recent Firefly value-added catalog.



Background on Stellar Mass Inference

Recall that some estimated stellar masses of the observed galaxies in SDSS-IV are missing in the most recent Firefly value-added catalog.



- **Scientific Questions:**

1. *How can we conduct valid inference on the (estimated) stellar mass based on the spectroscopic and photometric properties?*
2. *Is it statistically significant that the stellar mass of a galaxy is negatively correlated with its distance to the nearby cosmic filament structures?*

Study Design For Stellar Mass Inference

1. Consider all the observed galaxies by SDSS-IV within a thin redshift slice $0.4 \sim 0.4005$, among which 30.2% of their stellar masses are missing in the Firefly value-added catalog.

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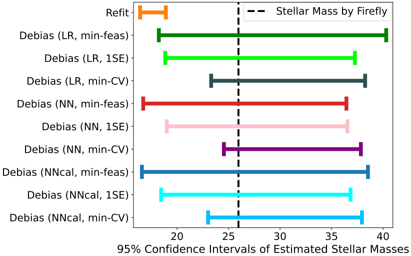
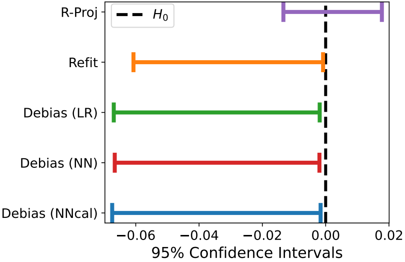
4. Incorporate RA, DEC, and the angular diameter distances from the galaxies to the two-dimensional spherical cosmic filaments by Zhang and Chen (2023); Zhang et al. (2022).
5. Control for the confounding effects by including the distances from galaxies to candidate galaxy clusters.

- **Final Dataset:** $n = 1185$ and $d = 1409$.

Results on Stellar Mass Inference





- *Left Panel:* 95% confidence intervals by different debiasing methods for the estimated stellar mass of a new galaxy.
- *Right Panel:* 95% confidence intervals by different debiasing methods for the estimated regression coefficient associated with the distance to nearby cosmic filaments.

Conclusions and Future Works

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We develop an efficient debiasing method for conducting valid inference on high-dimensional linear models with MAR outcomes.

Conclusions

We develop an efficient debiasing method for conducting valid inference on high-dimensional linear models with MAR outcomes.

- Its computational and statistical efficiencies follow from the dual formulation.
- Sample splitting and cross fitting are not required, and the nuisance propensity score can be estimated by any machine learning method.
- We provide interpretations to our debiasing method from the viewpoints of bias-variance trade-off and Neyman near-orthogonalization.
- Comprehensive simulation studies and motivating applications demonstrate the potential of our proposed debiasing method.

The observable data in causal inference are

$$\{(\mathbb{Y}_i, T_i, X_i)\}_{i=1}^n \subset \mathbb{R} \times \{0,1\} \times \mathbb{R}^d.$$

- $T_i \in \{0,1\}$ is a binary treatment assignment indicator;
- $\mathbb{Y}_i = T_i \cdot Y(1)_i + (1-T_i) \cdot Y(0)_i$ with $Y(0), Y(1)$ as potential outcomes.

▶ **Objective:** Conduct valid inference on the regression function (or conditional mean outcome) of the treatment group.

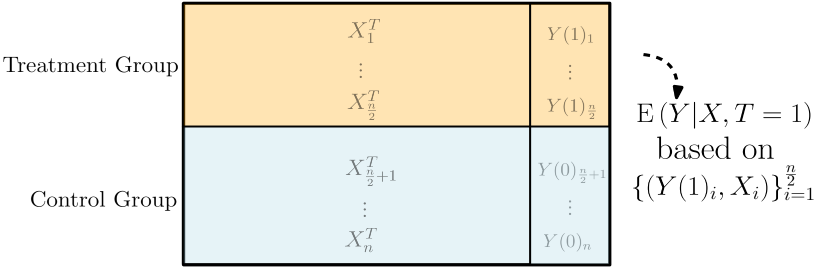

Figure 8: Traditional approaches for inferring $\mathrm{E}(Y|X, T=1)$.

Potential Application to Causal Inference (I)

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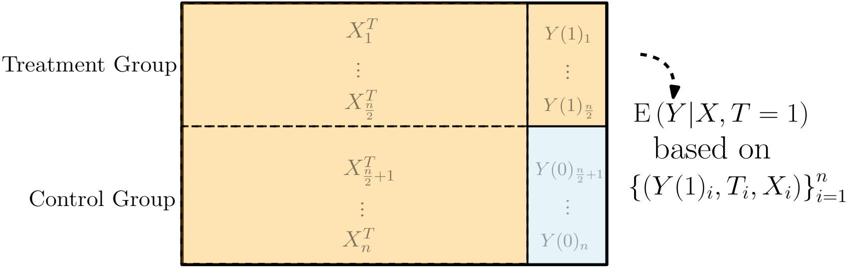

Figure 8: Our approach for inferring $\mathrm{E}(Y|X, T=1)$.

Potential Application to Causal Inference (II)

Our debiasing method can be extended to valid inference on the linear average conditional treatment effect (ACTE)

$$\mathrm{E}[Y(1) - Y(0)|X]$$

with no unmeasured confounding and high-dimensional covariates.

Potential Application to Causal Inference (II)

Our debiasing method can be extended to valid inference on the linear average conditional treatment effect (ACTE)

$$\mathrm{E}[Y(1) - Y(0)|X]$$

with no unmeasured confounding and high-dimensional covariates.

- The modified debiasing program with tuning parameters $\gamma_1, \gamma_2 > 0$ is

$$\begin{aligned}
&\arg\min_{\boldsymbol{w}_{(0)}, \boldsymbol{w}_{(1)} \in \mathbb{R}^n} \sum_{i=1}^n \left[\widehat{\pi}_i w_{i(1)}^2 + (1-\widehat{\pi}_i) w_{i(0)}^2\right] \\
&\text{s.t.} \left\|x - \frac{1}{\sqrt{n}} \sum_{i=1}^n w_{i(1)} \cdot \widehat{\pi}_i \cdot X_i\right\|_\infty \le \frac{\gamma_1}{n} \text{ and } \left\|x - \frac{1}{\sqrt{n}} \sum_{i=1}^n w_{i(0)} \left(1-\widehat{\pi}_i\right) X_i\right\|_\infty \le \frac{\gamma_2}{n}.
\end{aligned}$$

- The extended debiased estimator becomes

$$\begin{aligned}
&\widehat{m}^{\text{debias}}(x; \widehat{\boldsymbol{w}}_{(1)}, \widehat{\boldsymbol{w}}_{(0)}) \\
&= x^T \left(\widehat{\beta}_{(1)} - \widehat{\beta}_{(0)}\right) + \frac{1}{\sqrt{n}} \sum_{i=1}^n \left[\widehat{w}_{i(1)} \cdot T_i \left(\mathbb{Y}_i - X_i^T \widehat{\beta}_{(1)}\right) - \widehat{w}_{i(0)} \cdot (1-T_i) \left(\mathbb{Y}_i - X_i^T \widehat{\beta}_{(0)}\right)\right].
\end{aligned}$$

- The efficiency theory for this modified procedure is worth studying!

Thank you!

More details can be found in

[1] Y. Zhang, A. Giessing, and Y.-C. Chen. Efficient Inference on High-Dimensional Linear Models with Missing Outcomes. *arXiv preprint*, 2023. https://arxiv.org/abs/2309.06429.

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Implementation Details of the Proposed Debiasing Method

1. **Lasso pilot estimate:** We adopt the scaled Lasso (Sun and Zhang, 2012) with its universal regularization parameter $\lambda_0 = \sqrt{\frac{2\log d}{n}}$ as the initialization. Specifically, it iteratively updates $\widehat{\beta}(\widetilde{\lambda}), \widehat{\sigma}_\epsilon(\widetilde{\lambda}), \widetilde{\lambda}$ via the jointly convex optimization program:

$$\left(\widehat{\beta}(\widetilde{\lambda}), \widehat{\sigma}_\epsilon(\widetilde{\lambda})\right) = \arg\min_{\beta \in \mathbb{R}^d, \sigma_\epsilon > 0} \left[\frac{1}{2n\sigma_\epsilon} \sum_{i=1}^n R_i \left(Y_i - X_i^T \beta\right)^2 + \frac{\sigma_\epsilon}{2} + \widetilde{\lambda} \left|\left|\beta\right|\right|_1\right].$$

2. **Debiasing program:** We solve the primal program by Python package "`CVXPY`" (Diamond and Boyd, 2016; Agrawal et al., 2018) or R package "`CVXR`" (Fu et al., 2020). For the dual program, we formulate a coordinate descent algorithm (Wright, 2015) as:

$$\left[\widehat{\ell}(x)\right]_j \leftarrow \frac{\mathcal{S}_{\frac{\gamma}{n}}\left(-\frac{1}{2n}\sum_{i=1}^n \widehat{\pi}_i \left(\sum_{k\neq j} X_{ik}X_{jk}\left[\widehat{\ell}(x)\right]_k\right) - x_j\right)}{\frac{1}{2n}\sum_{i=1}^n \widehat{\pi}_i X_{ij}^2} \quad \text{for } \ j = 1, ..., d,$$

where $\mathcal{S}_{\frac{\gamma}{n}}(u) = \text{sign}(u)\cdot\left(u - \frac{\gamma}{n}\right)_+$ is the soft-thresholding operator.

One Standard Error (1SE) Rule For Model Selection

- Suppose that we conduct a K-fold cross-validation on a candidate set $\Gamma = \{\gamma_1, ..., \gamma_m\}$ of the tuning parameter.
- For each $\gamma_i \in \Gamma$, we compute the cross-validated risk or error on each fold of the data as:
$$CV_k(\gamma_i), \quad k = 1, ..., K.$$
- For each $\gamma_i \in \Gamma$, we calculate the standard error of $CV_1(\gamma_i), ..., CV_K(\gamma_i)$ as:
$$SD(\gamma_i) = \sqrt{\mathrm{Var}\left(CV_1(\gamma_i), ..., CV_K(\gamma_i)\right)}, \quad SE(\gamma_i) = SD(\gamma_i)/\sqrt{K}.$$
- Let
$$CV(\gamma) = \frac{1}{K}\sum_{k=1}^{K} CV_k(\gamma) \quad \text{and} \quad \widehat{\gamma} = \arg\min_{\gamma \in \Gamma} CV(\gamma).$$
The 1SE rule (Breiman et al., 1984; Chen and Yang, 2021) selects $\gamma_{1SE} \in \Gamma$ with as the one with the smallest $CV(\gamma)$ such that
$$CV(\gamma_{1SE}) \geq CV(\widehat{\gamma}) + SE(\widehat{\gamma}).$$

One Standard Error (1SE) Rule For Model Selection

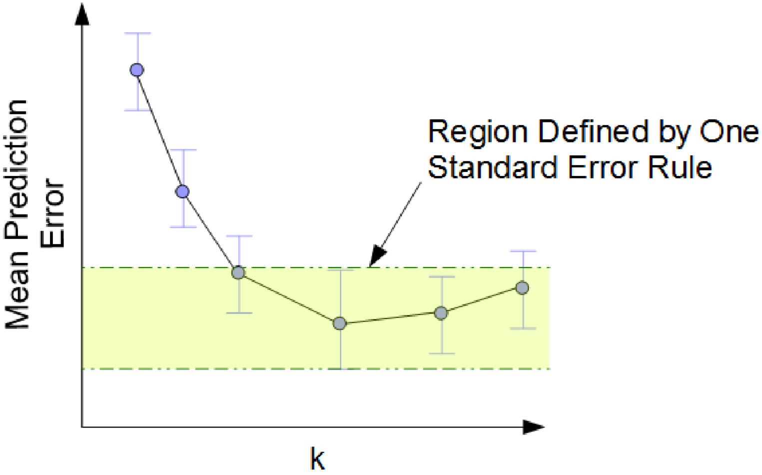

Figure 9: Illustration of the 1SE rule for selecting the model parameter.

Finger-of-God and Kaiser Effects

The galaxy distribution is distorted along the line of sight due to the peculiar velocities of galaxies, *i.e.*, the so-called *finger-of-god* (Jackson, 1972) and *Kaiser* (Kaiser, 1987) effects.

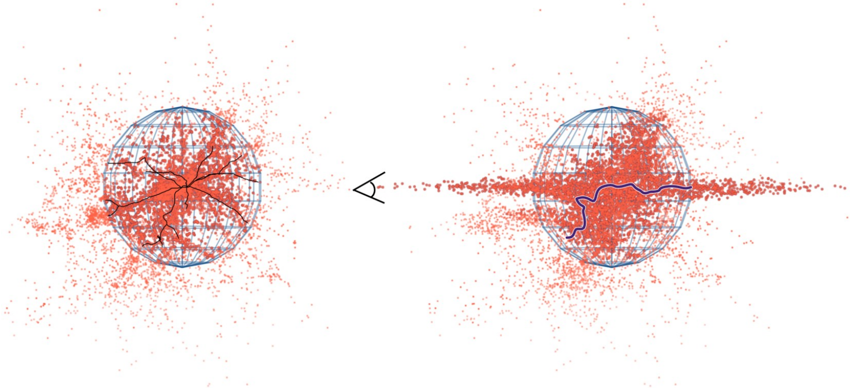

Figure 10: Redshift distortions along the line of sight (Kuchner et al., 2021).