Estimating Racial Disparities when Race is Not Observed

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Motivation

- Importance of racial disparity estimation in many fields:
  public health, employment, voting, criminal justice, taxation, housing, lending, and internet technology

- But, often individual race is not available
  - law may prohibit collection of information about race (e.g., Equal Credit Opportunity Act)
  - agencies and companies may not wish to collect such information

- How should we estimate racial disparities when race is not observed?
  - Standard methods use BISG (Bayesian Improved Surname Geocoding)
  - But, it has been shown that they are likely to yield biased estimates
- Can we improve the standard methods and eliminate their bias?

The Setup

- Data
  - Y_i: outcome of interest
  - R_i: (unobserved) race
  - S_i: surname
  - G_i: residence location
  - X_i: other Census variables (optional)
  - W_i: covariates of interest
- Census data
  - $\mathbb{P}(G_i = g, R_i = r, X_i = x)$
  - $\mathbb{P}(R_i = r, S_i = s)$ for frequently occurring surnames
- Regression estimands
  - short regression: $\mathbb{P}(Y_i = y \mid R_i = r)$
  - long regression: $\mathbb{P}(Y_i = y \mid R_i = r, X_i = x)$
- Racial disparity estimands
  - $\mathbb{P}(Y_i = y \mid R_i = r) - \mathbb{P}(Y_i = y \mid R_i = r')$ for $r \neq r'$
  - $\mathbb{P}(Y_i = y \mid R_i = r, W_i = w) - \mathbb{P}(Y_i = y \mid R_i = r', W_i = w)$

Standard Estimation Methods

1. Predict race via BISG (or its variant)
   - Assumption: $G_i \perp\!\!\!\perp S_i \mid R_i$
   - Bayes rule:

$$\begin{aligned}\hat{P}_{ir} &= \mathbb{P}(R_i = r \mid G_i = g, S_i = s) \\ &= \frac{\mathbb{P}(S_i = s \mid R_i = r)\,\mathbb{P}(G_i = g, R_i = r)}{\sum_{r'} \mathbb{P}(S_i = s \mid R_i = r')\,\mathbb{P}(G_i = g, R_i = r')}\end{aligned}$$

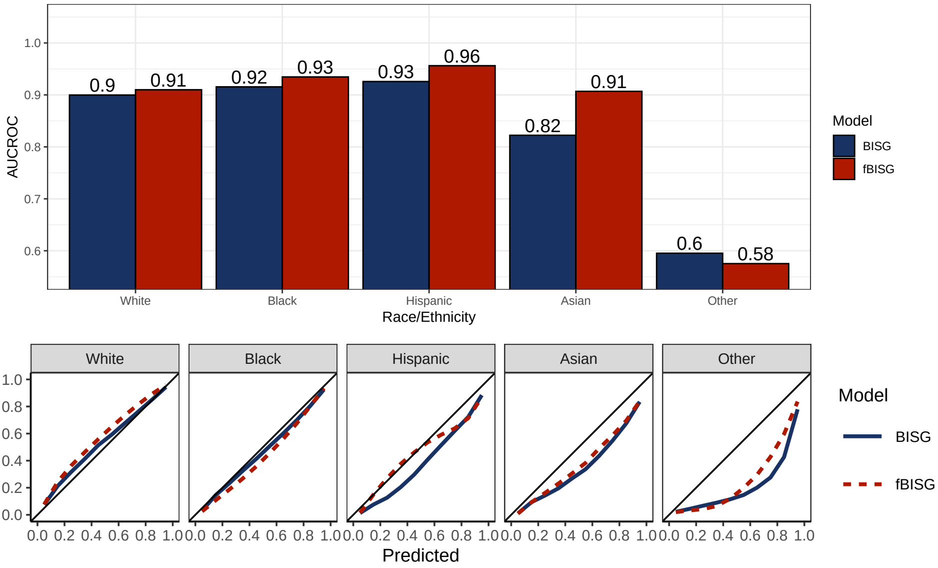
   - With covariates: $(G_i, X_i) \perp\!\!\!\perp S_i \mid R_i$
   - WRU software package (Imai and Kahna 2016)

2. Estimate racial disparities $\mu_{Y|R}(y \mid r) = \mathbb{P}(Y_i = y \mid R_i = r)$
   - weighting:

$$\hat{\mu}^{\text{wtd}}_{Y|R}(y \mid r) = \frac{\sum_i \mathbf{1}\{Y_i = y\}\hat{P}_{ir}}{\sum_i \hat{P}_{ir}}$$

   - thresholding: use the racial group with the largest probability as imputed race

BISG Prediction Works Reasonably Well (Imai et al. 2022. *Sci. Adv.*)



Good Race Prediction Can Bias Racial Disparity Estimates

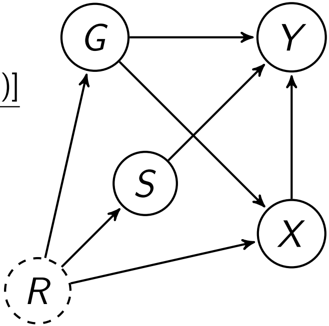
- Bias of the weighted estimator (Chen *et al.* 2019)

$$\hat{\mu}^{\text{wtd}}_{Y|R}(y \mid r) - \mathbb{P}(Y_i = y \mid R_i = r)$$
$$= -\frac{\mathbb{E}[\text{Cov}(\mathbf{1}\{Y_i = y\}, \mathbf{1}\{R_i = r\} \mid G_i, X_i, S_i)]}{\mathbb{P}(R_i = r)}$$

  - bias tends to be large for minority groups
  - racial disparity tends to be underestimated

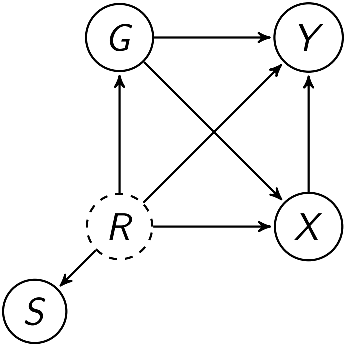
- Required assumption:

$$Y_i \perp\!\!\!\perp R_i \mid G_i, S_i, X_i$$



Problem: race affects many aspects of the society

New Identification Strategy



- Required assumption:

$$Y_i \perp\!\!\!\perp S_i \mid G_i, R_i, X_i$$

- Surname as a proxy for race
- Race can directly or indirectly affects the outcome
- Potential violations:
    - name-based discrimination
    - coarse racial categories
    - but conditional on true race
- Anonymous application

Surname as a High-dimensional Instrument

- Identification (see also Kuroki and Pearl, 2014):

$$\overbrace{\mathbb{P}(Y_i = y \mid G_i = g, X_i = x, S_i = s)}^{\text{observed data}}$$
$$= \sum_{r \in \mathcal{R}} \underbrace{\mathbb{P}(Y_i = y \mid R_i = r, G_i = g, X_i = x)}_{\text{unknown parameters}} \underbrace{\mathbb{P}(R_i = r \mid G_i = g, X_i = x, S_i = s)}_{\text{BISG probability}}$$

  - $(|\mathcal{Y}| - 1) \times |\mathcal{G}| \times |\mathcal{X}| \times |\mathcal{S}|$ equations
  - $(|\mathcal{Y}| - 1) \times |\mathcal{G}| \times |\mathcal{X}| \times |\mathcal{R}|$ unknown parameters

- OLS estimator (see also Fong and Tyler, 2021):

$$\hat{\boldsymbol{\mu}}^{(\text{ols})}_{Y|RGX}(y \mid \cdot, g, x) = (\hat{\mathbf{P}}^{\top}_{\mathcal{I}(xg)} \hat{\mathbf{P}}_{\mathcal{I}(xg)})^{-1} \hat{\mathbf{P}}_{\mathcal{I}(xg)} \mathbb{1}\{\mathbf{Y}_{\mathcal{I}(xg)} = y\},$$

  - compute this for each g and x, and aggregate
  - unbiased estimate of $\mathbb{P}(Y_i = y \mid R_i = r)$
  - ignores the fact that $\mathbb{P}(Y_i = y \mid R_i = r, G_i = g, X_i = x)$ is probability

BIRDiE (Bayesian Instrumental Regression for Disparity Estimation)

- Flexible and scalable probabilistic model that integrates BISG
- Posterior:

$$\pi(\Theta, \mathbf{R} \mid \mathbf{Y}, \mathbf{G}, \mathbf{X}, \mathbf{S}) \;\propto\; \pi(\Theta) \prod_{i=1}^{N} \underbrace{\pi(Y_i \mid R_i, G_i, X_i, \Theta)}_{\text{complete-data model}} \underbrace{\pi(R_i \mid G_i, X_i, S_i)}_{\text{BISG prob. } \hat{P}_{ir}}$$

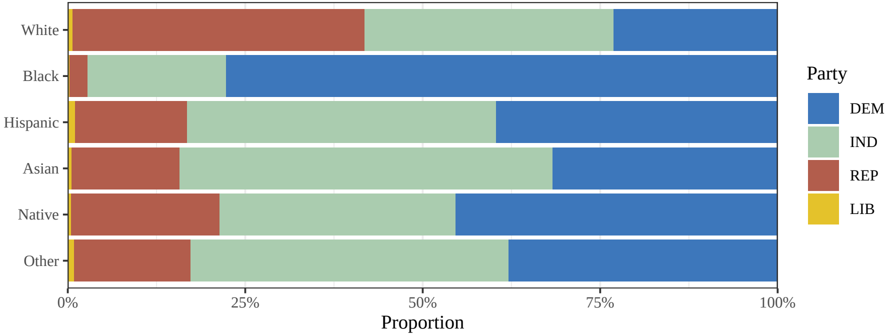
- Models (Categorical $\sim$ Dirichlet)
    1. Complete-pooling
    2. Saturated (no pooling)
    3. Partial pooling (mixed effects)

- Computation:
    1. Small samples: full MCMC (e.g., via Stan)
    2. Large samples: EM algorithm

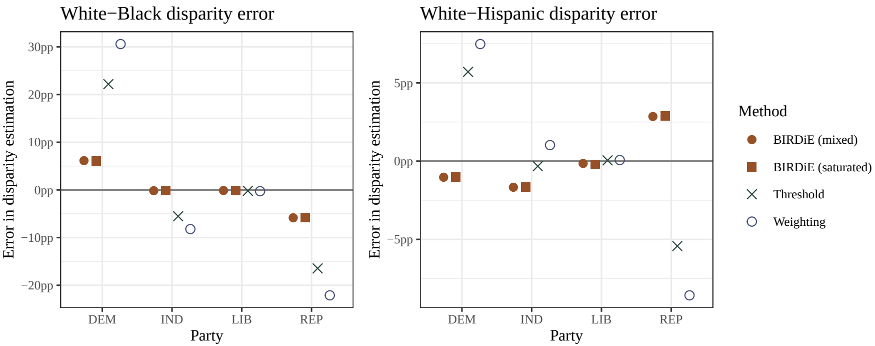
Empirical Validation

- 2022 North Carolina voter file: 5.8M voters with self-reported race
- Subset 1M voters $\rightsquigarrow$ negligible sampling uncertainty

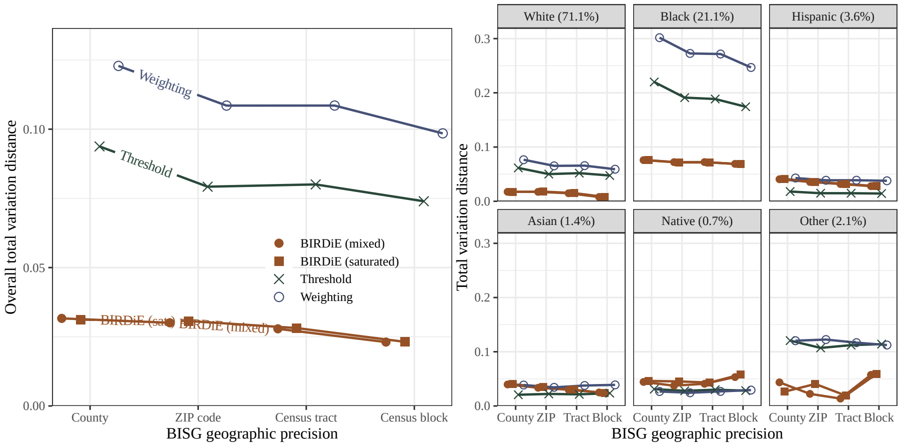
- Focus on party registration



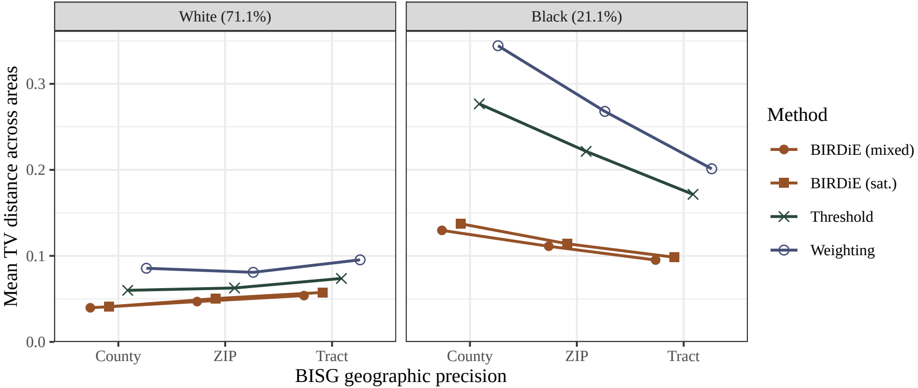
Estimates of Racial Disparity in Party Registration



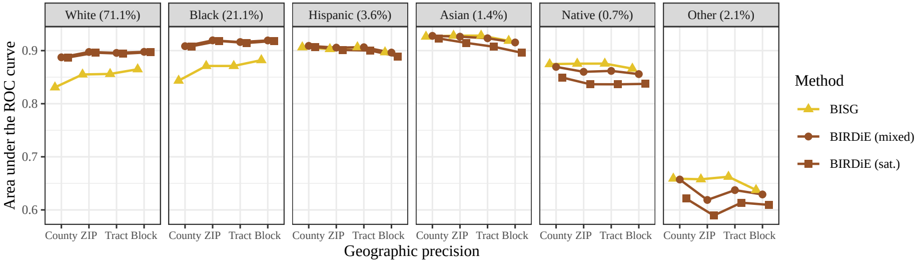
Total Variation Distance



Small Area Estimation



Improved Race Probabilities



Concluding Remarks

- BIRDiE
  - new identification assumption
  - flexible modeling with scalable estimation
  - improved BISG race probabilities
  - sensitivity analysis
- Future work
  - additional empirical validations: understanding bias
  - better use of auxiliary information in sensitivity analysis
  - make BIRDiE more robust to small bias in BISG probabilities
  - more general approach to data combination and record linkage

The paper is available at

https://imai.fas.harvard.edu/research/birdie.html

The software is available at

https://corymccartan.com/birdie/