

# PredSet-1Step: Distribution-Free Prediction Sets Adaptive to Unknown Covariate Shift

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## Background

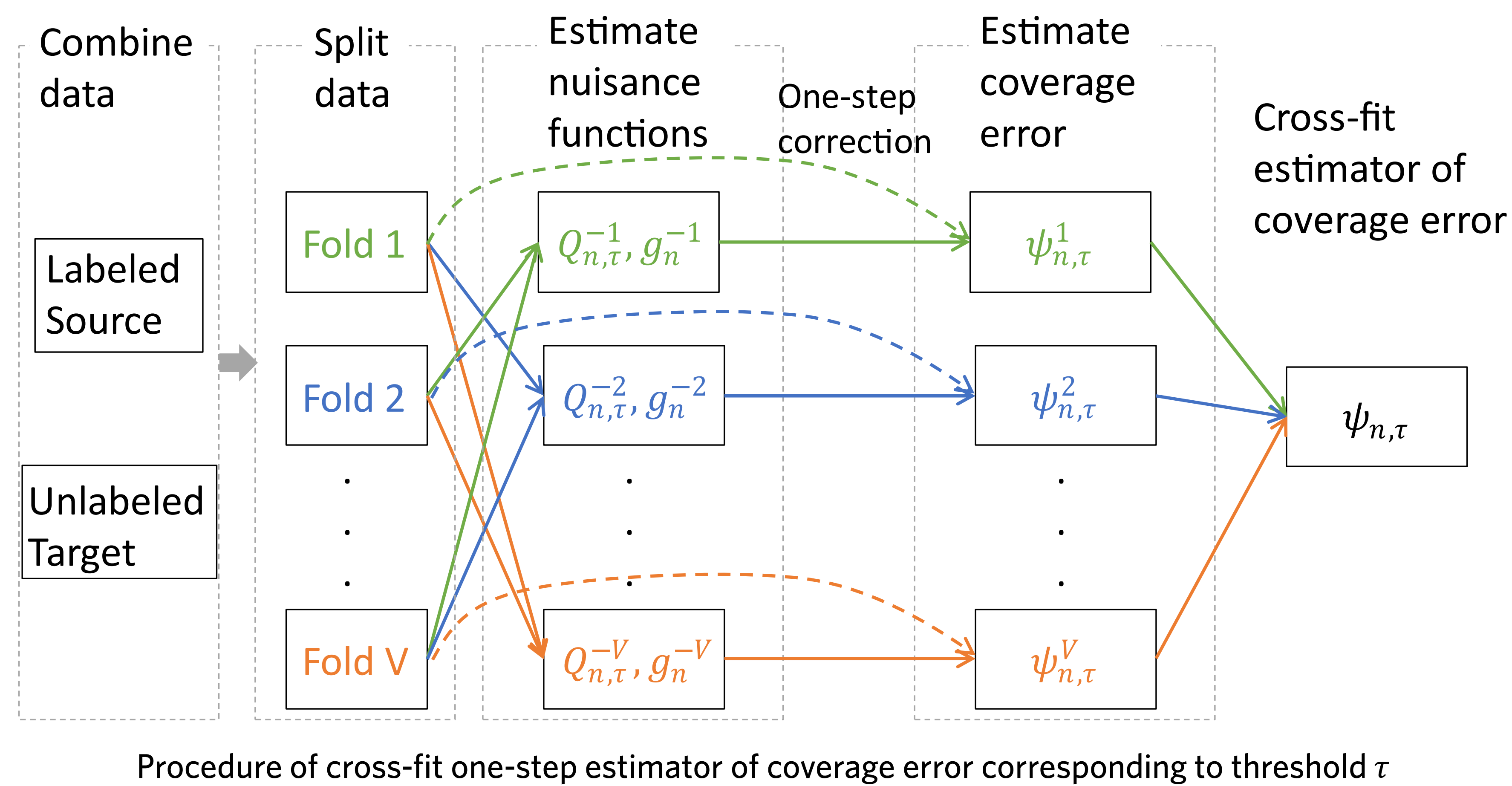
- Uncertainty quantification for prediction is a key issue in modern statistics: prediction sets, tolerance regions, conformal inference, etc
- Data:  $n$  observations consisting of Population indicator: source ( $A = 1$ ), target ( $A = 0$ ); Covariate:  $X$ ; outcome/label to be predicted:  $Y$
- Goal: *Asymptotically Probably Approximately Correct (APAC)* prediction set  $\hat{C}$  in the target population:

$$\Pr(\Pr(Y \notin \hat{C}(X) \mid \hat{C}, A = 0) \leq \alpha_{\text{error}}) \geq 1 - \alpha_{\text{conf}} - o(1)$$

- Interpretation: with high confidence approaching  $1 - \alpha_{\text{conf}}$ , the coverage error of  $\hat{C}$  is below  $\alpha_{\text{error}}$
- $Y$  missing in target population ( $A = 0$ )
- Key assumption: *covariate shift*  $p(Y \mid X, A = 0) = p(Y \mid X, A = 1)$
- Connection with causal inference & missing data: equivalent to missing at random & no unmeasured confounding
- Applications: predict individual treatment effect (ITE)  $Y(1) - Y(0)$ ; predict  $Y$  in a different target population
- A key quantity: likelihood ratio

$$w_0(x) := \frac{p(X = x \mid A = 0)}{p(X = x \mid A = 1)}$$

- Previous PAC prediction set works assume *known*  $w_0$  (ref in preprint); lack methods when  $w_0$  is *unknown*



## Prediction set coverage error estimator

- Fixed arbitrary scoring function  $s(X, Y)$   
E.g., estimated  $\Pr(Y \mid X)$  or  $p(Y \mid X)$  using separate source population data
- Candidate prediction set:  $C_\tau(x) = \{y: s(x, y) \geq \tau\}$  (threshold  $\tau$  in finite grid  $\mathcal{T}_n$ )
- Under nonparametric model, coverage error  $\psi_{0,\tau} := \Pr(Y \notin C_\tau(X) \mid A = 0)$  in target population is pathwise differentiable with gradient (similar to ATT)

$$(a, x, y) \mapsto \frac{a}{1 - \gamma_0} \frac{1 - g_0(x)}{g_0(x)} [I(y \notin C_\tau(x)) - Q_{0,\tau}(x)] + \frac{1 - a}{1 - \gamma_0} [Q_{0,\tau}(x) - \psi_{0,\tau}]$$

$Q_{0,\tau}: x \mapsto \Pr(Y \notin C_\tau(X) \mid X = x)$  is the conditional coverage error;

$g_0: x \mapsto \Pr(A = 1 \mid X = x)$  is the propensity score;  $\gamma_0 := \Pr(A = 1)$

- Cross-fit one-step corrected estimator  $\psi_{n,\tau}$ : split data into  $V$  folds, for each fold  $v$ ,
  - estimate  $(Q_{0,\tau}, g_0)$  with  $(Q_{n,\tau}^{-v}, g_n^{-v})$  using data out of fold  $v$
  - estimator with **one-step correction** based on gradient:

$$\psi_{n,\tau}^v = \frac{\sum_{i \in \text{fold } v} \left\{ (1 - A_i) Q_{n,\tau}^{-v}(X_i) + A_i \frac{1 - g_n^{-v}(X_i)}{g_n^{-v}(X_i)} [I(Y_i \notin C_\tau(X_i)) - Q_{n,\tau}^{-v}(X_i)] \right\}}{\sum_{i \in \text{fold } v} (1 - A_i)}$$

Average over folds:  $\psi_{n,\tau} = \sum_v \psi_{n,\tau}^v / V$

- Corrected estimator  $\psi_{n,\tau}$  is asymptotically normal:  $\sqrt{n}(\psi_{n,\tau} - \psi_{0,\tau}) \xrightarrow{d} N(0, \sigma_\tau^2)$

## Threshold selection

- Wald  $(1 - \alpha_{\text{conf}})$ -confidence upper bound for coverage error  $\psi_{0,\tau}$

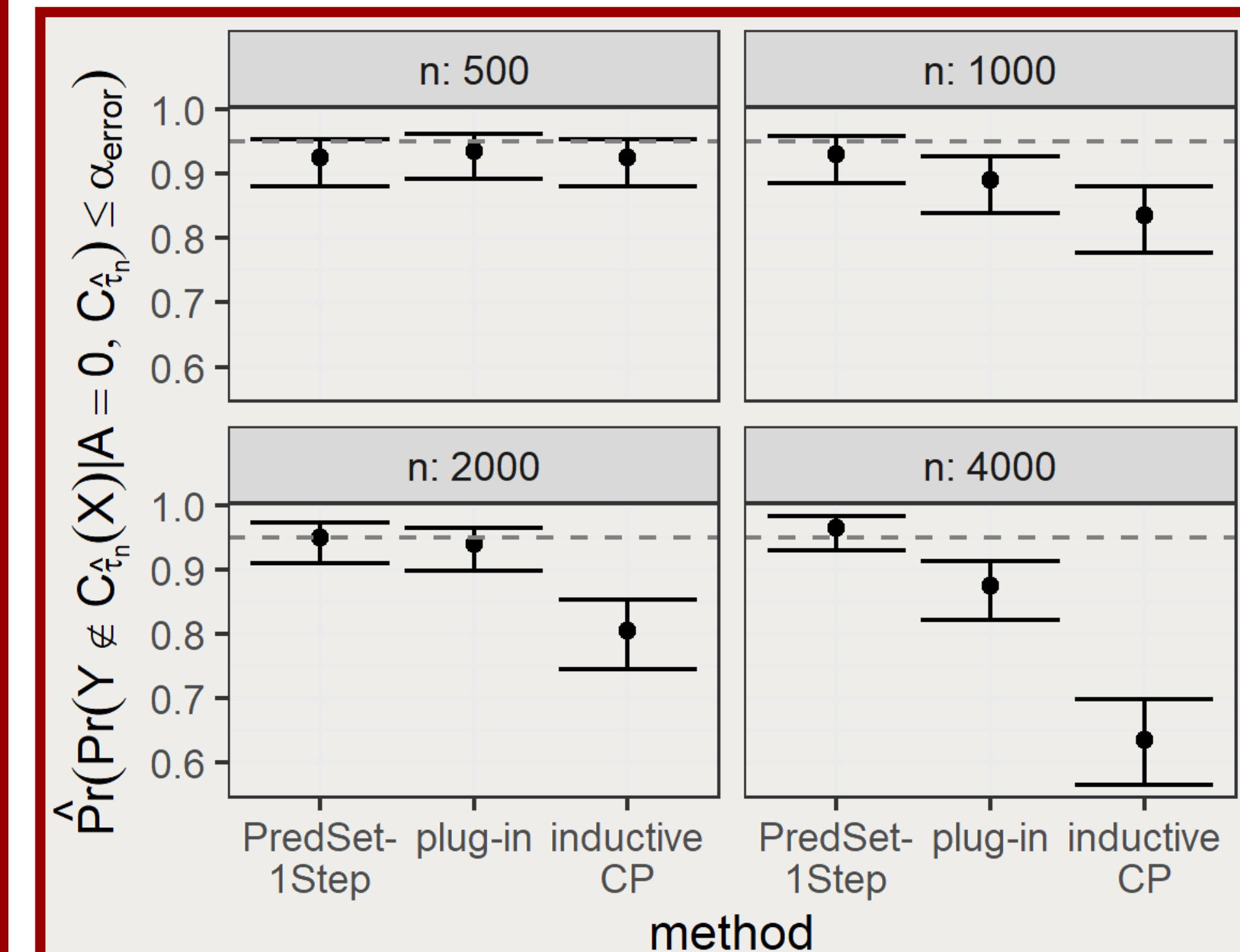
$$\lambda_n(\tau) = \psi_{n,\tau} + z_{\alpha_{\text{conf}}} \times \frac{\sigma_{n,\tau}}{\sqrt{n}}$$

- Select the max threshold in  $\mathcal{T}_n$  such that all confidence upper bounds for smaller thresholds are below  $\alpha_{\text{error}}$ :

$$\hat{\tau}_n := \max\{\tau \in \mathcal{T}_n: \lambda_n(\tau') < \alpha_{\text{error}}, \forall \tau' \in \mathcal{T}_n \text{ such that } \tau' \leq \tau\}$$

- $C_{\hat{\tau}_n}$  is APAC in the target population
- The  $o(1)$  term is of order

$$n^{1/4} \|g_n^{-v} - g_0\|_2^{1/2} \|Q_{n,\tau}^{-v} - Q_{0,\tau}\|_2^{1/2}$$



arXiv preprint:



Supported in part by  
NSF DMS, NIH,  
Analytics at Wharton

R package:

