

# Conformal Meta-learners for Predictive Inference of Individual Treatment Effects

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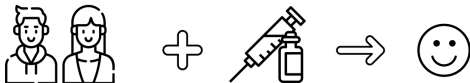
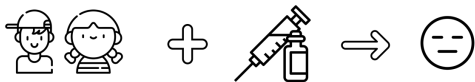
## What is the goal?

Consider following example:

$X$  : 나이,  $T \in \{0, 1\}$  : 백신 접종 여부,  $Y$  : 감염 취약도

$\rightarrow Y^t$  : 백신 접종 여부  $t$ 일 때의 감염 취약도.

나이( $X$ )에 따른 백신 접종( $T$ )에 따른 감염 취약도( $Y$ )의 감소 효과를 추정하자.



기존 causal inference 방법론을 통해서, 특정 나이에서 백신 접종이 감염 취약도에 미치는 평균 인과 효과를 estimate할 수 있었다.

가령  $X = 30$ 세인 사람이 백신을 접종할 경우 감염 취약도는 0.02만큼 감소( $\mathbb{E}(Y^1 - Y^0|X = 30) = -0.02$ )할 것으로 기대될 수 있으나, uncertainty 정보는 알지 못함.

본 논문을 통해서, 특정 나이에서 백신 접종이 감염 취약도에 미치는 개별 인과 효과에 대한 predictive interval을 구할 수 있다.

가령,  $X = 30$ 세인 사람이 백신을 접종할 경우, 감염 취약도는 유의수준  $\alpha$ 에서 0.01 ~ 0.03 정도가 감소할 것으로 기대될 수 있음.

$(\mathbb{P}(Y^1 - Y^0 \in (-0.03, -0.01)|X = 30) \geq 1 - \alpha)$  (Warning : Technically untrue.)

## What is the goal of individual treatment effects?

Individual treatment effect(ITE) :  $Y_i^1 - Y_i^0$

Goal of existing methods : Estimate the conditional expectation of treatment effect  $\tau$  such that

$$\tau(x) = \mathbb{E}[Y^1 - Y^0 | X = x]$$

Goal of proposed method : Construct a predictive interval of ITE  $\hat{C}_\alpha$  such that

$$\mathbb{P}[Y_{n+1}^1 - Y_{n+1}^0 \in \hat{C}_\alpha(X_{n+1})] \geq 1 - \alpha \quad (1)$$

for a predetermined target coverage of  $1 - \alpha$ , with  $\alpha \in (0, 1)$ , where the probability in (1) accounts for the randomness of the  $\hat{C}_\alpha$  and the test point  $(X_{n+1}, Y_{n+1}^1 - Y_{n+1}^0)$ .

How to construct a conformal interval on oracle data?

Spoiler : we can construct an oracle predictive interval as following form:

$$\hat{C}_\alpha^*(x) = [\hat{\tau}(x) - Q_{\mathcal{V}, 1-\alpha}^*, \hat{\tau}(x) + Q_{\mathcal{V}, 1-\alpha}^*]$$

우리가 상상속의 oracle data  $\mathcal{D}^* = \{(X_i, Y_i^1 - Y_i^0)\}_{i=1}^n$  를 얻었다고 가정하자.

$\mathcal{D}^*$  을 training set  $\mathcal{D}_t^*$  와 calibration set  $\mathcal{D}_c^*$  로 나누자.

$\mathcal{D}_t^*$  를 이용해서는 ML model  $\hat{\tau}$  을 학습하고,

$\mathcal{D}_c^*$  를 이용해서는 interval width  $Q_{\mathcal{V}, 1-\alpha}^*$  를 결정할 것이다.

이를 위한 procedure는 다음 페이지와 같다.

## How to construct a conformal interval on oracle data?

- 1 conformity score  $V(\cdot)$  is evaluated for all samples in  $\mathcal{D}_c^*$  as follows:

$$V_i^*(\hat{\tau}) = V(X_i, Y_i^1 - Y_i^0; \hat{\tau}), \forall i \in \mathcal{D}_c^* \quad (2)$$

A common choice of  $V(\cdot)$  is absolute residual  $V(x, y; \tau) = |y - \tau(x)|$ .

- 2 We then compute a quantile of the empirical distribution of conformity scores

$$Q_{\mathcal{V}, 1-\alpha}^* := (1 - \alpha) (1 + 1/|\mathcal{D}_c^*|) \text{-th quantile of } \mathcal{V}^*(\hat{\tau}) \quad (3)$$

where  $\mathcal{V}^*(\hat{\tau}) = \{V_i^*(\hat{\tau}) : i \in \mathcal{D}_c^*\}$ .

- 3 We can construct the oracle predictive interval at a new point  $X_{n+1} = x$  as follows:

$$\hat{C}_\alpha^*(x) = [\hat{\tau}(x) - Q_{\mathcal{V}, 1-\alpha}^*, \hat{\tau}(x) + Q_{\mathcal{V}, 1-\alpha}^*] \quad (4)$$

### Remarks

- Since the oracle problem is a standard regression, the oracle procedure is marginally valid - i.e., it satisfies the guarantee in (1),

$$\mathbb{P}[Y_{n+1}^1 - Y_{n+1}^0 \in \hat{C}_\alpha^*(X_{n+1})] \geq 1 - \alpha$$

- However, oracle CP is infeasible since we cannot observe  $Y_i^1 - Y_i^0$ , hence we need an alternative procedure that operates on the observed data  $\mathcal{D} = \{Z_i = (X_i, T_i, Y_i)\}_{i=1}^n$ .

## Conformal prediction of ITE (pseudo-intervals)

How to construct a conformal interval on real data?

IDEA : We can calculate pseudo-outcomes  $\tilde{Y}_\varphi$  and use it instead of  $Y_i^1 - Y_i^0$  to construct a conformal interval.

For nuisance parameter  $\varphi = (\pi, \mu_0, \mu_1)$  and observable data  $Z = (X, T, Y)$ , we can construct a proper pseudo-outcome  $\tilde{Y}_\varphi = f(Z; \varphi)$  by choosing proper  $f$  such that

$$\mathbb{E}[\tilde{Y}_\varphi | X = x] = \mathbb{E}[Y^1 - Y^0 | X = x] = \tau(x) \quad (5)$$

where  $\pi(x) = \mathbb{P}(T = 1 | X = x)$ ,  $\mu_t(x) = \mathbb{E}(Y^t | X = x)$ ,  $\forall t \in \{0, 1\}$

Options for  $f$  will be presented in the next page.

Using  $\tilde{Y}_{\hat{\varphi}, i} = f(Z_i, \hat{\varphi})$  instead of  $Y_i^1 - Y_i^0$ , we can construct  $\hat{C}_{\hat{\varphi}, \alpha}$  in a way similar to the oracle procedure of constructing  $\hat{C}_\alpha^*$ .



### How to construct a conformal interval on real data?(in detail)

Example of pseudo-outcome :

By choosing  $f$  in the table below, the condition in (5) can be satisfied.

$$\text{IPW-learner [27]} : \tilde{Y}_\varphi = f(Z; \varphi) = \frac{T - \pi(X)}{\pi(X)(1 - \pi(X))} Y$$

$$\text{X-learner [5]} : \tilde{Y}_\varphi = f(Z; \varphi) = T(Y - \mu_0(X)) + (1 - T)(\mu_1(X) - Y)$$

$$\text{DR-learner [20]} : \tilde{Y}_\varphi = f(Z; \varphi) = \frac{T - \pi(X)}{\pi(X)(1 - \pi(X))} (Y - \mu_T(X)) + \mu_1(X) - \mu_0(X)$$

Consider  $\hat{\varphi} = (\pi, \hat{\mu}_0, \hat{\mu}_1)$  which is an estimate of  $\varphi$  and use  $\tilde{Y}_{\hat{\varphi},i}$  instead of  $Y_i^1 - Y_i^0$ . (They assume  $\pi$  is known).

## Conformal prediction of ITE (pseudo-intervals)

### How to construct a conformal interval on real data?(in detail)

Given a dataset  $\mathcal{D} = \{Z_i = (X_i, T_i, Y_i)\}_i$ , we create three mutually-exclusive subsets:  $\mathcal{D}_\varphi$ ,  $\mathcal{D}_t$  and  $\mathcal{D}_c$ .

$\mathcal{D}_\varphi$  : used to estimate the nuisance parameters  $\varphi$ . (obtain  $\hat{\varphi}$ )

$\mathcal{D}_t$  : used to train a CATE model  $\tau$ . (obtain  $\hat{\tau}$ )

$\mathcal{D}_c$  : used to compute conformity scores for  $\hat{\tau}$ . (obtain  $V_{\varphi,i} \Rightarrow \hat{C}_\varphi(x)$ )

## Conformal prediction of ITE (pseudo-intervals)

### How to construct a conformal interval on real data?(in detail)

Next, the estimates  $\hat{\varphi} = (\pi, \hat{\mu}_0, \hat{\mu}_1)$  are used to transform  $\{Z_i = (X_i, T_i, Y_i) : i \in \mathcal{D}_t\}$  into covariate/pseudo-outcome pairs  $\{(X_i, \tilde{Y}_{\varphi,i}) : i \in \mathcal{D}_t\}$  which are used to train a CATE model  $\hat{\tau}$ .

Finally, we compute conformity scores for  $\hat{\tau}$  on pseudo-outcomes, i.e.,

$$V_{\varphi,i}(\hat{\tau}) := V(X_i, \tilde{Y}_{\varphi,i}; \hat{\tau}), \forall i \in \mathcal{D}_c,$$

$$Q_{\mathcal{V}_{\varphi},1-\alpha} := (1 - \alpha) (1 + 1/|\mathcal{D}_c|)\text{-th quantile of } \mathcal{V}(\hat{\tau})$$

For a target coverage of  $1 - \alpha$ , we construct a predictive interval at a new point  $X_{n+1} = x$  as follows:

$$\hat{C}_{\varphi}(x) = [\hat{\tau}(x) - Q_{\mathcal{V}_{\varphi},1-\alpha}, \hat{\tau}(x) + Q_{\mathcal{V}_{\varphi},1-\alpha}]$$

where  $\mathcal{V}_{\varphi} = \{V_{\varphi,k}(\hat{\tau}) : k \in \mathcal{D}_c\}$ . We call  $\hat{C}_{\varphi}(x)$  a pseudo-interval.

Does psuedo-interval satisfy (1)?

In the following Theorem, we provide sufficient conditions for the validity of conformal meta-learners in terms of the stochastic orders of their conformity scores.

**Theorem 1.** If  $(X_i, T_i, Y_i(0), Y_i(1)), i = 1, \dots, n + 1$  are exchangeable, then  $\exists \alpha^* \in (0, 1)$  such that the pseudo-interval  $\hat{C}_\varphi(X_{n+1})$  constructed using the dataset  $\mathcal{D} = \{(X_i, T_i, Y_i)\}_{i=1}^n$  satisfies

$$\mathbb{P}\left(Y_{n+1}(1) - Y_{n+1}(0) \in \hat{C}_\varphi(X_{n+1})\right) \geq 1 - \alpha, \forall \alpha \in (0, \alpha^*)$$

if at least one of the following **stochastic ordering conditions** hold:

Does psuedo-interval satisfy (1)?

## Stochastic ordering conditions

Let  $F_{V_\varphi}$  and  $F_{V^*}$  be the corresponding cumulative distribution functions (CDFs) of variable  $V_\varphi$  and  $V^*$  respectively.

- i  $V_\varphi$  has first-order stochastic dominance (FOSD) on  $V^*$  ( $V_\varphi \underset{(1)}{\geq} V^*$ )  
 $\Leftrightarrow F_{V_\varphi}(x) \leq F_{V^*}(x), \forall x$ , with strict inequality for some  $x$ .
- ii  $V_\varphi$  has second-order stochastic dominance (SOSD) over  $V^*$  ( $V_\varphi \underset{(2)}{\leq} V^*$ )  
 $\Leftrightarrow \int_{-\infty}^x [F_{V_\varphi}(t) - F_{V^*}(t)] dt \geq 0, \forall x$ , with strict inequality for some  $x$ .
- iii  $V_\varphi$  has monotone convex dominance (MCX) over  $V^*$  ( $V_\varphi \underset{mcx}{\geq} V^*$ )  
 $\Leftrightarrow \mathbb{E}_{X \sim F_{V_\varphi}} [u(X)] \geq \mathbb{E}_{X \sim F_{V^*}} [u(X)]$  for all non-decreasing convex functions  $u : \mathbb{R} \rightarrow \mathbb{R}$ .

(Under condition i, we have  $\alpha^* = 1$ )

Do  $V_\varphi$  and  $V^*$  satisfy the stochastic ordering conditions?

**Theorem 2.** Let  $V_\varphi(\hat{\tau}) = \left| \hat{\tau}(X) - \tilde{Y}_\varphi \right|$  and assume that the propensity score function  $\pi : \mathcal{X} \rightarrow [0, 1]$  is known.

Then, the following holds:

- i For the  $X$ -learner,  $V_\varphi$  and  $V^*$  do not admit to a model- and distribution-free stochastic order.
- ii The IPW- and the DR-learners satisfy  $V_\varphi \underset{mcx}{\geq} V^*$ . (for any distribution  $P(X, T, Y(0), Y(1))$ , CATE estimate  $\hat{\tau}$ , and nuisance estimate  $\hat{\varphi}$ !)