On Testing Conditional Qualitative Treatment Effects

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Joint work with Wenbin Lu and Rui Song

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A few words on causal inference

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- A: Treatment (0 or 1)
- X: Covariates
- Y: Observed outcome (usually the larger the better)

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Identify the optimal regime d_{opt} to reach the best clinical outcome

- Maximize $\mathrm{E}Y^*(d) = \mathrm{E}[d(X)Y^*(1) + \{1 - d(X)\}Y^*(0)]$

$$d : X \to \{0, 1\}.$$

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Conditional qualitative treatment effects (CQTE)

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- X^B and X^C are the subsets of X.
- X^C have CQTE given X^B, if there exists some nonempty subsets $\mathcal{C}_1$, $\mathcal{C}_2$ and $\mathcal{B}$ such that

  (i) $\Pr\left\{(X^B, X^C) \in \mathcal{B} \times \mathcal{C}_1\right\} > 0$ and $\Pr\left\{(X^B, X^C) \in \mathcal{B} \times \mathcal{C}_2\right\} > 0$.
  (ii) For any $x_1^C \in \mathcal{C}_1$, $x_2^C \in \mathcal{C}_2$ and $x^B \in \mathcal{B}$, we have

$$\begin{aligned} & \arg\max_a \mathrm{E}\left\{Y^*(a) | X^B = x^B, X^C = x_1^C\right\} \\ \neq \; & \arg\max_a \mathrm{E}\left\{Y^*(a) | X^B = x^B, X^C = x_2^C\right\}. \end{aligned}$$

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No CQTE means $\tau_0^C(X^C) \geq 0, a.s$ or $\tau_0^C(X^C) \leq 0, a.s.$

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Conditional qualitative treatment effects

- B is not empty.
- Assume X^B have QTE.
- CQTE measures whether X^C are "important" in decision making given X^B.

- For any $D \subseteq [1, \dots, p]$, define

$$\tau_0^D(x^D) = \mathrm{E}\{\tau_0(X)|X^D = x^D\},$$
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- Let $W = B \cup C$. Define

$$\begin{aligned}
\mathrm{ER}^{W,B} &= \begin{cases} 0, \quad \text{if} \ \ \tau_0^W(X) = 0, a.s. \\ \dfrac{\mathrm{E}[|d_{opt}^W(X) - d_{opt}^B(X)|I\{\tau_0^W(X^W) \neq 0\}]}{\Pr\{\tau_0^W(X^W) \neq 0\}}, \quad \text{otherwise}, \end{cases} \\
\mathrm{VD}^{W,B} &= V(d_{opt}^W) - V(d_{opt}^B) \\
&= \mathrm{E}\left(\tau_0^W(X^W)[I\{\tau_0^W(X^W) \geq 0\} - I\{\tau_0^B(X^B) \geq 0\}]\right).
\end{aligned}$$

Theorem (Charaterization of No CQTE)

Under certain conditions, the followings are equivalent:

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(iv) *For any* x^W *such that* $\tau_0^W(x^W) \neq 0$, $d_{opt}^W(x) = d_{opt}^B(x)$.

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(iv) *For any* x^W *such that* $\tau_0^W(x^W) \neq 0$, $d_{opt}^W(x) = d_{opt}^B(x)$.

(v) *For any fixed* x^B, $\tau_0^W(x^B, x^C) \geq 0$ *for any* x^C *or* $\tau_0^W(x^B, x^C) \leq 0$ *for any* x^C.

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- Hypothesis testing:

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- Otherwise, estimate $d_{opt}^W(x)$.

- Let f^W be the probability density function of X^W.

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- Estimate $\tau_0^W(x^W)f^W(x^W)$ by

$$\tau_n^W(x^W) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{A_i}{\pi_i} - \frac{1-A_i}{1-\pi_i}\right) Y_i K_{h^W}^W(x^W - X_i^W),$$

for some multivariate kernel function $k_{h^W}^W$ with the bandwidth h^W.

Testing procedure

$$S_n^{W,B} = \int_{x^W \in \Omega^W} \tau_n^W(x^W)\{d_n^W(x^W) - d_n^B(x^B)\} I(x^W \notin \hat{E}) d\nu(x^W),$$

where

$$\hat{E} = \left\{ x^W : \left| \frac{\tau_n^W(x^W)}{\hat{f}^W(x^W)} \right| \le \eta_n, \left| \frac{\tau_n^B(x^B)}{\hat{f}^B(x^B)} \right| \le \eta_n \right\},$$

for some sequence $\eta_n \to 0$. Here, $\hat{f}^W$ and $\hat{f}^B$ are the kernel density estimators of f^W and f^B, respectively.

Testing procedure (Cont'd)

Let

$$\hat{F} = \{x^W : |\tau_n^W(x^W)/\hat{f}^W(x^W)| \le \eta_n, |\tau_n^B(x^B)/\hat{f}^B(x^B)| > \eta_n\}.$$

The test statistic is defined by

$$T_n^{W,B} = \begin{cases} \{\sqrt{n}S_n^{W,B} - \hat{a}_n(\hat{F})\}/\hat{\sigma}_n(\hat{F}), & \text{if } \nu(\hat{F}) \neq 0, \\ \{\sqrt{n}S_n^{W,B} - \hat{a}_n(\Omega^W)\}/\hat{\sigma}_n(\Omega^W), & \text{otherwise.} \end{cases}$$

We reject the null when $T_n^{W,B} > z_\alpha$.

Theorem (Consistency)

Under certain conditions, when H_0 is true, we have

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Theorem (Informal statement)

Under certain conditions, $T_n^{W,B}$ has non-negligible powers against some nonstandard $n^{-1/2}$ local alternatives.

Simulation models:

$$Y = 1 - \frac{X_1 - X_2}{2} + A\phi_1(X_1)\phi_2(X_2) + e,$$

Table: Simulation results.

		VD = 0		VD = 4%		VD = 8%		VD = 12%	
		α level		α level		α level		α level	
	n	0.05	0.1	0.05	0.1	0.05	0.1	0.05	0.1
Scenario 1	300	4.3%	6.0%	24.0%	34.0%	58.7%	68.1%	82.2%	87.5%
	600	1.5%	3.3%	36.7%	45.5%	75.8%	83.3%	95.7%	97.3%
Scenario 2	300	7.0%	11.1%	23.8%	32.7%	60.5%	69.3%	88.2%	92.3%
	600	5.5%	10.0%	31.0%	41.8%	83.0%	90.5%	98.3%	99.5%
Scenario 3	300	3.8%	6.5%	37.3%	48.5%	76.3%	79.7%	92.7%	94.7%
	600	2.7%	6.7%	52.5%	61.8%	99.2%	100%	99.8%	99.8%
Scenario 4	300	6.2%	9.8%	39.8%	47.7%	79.2%	87.3%	94.8%	96.7%
	600	5.2%	8.8%	59.3%	68.2%	96.8%	98.3%	99.5%	99.5%
Scenario 5	300	5.2%	9.7%	29.3%	40.5%	68.0%	76.3%	94.0%	96.8%
	600	5.3%	9.5%	36.7%	45.5%	75.8%	83.3%	95.7%	97.3%

1. Set $B = \emptyset$. In Step 1, for each variable i, define the set $W_i = \{i\}$ and calculate the p-value p_i for each test statistic $T^{W_i,B}$. Stop if $\min_i p_i > \alpha$. Include the variable that gives the smallest p-value in the set B, i.e,

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2. In Step 2, for each variable $i \notin B$, define $W_i = B \cup \{i\}$ and calculate the p-value p_i for each test statistic $T^{W_i,B}$. Stop if $\min_i p_i > \alpha$. Include the variable that gives the smallest p-value,

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3. Continue the second step until it stops. Output B.

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- Extend the testing procedure to a high-dimensional setting.

Thank you!