# On Sensitivity Value of Pair-Matched Observational Studies

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Manuscript and slides are available at http://www-stat.wharton.upenn.edu/~qyzhao/.

## Sensitivity Analysis

- Observational studies = Treatment is not randomized.
- ► The core but unverifiable assumption: treatment ignorability, aka no unmeasured confounding. (Fisher's criticism of "smoking causes lung cancer".)
- Sensitivity analysis: what if this assumption is violated (in a controlled way captured by one or a few sensitivity parameters)?
- ► There is a long list of approaches of sensitivity analysis. I will consider Rosenbaum's sensitivity analysis for a pair-matched study. (Cornfield's response to Fisher.)

## What does a sensitivity analysis look like?

• Sensitivity parameter  $\Gamma \geq 1$  in Rosenbaum's model: within each matched pair,

 $1/\Gamma \le \text{odds ratio}(1\text{st unit treated}, 2\text{nd unit treated}) \le \Gamma.$ 

- ho  $\Gamma = 1$  corresponds to ignorable treatment. Can test the sharp null hypothesis by e.g. Wilcoxon's signed rank test.
- When Γ > 1: Rosenbaum obtained lower and upper bounds of the p-value of any signed score test.
- An example:

probe set	sensitivity analysis							sensitivity value	
37583_at	Γ	1	2	3	5	7	10	1.84	2.44
	$\overline{p}_{\Gamma}$	0.00	0.02	0.13	0.60	1.00	1.00	0.01	0.05

#### Sensitivity value

#### Definition ("Truncated" sensitivity value)

$$\Gamma_{\alpha}^{**} = \inf \Big\{ \Gamma \ge 1 \, | \, \overline{p}_{\Gamma} > \alpha \Big\}.$$

Interpretation: If the unmasured confounder changes the within-pair odds ratio of treatment by more than  $\Gamma_{\alpha}^{**}$ , then the sharp null hypothesis could be not significant.

- ▶  $\Gamma_{\alpha}^{**} > 1$  iff  $\overline{p}_1 = p_1 \le \alpha$ . What if the null hypothesis is not significant even when  $\Gamma = 1$ ?
- ▶ Mathematically,  $\overline{p}_{\Gamma}$  can be defined for  $0 < \Gamma < 1$  as well. It is more convenient to work with  $\Gamma_{\alpha}^*$  that takes the infimum over  $\Gamma > 0$ .

#### Some motivations I

- Sensitivity value is a concise summary of the study's "sensitivity to measured confounding".
- A value vs. A table.
- ▶ Analogy: *p*-value for a randomized experiment vs. sensitivity value for an observational study.

#### Some motivations II

▶ Asymptotics of sensitivity value ↔ Power of sensitivity analysis:

$$P(\Gamma_{\alpha}^* \geq \Gamma) = P(\overline{p}_{\Gamma} \leq \alpha).$$

- The "favorable situation": no unmeasured confounding and nonzero causal effect.
- ▶ Fixed  $\Gamma$  asymptotics: Rosenbaum [2015] considered the Bahadur efficiency of a sensitivity analysis by studying how fast  $\overline{p}_{\Gamma} \rightarrow 0$ .
- ▶ Fixed  $\alpha$  asymptotics: examine the distribution of  $\Gamma_{\alpha}^*$ .

## Background

▶ A general and common strategy is to use the signed score test (Y<sub>i</sub> is the within-pair difference)

$$T = \frac{\sum_{i=1}^{I} \operatorname{sgn}(Y_i) q_i}{\sum_{i=1}^{I} q_i}, \ q_i = \psi\left(\frac{\operatorname{rank}(|Y_i|)}{I+1}\right).$$

**Problem** Rosenbaum found bounding variable  $\bar{T}_{\Gamma}$  in the sense that

$$P(T \ge t|\mathcal{F}) \le P(\overline{T}_{\Gamma} \ge t|\mathcal{F}) = \overline{p}_{\Gamma},$$

▶ CLT for  $\bar{T}_{\Gamma}$ :

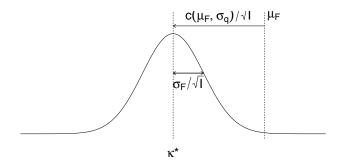
$$\sqrt{I} \cdot \frac{\overline{T}_{\Gamma} - \Gamma/(1+\Gamma)}{\sqrt{\Gamma/(1+\Gamma)^2 \sigma_{q,I}^2}} \xrightarrow{d} N(0,1), \ \sigma_{q,I}^2 = \frac{I^{-1} \sum_{i=1}^{I} q_i^2}{\left(I^{-1} \sum_{i=1}^{I} q_i\right)^2}.$$

#### CLT for sensitivity value

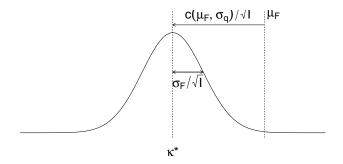
#### Theorem (Z, 2017)

Suppose  $Y_i \overset{i.i.d.}{\sim} F$  and  $\sqrt{I} \cdot (T - \mu_F)/\sigma_F \overset{d}{\rightarrow} \mathrm{N}(0,1)$ , the transformed sensitivity value  $\kappa_{\alpha}^* = \Gamma_{\alpha}^*/(1 + \Gamma_{\alpha}^*)$  for fixed  $0 < \alpha < 1$  satisfies

$$\sqrt{I} \cdot \left[ \kappa_{\alpha}^* - \mu_F \right] \stackrel{d}{\to} \mathcal{N} \left( -\sigma_q \bar{\Phi}^{-1}(\alpha) \sqrt{\mu_F (1 - \mu_F)}, \ \sigma_F^2 \right).$$

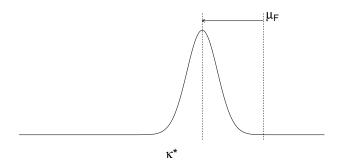


## Design sensitivity



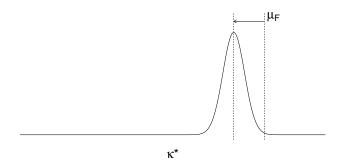
- ▶ Rosenbaum [2004] noticed a phase transition at  $\mu_F$ :
  - If  $\kappa > \mu_F$ , sensitivity analysis has no asymptotic power.
  - ▶ If  $\kappa < \mu_F$ , power  $\to 1$  as  $I \to \infty$ .
  - ▶ He calls the value  $\mu_F/(1-\mu_F)$  "design sensitivity".
- ► The CLT for sensitivity value separates the contribution by design and by obtaining more sample.

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#### Implication: select statistics

▶ The goal: maximize  $\Gamma_{\alpha}^*$  stochastically.

$$\sqrt{I} \cdot \left[ \kappa_{\alpha}^* - \mu_F \right] \stackrel{d}{\to} N \left( -\sigma_q \bar{\Phi}^{-1}(\alpha) \sqrt{\mu_F (1 - \mu_F)}, \ \sigma_F^2 \right).$$

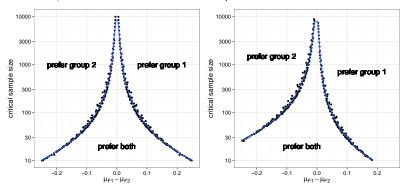
- ▶ The expecation of  $\Gamma_{\alpha}^*$  is determined by two quantities:
  - 1.  $\mu_F = <\psi, g_F>;$
  - 2.  $\sigma_q = \|\psi\|_2^2 / \|\psi\|_1^2$ .
- ▶ Tradeoff: want to maximize  $\mu_F$  without making  $\sigma_q$  too large.
- ▶ Manuscript has detailed comparison of different choices of  $\psi$  under different F.
- ▶ Practically, can estimate  $\mu_F$  by sample splitting and then decide.

#### Implication: select subgroups

- ▶ Hsu, Small, and Rosenbaum [2013] noticed a dilemma. Suppose there are two subgroups with unequal  $\mu_F$ . Heuristically,
  - If  $I \to \infty$ , should use the subgroup with larger  $\mu_F$ .
  - ▶ If *I* is small, should combine the samples.

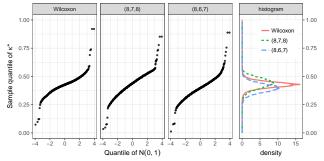
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  - ▶ If *I* is small, should combine the samples.
- ▶ Can use the asymptotics to compute the critical sample size.
- ▶ For example, for Noether's statistics  $\psi(u) \equiv 1$  (ratio of sample sizes below: 1:1 and 3:1).



#### Implication: select hypotheses

- One treatment and hundreds of outcomes that are susceptible to unmeasured confounding.
- Can use sensitivity value to screen causal hypotheses.
- The manuscript has an application to genomics screening.



▶ Zhao, Small, and Rosenbaum [2017] proposed a related method called "Cross Screening".

#### References

#### Manuscript:

 Q. Zhao. On sensitivity value of pair-matched observational studies. arXiv:1702.03442.

#### Additional references:

- J. Y. Hsu, D. S. Small, and P. R. Rosenbaum. Effect modification and design sensitivity in observational studies. *Journal of the American Statistical Association*, 108(501):135–148, 2013.
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- Q. Zhao, D. S. Small, and P. P. Rosenbaum. Cross-screening in observational studies that test many hypotheses. arXiv:1703.02078, 2017.