

Propensity Score-Based Methods for Causal Inference and External Data Leveraging in Regulatory Clinical Studies

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Outline

- Propensity score-based methods for the regulatory clinical studies
- Application of propensity score-based methods for causal inference and external data leveraging in hybrid clinical studies
- Concluding Remarks



Propensity Score-Based Methods

- Traditional Propensity score (PS) methods For causal inference
 - Matching on propensity scores
 - Stratification on propensity scores
 - Inverse probability of treatment weighting using propensity scores
- Propensity score-integrated approaches For augmenting a prospective study with external data
 - Propensity score-integrated Power prior Bayesian
 - Propensity score-integrated Composite likelihood Frequentist
- External data data external to traditional clinical study being planned, such as Real-world data or historical clinical study data



Adapting and Advancing Propensity Score Methodology in the Regulatory Settings

- Propensity score methodology A ground-breaking statistical innovation for the *design* and *analysis* of observational studies, developed by Rosenbaum and Rubin in 1983.
- In 2002, it was adopted first by FDA/CDRH, for pre-market *confirmatory* non-randomized medical device studies (Yue, LQ, 2007, *JBS*).
- Around 2013, the 2-stage outcome-free PS study design framework was proposed to ensure the study integrity and transparency.
- Since 2018, the propensity score-integrated approaches, Bayesian and Frequentist, have been developed to augment a prospective study.
- It has been utilized for post-market safety evaluation of drugs and devices (Levenson and Yue, 2013).



Traditional Propensity Score Methodology

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- Propensity score (PS): Conditional probability of receiving treatment A rather than treatment B, given a collection of observed baseline covariates.
- Replace the <u>collection</u> of confounding covariates with <u>one scalar function</u> of these covariates: the propensity score.
- Goal: Simultaneously balance many observed covariates between the two treatment groups, and then reduce bias in treatment comparison on outcomes.
- Propensity score is a balancing score Conditional on the propensity score, the distribution of observed baseline covariates is the same between the two treatment groups.
- PS estimation: Statistical modeling of relationship between treatment group membership and covariates.



Limitations

- Propensity score methods can only adjust for observed confounding covariates and not for unobserved ones.
- Propensity score is seriously degraded when important variables influencing treatment assignment and outcome have not been collected or included in PS model.
 - E.g., variable in data source level clinical practice, availability of adjunct therapy, data collection, region, time of data collection.
- Propensity score may not eliminate all selection bias.
- It may not work when there are significant amount of missing data in covariates.



When Does It Work Better?

Braitman and Rosenbaum (2002):

- When outcome event is rare.
- When there are a large number of subjects in each treatment group.
- When there are many covariates observed.

Braitman, L., Rosenbaum, P. R. (2002). Rare outcomes, common treatments: Analytic strategies using propensity scores. Ann. Intern. Med. 137:693–696.



Propensity Score-Integrated Approaches

- Propensity score-integrated Power prior Bayesian
- Propensity score-integrated Composite likelihood Frequentist

for augmenting a prospective study, single-arm or randomized controlled trial (RCT), with external data



Propensity Score Redefined

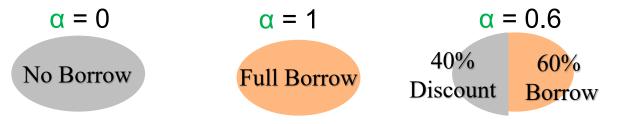
- Traditional propensity score: Conditional probability of receiving treatment A rather than treatment B, given a collection of observed baseline covariates.
 - Used to balance patient characteristics (covariates) between the two treatment groups.
 - For causal inference
- Re-defined propensity score: Conditional probability of being in the traditional study rather than in the external data source, given patient baseline covariates.
 - Used to balance patient characteristics (covariates) between the two patient groups: traditional study patients and external patients.
 - For augmenting a prospective study

Power Prior (Bayesian)

• A power prior is constructed as

$$\pi(\boldsymbol{\theta}|D_0, \alpha) \propto [L(\boldsymbol{\theta}|D_0)]^{\boldsymbol{\alpha}} \pi_0(\boldsymbol{\theta})$$

- θ : parameter of interest
- $L(\theta|D_0)$: likelihood function of the external data
- $-\pi_0(\theta)$: initial prior distribution for θ
- α : power prior parameter, $0 \le \alpha \le 1$
- $-\alpha$ controls how much external data to borrow



• Q: how and when to determine α for a prospective study?

Ref. Chen, M-H and Ibrahim, J.G., (2000) Power Prior Distribution for Regression Models. Statistical Science, 15(1): 46-60



Composite Likelihood (Frequentist)

• General form (weighted product of probability density functions):

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L(\theta|Y) = \prod_{i} f(y_i |\theta)^{\lambda_i}
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where λ_i is nonnegative weight to be chosen, and can be used to down-weight external patient info.

- Set:
 - $-\lambda_i = 1$, if the patient *i* is from the traditional study
 - $0 < \lambda_i \le 1$, if the patient *i* is from the external data source

Q: how and when to determine λ for a prospective study?

Ref. Lindsay, BG (1988). Composite likelihood method. *Contemporary mathematics*, 80(1): 221-239. Varin et al (2011). An overview of composite likelihood methods. *Statistica Sinica*, P5-42.



Propensity Score-Integrated Approaches for Augmenting

- Propensity score methodology
 - Study design
 - PS estimation
 - Using estimated PS, to
 - \checkmark Select comparable patients from external data source
 - ✓ Determine how much info to borrow from each external patient, i.e., determine α in power prior or λ in composite likelihood.
- Power prior or composite likelihood method
 - Outcome analysis
 - Down-weight external data when needed.



Outline

- Propensity score-based methods for the regulatory clinical studies
- Application of propensity score-based methods for causal inference and external data leveraging in hybrid clinical studies
 - Hybrid study data consist of two parts:
 - Data on patients prospectively enrolled in an investigational clinical study
 - External data
- Concluding Remarks



Three Types of Hybrid Study

 Type 1: Non-randomized comparative study with external control group

 Prospectively Enrolled Treated Patients (Traditional Patients)

Control Patients from External Source

to approximate a traditional randomized controlled trial (RCT)

Type 2: Single-arm hybrid study

Prospectively Enrolled Treated Patients (Traditional Patients) **External Treated Patients**

to approximate a traditional single-arm study

Type 3. RCT with hybrid control group

Prospectively Enrolled Randomized Treated Patients (Traditional Patients)

Prosp. Enrolled Randomized Control Patients (Traditional Patients) External Ctrl. patients

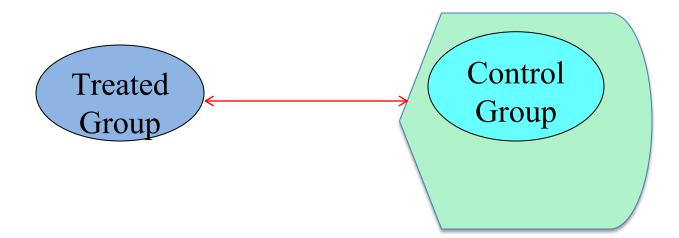
to approximate a traditional RCT

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Type 1 Hybrid Study: Construct a Control Group

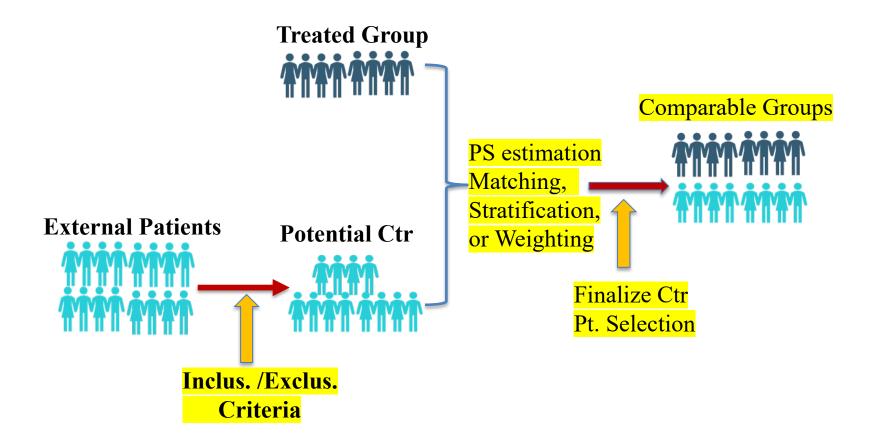
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- Using PS, identify patients and construct a control group from external patients, based on patient baseline characteristics (not outcomes!) such that
 - the distribution of observed baseline covariates is similar between the treated and control patients
 - leading to comparable treatment groups in terms of baseline covariates.





External Control Group Construction





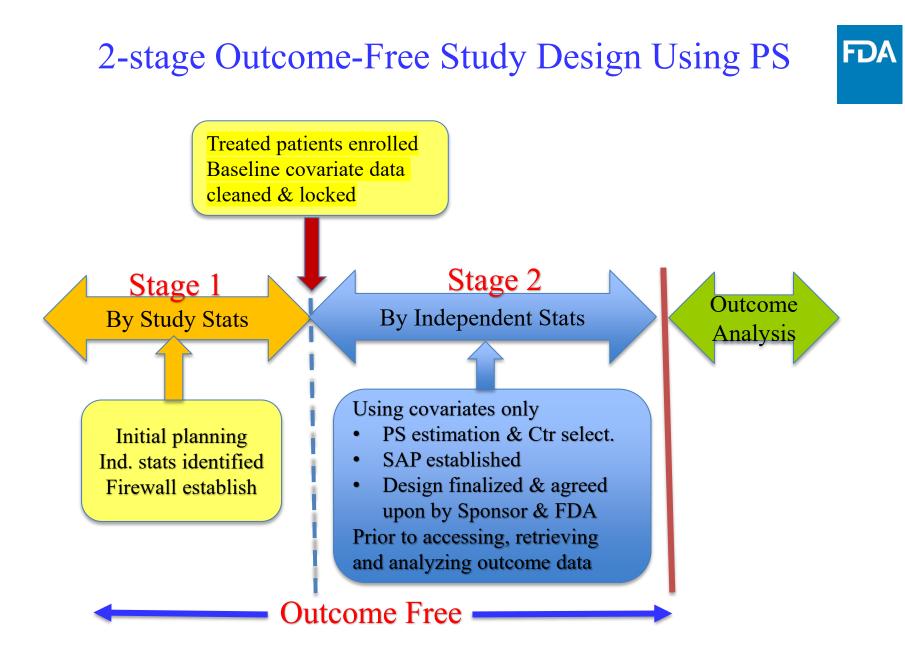
A Critical Question – Study Integrity

- Given that in many cases when designing a prospective study, data on external patients have already been collected and clinical outcomes are already available,
- And given the iterative nature of PS design,

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Q: How to ensure the scientific validity of the study design and the interpretability of study results?

A: Outcome data need to be kept out of sight during study design.





Data Leveraging: Type 2 and Type 3 Hybrid Studies

Type 2: Single-arm study leveraging external patients

Prospectively Enrolled Treated Patients (Traditional Patients)

External Treated Patients

Prespecified amount of information contributed by external patients (nominal number of patients)

to approximate a traditional single-arm study (target study)

Type 3: RCT leveraging external patients

Prospectively Enrolled Randomized Treated Patients (Traditional Patients)

Prosp. Enrolled Randomized Control Patients (Traditional Patients) **External Control Patients**

Prespecified amount of information contributed by external patients (nominal number of patients)

to approximate a traditional RCT (target study)



Balancing Covariates for Data Leveraging

• What if external patients and traditional patients "look different"?

Looking different means:

The distribution of patient characteristics among the external patients

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The distribution of patient characteristics among the traditional patients

• Some statistical adjustment is needed for a hybrid study to approximate the target study well ---- covariate balance.



Redefining Propensity Score for a Hybrid Study

- Propensity score (PS) (modified definition): Conditional probability of being a traditional patient rather than an external patient, given a collection of observed baseline covariates (applicable to data leveraging)
- Propensity score stratification with 5 strata
- Yellow---external patients, grey---traditional patients
- With equal number of traditional patients in each stratum
- Using PS quintiles among traditional patients as boundaries for PS strata



• 2-stage outcome-free propensity score design framework



Summary of Propensity Score Design Determination of α or λ for a type 3 hybrid study

<u>PS Stratum</u>						
	1	2	3	4	5	Total
Traditnl. Pts (n)	54	53	53	53	54	267
Treated (n)	41	28	39	36	39	183
Control (n)	13	25	14	17	25	84
External Pts (n)	332	270	233	201	156	1192
Leveraged Info. (n)	19	17	17	16	18	87
$\alpha \text{ or } \lambda$	0.06	0.06	0.0	8 0.0	8 0.11	



Concluding Remarks

- Novel statistical methods play a critical role in leveraging external data to support regulatory decisions
- Propensity score-based methods can be applied to the design and analysis of all three types of hybrid study
- Propensity score-integrated approaches have drawn a great deal of attention
- Software for implementation is available

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Thank You!