

Mitigating study power loss in disrupted clinical trials: Leveraging external data via the propensity score-integrated approach

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Outline

- A novel statistical procedure for leveraging external data in medical product evaluation
 - Today's focus: Propensity score-integrated approach
- Application: mitigating study power loss for a clinical study cut short due to the COVID-19 pandemic (this study will be called the “current study” henceforth)
- Concluding remarks



Basic Statistical Ingredients

- Power prior (Bayesian)
 - Borrow external subjects with discounting
- Composite likelihood (frequentist)
 - Incorporate external subjects with down-weighting
- Propensity score methodology
 - Balance subject characteristics (covariates) between two groups: current study subjects and external subjects
- Propensity score-integrated approach – **Today's focus**
 - Propensity score-integrated power prior – **Bayesian**
 - Propensity score-integrated composite likelihood – **Frequentist**
 - Goal: the augmentation of the current study with external data while maintaining study integrity

Bayesian Power Prior

- A power prior is constructed as

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

- $\boldsymbol{\theta}$: parameter of interest
- $L(\boldsymbol{\theta}/D_0)$: likelihood of the external data
- $\pi_0(\boldsymbol{\theta})$: initial prior distribution for $\boldsymbol{\theta}$
- α : *power prior parameter*, $0 \leq \alpha \leq 1$
- α : control how much external data to leverage
 - $\alpha = 0$: no leverage
 - $\alpha = 1$: full leverage
- Question: **how** and **when** to determine α for a prospective investigational study?

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

Composite Likelihood

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

$$L(\theta|Y) = \prod_i f(y_i | \theta)^{\lambda_i}$$

where λ_i is nonnegative weight to be chosen, and can be used to discount subject info from external data source.

- We set:
 - $\lambda_i = 1$, if the subject i is from the investigational study
 - $0 < \lambda_i \leq 1$, if the subject i is from the external data source
 - E.g. If $\lambda_i = 0.6$, 60% of this subject's info is leveraged and 40% discounted.
- Question: **how** and **when** to determine λ for a prospective investigational 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 Methodology

- A ground-breaking statistical innovation for the *design* and *analysis* of observational studies, developed by Rosenbaum and Rubin in 1983 (Rosenbaum and Rubin, 1983).
- **Propensity score (PS)**: Conditional probability of receiving treatment A rather than treatment B, given a collection of observed baseline covariates.
- Replace a **(large) number of observed** confounding covariates with **one scalar function** of these covariates: the propensity score.
- **Goal in observational studies: Simultaneously** balance many observed covariates between the two treatment groups, and then **reduce bias** in treatment comparison on outcomes.
- **Our Goal**: Simultaneously balance many observed covariates between the external subjects as one group and current study subjects as the other group, to make leveraging external subjects more justified



Propensity Score Methods

- Propensity score is estimated through statistical modeling of relationship between **the covariates** and **membership of the groups between which covariates are to be balanced**.
- Commonly used PS methods in the regulatory settings:
 - Matching on propensity scores
 - **Stratification on propensity scores**
 - Weighting using propensity scores
- All these methods can separate study *design* from outcome *analysis*.
- In our application, propensity score stratification is used, propensity scores are estimated by independent statistician blinded to outcome data

Propensity Score-Integrated Approach

- A new methodology for leveraging external data to augment a prospective investigational study.
 - PS-integrated power prior (PS + PP) - Bayesian
 - PS-integrated composite likelihood (PS + CL) – Frequentist
- Used to
 - augment a single-arm investigational study with external data,
 - augment one or both arms of an RCT,
 - with the option of discounting/down-weighting information from external data.
- PS -> Study design
- PP or CL -> Outcome analysis



PS-Integrated Approach – Study Design

- **Define** PS as the conditional probability of being in the current study vs external source, given subject baseline covariates.
- **Use** PS to design the study:
 - Select comparable subjects from external data source
 - Stratify the pooled current study and external subjects
 - Specify the amount by which information of external subjects is discounted/down-weighted (i.e., determine α in PP or λ in CL)
- Only baseline covariates are used in the above: **Outcome free!**



Leveraging External Data -- Caveats

- It is critical to assess whether leveraging external data *fits for purpose* for the specific objectives of the current study.
- Sufficient external data *quality* and *integrity* are *essential* for regulatory decision-making – *relevance and reliability*.
- Outcome-free planning is critical – *trial integrity and transparency*.
- Early consultation with relevant FDA review division is important (FDA guidance documents).
- *The propensity score-integrated approach can be used*
 - To augment single-arm study with external data
 - To augment one or both arms of RCT with external data

A Illustrative Example

- A single-arm clinical study
- Primary endpoint: one-year adverse event
- Parameter of interest: θ , probability of a subject experiencing adverse event(s) within the first year.
- Associated hypothesis testing:

$$H_0 : \theta \geq 36\% \quad vs: \quad H_a : \theta < 36\%$$
- Sample size determination
 - Assume $\theta = 0.30$
 - Set: power = 80%; significance level = 0.05
 - Then, **N = 380**

A Illustrative Example (cont.)

- The enrolment was stopped at **290** due to the pandemic, and that it is not practical to reopen the enrolment at a later time.
- It was proposed to
 - borrow **90 = 380 - 290** subjects from a registry for this device in Europe (the device was approved in EU), using the **PS-integrated approaches**.
 - identify an independent statistician who was blinded to the outcomes data.
- Based on the subject inclusion/exclusion criteria specified in the current study, **941** subjects were selected from the registry.
- With the covariate data of **1,231** ($290 + 941$) subjects from the current study and registry, a propensity score model was created by the independent statistician, using logistic regression.
- Propensity score is defined as the probability of a subjects being in the current study instead of the registry conditional on all the covariates.

Table 1. Sample Sizes in PS Stratum

	1	2	3	4	5	Total
Current Study (n)	58	58	58	58	58	290
Registry (n)	281	210	154	187	109	941

- Five PS strata were formed, and balance for each covariate was checked using numerical and graphical methods.
- Note:
 - 90 external subjects were to be leveraged, but 941 identified.
 - Only partial info from each of 941 external subjects could be leveraged.
 - Partial? How much? Depending on what?

Step 1 – Split 90 nominal subjects into 5 PS strata

Step 2 – Determine power parameter α or exponent λ within each stratum

Step 1. Split 90 nominal subjects

- Split 90 nominal subjects into 5 PS strata, *proportional* to the *similarity* of external and the current subjects *in terms of baseline covariates*.
- The similarity is measured by an *overlapping coefficient*, the *overlapping area* of propensity score distributions of the two groups of subjects.

Overlapping Coefficients

	PS Stratum					Total
	1	2	3	4	5	
Current Study (n)	58	58	58	58	58	290
Registry (n)	281	210	154	187	109	941
Overlap Coeff	0.87	0.78	0.86	0.84	0.77	

Standardized Overlapping Coefficients

	PS Stratum					Total
	1	2	3	4	5	
Current Study (n)	58	58	58	58	58	290
Registry (n)	281	210	154	187	109	941
Overlap Coeff	0.87	0.78	0.86	0.84	0.77	
Std. Overlap Coef.	21%	19%	21%	20%	19%	100%

Splitting 90 Nominal External subjects

	PS Stratum					Total
	1	2	3	4	5	
Current Study (n)	58	58	58	58	58	290
Registry (n)	281	210	154	187	109	941
Overlap Coeff	0.87	0.78	0.86	0.84	0.77	
Std. Overlap Coef.	21%	19%	21%	20%	19%	100%
Subjects Leveraged	19	17	19	18	17	90
	$(90 \times 21\% = 19)$				$(90 \times 19\% = 17)$	

- The number of external subjects allocated to each **PS stratum** is proportional to their *standardized overlapping coefficient*.

Step 2. Determining How Much Info to Leverage

- The info leveraged from **each individual** external subject depends on how many external subjects in that PS stratum.
- The power prior parameter for each individual external subject, α , is **inversely proportional** to the sample size of external subjects in the PS stratum.

	PS Stratum					Total
	1	2	3	4	5	
Current Study (n)	58	58	58	58	58	290
Registry (n)	281	210	154	187	109	941
Subjects Lev. (n)	19	17	19	18	17	90
α (or λ)	0.07	0.08	0.12	0.10	0.15	
	(19/281 = 0.07)					

Leveraging External Data Planning – Finished

- We know
 - The PS stratum each subject would belong to.
 - How much info each external subject could contribute.
 - Study operating characteristics: 80% power; 5% Type I error rate.

	PS Stratum					Total
	1	2	3	4	5	
Current Study (n)	58	58	58	58	58	290
Registry (n)	281	210	154	187	109	941
α (or λ)	0.07	0.08	0.12	0.10	0.15	

Outcome Analysis (Power Prior)

- After the clinical outcome was observed from all the subjects, the final analysis was conducted, based on the PS study design:

	PS Stratum					
	1	2	3	4	5	Total
Current Study (n)	58	58	58	58	58	290
Registry (n)	281	210	154	187	109	941
α	0.07	0.08	0.12	0.10	0.15	

- Apply the power prior approach within each stratum to get stratum-specific posterior distribution, which are then combined to complete the inference for the parameter of interest.
- The posterior probability of $\theta < 36\%$ is 96.9%, which meets the study success criterion.

Outcome Analysis (Composite Likelihood)

- After the clinical outcome was observed from all the subjects, the final analysis was conducted.

	PS Stratum					
	1	2	3	4	5	Total
Current Study (n)	58	58	58	58	58	290
Registry (n)	281	210	154	187	109	941
λ	0.07	0.08	0.12	0.10	0.15	

- Apply the composite likelihood approach to get stratum-specific parameter estimates, which are then combined to complete the inference for the parameter of interest.
- Maximum likelihood estimate of $\theta = 31\%$, $p\text{-value} = 0.01$.



Concluding Remarks

- Novel statistical methods play a critical role in leveraging external data to support regulatory decisions.
- Propensity score-integrated approaches can be applied to incorporate external data for a prospective investigational clinical study.
- Propensity score-integrated approach can be utilized to mitigate study power loss due to the COVID-19 pandemic.

US FDA Guidance

- US Food and Drug Administration (2020), “FDA Guidance on Conduct of Clinical Trials of Medical Products during COVID-19 Public Health Emergency,” available at <https://www.fda.gov/regulatory-information/search-fda-guidance-documents/fda-guidance-conduct-clinical-trials-medical-products-during-covid-19-public-health-emergency>.
- US Food and Drug Administration (2020), “Statistical Considerations for Clinical Trials During the COVID-19 Public Health Emergency Guidance for Industry,” available at <https://www.fda.gov/regulatory-information/search-fda-guidance-documents/statistical-considerations-clinical-trials-during-covid-19-public-health-emergency-guidance-industry>.

PS-Integrated Approaches - Reference

- Wang, C., Li, H., Chen, W., Lu, N., Tiwari, R., Xu, Y., Yue, L. (2019). Propensity Score-Integrated Power Prior Approach for Incorporating Real-World Evidence in Single-Arm Clinical Studies. *Journal of Biopharmaceutical Statistics*, 29 (5),731-748.
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Thank You!