



Evaluation of Randomization Procedures for Clinical Trial Design Optimization with various clinical trial layouts

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Workshop on Design of Experiments, April 30–May 4 2018, CIRM,
Marseilles, France

This research is part of WP 1 of the IDeAI project funded from the European Union Seventh Framework Programme [FP7 2007-2013] under grant agreement No. 602552.



FP7 HEALTH 2013 - 602552





- What the theory tells us:
 - ▶ no randomization procedure performs best with all criteria, Rosenberger (2016), Atkinson (2014)
- What applied scientist mostly feel:
 - ▶ scepticism to randomization
 - ▶ do not well understood randomization principle
 - ▶ is just allocation and think unequal group size is a major problem
 - ▶ think that randomization is for balancing covariates but does mostly not work
 - ▶ select a procedure by opinion or software availability
- What the literature mirrors:
 - ▶ no training in randomization
 - ▶ no recommendation to give scientific arguments for the choice of randomization procedure, neither ICH Guidelines nor CONSORT Statement





Propose a tool for assessing the impact of selection bias as well as chronological bias on the type one error probability for a given randomization sequence (procedure) and thus enabling a scientific discussion of the appropriate choice of the randomization procedure

clinical trial design

- continuous normal endpoint to prove a superiority hypothesis
- multicenter, 2-arm parallel group design with intended 1:1 allocation ratio
- no interim analysis and no adaptation in the randomization process





Model for two arm parallel group multicenter trial involving K centers
allocation sequence notation of the statistical model assuming no
treatment by center interaction by

$$y_{ji} = \mu_E Z_{ji} + \mu_C(1 - Z_{ji}) + \tau_{ji} + \epsilon_{ji} \quad (1)$$

- 1 E, C : treatment indicator
- 2 j : index for center $j, 1 \leq j \leq K$
- 3 i : index for patient number $i, 1 \leq i \leq n_j = n_{jE} + n_{jC}$ in Center j
- 4 μ_ℓ expected response under treatment $\ell = E, C$
- 5 τ_{ji} denotes the fixed unobserved "bias" effect acting on the response of patient i in center j
- 6 errors ϵ_{ji} iid $N(0, \sigma^2)$
- 7 allocation $Z_{ji} = \begin{cases} 1 & \text{if patient } i \text{ in center } j \text{ is allocated to } E \\ 0 & \text{if patient } i \text{ in center } j \text{ is allocated to } C \end{cases}$





Aim

$$H_0 : \mu_E = \mu_C \text{ vs. } H_1 : \mu_E \neq \mu_C$$

use t-Test

$$t = \frac{\sum_{j=1}^K w_j D_j}{s_p \sqrt{\sum_{j=1}^K w_j^2 / w_j^*}}$$

Notations:

- weights w_j and $w_j^* = \frac{n_{jE} \times n_{jC}}{n_{jE} + n_{jC}}$, $n_j = n_{jE} + n_{jC}$
- $D_j = \tilde{y}_{jE} - \tilde{y}_{jC}$ is the mean treatment difference in center j
- $\tilde{y}_{jE} = \frac{1}{n_{jE}} \sum_{i=1}^{n_j} y_{ji} Z_{ji}$ and $\tilde{y}_{jC} = \frac{1}{n_{jC}} \sum_{i=1}^{n_j} y_{ji} (1 - Z_{ji})$
- $s_p^2 = \left(\sum_{j=1}^K \sum_{l=E,C} (n_{jl} - 1) s_{jl}^2 \right) / \left(\sum_{j=1}^K \sum_{l=E,C} (n_{jl} - 1) \right)$





Theorem: Under $H_0 : \mu_E = \mu_C$ the type 1 error probability in (1) (under misspecification) for the allocation sequence $\mathbf{Z} = (Z_1, \dots, Z_n)$ is

$$\begin{aligned} P(|T| > t_{df}(1 - \frac{\alpha}{2}) | \mathbf{Z}) \\ = F_{df, \delta(\mathbf{Z}), \lambda(\mathbf{Z})}(t_{df}(1 - \frac{\alpha}{2})) + F_{df, -\delta(\mathbf{Z}), \lambda(\mathbf{Z})}(t_{df}(\frac{\alpha}{2})). \end{aligned}$$

$F_{df, \delta(\mathbf{Z}), \lambda(\mathbf{Z})}$ denotes the distribution function of the doubly non-central t-distribution with $df = \sum_{j=1}^K \sum_{\ell=E, C} (n_{j\ell} - 1)$ degrees of freedom

$$\mathbf{Z}^t = (\mathbf{Z}_1^t, \dots, \mathbf{Z}_K^t) = (Z_{11}, \dots, Z_{1n_1}, \dots, Z_{K1}, \dots, Z_{Kn_K})$$





non-centrality parameters:

$$\delta(\mathbf{Z}) = \left(\sigma \sqrt{\sum_{j=1}^K w_j^2 / w_j^*} \right)^{-1} \left((\mu_E - \mu_C) \sum_{j=1}^K w_j + \sum_{j=1}^K w_j (\tilde{\tau}_{jE} - \tilde{\tau}_{jC}) \right)$$

$$\lambda(\mathbf{Z}) = \frac{1}{\sigma^2} \left(\sum_{j=1}^K \sum_{i=1}^{n_j} \tau_{ji}^2 - \sum_{j=1}^K n_{jE} \tilde{\tau}_{jE}^2 - \sum_{j=1}^K n_{jC} \tilde{\tau}_{jC}^2 \right)$$

$$\text{where } \tilde{\tau}_E = \frac{1}{n_E} \sum_{i=1}^n \tau_i Z_i ; \quad \tilde{\tau}_C = \frac{1}{n_C} \sum_{i=1}^n \tau_i (1 - Z_i)$$





$$\frac{\sum_{j=1}^K w_j D_j}{\sigma \sqrt{\sum_{j=1}^K w_j^2 / w_j^*}} \sim \mathcal{N}(\delta, 1)$$

$$\begin{aligned} E(\sum w_j D_j) &= E\left(\sum_{j=1}^K w_j \left(\frac{1}{n_{jE}} \sum_{i=1}^{n_j} y_{ji} Z_{ji} - \frac{1}{n_{jC}} \sum_{i=1}^{n_j} y_{ji} (1 - Z_{ji})\right)\right) \\ &= \left((\mu_E - \mu_C) \sum_{j=1}^K w_j + \sum_{j=1}^K w_j (\tilde{\tau}_{jE} - \tilde{\tau}_{jC}) \right) := \delta \left(\sigma \sqrt{\sum_{j=1}^K w_j^2 / w_j^*} \right) \\ \text{Var}(\sum w_j D_j) &= \sum_{j=1}^K w_j^2 \left(\frac{1}{n_{jE}^2} \sum_{i=1}^{n_j} \text{Var}(y_{ji}) Z_{ji} + \frac{1}{n_{jC}^2} \sum_{i=1}^{n_j} \text{Var}(y_{ji}) (1 - Z_{ji}) \right) \\ &= \sigma \sqrt{\sum_{j=1}^K w_j^2 / w_j^*} \end{aligned}$$



$$\frac{s_p^2}{\sigma^2} \sim \chi^2_{\sum_{j=1}^K (n_{jE} + n_{jC} - 2)} \left(\frac{1}{\sigma^2} \left(\sum_{j=1}^K \sum_{i=1}^{n_j} \tau_{ji}^2 - \sum_{j=1}^K n_{jE} \tilde{\tau}_{jE}^2 - \sum_{j=1}^K n_{jC} \tilde{\tau}_{jC}^2 \right) \right)$$

Using Johnson & Kotz (1970) page 130 the distribution of $\frac{s_p^2}{\sigma^2}$ results from

$$\sum_{i=1}^{n_j} Z_{ji} (y_{ji} - \tilde{y}_{jE})^2 / \sigma^2 \sim \chi^2_{n_{jE}-1} \left(\sum_{i=1}^{n_j} \frac{Z_{ji}}{\sigma^2} (\tau_{ji} - \tilde{\tau}_{jE})^2 \right)$$

$$\sum_{i=1}^{n_j} (1 - Z_{ji}) (y_{ji} - \tilde{y}_{jC})^2 / \sigma^2 \sim \chi^2_{n_{jC}-1} \left(\sum_{i=1}^{n_j} \frac{(1 - Z_{ji})}{\sigma^2} (\tau_{ji} - \tilde{\tau}_{jC})^2 \right)$$





show the independence of the nominator and the denominator statistic
Searle (1971): If $\mathbf{x} \sim N(\mu, \mathbf{V})$, then $\mathbf{x}^t \mathbf{A} \mathbf{x}$ and $\mathbf{B} \mathbf{x}$ are independent if and only if $\mathbf{B} \mathbf{V} \mathbf{A} = 0$. Use matrix notation

$$\mathbf{B}_j = w_j \left(\frac{1}{n_{jE}} \mathbb{1}_{n_{jE}}^t, -\frac{1}{n_{jC}} \mathbb{1}_{n_{jC}}^t \right)^t$$

and with $\mathbf{H}_{ij} = \mathbf{I}_{n_{ij}} - \frac{1}{n_{ij}} \mathbb{1}_{n_{ij} \times n_{ij}}$

$$\mathbf{A}_j = (\mathbf{H}_{n_{jE}}, \mathbf{H}_{n_{jC}}) = \left(\mathbf{I}_{n_{jE}} - \frac{1}{n_{jE}} \mathbb{1}_{n_{jE} \times n_{jE}}, \mathbf{I}_{n_{jC}} - \frac{1}{n_{jC}} \mathbb{1}_{n_{jC} \times n_{jC}} \right)$$





Randomization Procedure

$$P(\mathbf{Z}_j = \mathbf{z}_j | \mathbf{z}_j \in \{0, 1\}^{n_j})$$

within center

Stratified Randomization Procedure

$$\prod_{j=1}^K P(\mathbf{Z}_j = \mathbf{z}_j | \mathbf{z}_j \in \{0, 1\}^{n_j})$$

Randomization Procedures

CR Complete randomization: probability that patient i will receive treatment 1 is always $\frac{1}{2}$

BSD(a) (Big Stick design) CR allow for imbalance within a limit a

RAR Randomize so that half of the N patients receive E

PBR(m_s) (Permuted Block Randomization) Implementation of RAR within k Blocks of size m_s , $1 \leq s \leq k$

MP(a) (Maximal Procedure) allow for imbalance within a limit (a) but force terminal balance at the end, resulting sequences are set to be equiprobable





Joint additive linear bias model

$$\tau_{ji} = \underbrace{\theta_j \frac{i}{n_{jE} + n_{jC}}}_{\text{linear time trend}} + \underbrace{\eta_j \text{sign}(n_{jE}(i-1) - n_{jC}(i-1))}_{\text{selection bias with } q=0.5}$$

- 1 θ_j of the linear time trend varying between centers
- 2 formulate θ_j as fraction of the variance σ^2
- 3 different shape of time trend can be incorporated
- 4 weights via definition of θ_j and η_j
- 5 $\eta_j \geq 0$ selection bias effect depend on the center
- 6 relaxed version of selection bias possible
- 7 Joint multiplicative linear bias model could also be done





ICH E9: The interpretation of statistical measures of uncertainty of the treatment effect and treatment comparisons should involve consideration of the potential contribution of bias to the p-value, confidence interval, or inference.

Metric (empirical type-I-error rate)

$$P_{RP,\tau}(H_1|H_0) = P_{RP,\tau} \left(\mathbf{Z} \in \{0, 1\}^N : |t_{df,\delta(\mathbf{Z}),\lambda(\mathbf{Z})}(1 - \frac{\alpha}{2})| \geq |t_{df}(1 - \frac{\alpha}{2})| \right)$$

- study the empirical type-I-error rate or empirical test size via simulation
- other metrics are implemented





Table: Evaluation scenarios

Senario	Item	Center	
		1	2
1	Sample size	40	40
	η	$0.2 \cdot \Delta$	$0.2 \cdot \Delta$
	θ	$0.1 \cdot \sigma$	$0.1 \cdot \sigma$
2	Sample size	40	40
	η	$0.1 \cdot \Delta$	$0.1 \cdot \Delta$
	θ	$0.05 \cdot \sigma$	$0.05 \cdot \sigma$

- Using Fleiss (1986) optimal weights $w_j = w_j^* = \frac{n_{jE} \times n_{jC}}{n_{jE} + n_{jC}}$
- 100 000 drawing of allocation sequences
- CR, EBC(2/3) , RAR, PBR (2), BSD(4), MP





Table: $P_{RP,\tau}(H_1|H_0)$ for different tests two center, $n_1 = n_2 = 40$

Senario	Randomization Procedure	weighted stratified analysis	unstratified randomization
1	CR	0.34	0.50
1	EBC(2/3)	0.01	0.02
1	RAR	0.02	0.20
1	PBR(2)	0	0
1	BSD(4)	0.31	0.46
1	MP(4)	0.02	0.14
2	CR	0.33	0.50
2	EBC(2/3)	0.01	0.02
2	RAR	0.02	0.20
2	PBR(2)	0	0
2	BSD(4)	0.30	0.46
2	MP(4)	0.02	0.15





Table: ERDO handled trial designs

Design parallel group	Endpoint	Hypothesis	Test	Selection Bias	Time Trend
2-arm single center	continuous (Hilgers, 2017)	$H_0 : \mu_E = \mu_C$	t-Test	yes, additiv	stepwise, linear, logarithmic
2-arm multicenter	continuous (Hilgers, 2018)	$H_0 : \mu_E = \mu_C$	t-Test	yes, additiv	stepwise, linear, logarithmic
2-arm single center	time to event (Rückbeil, 2017)	$H_0 : \lambda_E / \lambda_C = 1$ ($H_0 : S_E = S_C$)	F-Test (logRank)	yes, multiplicative	stepwise, linear, logarithmic
multi-arm single center	continuous (Uschner, 2018)	$H_0 : \mu = \mathbf{0}$	ANOVA	yes, additiv	
group sequential design	continuous (Ventsch, 201x)	$H_0 : \mu = \mathbf{0}$		yes, additiv	stepwise, linear, logarithmic
2-arm single center	continuous (Hilgers, 201x)	$H_0 : \beta_E = \beta_C$	LMEM	yes, additiv	stepwise, linear, logarithmic
2-arm single center	binary (stratified)	$H_0 : OR = 1$	χ^2 (stratified)	yes, multiplicative	stepwise, linear, logarithmic





FDA, Providing Clinical Evidence of Effectiveness for Human Drugs and Biological Products, 1998)

Any clinical trial may be subject to unanticipated, undetected, systematic biases. These biases may operate despite the best intentions of sponsors and investigators, and may lead to flawed conclusions.

- presented a framework for scientific evaluation of stratified randomization procedures in the presence of bias with multicenter trials
- work on LMEM
- start understanding the effect in clinical trials with dichotomous endpoint
- start understanding the effect in clinical trials with interim analysis





-  Kennes LN, Cramer E, Hilgers RD and Heussen N. (2011). The impact of selection bias on test decisions in randomized clinical trials *SIM* 2011; DOI: 10.1002/sim.4279.
-  Tamm M, Cramer E, Kennes LN and Heussen N. Influence of Selection Bias on the Test Decision - A Simulation Study *Methods of Information in Medicine* 2012, DOI: 10.3414/ME11-01-0043.
-  Tamm M and Hilgers RD. Chronological Bias in Randomized Clinical Trials Arising from Different Types of Unobserved Time Trends *Methods of Information in Medicine* 2014; DOI: 10.3414/ME14-01-0048.
-  Rückbeil M, Hilgers RD and Heussen N. Assessing the impact of selection bias on test decisions in trials with a time-to-event outcome *SIM* 2017 DOI: 10.1002/sim.7299
-  Hilgers RD, Uschner D, Rosenberger WF, Heussen N. ERDO - a framework to select an appropriate randomization procedure for clinical trials. *BMC Medical Research Methodology* 2017 DOI: 10.1186/s12874-017-0428-z
-  Rückbeil M, Hilgers RD and Heussen N. The impact of selection bias in randomized multi-arm parallel group clinical trials. *PlosOne* 2018 DOI: 10.1371/journal.pone.0192065
-  Uschner D, Schindler D, Heussen N and Hilgers RD. randomizeR: An R Package for the Assessment and Implementation of Randomization in Clinical Trials *J Statistical Software* 2018

