



Linked assessment criterion for the choice of a randomization procedure

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June 14th, 2016



- Choice of a randomization procedure does not follow scientific arguments up to now.
- Treatment comparisons should involve consideration of the potential influence of bias on the p -value (ICH E9, 1998).
- Unequal performance of randomization procedures with respect to the following objectives:
 - ▶ Selection bias
 - ▶ Chronological bias
 - ▶ Balancing behavior

⇒ Presentation of a linked assessment criterion for the choice of a randomization procedure





Assuming a (random) bias vector $\mathbf{B} = (b_1, b_2, \dots, b_N)^T$ the i th patient's response with $i \in \{1, 2, \dots, N\}$ can be expressed as:

$$y_i = \mu_E T_i + \mu_C (1 - T_i) + b_i + \epsilon_i. \quad (1)$$

- The treatment indicator takes the values:

$$T_i = \begin{cases} 1, & \text{if patient } i \text{ is allocated to group } E \\ 0, & \text{if patient } i \text{ is allocated to group } C \end{cases}.$$

- Expected response μ_j under treatment $j \in \{E, C\}$.
- Errors $\epsilon_i \underset{iid}{\sim} \mathcal{N}(0, 1)$.





We test the hypotheses

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

with Student's t -test (under misspecification) and test statistic

$$W := \sqrt{\frac{N_E N_C}{N_E + N_C}} \frac{\bar{y}_E - \bar{y}_C}{S_{\text{pooled}}}$$

$$\text{with } \bar{y}_E = \frac{1}{N_E} \sum_{i=1}^N y_i T_i \text{ and } \bar{y}_C = \frac{1}{N_C} \sum_{i=1}^N y_i (1 - T_i),$$

where N_E and N_C are the final numbers of patients assigned to the corresponding treatment group.





Lemma (Generalization of Langer (2014)):

The test statistic W follows a doubly-noncentral t -distribution with noncentrality parameters $\delta := \delta(\mathbf{T}, \mathbf{B})$ and $\lambda := \lambda(\mathbf{T}, \mathbf{B})$. Under $H_0 : \mu_E = \mu_C$ and $\mathbf{B} = (b_1, b_2, \dots, b_N)^T$ it follows that the noncentrality parameters are given by:

$$\delta = \sqrt{\frac{N_E N_C}{N_E + N_C}} (\bar{B}_E - \bar{B}_C) \quad \text{and} \quad \lambda = \sum_{i=1}^N (B_i^2 - N_E \bar{B}_E^2 - N_C \bar{B}_C^2)$$

$$\text{with } \bar{B}_E = \frac{1}{N_E} \sum_{i=1}^N b_i \mathbb{1}_{\{T_i=1\}} \quad \text{and} \quad \bar{B}_C = \frac{1}{N_C} \sum_{i=1}^N b_i \mathbb{1}_{\{T_i=0\}}.$$





Theorem:

Assuming $H_0 : \mu_E = \mu_C$, the rejection probability dependent on \mathbf{T} and \mathbf{B} can be calculated as follows:

$$\begin{aligned}\alpha(\mathbf{T}) &:= \alpha(\mathbf{T}, \mathbf{B}) := P(|W| > t_{N-2, 1-\alpha/2} | \mathbf{T}, \mathbf{B}) \\ &= F_{N-2, \delta, \lambda}(t_{N-2, \alpha/2}) + 1 - F_{N-2, \delta, \lambda}(t_{N-2, 1-\alpha/2}),\end{aligned}$$

where $F_{N-2, \delta, \lambda}(x)$ is the distribution function of the doubly noncentral t -distribution with $N - 2$ degrees of freedom and noncentrality parameters δ and λ .

Corollary:

The noncentrality parameter λ is invariant with respect to a treatment difference, δ not.





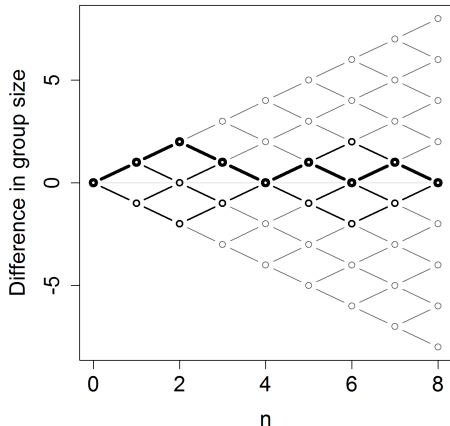
For **chronological bias** according to Tamm and Hilgers (2014) b_i is assumed to be increasing/decreasing in N . For a linear time trend we define:

$$b_i = \frac{(i-1) \vartheta}{N} \quad \text{with } \vartheta \in \mathbb{R} \text{ and } i \in \{1, 2, \dots, N\} .$$

In the situation of **selection bias** b_i is dependent on the patients assigned to the corresponding treatment groups (Proschan, 1994):

$$b_i = \begin{cases} \eta, & \text{if } N_E(i-1) < N_C(i-1) \\ -\eta, & \text{if } N_E(i-1) > N_C(i-1) \\ 0, & \text{if } N_E(i-1) = N_C(i-1) \end{cases} \quad \text{with } \eta \in \mathbb{R}_+ .$$





- At the end of each block there is no difference in patient numbers
- All sequences are equiprobable

PBR(4): Permuted Block Randomization with block length 4





Investigated settings for selection bias:

- $\alpha = 0.05$
- $\eta = 1.42$ (one quarter of the effect size)
- $\alpha_{SB}(\mathbf{T}_j) :=$ Type-I-error of \mathbf{T}_j in case of selection bias

j	\mathbf{T}_j	$P(\mathbf{T}_j)$	$\alpha_{SB}(\mathbf{T}_j)$	$\alpha_{TT}(\mathbf{T}_j)$	$1 - \beta_{TT}(\mathbf{T}_j)$	$1 - \beta_0(\mathbf{T}_j)$	overall
1	CCEE	1/6	0.047				
2	CECE	1/6	0.138				
3	ECCE	1/6	0.060				
4	CEEC	1/6	0.060				
5	ECEC	1/6	0.138				
6	EECC	1/6	0.047				
average value:			0.081				





Investigated settings for chronological bias:

- $\alpha = 0.05$, $(1 - \beta) = 0.8$, $\mu_E - \mu_C = 5.65$
- $\vartheta = 1$
- $\alpha_{TT}(\mathbf{T}_j)$:= Type-I-error of \mathbf{T}_j in case of a linear time trend
- $1 - \beta_{TT}(\mathbf{T}_j)$:= Power of \mathbf{T}_j in case of a linear time trend

j	\mathbf{T}_j	$P(\mathbf{T}_j)$	$\alpha_{SB}(\mathbf{T}_j)$	$\alpha_{TT}(\mathbf{T}_j)$	$1 - \beta_{TT}(\mathbf{T}_j)$	$1 - \beta_0(\mathbf{T}_j)$	overall
1	CCEE	1/6	0.047	0.060	0.842		
2	CECE	1/6	0.138	0.047	0.792		
3	ECCE	1/6	0.060	0.043	0.755		
4	CEEC	1/6	0.060	0.043	0.755		
5	ECEC	1/6	0.138	0.047	0.734		
6	EECC	1/6	0.047	0.060	0.730		
average value:			0.081	0.050	0.768		





Investigatd settings for the balancing behavior:

- $(1 - \beta) = 0.8$
- $\mu_E - \mu_C = 5.65$

j	\mathbf{T}_j	$P(\mathbf{T}_j)$	$\alpha_{SB}(\mathbf{T}_j)$	$\alpha_{TT}(\mathbf{T}_j)$	$1 - \beta_{TT}(\mathbf{T}_j)$	$1 - \beta_0(\mathbf{T}_j)$	overall
1	CCEE	1/6	0.047	0.060	0.842	0.800	
2	CECE	1/6	0.138	0.047	0.792	0.800	
3	ECCE	1/6	0.060	0.043	0.755	0.800	
4	CEEC	1/6	0.060	0.043	0.755	0.800	
5	ECEC	1/6	0.138	0.047	0.734	0.800	
6	EECC	1/6	0.047	0.060	0.730	0.800	
average value:			0.081	0.050	0.768	0.800	





- No linked assessment score available
 \Rightarrow How is the performance of PBR(4) in comparison to other randomization procedures?

j	\mathbf{T}_j	$P(\mathbf{T}_j)$	$\alpha_{SB}(\mathbf{T}_j)$	$\alpha_{TT}(\mathbf{T}_j)$	$1 - \beta_{TT}(\mathbf{T}_j)$	$1 - \beta_0(\mathbf{T}_j)$	overall
1	CCEE	1/6	0.047	0.060	0.842	0.800	?
2	CECE	1/6	0.138	0.047	0.792	0.800	?
3	ECCE	1/6	0.060	0.043	0.755	0.800	?
4	CEEC	1/6	0.060	0.043	0.755	0.800	?
5	ECEC	1/6	0.138	0.047	0.734	0.800	?
6	EECC	1/6	0.047	0.060	0.730	0.800	?
average value:			0.081	0.050	0.768	0.800	?





Definition (Derringer and Suich, 1980):

$$d_i(\mathbf{T}) = d(c_i(\mathbf{T})) := \begin{cases} 1 & c_i(\mathbf{T}) \leq TV_i \\ \frac{USL_i - c_i(\mathbf{T}_i)}{USL_i - TV_i} & TV_i < c_i(\mathbf{T}) \leq USL_i \\ 0 & c_i(\mathbf{T}) \geq USL_i \end{cases}$$

TV: Target Value

USL: Upper Specification Limit

i	Criterion _i (c_i)	TV _i	USL _i
1	$\alpha_{SB}(\mathbf{T})$	0.05	0.10
2	$\alpha_{TT}(\mathbf{T})$	0.05	0.10
3	$\beta_{TT}(\mathbf{T})$	0.20	0.40
4	$\beta_0(\mathbf{T})$	0.20	0.25





- Desirability scores take values in the interval $[0, 1]$.
- Desirability scores can be summarized with the geometric mean:

$$\bar{d}(\mathbf{T}) := \prod_{i=1}^4 d_i(\mathbf{T})^{\omega_i} \text{ with } \sum_{i=1}^4 \omega_i = 1.$$

- The geometric means serves as linked assessment criterion.





- Desirability scores take values in the interval $[0, 1]$.
- Desirability scores can be summarized with the geometric mean:

$$\bar{d}(\mathbf{T}) := \prod_{i=1}^4 d_i(\mathbf{T})^{\omega_i} \text{ with } \sum_{i=1}^4 \omega_i = 1.$$

- The geometric means serves as linked assessment criterion.
- Weights should be chosen dependent on the planned trial.
- Heuristical approach:
Distribute the weight uniformly on selection bias, chronological bias, and balancing behavior.

$$\Rightarrow \omega_1 = 1/3, \omega_2 = \omega_3 = 1/6, \text{ and } \omega_4 = 1/3$$



Assessment of PBR(4) with $N = 4$



j	\mathbf{T}_j	$P(\mathbf{T}_j)$	$\alpha_{SB}(\mathbf{T}_j)$	$d_1(\mathbf{T}_j)$	$\alpha_{TT}(\mathbf{T}_j)$	$d_2(\mathbf{T}_j)$	$1 - \beta_{TT}(\mathbf{T}_j)$	$d_3(\mathbf{T}_j)$	$1 - \beta_0(\mathbf{T}_j)$	$d_4(\mathbf{T}_j)$	$d(\mathbf{T}_j)$
1	EECC	1/6	0.047	1.000							
2	ECEC	1/6	0.138	0.000							
3	CEEC	1/6	0.060	0.809							
4	ECCE	1/6	0.060	0.809							
5	CECE	1/6	0.138	0.000							
6	CCEE	1/6	0.047	1.000							
average value:			0.081	0.603							

$$d_1(\mathbf{T}_1) = d(\alpha_{SB}(\mathbf{T}_1)) = 1, \text{ because } 0.047 < 0.05$$



Assessment of PBR(4) with $N = 4$



j	\mathbf{T}_j	$P(\mathbf{T}_j)$	$\alpha_{SB}(\mathbf{T}_j)$	$d_1(\mathbf{T}_j)$	$\alpha_{TT}(\mathbf{T}_j)$	$d_2(\mathbf{T}_j)$	$1 - \beta_{TT}(\mathbf{T}_j)$	$d_3(\mathbf{T}_j)$	$1 - \beta_0(\mathbf{T}_j)$	$d_4(\mathbf{T}_j)$	$\bar{d}(\mathbf{T}_j)$
1	EECC	$1/6$	0.047	1.000	0.060	0.804	0.842	1.000	0.8000	1.000	0.964
2	ECEC	$1/6$	0.138	0.000	0.047	1.000	0.792	0.961	0.8000	1.000	0.000
3	CEEC	$1/6$	0.060	0.809	0.043	1.000	0.755	0.776	0.8000	1.000	0.893
4	ECCE	$1/6$	0.060	0.809	0.043	1.000	0.755	0.776	0.8000	1.000	0.893
5	CECE	$1/6$	0.138	0.000	0.047	1.000	0.734	0.668	0.8000	1.000	0.000
6	CCEE	$1/6$	0.047	1.000	0.060	0.897	0.730	0.649	0.8000	1.000	0.850
average value:			0.081	0.603	0.050	0.935	0.768	0.805	0.8000	1.000	0.608

$$\begin{aligned}
 \bar{d}(\mathbf{T}_1) &= \sqrt[3]{d_1(\mathbf{T}_1)} \cdot \sqrt[6]{d_2(\mathbf{T}_1)} \cdot \sqrt[6]{d_3(\mathbf{T}_1)} \cdot \sqrt[3]{d_4(\mathbf{T}_1)} \\
 &= \sqrt[3]{1} \cdot \sqrt[6]{0.804} \cdot \sqrt[6]{1} \cdot \sqrt[3]{1} \\
 &= 0.964
 \end{aligned}$$



Assessment of PBR(4) with $N = 4$



j	\mathbf{T}_j	$P(\mathbf{T}_j)$	$\alpha_{SB}(\mathbf{T}_j)$	$d_1(\mathbf{T}_j)$	$\alpha_{TT}(\mathbf{T}_j)$	$d_2(\mathbf{T}_j)$	$1 - \beta_{TT}(\mathbf{T}_j)$	$d_3(\mathbf{T}_j)$	$1 - \beta_0(\mathbf{T}_j)$	$d_4(\mathbf{T}_j)$	$\bar{d}(\mathbf{T}_j)$
1	EECC	$1/6$	0.047	1.000	0.060	0.804	0.842	1.000	0.8000	1.000	0.964
2	ECEC	$1/6$	0.138	0.000	0.047	1.000	0.792	0.961	0.8000	1.000	0.000
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6	CCEE	$1/6$	0.047	1.000	0.060	0.804	0.730	0.649	0.8000	1.000	0.897
average value:			0.081	0.603	0.050	0.935	0.768	0.805	0.8000	1.000	0.608

$$\begin{aligned}\varnothing \bar{d}(\mathbf{T}) &= 1/6 (0.964 + 0 + 0.893 + 0.893 + 0 + 0.897) \\ &= 0.608\end{aligned}$$



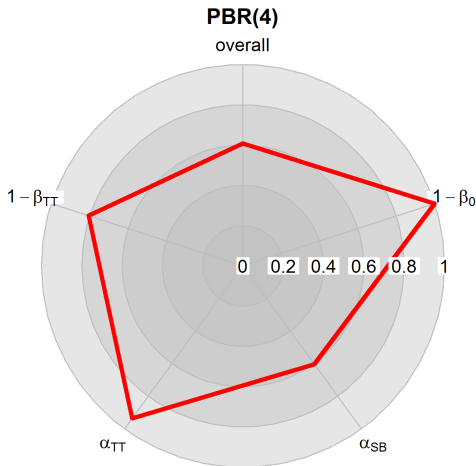
Assessment of PBR(4) with $N = 4$



j	\mathbf{T}_j	$P(\mathbf{T}_j)$	$\alpha_{SB}(\mathbf{T}_j)$	$d_1(\mathbf{T}_j)$	$\alpha_{TT}(\mathbf{T}_j)$	$d_2(\mathbf{T}_j)$	$1 - \beta_{TT}(\mathbf{T}_j)$	$d_3(\mathbf{T}_j)$	$1 - \beta_0(\mathbf{T}_j)$	$d_4(\mathbf{T}_j)$	$\bar{d}(\mathbf{T}_j)$
1	EECC	1/6	0.047	1.000	0.060	0.804	0.842	1.000	0.8000	1.000	0.964
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4	ECCE	1/6	0.060	0.809	0.043	1.000	0.755	0.776	0.8000	1.000	0.893
5	CECE	1/6	0.138	0.000	0.047	1.000	0.734	0.668	0.8000	1.000	0.000
6	CCEE	1/6	0.047	1.000	0.060	0.804	0.730	0.649	0.8000	1.000	0.897
average value:			0.081	0.603	0.050	0.935	0.768	0.805	0.8000	1.000	0.608

- Average desirability scores can be visualized in a radar plot, which is available in the randomizeR package (Schindler et al., 2015).

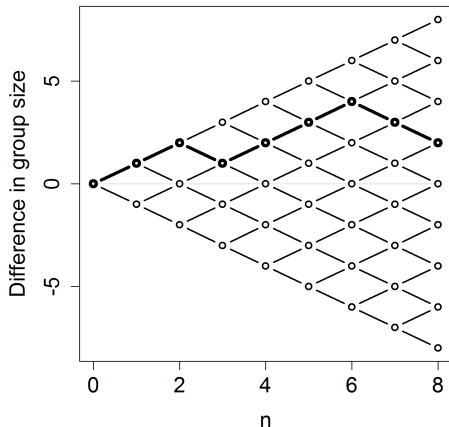




- PBR(4) is ...

- ▶ good in handling the assumed linear time trend
- ▶ susceptible to selection bias
- ▶ perfect with respect to its balancing behavior

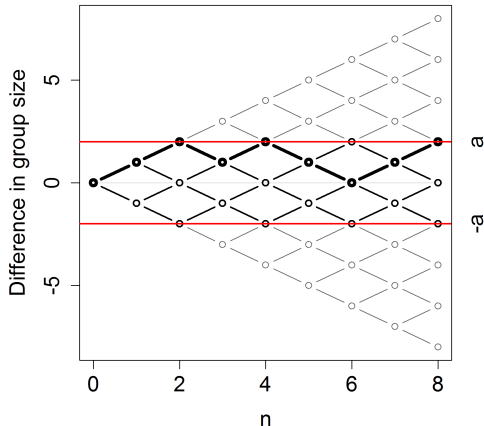




- Fair coin toss for each patient allocation

CR: Complete Randomization

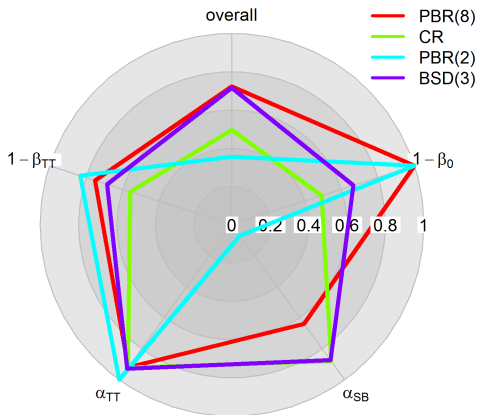




- Fair coin toss with an imbalance boundary

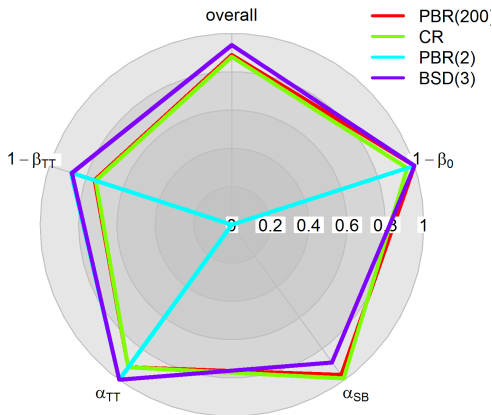
BSD(2): Big Stick Design with tolerated imbalance boundary 2





- PBR(2) seems to be very susceptible to selection bias
- CR has worse balancing behavior
- BSD(3) and PBR(8) manage the investigated criteria the best





- PBR(2) far too susceptible to selection bias
- CR and PBR(200) have nearly the same behavior
- BSD(3) manages the investigated criteria the best





- The linked assessment criterion summarizes all imaginable criteria to one unified score and takes their importance into account.
- Other suggested criteria in the literature are:
 - ▶ Correct Guesses (Blackwell and Hodges Jr., 1957)
 - ▶ Loss in treatment estimation (Atkinson, 2001)
- Other randomization procedures can be easily assessed such as:
 - ▶ Efron's Biased Coin Design
 - ▶ Truncated Binomial Design
 - ▶ Randomized Permuted Block Randomization
 - ▶ Maximal Procedure





- Randomization procedures differ in terms of their susceptibility to selection bias, chronological bias, and balancing behavior.
- The linked assessment criterion makes a fair comparison of different randomization procedures possible.
- The radar plot compares the behavior of randomization procedures at a glance.
- We developed `randomizeR` (Schindler et al., 2015) for making fair comparisons of randomization procedures concerning different types of bias and their balancing behavior.

The IDeAI project has received funding from the European Union's 7th Framework Programme for research, technological development and demonstration under Grant Agreement no 602552.





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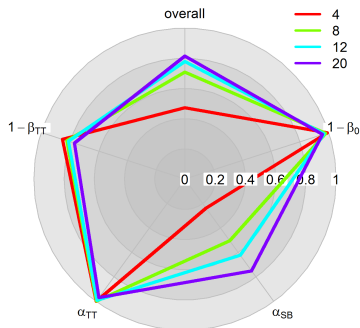


Figure: $N = 20$

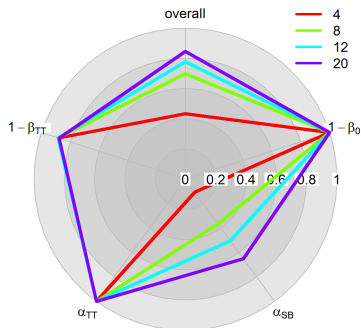


Figure: $N = 200$



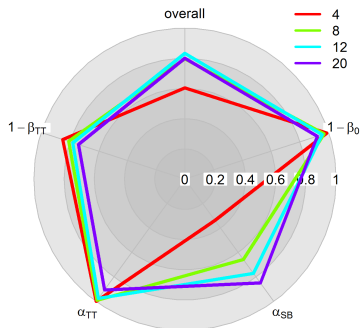


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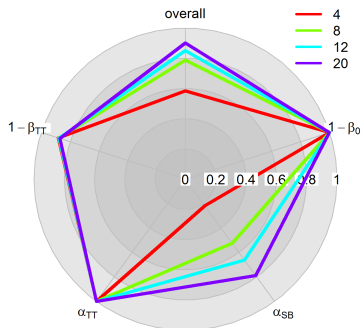


Figure: $N = 200$



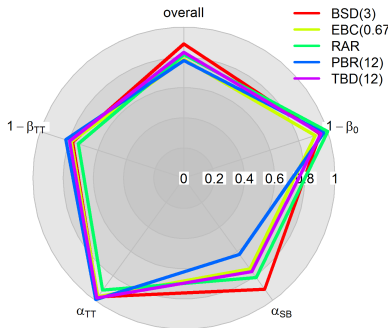


Figure: $N = 20$

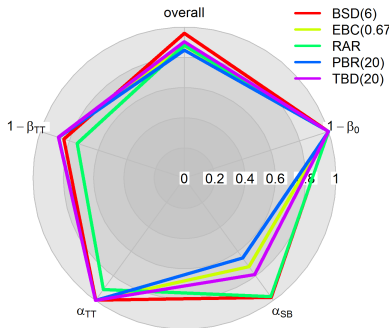


Figure: $N = 200$





Under the assumption of the following model

$$\mathbf{Y} = \begin{pmatrix} 1 & T_1 \\ 1 & T_2 \\ \vdots & \vdots \\ 1 & T_N \end{pmatrix} \begin{pmatrix} \theta_0 \\ \theta_1 \end{pmatrix} + \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_N \end{pmatrix} = \mathbf{A}\boldsymbol{\theta} + \boldsymbol{\epsilon}$$

we can compute $\text{Var}(\hat{\theta}_1)$ as follows:

$$\text{Var}(\hat{\theta}_1) = \frac{\sigma^2}{N - \frac{D(N, \mathbf{T})^2}{N}} = \frac{\sigma^2}{N - L(\mathbf{T})},$$

where $D(N, \mathbf{T})$ defines the imbalance in group sizes at the end of the clinical study and $L(\mathbf{T})$ the loss.





Assuming a balanced trial it is opportune for the experimenter to guess the i -th allocation according to the convergence strategy (Blackwell and Hodges Jr., 1957) :

$$g_{CS}(i, \mathbf{T}) = \begin{cases} E & N_E(i-1, \mathbf{T}) < N_C(i-1, \mathbf{T}) \\ \text{random guess} & N_E(i-1, \mathbf{T}) = N_C(i-1, \mathbf{T}) \\ C & N_E(i-1, \mathbf{T}) > N_C(i-1, \mathbf{T}) \end{cases}.$$

Expected proportion of Correct Guesses (CG) of \mathbf{T} is defined as:

$$CG(\mathbf{T}) = \frac{\mathbb{E} \left(\sum_{i=1}^N \mathbb{1}_{\{T_i = g_{CS}(i, \mathbf{T})\}} \right)}{N}$$





Definition (Derringer and Suich (1980)):

$$d_i(\mathbf{T}) = d(c_i(\mathbf{T})) := \begin{cases} 1 & c_i(\mathbf{T}) \leq TV_i \\ \frac{USL_i - c_i(\mathbf{T}_i)}{USL_i - TV_i} & TV_i < c_i(\mathbf{T}) \leq USL_i \\ 0 & c_i(\mathbf{T}) \geq USL_i \end{cases}$$

TV: Target Value

USL: Upper Specification Limit

i	Criterion _i (<i>c_i</i>)	TV _i	USL _i
1	<i>L</i> (T)	0	1
2	<i>CG</i> (T)	0.5	0.75





Figure: $N = 20$

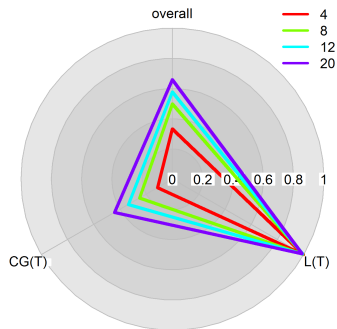


Figure: $N = 200$



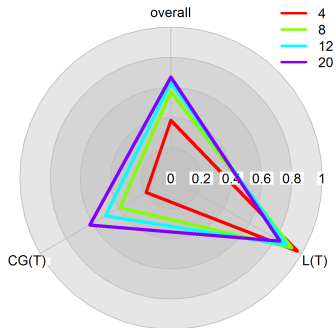


Figure: $N = 20$

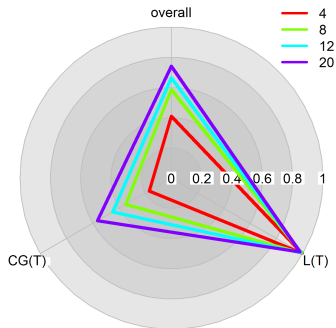


Figure: $N = 200$



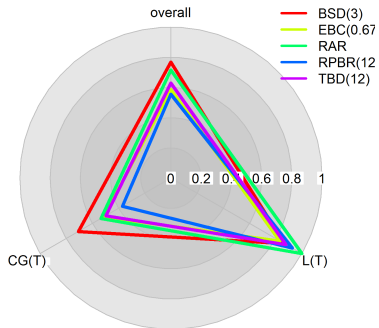


Figure: $N = 20$

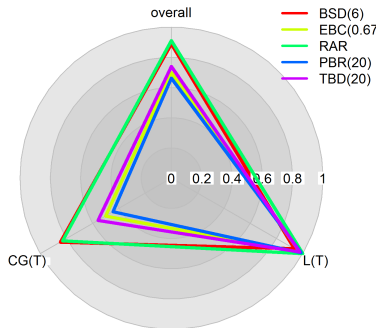
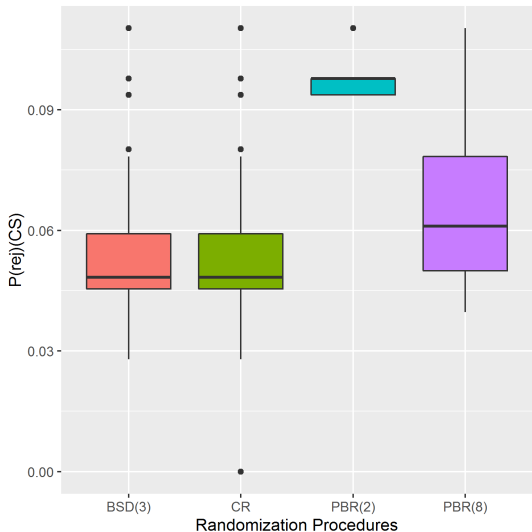


Figure: $N = 200$



Distribution of α_{SB} with $N = 8$



- Settings:

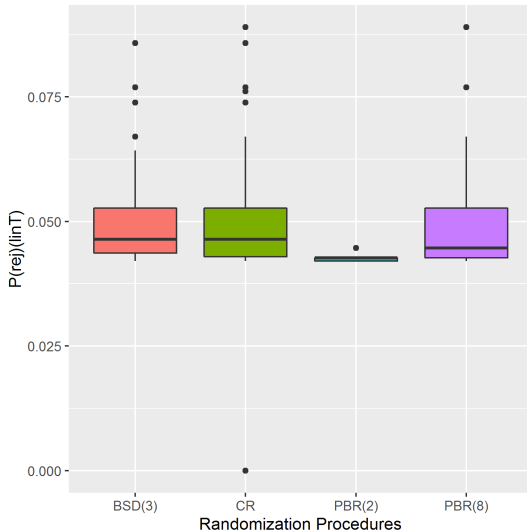
- ▶ $\eta = \Delta_0/4 = 0.6$
- ▶ $\alpha_0 = 0.05$

- Results:

- ▶ PBR(2) most susceptible to selection bias
- ▶ CR and BSD(3) have the best performance



Distribution of α_{CB} for $N = 8$



- Settings:

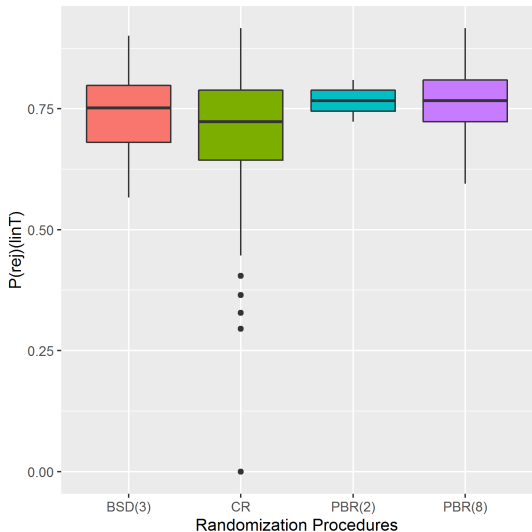
- ▶ $\vartheta = 1$
- ▶ $\alpha_0 = 0.05$

- Results:

- ▶ All sequences of PBR(2) are conservative
- ▶ CR, BSD(3), and PBR(8) have a similar performance



Distribution of $(1 - \beta_{SB})$ with $N = 8$



● Settings:

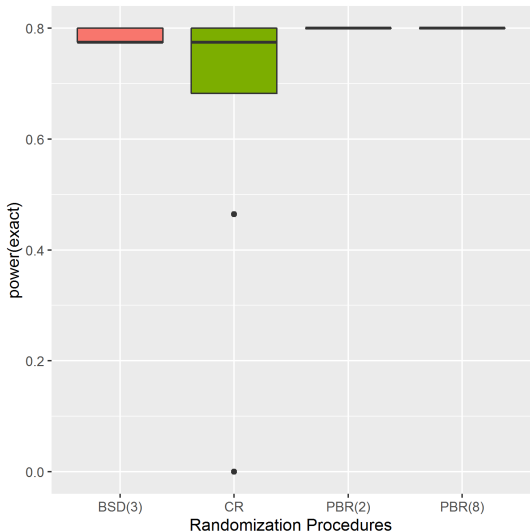
- ▶ $\vartheta = 1$
- ▶ $(1 - \beta_0) = 0.8$

● Results:

- ▶ PBR(2) has lowest variance
- ▶ CR has greatest variability and outliers are possible



Distribution of $(1 - \beta_0)$ with $N = 8$



- Settings:
 - ▶ $(1 - \beta_0) = 0.8$
- Results:
 - ▶ PBR maintains the planned power
 - ▶ BSD controls the loss in power, CR does not

