

Choosing a suitable randomization procedure with randomizeR

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Introduction



- Randomized Controlled Clinical Trial with K ≥ 2 treatment arms
- Restricted Randomization is used for the allocation of treatments to patients.
- Aim: Choose suitable randomization procedure according to problems that might occur during the trial
- Propose a tool for the design of a clinical trial to
 - Assess and compare randomization procedures sequence wise wrt issues (e.g. selection bias)
 - Calculate the exact distribution of the issue (e.g. distribution of the type-l-error for the sequences).









Example: Exact distribution of the type-I-error in case the responses are influenced by selection bias (Convergence Strategy).

	Sequence	Probability	P(rej)(CS)
1	BBAA	0.1666667	0.04229902
2	BABA	0.1666667	0.18880215
З	ABBA	0.1666667	0.04972876
4	BAAB	0.1666667	0.04972876
5	ABAB	0.1666667	0.18880215
6	AABB	0.1666667	0.04229902







Process

- 1. Identify constraints that impact the validity of the trial.
- 2. Define **issues** that measure the constraint.
- 3. Assess randomization procedures according to the issues.
- 4. Select appropriate randomization procedure on the basis of the assessment.

Definition of issue

An *issue* is a criterion for the assessment of randomization procedures that can be measured for each randomization sequence.















Randomization procedure ß LO in group size A randomization procedure \mathcal{M} is a probability distribution on $\Gamma = \{0, 1\}^N$. $t \in \Gamma$ is called randomization sequence. \mathcal{M} produces the 0 sequences Difference $\Gamma_{\mathcal{M}} = \{t \in \Gamma \mid \mathbb{P}_{\mathcal{M}}(t) \neq 0\}$ S install.packages('randomizeR') library(randomizeR) N<-8 6 HEALTH 2013 . 602552 Patient i





Permuted Block Randomization

Equally probable balance sequences that attain balance after each block:

$$\mathbb{P}_{PBR}(t) = egin{cases} {\binom{k}{k/2}}^{-N/k} & \sum_{i=1}^{j \cdot k} (2 \cdot t_i - 1) = 0 \ 0 & ext{else.} \end{cases}$$

for $j = 1, \ldots, N/k$.

k <- 4 #block length

bc <- rep(k, N/k) #block constellation
pbrPar(bc)</pre>







Difference in group size





$$\mathbb{P}_{MP}(t) = egin{cases} rac{1}{|\Gamma_{MP}|} & D_N = 0, orall i: \ |D_i| \leq b \ 0 & ext{else.} \end{cases}$$

b <- 2

mpPar(N,b)





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Difference in group size



Big Stick Design

Toss a fair coin in until you hit the imbalance boundary. Then make a deterministic allocation.

$$\mathbb{P}_{BSD}(t) = egin{cases} 0.5^{N-da} & \sum_{i=1}^N |2 \cdot t_i - 1| \leq b \ 0 & ext{else.} \end{cases}$$

with imbalance boundary *b* and number of deterministic allocations $da := |\{j : \sum_{i=1}^{j} t_i = b\}|.$

bsdPar(N,b)



Ю ß 0 0 ŝ 0 2 6 8 Patient i

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Difference in group size





createParam() createSeq() genSeq() getAllSeq(myPar) getProb(seqs) saveRand(seqs)

Creates a <.>Par object according to user input. Generates a random sequence according to user input.

Generate a random sequence from a <.>Par object.

Compute $\Gamma_{\mathcal{M}}$ for N < 20.

Compute the theoretical probabilities for an object seqs of type randSeq.

Save the randomization protocol inluding a the randomization sequence(s) to .csv.







Performance of generating 10^{x} RAR sequences, $x \in \{3, 4, 5, 6\}$.

<pre>system.time(genSeq(rarPar(100),10³))</pre>	<pre>system.time(genSeq(rarPar(100),10⁵))</pre>
user system elapsed	user system elapsed
0.06 0.00 0.06	6.16 0.05 6.23
<pre>system.time(genSeq(rarPar(100),10⁴))</pre>	<pre>system.time(genSeq(rarPar(100),10⁶))</pre>
user system elapsed	user system elapsed
0.70 0.00 0.71	62.95 0.44 63.48









Definition

An issue is a criterion for the assessment of randomization procedures that can be measured **for each randomization sequence**.

selBias	Represent exact rejection probability (size/ power) in case
	the responses are influenced by selection bias.
corGuess	Represent the proportion of correct guesses.
chronBias	Represent exact rejection probability (size/ power) in case
	the responses are influenced by chronological bias.
setPower	Represent the power for a given detectable effect and size.
imbal	Represent the imbalance in allocation numbers.

Table: Issues implemented in randomizeR





Response

Let E and C be treatments that influence a continuous outcome Y. For $i = 1, \ldots, N$, we write

$$Y_i \sim \mathcal{N}(\mu + d \cdot T_i, \sigma^2)$$
 (1)

where $d \in \mathbb{R}$ denotes the *treatment effect*, $\mu > 0$ the overall mean and $\sigma^2 > 0$ the equal but unknown variance. Y_i is called *response* of patient *i*. Higher values of *Y* are regarded as better. Represent normal endpoints in randomizeR

normEndp(mu=c(0,0), sigma=c(1,1))







(Joen)

Test Model:

$$Y_i \sim \mathcal{N}(\mu + d \cdot T_i, \sigma^2)$$

Test the hypothesis under model miss-specification!

True Model:

$$Y_i \sim \mathcal{N}(\mu + d \cdot T_i + g(\theta, i), \sigma^2)$$

Null hypothesis

We test the null hypothesis that the expected effect of the experimental treatment does not differ from the expected effect of the control treatment

 $H_0: d = 0$

against the two-sided alternative that the expected treatment effects differ

 $H_1: d \neq 0$







Third order selection bias

- Trial is randomized.
- Allocation list is concealed.
- But: the investigator can guess the next treatment assignment due to
 - unmasking of past assignments (e.g. due to side effects).
 - restrictions of the randomization procedure.
- Investigator can deny enrollment due to soft inclusion criteria.



WE'VE DESIGNED A DOUBLE-BLIND

THE LIMITATIONS OF BLIND TRIALS





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Berger (2005)

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Berger (2005)



Biasing Policy



Selection bias



Choose patient i + 1 with expected response

$$E(Y_{i+1}) = \begin{cases} \mu - \eta & N_E(i) > N_C(i) \\ \mu & N_E(i) = N_C(i) \\ \mu + \eta & N_E(i) < N_C(i) \end{cases}$$

with selection effect $\eta > 0$.

Proschan (1994)





Given the randomization sequence $t \in \Gamma$ and using Student's *t*-test in order to test the hypothesis $H_0: d = 0$ of no treatment effect, the test statistic

$$S = \frac{\sqrt{\frac{N_E N_C}{N_E + N_C}} (\tilde{y}_E - \tilde{y}_C)}{\frac{1}{N_E + N_C - 2} \left(\sum_{i=1}^N t_i (y_i - \tilde{y}_E)^2 + \sum_{i=1}^N (1 - t_i) (y_i - \tilde{y}_C)^2 \right)}$$

with $\tilde{y}_E = \frac{1}{N_E} \sum_{i=1}^{N} y_i t_i$, $\tilde{y}_C = \frac{1}{N_C} \sum_{i=1}^{N} y_i (1 - t_i)$ and $N = N_E + N_C$ is doubly noncentrally *t*-distributed with parameters δ and λ .







The noncentrality parameters can be determined as follows

$$\delta = \eta \sqrt{\frac{1}{\sigma^2 N}} \sum_{i=1}^N 2 \cdot (t_i - \frac{1}{2}) \cdot \operatorname{sign}(D_{i-1})$$
$$\lambda = \frac{\eta^2}{\sigma^2} \left(\sum_{i=1}^N \operatorname{sign}(D_{i-1})^2 - \frac{2}{N} \left(\sum_{i=1}^N t_i \cdot \operatorname{sign}(D_{i-1}) \right)^2 - \frac{2}{N} \left(\sum_{i=1}^N (1 - t_i) \cdot \operatorname{sign}(D_{i-1}) \right)^2 \right)$$



Langer (2014) Figure: Doubly noncentral t-distribution, N = 12



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MS



```
pbr <- getAllSeq(pbrPar(bc))</pre>
```

```
sb <- selBias("CS",eta = 0.6, method = "exact")</pre>
```

```
endp <- normEndp(mu=c(0,0), sigma = c(1,1))
```

assess(pbr, sb, endp = endp)





Comparison of randomization procedures







- randomizeR makes it easy to generate randomization sequences for a large number of randomization procedures.
- Easy to assess and compare randomization procedures for a large number of issues.
- Assessment should be done before conducting a clinical trial.







Try it yourself! Just type

```
install.packages("randomizeR")
library("randomizeR")
vignette("comparison-example")
```

in your R command line.







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