

# Designs for dose-escalation trials

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How should such trials be designed?

# Standard designs

There are  $n$  doses, with dose  $1 < \text{dose } 2 < \dots < \text{dose } n$ .

0 denotes the placebo.

There are  $n$  cohorts of  $m$  subjects each.

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In Cohort  $i$ , some subjects receive dose  $i$ ;  
no subject receives dose  $j$  if  $j > i$ .

Put  $s_{ki}$  = number of subjects who get dose  $i$  in cohort  $k$ . Then

$$s_{ki} > 0 \quad \text{if } i = k$$

$$s_{ki} = 0 \quad \text{if } i > k.$$

# How to assess designs?

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(there is analogous work for random cohort effects).

I shall seek to minimize the average of the pairwise variances,  
comparing dose  $i$  with dose  $j$  for  $0 \leq i < j \leq n$ .  
(Another approach is to concentrate on comparisons with placebo  
and seek to minimize the average of the variances for  
comparing dose 0 with dose  $j$  for  $1 \leq j \leq n$ .)

## Scaled variance

Assume that the expectation of the response of a subject who gets dose  $i$  in cohort  $k$  is  $\tau_i + \beta_k$ ,  
and that responses are uncorrelated with common variance  $\sigma^2$ .

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so define the **scaled variance**  $v_{ij}$  to be

$$\frac{\text{Variance (dose } i - \text{dose } j) \times \text{number of observations}}{2(n+1)\sigma^2}.$$

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Example:  $n = 4, m = 10$

Dose	0	1	2	3	4
Cohort 1	2	8	0	0	0
Cohort 2	2	0	8	0	0
Cohort 3	2	0	0	8	0
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$$v_{0i} = \frac{n+1}{2}$$

$$v_{ij} = n+1$$

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$$v_{0i} = \frac{2n}{n+1} \quad v_{ij} = \frac{4n}{n+1}$$

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In 2006–2009 I investigated various patterns of design satisfying these principles.

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In Cohort 1:  $\frac{m}{2}$  subjects get dose 1;  $\frac{m}{2}$  subjects get placebo.

In Cohort  $k$ :  $\frac{m}{2}$  subjects get dose  $k$ ; remaining subjects are allocated as equally as possible to treatments 0 to  $k - 1$ , with larger values given to make the ‘replication so far’ as equal as possible.

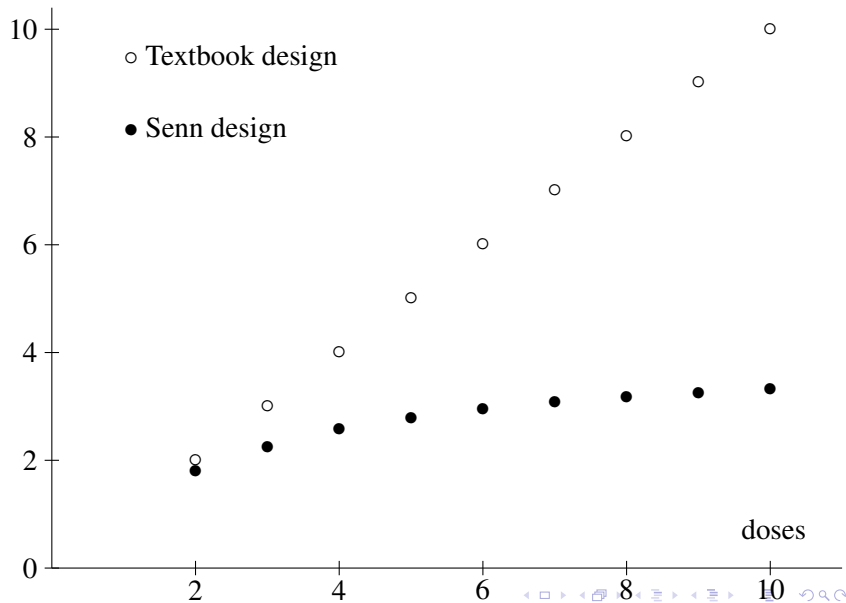
## Example of a uniform halving design

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Cohort 2	2	2	4	0	0
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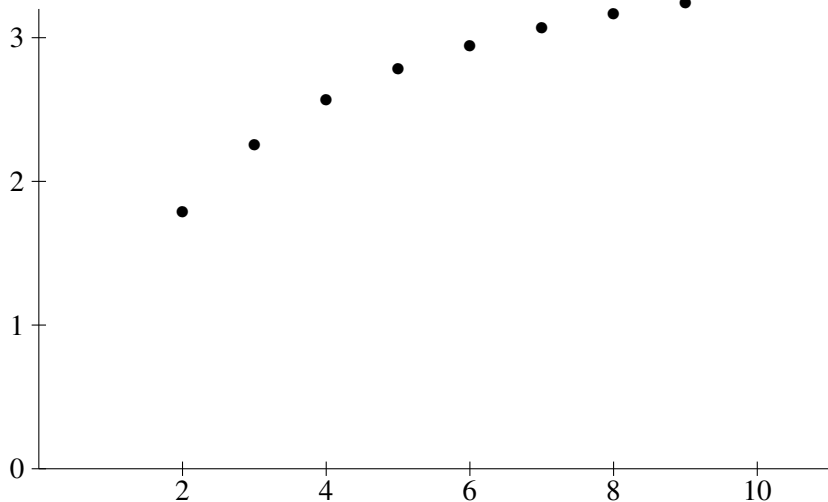
The scaled variances  $v_{ij}$  have to be calculated numerically.

# Average scaled pairwise variance



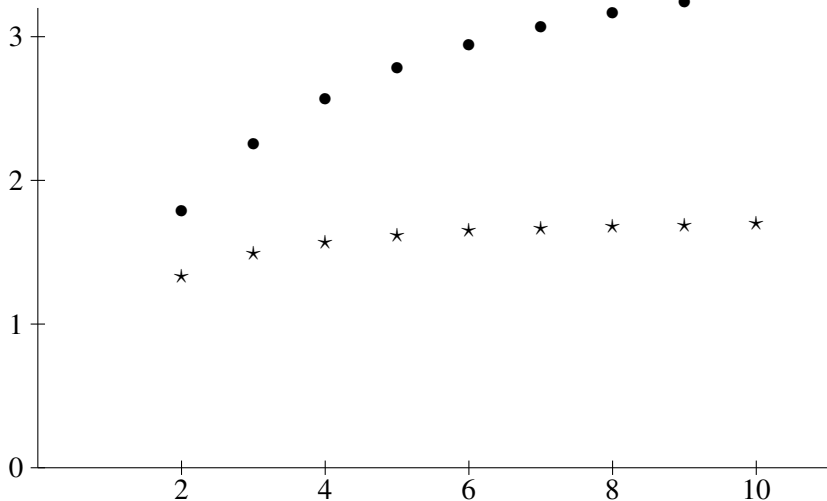
## Average scaled pairwise variance: continued

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- ★ uniform halving design



## Lessons from experience with block designs: II

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so you would never limit any treatment to just one block.

## Principle

*There should be one more cohort than there are doses,  
so that every dose can occur in at least two cohorts.*



# Extended designs

There are  $n$  doses, with dose  $1 < \text{dose } 2 < \dots < \text{dose } n$ .

0 denotes the placebo.

There are  $n + 1$  cohorts of  $m$  subjects each.

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In Cohort  $i$ , for  $2 \leq i \leq n$ , some subjects receive dose  $i$ ;  
no subject receives dose  $j$  if  $j > i$ .

In Cohort  $n + 1$ , any dose, or placebo, may be used.

# Extended Senn design

In the final cohort,  
compensate for the previous over-replication of placebo.

$$s_{n+1,i} = \begin{cases} 0 & \text{if } i = 0 \\ \frac{m}{n} & \text{otherwise} \end{cases}$$

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Cohort 5	0	2	2	2	2

$$v_{0i} = \frac{2(n^2 + 4)}{n(n + 4)} \quad v_{ij} = \frac{4n}{n + 4}$$

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About half the subjects in the final cohort are equally split between all treatments,  
the remainder being allocated to make the overall replications as equal as possible, with any inequalities favouring the higher doses.

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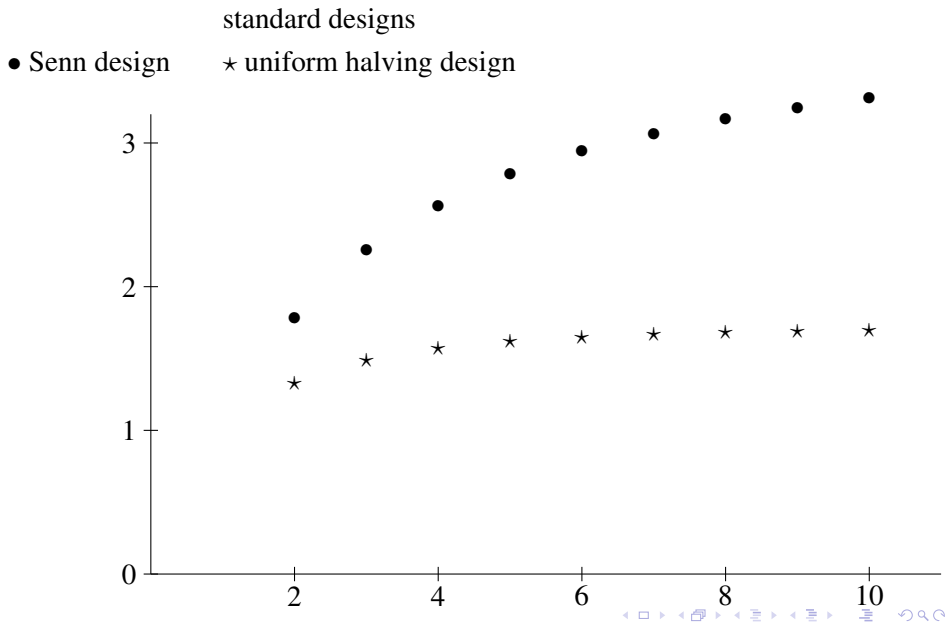
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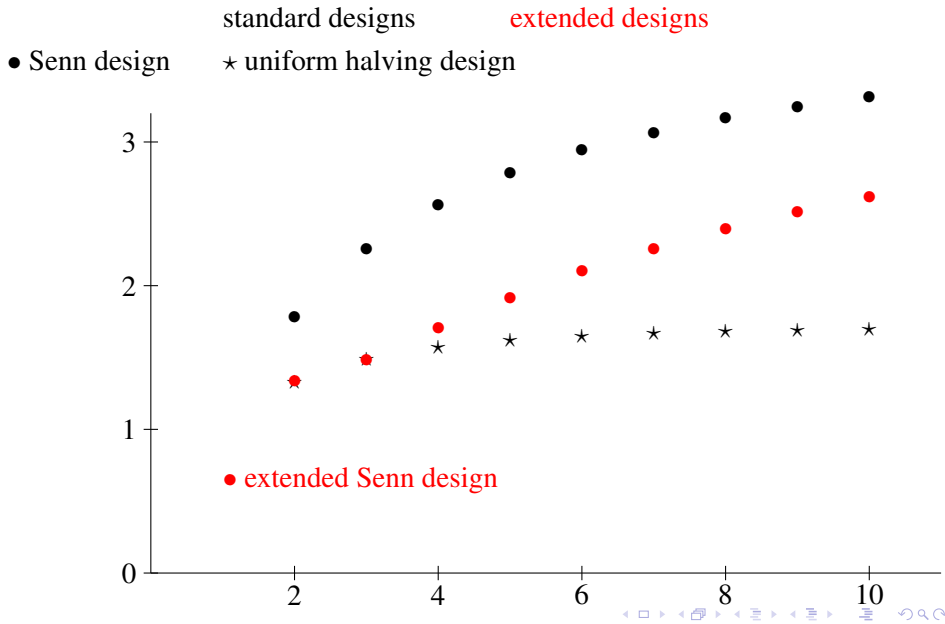
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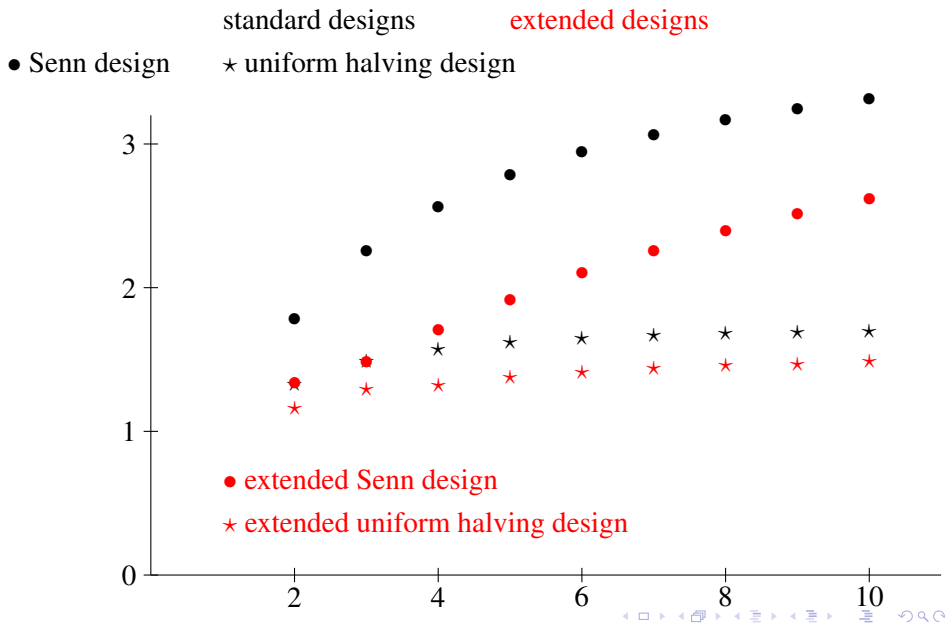
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## Two designs for 4 doses using 40 subjects

		Numbers of subjects					Actual pairwise variances/ $\sigma^2$				
		Dose	0	1	2	3	4	1	2	3	4
Std TB	Cohort 1	2	8	0	0	0	0	0.625	0.625	0.625	0.625
	Cohort 2	2	0	8	0	0	1		1.250	1.250	1.250
	Cohort 3	2	0	0	8	0	2			1.250	1.250
	Cohort 4	2	0	0	0	8	3				1.250
Ext UH	Cohort 1	4	4	0	0	0	0	0.222	0.285	0.348	0.370
	Cohort 2	2	2	4	0	0	1		0.285	0.348	0.370
	Cohort 3	1	1	2	4	0	2			0.330	0.378
	Cohort 4	1	1	1	1	4	3				0.375
	Cohort 5	1	1	1	2	3					



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	Cohort 3	1	1	2	4	0	2			0.330	0.378
	Cohort 4	1	1	1	1	4	3				0.375
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Both types can be described by the following simple rule:

## Principle

*In each cohort, half of the subjects should be distributed (approximately) equally among all the treatments that have been used in any previous cohort; the remaining subjects should be used to make the replication so far as equal as possible by compensating for previous under-replication.*

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- ▶ If cohort effects are small and random, the variance is very little more than for the textbook design (not shown here).
- ▶ Blinding is more effective than in textbook designs.

## More recent work: Integer optimization

Dose	0	1	...	$n$
Cohort 1	$s_{10}$	$s_{11}$	...	0
...				
Cohort $k$	$s_{k0}$	$s_{k1}$	...	$s_{kn}$
...				

$s_{ki}$  is an integer and  $\sum_{i=0}^n s_{ki} = m$

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Cohort 1	$s_{10}$	$s_{11}$	...	0
...				
Cohort $k$	$s_{k0}$	$s_{k1}$	...	$s_{kn}$
...				

$$s_{ki} \text{ is an integer and } \sum_{i=0}^n s_{ki} = m$$

Linda Haines and Allan Clark have used complete enumeration (for small values of  $n$  and  $m$ ) and exchange algorithms (for larger values) to find the optimal allocation for various combinations of values of  $n$  and  $m$ .

They consider various optimality criteria, including A-optimality, which is the criterion that I am using.

# An example of an optimized design

For 4 doses, 4 cohorts and 8 volunteers per cohort, Haines and Clark found that this design is A-optimal.

Dose	0	1	2	3	4
Cohort 1	4	4	0	0	0
Cohort 2	2	3	3	0	0
Cohort 3	2	1	2	3	0
Cohort 4	1	1	1	2	3

## More recent work: II continuous designs, using best so far

Dose	0	1	...	$n$
Cohort 1	$w_{10}$	$w_{11}$	...	0
...				
Cohort $k$	$w_{k0}$	$w_{k1}$	...	$w_{kn}$
...				

$$0 \leq w_{ki} \text{ and } \sum_{i=0}^n w_{ki} = 1$$

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Brendan O'Neill optimized the proportions  $w_{ki}$ , but cut down the search by restricting a design for  $c$  cohorts to use the best design for  $c - 1$  cohorts and just optimize the proportions in the final cohort.



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Given the number  $m$  of volunteers per cohort,

set  $s_{ki}$  to be an integer close to  $m w_{ki}$  such that  $\sum_{i=0}^n s_{ki} = m$ .

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Cohort 1	$w_{10}$	$w_{11}$	...	0
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Given the number  $m$  of volunteers per cohort,

set  $s_{ki}$  to be an integer close to  $mw_{ki}$  such that  $\sum_{i=0}^n s_{ki} = m$ .

Different ways of doing this give almost identical variances.

# An example of an optimized best-so-far continuous design

Dose	0	1	2	3	4
Cohort 1	0.500	0.500	0	0	0
Cohort 2	0.270	0.270	0.460	0	0
Cohort 3	0.170	0.170	0.219	0.441	0
Cohort 4	0.118	0.118	0.138	0.196	0.430
Cohort 5	0.135	0.135	0.163	0.219	0.348

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Cohort 5	0.135	0.135	0.163	0.219	0.348

If there are 8 volunteers per cohort, this gives the following design for 2 doses in 2 cohorts, 3 doses in 3 cohorts, and 4 doses in 4 or 5 cohorts.

Dose	0	1	2	3	4
Cohort 1	4	4	0	0	0
Cohort 2	2	2	4	0	0
Cohort 3	1	1	2	4	0
Cohort 4	1	1	1	2	3
Cohort 5	1	1	1	2	3

## More recent work: III continuous designs, using constant ratios

Heiko Großmann and I are optimizing the proportions  $w_{ki}$ , but cut down the search by imposing the condition

$\frac{w_{ki}}{w_{kj}}$  does not depend on  $k$  if  $j \geq k$  and  $i \geq k$

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(in some cases, we can prove that the optimal designs must satisfy this).

# Examples of optimized designs

Dose	0	1	2
Cohort 1	0.50	0.50	0
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Dose	0	1	2
Cohort 1	0.50	0.50	0
Cohort 2	0.29	0.29	0.42
Cohort 3	0.29	0.29	0.42



# References

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