

# Decision making in phase II/III trials using early endpoint data

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# Acknowledgments

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# 1. Phase II/III trials - motivation

## 1.1 Setting

A trial in Alzheimer's disease

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Primary endpoint

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Aims

- select most effective dose
- provide a valid comparison with control

## 1.2 Conventional approach

### Phase II trial

- exploratory trial compares three doses (with placebo)
- select best dose
- go on to phase III if sufficiently promising
- short-term endpoint: ADAS-cog change over 6 weeks

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- exploratory trial compares three doses (with placebo)
- select best dose
- go on to phase III if sufficiently promising
- short-term endpoint: ADAS-cog change over 6 weeks

### Phase III trial

- compares single selected dose with placebo
- long-term endpoint: ADAS-cog change over 12 weeks
- control error rates

## 1.3 Combining phases II and III

Trial is conducted in two stages

### Stage 1

- 3 doses + placebo
- short and long term endpoints
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### Stage 1

- 3 doses + placebo
- short and long term endpoints
- conduct interim analysis to select most promising dose

### Stage 2

- selected dose + placebo
- long term endpoint

### Final analysis

- use all long term endpoint data on selected dose
- control overall type I error rate providing valid comparison

## 2. Group-sequential phase III method

### 2.1 Notation and test statistics

Treatments:  $T_0$  = control,  $T_1$  = experimental

Data  $\sim N(\mu_i, \sigma^2)$  for treatment  $T_i, i = 0, 1$  (known  $\sigma^2$ )

$\theta = \mu_1 - \mu_0$  is a measure of superiority of  $T_1$  over  $T_0$

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Stage  $j$  ( $j = 1, 2$ ):

cumulative data from total of  $n_j$  patients per treatment

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obtain  $\hat{\theta}_j$  and  $var(\hat{\theta}_j) = 2\sigma^2/n_j$

$S_j = \hat{\theta}_j/var(\hat{\theta}_j)$  is efficient score statistic

$I_j = 1/var(\hat{\theta}_j)$  is Fisher's information

## 2.2 Stopping boundary

Test  $H_0 : \theta = 0$

At first interim analysis

$S_1 \geq u_1$ : stop and reject  $H_0$

$S_1 \leq l_1$ : stop do not reject  $H_0$  (one-sided test)

$l_1 < S_1 < u_1$ : continue to next interim analysis

At second interim (final) analysis

$S_2 \geq u_2$ : stop and reject  $H_0$

$S_2 < l_2 = u_2$ : stop do not reject  $H_0$

## 2.3 Spending function

Stopping boundary determined by an  $\alpha$ -spending function

Specify  $0 \leq \alpha^*(1) \leq \alpha^*(2) = \alpha$

Find  $u_1, u_2$  such that for  $j = 1, 2$

$$pr_{H_0}(S_1 \geq u_1) = \alpha^*(1) \quad (1)$$

$$pr_{H_0}(S_1 \geq u_1) + pr_{H_0}(S_2 \geq u_2, l_1 < S_1 < u_1) = \alpha^*(2) \quad (2)$$

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( $l_1$  specified by similar spending function or given in advance)

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$$\begin{pmatrix} S_1 \\ S_2 \end{pmatrix} \sim N \left( \begin{pmatrix} \theta I_1 \\ \theta I_2 \end{pmatrix}, \begin{pmatrix} I_1 & I_1 \\ I_1 & I_2 \end{pmatrix} \right)$$

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First analysis: under  $H_0$ ,  $S_1 \sim N(0, I_1)$

$$f_1(s_1) = \frac{1}{\sqrt{I_1}} \phi \left( \frac{s_1}{\sqrt{I_1}} \right)$$

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Second analysis:  $S_2$  is sum of  $S_1 \in (l_1, u_1)$  and  $N(0, I_2 - I_1)$

$$f_2(s_2) = \int_{l_1}^{u_1} \frac{1}{\sqrt{I_2 - I_1}} \phi \left( \frac{s_2 - s_1}{\sqrt{I_2 - I_1}} \right) f_1(s_1) ds_1$$

Find  $u_2$  to satisfy (2)

## 3. Adaptive seamless phase II/III trial

### 3.1 Idea

Start with  $k$  experimental treatments and control

At interim analysis:

- select treatment with largest estimated effect

- compare test statistic for this treatment with boundary

- stop if appropriate

- otherwise continue with this treatment + control

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Final analysis allows for interim analyses and selection (here with same endpoint at interim and final analyses)

## 3.2 Notation and test statistics

Treatments:  $T_0 = \text{control}$ ,  $T_1, \dots, T_k = \text{experimental}$

Normally distributed data with mean  $\mu_i$  for treatment  $T_i$ ,  $i = 0, \dots, k$  and known common variance

$\theta_i = \mu_i - \mu_0$  is a measure of superiority of  $T_i$  over  $T_0$   
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$S_{ij} = \hat{\theta}_{ij}/\text{var}(\hat{\theta}_{ij})$  efficient score statistic for  $\theta_i$

$I_j = 1/\text{var}(\hat{\theta}_{ij})$  Fisher's information for  $\theta_i$  (same for all  $i$ )

Consider density of  $S_{ij}$ ,  $i = 1, \dots, k$ ,  $j = 1, 2$  under  $H_0$

$$\begin{pmatrix} S_{11} \\ \vdots \\ S_{k1} \end{pmatrix} \sim N \left( \begin{pmatrix} \theta_1 I_1 \\ \vdots \\ \theta_k I_1 \end{pmatrix}, \begin{pmatrix} I_1 & I_1/2 & \cdots & I_1/2 \\ I_1/2 & I_1 & \cdots & I_1/2 \\ \vdots & & \ddots & \vdots \\ I_1/2 & I_1/2 & \cdots & I_1 \end{pmatrix} \right)$$

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Density of  $\max\{S_{i1}\}$ ; under  $H_0$

$$\int_{-\infty}^{\infty} \frac{k}{I_1/2} \phi \left( \frac{x}{\sqrt{I_1/2}} \right) \left\{ \Phi \left( \frac{x}{\sqrt{I_1/2}} \right) \right\}^{k-1} \phi \left( \frac{x-s}{\sqrt{I_1/2}} \right) dx$$

First look:

Replace normal density in single treatment case with density of  $\max\{S_{i1}\}$

Second look:

$S_{i2} - S_{i1} \sim N(\theta(I_2 - I_1), I_2 - I_1)$  ind. of  $S_{i1}$ .

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Type I error rate also controlled for any other selection as any  $S_{i1}$  is stochastically no larger than  $\max\{S_{i1}\}$

## 4. Using an early endpoint

### 4.1 Notation

Treatments:  $T_0 = \text{control}$ ,  $T_1, \dots, T_k = \text{experimental}$

Short- and long-term endpoints  $X, Y$  for treatment  $T_i$  with

$$\begin{pmatrix} X \\ Y \end{pmatrix} \sim N \left( \begin{pmatrix} \nu_i \\ \mu_i \end{pmatrix}, \begin{pmatrix} \sigma_s^2 & \rho\sigma\sigma_s \\ \rho\sigma\sigma_s & \sigma^2 \end{pmatrix} \right)$$

$\theta_i = \mu_i - \mu_0$  is parameter of interest

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Some patients have  $X$  and  $Y$  observed

Some patients have  $X$  only observed

## 4.2 Test statistic distributions

For two stages:

Stage 1

long-term data on  $n_1$  per treatment

short term data on  $N_1 (\geq n_1)$  per treatment

obtain  $\hat{\theta}_{i1}$  and  $var(\hat{\theta}_{i1}) = 2\sigma^2/n_1 - 2\sigma^2\rho^2(1/n_1 - 1/N_1)$

Select treatment with largest  $\hat{\theta}_{i1}$

Stage 2

long-term data on  $n_2 \geq N_1$  in total per treatment

obtain  $\hat{\theta}_{i2}$  and  $var(\hat{\theta}_{i2}) = 2\sigma^2/n_2$

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$S_{11}, \dots, S_{k1}, S_{i2} - S_{i1}$  have normal distributions as above

Construct critical values to control type I error rate

## 5. Example and simulation study

$k = 3$ ,  $N_1 = 100$ ,  $n_1 = 40$ ,  $n_2 = 200$ , no stopping at stage 1

$\rho$	Effective stage 1 $n/gp$	Standardised stage 2 critical value	Type I error rate	Power at $\theta_1 = \theta_2 = 0$ $\theta_3 = \sigma/3$
0.0	40	2.19	0.0256	0.782
0.5	47	2.20	0.0246	0.802
0.6	51	2.21	0.0246	0.801
0.7	57	2.22	0.0245	0.819
0.8	65	2.23	0.0249	0.829
0.9	80	2.25	0.0246	0.839

## 6. Flexible treatment selection

### 6.1 Error rate inflation ignoring flexible selection

Type I error rate is controlled provided treatment with largest  $\hat{\theta}_i$  is selected

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What if some other selection rule is used?

Suppose we knew (or could guess)  $\nu_i$

Make selection to maximise type I error rate given all stage 1 data

Given stage 1 data

$$S_{i2} \sim N((n_2 - n_1)\theta_i + n_1\tilde{\theta}_i, 2\sigma^2(n_2 - n_1 - \rho^2(N_1 - n_1)))$$

where

$$\tilde{\theta}_i = \frac{1}{n_1} \sum_{j=1}^{n_1} (Y_{ij} - Y_{0j}) + \rho \frac{\sigma}{\sigma_s} \sum_{j=n_1+1}^{N_1} (X_{ij} - X_{0j} - (\nu_i - \nu_0))$$

Type I error rate maximised by choosing treatment with largest  $\tilde{\theta}_i$

$\rho$	Type I error	
	using $\hat{\theta}_i$	using $\tilde{\theta}_i$
0.0	0.0256	0.0256
0.5	0.0246	0.0258
0.6	0.0246	0.0258
0.7	0.0245	0.0258
0.8	0.0249	0.0263
0.9	0.0246	0.0256

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Use joint distribution of  $\max\{\tilde{\theta}_{i1}\}$  and  $\hat{\theta}_{i2}$  to get critical values to control type I error rate for any selection rule

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	Effect. $n/gp$	Power	Effect. $n/gp$	Type I error using $\tilde{\theta}_i$	Type I error using $\hat{\theta}_i$	Power using $\hat{\theta}_i$
0.0	40	0.782	40	0.0256	0.0256	0.782
0.5	47	0.802	55	0.0250	0.0240	0.799
0.6	51	0.810	62	0.0246	0.0233	0.806
0.7	57	0.819	70	0.0247	0.0234	0.815
0.8	65	0.829	78	0.0250	0.0236	0.825
0.9	80	0.839	89	0.0247	0.0237	0.836

## 7. Conclusions and comments

New method:

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can incorporate early stopping

gains power through use of short-term endpoint if  $\rho \neq 0$

can allow for flexible treatment selection if appropriate critical values are used