

# Group Sequential Clinical Trial Designs for Normally Distributed Outcome Variables

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# Outline

- 1 Introduction
- 2 Group Sequential Design Theory
- 3 Commands
- 4 Discussion

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# Randomised Controlled Trial Design

- Choose a sample size that provides some level of statistical power for a target treatment effect.
- Recruit the number of patients required.
- Perform an analysis after all patients have been assessed.
- Design, analysis, and reporting of such trials well characterised.
- Incredibly effective way to assess the efficacy of a treatment.
- But is this the best we can do?

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- Trials gather a lot of data during their progress!
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- What if the new treatment is harmful?
- What if the new treatment works only in a subset of patients?
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- Focus on the design of a two-arm group sequential trial testing for superiority, with normally distributed outcomes.
- Assume a maximum of  $L$  analysis planned, and that analysis  $l = 1, \dots, L$  takes place after  $n_{0l} = ln$  and  $n_{1l} = rln$  patients evaluated in arms 0 and 1 respectively.
- Suppose that  $Y_{dli} \sim N(\mu_d, \sigma_d^2)$  for  $d = 0, 1$ .
- Defining  $\tau = \mu_1 - \mu_0$ , interest is in testing

$$H_0 : \tau \leq 0, \quad H_1 : \tau > 0.$$

- Want overall type-I error-rate when  $\tau = 0$  of  $\alpha$ , and power of  $1 - \beta$  when  $\tau = \delta > 0$ .

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# Analysis

- To test  $H_0$ , the following test statistic is used after analysis  
 $l = 1, \dots, L$

$$Z_l = \left( \frac{1}{n_{1l}} \sum_{j=1}^l \sum_{i=1}^{rn} Y_{1jl} - \frac{1}{n_{0l}} \sum_{j=1}^l \sum_{i=1}^n Y_{0jl} \right) I_l^{1/2},$$
$$I_l = \left( \frac{\sigma_0^2}{n_{0l}} + \frac{\sigma_1^2}{n_{1l}} \right)^{-1}.$$

- Importantly  $(Z_1, \dots, Z_L)$  is multivariate normal with

$$\mathbb{E}(Z_l) = \tau I_l^{1/2}, \quad l = 1, \dots, L,$$
$$\text{Cov}(Z_l, Z_k) = (I_l/I_k)^{1/2}, \quad 1 \leq l \leq k \leq L.$$

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# Stopping Rules

- ...given choices for  $f_1, \dots, f_L$  and  $e_1, \dots, e_L$ . Use these in the following stopping rules at analysis  $l = 1, \dots, L$ 
  - If  $Z_l \geq e_l$  stop and reject  $H_0$ .
  - If  $Z_l < f_l$  stop and accept  $H_0$ .
  - otherwise continue to stage  $l + 1$ .
- Then

$$\begin{aligned}\mathbb{P}(\text{Reject } H_0 \mid \tau) &= \sum_{l=1}^L \mathbb{P}(\text{Reject } H_0 \text{ at stage } l \mid \tau), \\ &= \mathbb{P}(Z_1 \geq e_1 \mid \tau) \\ &\quad + \sum_{l=2}^L \mathbb{P}(f_1 \leq Z_1 < e_1, \dots, f_{l-1} \leq Z_{l-1} < e_{l-1}, Z_l \geq e_l \mid \tau).\end{aligned}$$

- Similar formulae for  $\mathbb{E}(N \mid \tau)$ .
- Evaluate these formulae using `mvnnormal_mata()`.

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# Boundaries

- Functional form assumed, then search to find group size and exact values for correct operating characteristics.
- For example

$$e_l = C_e(l/L)^{\Omega-1/2},$$
$$f_l = \delta I_l^{1/2} - C_f(l/L)^{\Omega-1/2}.$$

- Then take  $I_L^{1/2} = (C_e + C_f)/\delta$ , to ensure  $e_L = f_L$ .
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# Commands

- Six commands in total. Four for two-sided tests, and two for one-sided tests as discussed here.
- One-sided tests as follows

```
powerFamily, [l(integer 3) delta(real 0.2)  
              alpha(real 0.05) beta(real 0.2)  
              sigma(numlist) ratio(real 1) Omega(real 0.5)  
              performance *]
```

```
triangular, [l(integer 3) delta(real 0.2) alpha(real 0.05)  
              beta(real 0.2) sigma(numlist) ratio(real 1)  
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```

# Example Output

```
. powerFamily, l(3) alpha(0.05) beta(0.2) delta(0.2) sigma(1, 2) omega(-0.5) r(2)
```

## 3-stage Group Sequential Trial Design

---

The hypotheses to be tested are as follows:

$H_0: \tau \leq 0$   $H_1: \tau > 0$ ,

with the following error constraints:

$P(\text{Reject } H_0 \mid \tau = 0) = .05$ ,

$P(\text{Reject } H_0 \mid \tau = .2) = 1 - .2$ .

```
Power family boundaries selected with Omega = -.5...  
...now determining design.....  
...output from optimize() to follow.....  
Iteration 0: f(p) = .01419449  
Iteration 1: f(p) = .00121018  
Iteration 2: f(p) = .00105648
```

# Example Output

```
Iteration 15: f(p) = 1.956e-08
...design determined. Returning the results.....
...Exact required group size n determined to be:

159.

...Efficacy boundaries e determined to be:

(4.87,2.44,1.62).

...Futility boundaries f determined to be:

(-1.24,.71,1.62).

...Operating characteristics of the design are:

P(Reject H0 | tau = 0) = .0499,
P(Reject H0 | tau = .2) = .7999,
E(N | tau = 0) = 1013,
E(N | tau = .2) = 1218.2,
max_tau E(N | tau) = 1241.3,
max N = 1431.4.
```

# Example: Comparison

```
. qui powerFamily, l(3) alpha(0.1) beta(0.1) delta(0.25) sigma(1, 2) omega(-0.25)
> r(2) perf saving(gsdesign1) nodraw title(Power family with {&0omega} = -0.25)
> scale(0.75)

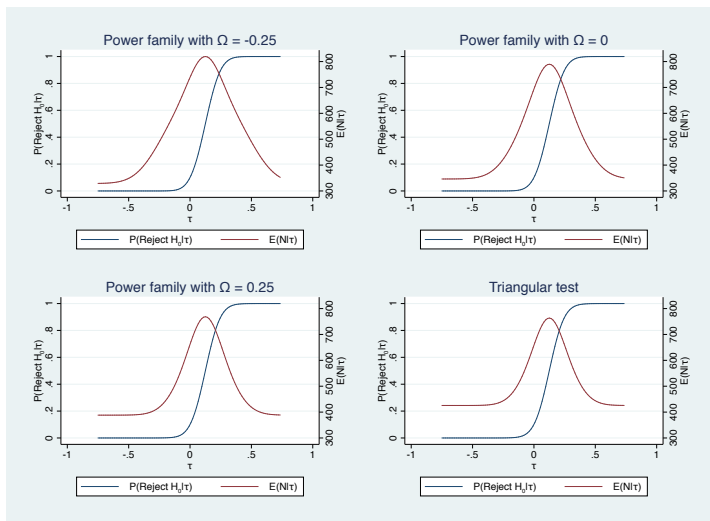
. qui powerFamily, l(3) alpha(0.1) beta(0.1) delta(0.25) sigma(1, 2) omega(0) r(2
> ) perf saving(gsdesign2) nodraw title(Power family with {&0omega} = 0) scale(0.7
> 5)

. qui powerFamily, l(3) alpha(0.1) beta(0.1) delta(0.25) sigma(1, 2) omega(0.25)
> r(2) perf saving(gsdesign3) nodraw title(Power family with {&0omega} = 0.25) sca
> le(0.75)

. qui triangular, l(3) alpha(0.1) beta(0.1) delta(0.25) sigma(1, 2) r(2) perf sav
> ing(gsdesign4) nodraw title(Triangular test) scale(0.75)

. graph combine gsdesign1.gph gsdesign2.gph gsdesign3.gph gsdesign4.gph, ycommon
```

# Example: Comparison





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# Discussion

- Group sequential designs provide gains in efficiency, easy to find (at least in this case).
- Key commands working.
- Only considered design so far.
- Only considered two-arm; multi-arm multi-stage designs of increasing interest.
- An option to use simulation instead of integration would also be a good step.

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- Only considered two-arm; multi-arm multi-stage designs of increasing interest.
- An option to use simulation instead of integration would also be a good step.

# Discussion

- Group sequential designs provide gains in efficiency, easy to find (at least in this case).
- Key commands working.
- Only considered design so far.
- Only considered two-arm; multi-arm multi-stage designs of increasing interest.
- An option to use simulation instead of integration would also be a good step.

# References

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