Group Sequential Tests for Delayed Responses

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- Group sequential tests
- Optimal designs

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- 3 Extensions



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- Recovering efficiency



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- Summary



Superiority trials

We conduct a clinical trial comparing a new treatment versus control. As the trial progresses, we accumulate responses

- $X_{A,i} \sim N(\mu_A, \sigma^2)$, i = 1, 2, ..., on the new treatment
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We assume that all responses are independent and σ^2 is known.

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We wish to test

$$H_0: \theta \leq 0$$
 vs $\theta > 0$

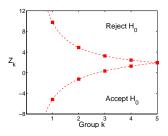
with type I error rate α at $\theta = 0$ and power $1 - \beta$ at $\theta = \delta > 0$.



Summary

One-sided group sequential tests

A one-sided group sequential test of $H_0: \theta \leq 0$ against $\theta > 0$ is of the form

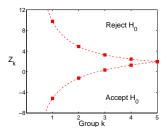


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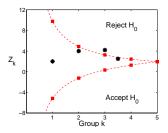


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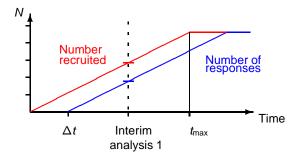


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Incorporating delayed responses into GSTs

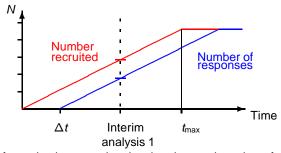
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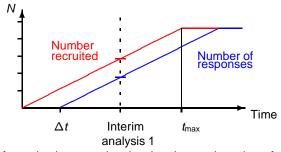


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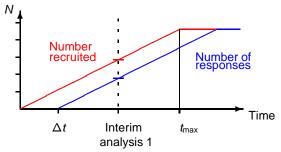
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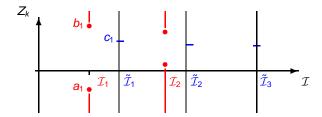
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T.W. Anderson (*JASA*, 1964) considers sequential tests for delayed responses. We follow this basic structure to construct GSTs.



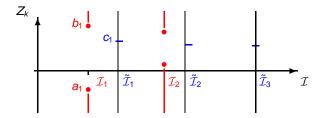
Boundaries for a Delayed Response GST

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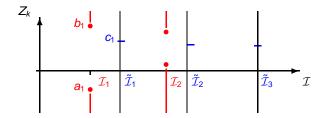


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At the decision analysis, based on information $\tilde{\mathcal{I}}_k$, reject H_0 if $\tilde{\mathcal{Z}}_k > c_k$.



Calculating properties of Delayed Response GSTs

Calculations of test properties (type I error rate, power, $\mathbb{E}_{\theta}(N)$) require the joint distributions of test statistic sequences:

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Each sequence is based on accumulating datasets.

Given $\{\mathcal{I}_1, \dots, \mathcal{I}_k, \tilde{\mathcal{I}}_k\}$, the sequence $\{Z_1, \dots, Z_k, \tilde{Z}_k\}$ follows the canonical distribution for statistics generated by a GST for immediate responses (Jennison & Turnbull, JASA, 1997).



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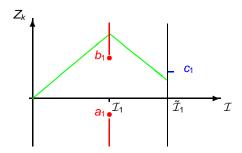
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Properties of Delayed Response GSTs can therefore be calculated using numerical routines devised for standard designs.



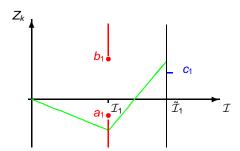
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Stopping with $Z_k > b_k$ or $Z_k < a_k$ indicates our *likely* final decision but there there may be a reversal. We could observe



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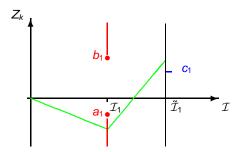
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We optimise our designs to maximise the value of the additional pipeline responses for increasing the test's power.



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Objective: For a given r, maximum sample size n_{max} , stages K and analysis schedule, we find the Delayed Response GST minimising

$$F = \int \mathbb{E}_{\theta}(N) f(\theta) d\theta$$

with type I error rate α at $\theta = 0$ and power $1 - \beta$ at $\theta = \delta$. Here $f(\theta)$ is the density of a $N(\delta/2, (\delta/2)^2)$ distribution.

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We create an unconstrained Bayes problem by adding a prior on θ and costs for sampling and for making incorrect decisions. We search for the combination of prior and costs which gives a solution with frequentist error rates α and β .



Efficiency loss when there is a delay in response

It is required to test $H_0: \theta \le 0$ against $\theta > 0$ with $\alpha = 0.025$ and $\beta = 0.1$. Suppose the fixed sample test requires n_{fix} subjects and set $n_{\text{max}} = 1.1 \, n_{\text{fix}}$.

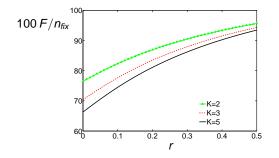


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We plot the minima of F attained by optimal tests with K = 2, 3 and 5 stages.



When r = 0.1, almost 25% of the gains of group sequential testing are lost. When r = 0.3, this increases up to 60%.



Example A: Cholesterol reduction after 4 weeks of treatment

Responses are assumed normally distributed with variance $\sigma^2 = 2$.

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We consider designs with a maximum sample size of 96, assuming a recruitment rate of 4 per week, giving $4 \times 4 = 16$ pipeline subjects at each interim analysis.



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A decision analysis will be based on

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- $\tilde{n}_2 = 70$ responses if recruitment stops at interim analysis 2
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We derive a Delayed Response GST minimising

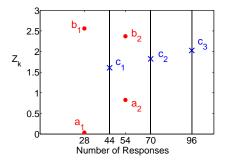
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where $f(\theta)$ is the density of a $N(0.5, 0.5^2)$ distribution.



Designing a Delayed Response GST

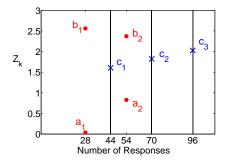
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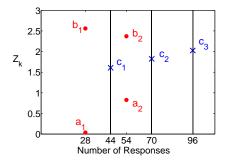


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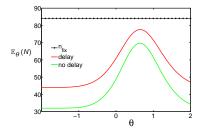
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Both c_1 and c_2 are less than 1.96. If desired, these can be raised to 1.96 with little change to the design's power curve.

Designing a Delayed Response GST

The figure shows expected sample size curves for

- the fixed sample test with $n_{\text{fix}} = 85$ patients,
- the Delayed Response GST minimising F,
- the GST for immediate responses with analyses after 32, 64 and 96 responses, also minimising F.

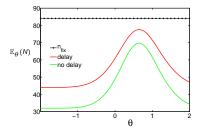




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The delay in response means savings in $\mathbb{E}_{\theta}(N)$ are smaller than they would be if response were immediate.

Making inferences on termination

How can we calculate a p-value for $H_0: \theta \leq 0$ and a CI for θ ?

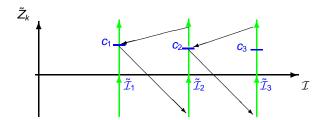
On termination of the test at stage T, $(\tilde{I}_T, \tilde{Z}_T)$ is a sufficient statistic for θ . We base inferences on a "stage-wise" ordering of the test's sample space for this pair.



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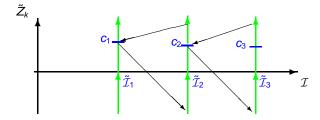




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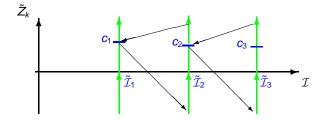
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This ordering ensures p-value calculations do not depend on future, possibly *unpredictable*, information levels.

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Choosing c_k to balance reversal probabilities under $\theta=0$ implies we may choose (a_k,b_k) to satisfy

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$$\mathbb{P}_{\theta=\delta}\{Z_1 \in C_1, \dots, Z_{k-1} \in C_{k-1}, Z_k \le a_k\} = \gamma_k - \gamma_{k-1},$$

and control the type I error rate at level α , and the type II error rate at a level just below β .



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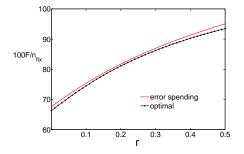
Under this construction, the stage k stopping rule can be set without knowledge of $\tilde{\mathcal{I}}_k$.



Efficiency of error spending tests

In the figure below, error spending tests are designed using the $\rho\text{-family}$ of error spending functions.

Values of F are attained by tests designed and conducted with K=5, $n_{\text{max}}=1.1\,n_{\text{fix}},\,\alpha=0.025$ and $\beta=0.1$.



Error spending Delayed Response GSTs are flexible and closely match the optimal tests for savings in $\mathbb{E}_{\theta}(N)$.

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Solution: We partition the sample space at $\tilde{\mathcal{I}}_{k^*}$ such that

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Requiring c_{k^*} to balance the probabilities of reversing decisions under $\theta = 0$ at stage k^* preserves the test's overall type I error rate.

In addition, p-value calculations do not depend on $\tilde{\mathcal{I}}_1, \dots, \tilde{\mathcal{I}}_{k^*-1}$, nor on information levels beyond stage k^* .

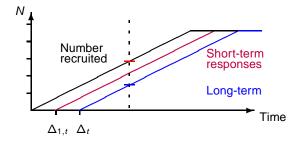


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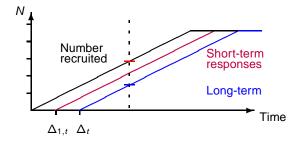
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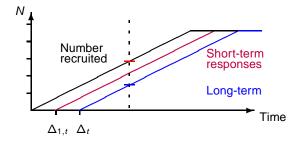
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At interim analysis k, we estimate $\theta = \mu_{A,2} - \mu_{B,2}$ from all available data, using maximum likelihood estimation to fit the full model then extracting $\widehat{\theta}_k$ and $\mathcal{I}_k = \text{Var}(\widehat{\theta}_k)$.

Given $\{\mathcal{I}_1,\ldots,\mathcal{I}_k,\tilde{\mathcal{I}}_k\}$, the sequence of estimates $\{\widehat{\theta}_k\}$ follows the canonical joint distribution for a group sequential trial.



Suppose each pair $(Y_{T,i}, X_{T,i})$ has joint distribution

$$\begin{pmatrix} Y_{T,i} \\ X_{T,i} \end{pmatrix} \sim N \begin{pmatrix} \begin{pmatrix} \mu_{T,1} \\ \mu_{T,2} \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & \tau \sigma_1 \sigma_2 \\ \tau \sigma_1 \sigma_2 & \sigma_2^2 \end{pmatrix} \end{pmatrix}.$$

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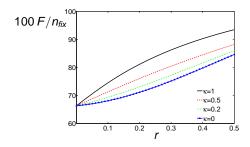
Given $\{\mathcal{I}_1,\ldots,\mathcal{I}_k,\tilde{\mathcal{I}}_k\}$, the sequence of estimates $\{\widehat{\theta}_k\}$ follows the canonical joint distribution for a group sequential trial.

At decision analysis k when all subjects are fully observed, short-term responses don't contribute any additional information for θ .



Revisiting Example A

Example A: Incorporating a second, short-term endpoint

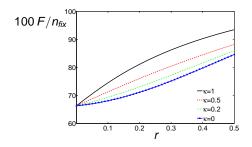


We assume $Y_{T,i}$ and $X_{T,i}$ have correlation 0.9.



Revisiting Example A

Example A: Incorporating a second, short-term endpoint



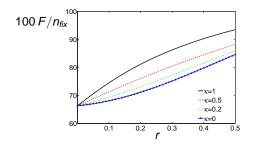
We assume $Y_{T,i}$ and $X_{T,i}$ have correlation 0.9.

The ratio of time to short-term and long-term endpoints is κ .



Revisiting Example A

Example A: Incorporating a second, short-term endpoint



We assume $Y_{T,i}$ and $X_{T,i}$ have correlation 0.9.

The ratio of time to short-term and long-term endpoints is κ .

The solid line for $\kappa = 1$ is the case of no short-term endpoint.



Conclusions

In this presentation, we have presented

- Delayed Response GSTs as a coherent approach to handling delayed data in a sequential setting.
- Versions of Delayed Response GSTs that can accommodate unpredictable group sizes and unexpected overrunning.
- P-values and confidence intervals on termination.

The impact on efficiency of a delay in response can be ameliorated by

- incorporating information on correlated short-term endpoints
- slowing recruitment rates
- ensuring rapid data cleaning before an analysis.

