Adaptive Enrichment Designs for Clinical Trials

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30/1/2017



What is Adaptive Enrichment

Familywise Error Rate (FWER)

Hypothesis testing

Bayes optimal decisions

What is Adaptive Enrichment









 $H_{01}: \theta_1 \leq 0 \qquad \qquad H_{02}: \theta_2 \leq 0$





 $H_{03}: \theta_3 \leq 0$ where $\theta_3 = \lambda \theta_1 + (1 - \lambda) \theta_2$



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Pre-interim recruitment

Post-interim recruitment

Pre-interim recruitment



Post-interim recruitment

Pre-interim recruitment



Post-interim recruitment



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 $H_{02}: \theta_2 \leq 0$

Pre-interim recruitment



Post-interim recruitment



 $H_{01}: \theta_1 \leq 0$

Pre-interim recruitment



Post-interim recruitment



 $H_{02}: \theta_2 \leq 0$

Familywise Error Rate (FWER)



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True null hypotheses	Familywise error to reject
H ₀₁	H ₀₁
H_{02}	H ₀₂
H_{01} and H_{02}	H_{01} , H_{02} or both

Achieving strong control of FWER

 $\mathbb{P}_{\boldsymbol{\theta}}(\mathsf{Reject} \text{ any combination of true null hypotheses}) \leq \alpha$ for all $\boldsymbol{\theta}$

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To achieve this we require:

- If H_{01} true, $\mathbb{P}(\mathsf{Reject}\ H_{01}) \leq \alpha$
- If H_{02} true, $\mathbb{P}(\mathsf{Reject}\ H_{02}) \leq \alpha$
- ▶ If H_{01} and H_{02} true, $\mathbb{P}(\mathsf{Reject \ both}\ H_{01}$ and $H_{02}) \leq \alpha$

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The Bonferroni correction where both H_{01} and H_{02} are tested at $\alpha/2$ is the simplest procedure that ensures strong control of the FWER.

Hypothesis testing

Closed testing procedures

For testing H_{01} and H_{02} we construct level α tests for

•
$$H_{01}: \theta_1 \leq 0$$
,

- $H_{02}: \theta_2 \le 0$,
- $H_{01} \cap H_{02}$: $\theta_1 \leq 0$ and $\theta_2 \leq 0$.

Then:

- ▶ Reject H_{01} globally if H_{01} and $H_{01} \cap H_{02}$ are both rejected.
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Simes rule and the method proposed by Dunnett provide two methods for testing the intersection hypothesis that are suitable for Adaptive Enrichment designs.

Combination tests

Suppose $P^{(1)}$ and $P^{(2)}$ are the p-values from the first and second stages of the trial. Using the weighted inverse Normal we find $P^{(c)}$ the p-value for the whole trial.

$$Z^{(1)} = \phi^{-1}(1 - P^{(1)})$$
 and $Z^{(2)} = \phi^{-1}(1 - P^{(2)})$

With
$$w_1$$
 and w_2 such that $w_1^2 + w_2^2 = 1$
$$Z^{(c)} = w_1 Z^{(1)} + w_2 Z^{(2)}$$

$$P^{(c)} = 1 - \phi(Z^{(c)})$$

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Choosing w_1 and w_2 in proportion to the sample size from each stage gives the optimal procedure.

Overall testing procedure

	<i>H</i> ₀₁	H ₀₂	$H_{01} \cap H_{02}$
Pre-interim recruitment cohort	$p_1^{(1)}$	$p_2^{(1)}$	$p_{12}^{(1)}$
Post-Internit recruitment conort	ρ_1	P_2	p_{12}
Overall	$p_1^{(c)}$	$p_{2}^{(c)}$	$p_{12}^{(c)}$

Bayes optimal decisions

Optimisation components

Prior distribution:

 $\pi(\boldsymbol{\theta})$

Utility function (gain):

 $G(\boldsymbol{\theta}) = \gamma_1(\theta_1)\mathbb{I}(\text{Reject } H_{01}) + \gamma_2(\theta_2)\mathbb{I}(\text{Reject } H_{02})$

Simple optimisation

$$\mathbb{E}_{\pi(\theta)}(G(\theta))$$

Simple decision rule



Bayes optimal decision

Data available at the interim analysis:

Χ

Bayes expected gain:

 $\mathbb{E}_{\pi(\theta),X}(G(\theta))$ **† † †**

Bayes optimal decision

Data available at the interim analysis:

Χ



Choose sub-population that maximises $\mathbb{E}_{\pi(\theta),X}(G(\theta))$

Bayes optimal rule

$$\mathbb{E}_{\pi(\boldsymbol{ heta}),X}(G(\boldsymbol{ heta}))$$

Bayes optimal decision



Key points

- Strong control of FWER
- Prior distribution
- Gain function
- $\mathbb{E}_{\pi(\theta),X}(G(\theta))$ for optimisation
- $\mathbb{E}_{\pi(\theta)}(G(\theta))$ for overall behaviour

Any questions?