
Graph Based Adaptive MAMS Designs

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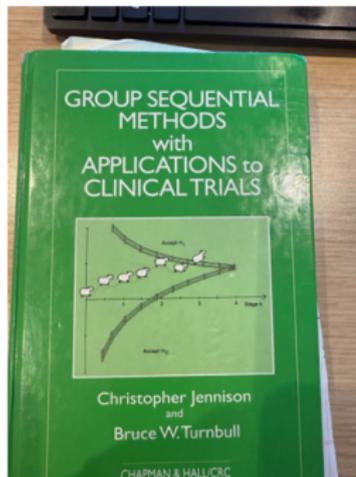
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Acknowledgments

- Joint collaboration with [Martin Posch](#) and [Ajoy Mukhopadhyay](#)
- Builds upon prior work of:
 - [Bretz, Maurer, Brannath, Posch \(2009\)](#); A graphical approach to sequentially rejective multiple testing procedures
 - [Bretz, Posch, Glimm, Klingmueller, Maurer, Rohmeyer \(2011\)](#); Graphical approaches for multiple comparison procedures using weighted Bonferroni, Simes or parametric tests
 - [Klingmueller, Posch, Koenig \(2014\)](#); Adaptive graph-based multiple testing procedures

History of Adaptive Group Sequential Design

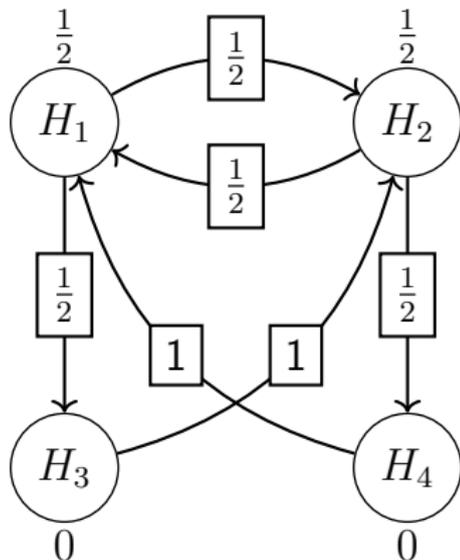
1950 to 2000 (Classical)	2000 to 2025 (Adaptive)
<ul style="list-style-type: none">• Two arm group sequential designs• Early stopping for efficacy or futility• Flexible monitoring with α-spending	<p>2000-2005 Sample size re-estimation in two-arm designs</p> <ul style="list-style-type: none">• Type-1 error preserved by p-value combination(PVcombo)• Type-1 error preserved conditional error rate (CER) (The two methods are functionally equivalent in 2-arm trials)



<p>2005-2010 Seamless phase 2/3 designs</p> <ul style="list-style-type: none">• Test multiple treatments vs control at stage one• Select a subset of treatments for stage two• FWER controlled by Closed Testing and PVcombo
<p>2010-2025 Multi-arm, Multi-stage, Multi-endpoint</p> <ul style="list-style-type: none">• Extended classical 2-arm designs to MAMS designs• Adaptive MAMS with SSR and treatment selection• Inclusion of multiple-endpoints• Graph based weights assigned to the multiple hypotheses reflecting priorities of study team• FWER controlled by Closed Testing, Pvcombo, CER

Schizophrenia Trial: two primary, two secondary endpoints

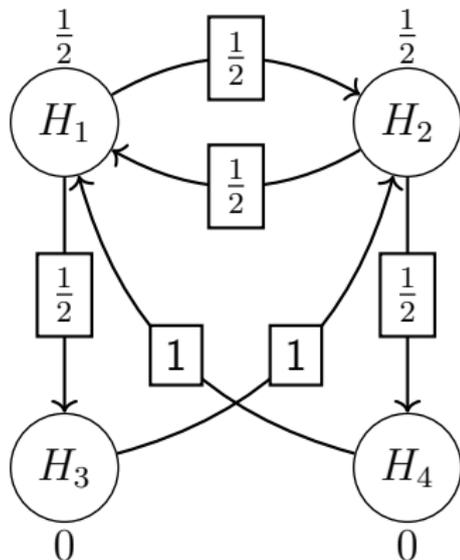
PANSS score at week 12 for High Dose, Low Dose and Placebo



- H1: Hi vs Pbo; PANSS_tot
- H2: Low vs Pbo; PANSS_tot
- H3: Hi vs Pbo; PANSS_neg
- H4: Low vs Pbo; PANSS_neg

Schizophrenia Trial: two primary, two secondary endpoints

PANSS score at week 12 for High Dose, Low Dose and Placebo



- H_1 : Hi vs Pbo; PANSS_tot
- H_2 : Low vs Pbo; PANSS_tot
- H_3 : Hi vs Pbo; PANSS_neg
- H_4 : Low vs Pbo; PANSS_neg

$$\text{corr}(H_1, H_2) = 0.5$$

$$\text{corr}(H_3, H_4) = 0.5$$

$$\text{corr}(H_1, H_3) \text{ unknown}$$

$$\text{corr}(H_2, H_4) \text{ unknown}$$

Sources of Multiplicity and FWER Control

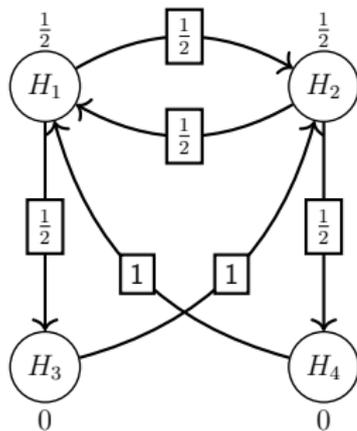
- Can make up to 15 different claims for $\{H_1, H_2, H_3, H_4\}$
- FWER is the probability of making **one or more false claims**
- Sources of FWER inflation include:
 - Testing multiple hypotheses
 - Testing same hypothesis twice; at stages one and two
 - Making adaptive changes at the end of stage one
- Strong FWER control means $\text{FWER} \leq \alpha$ under **any** configuration of true and false null hypotheses

Analysis of Schizophrenia Trial

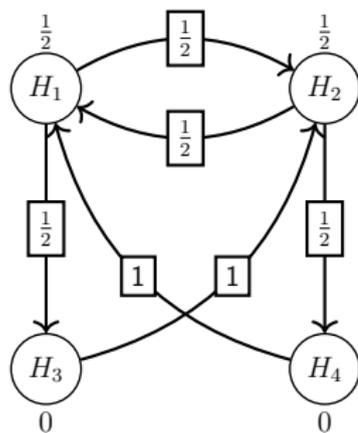
Split $\alpha = 0.025$ into $\alpha_1 = 0.00153$ and $\alpha_2 = 0.02347$
(Lan-DeMets α -spending at 50% information)

1. At stage one, test each hypothesis at $\alpha_1 = 0.00153$
2. Eliminate statistically significant hypotheses from further testing
3. Make adaptive decisions for stage two testing
 - drop hypotheses no longer of interest
 - change testing strategy by altering the graph
 - re-assess the sample size and allocation ratio
4. At stage two, test remaining hypotheses with $\alpha_2 = 0.02347$

Stage One Analysis (at $\alpha = 0.00153$)



Stage One Analysis (at $\alpha = 0.00153$)

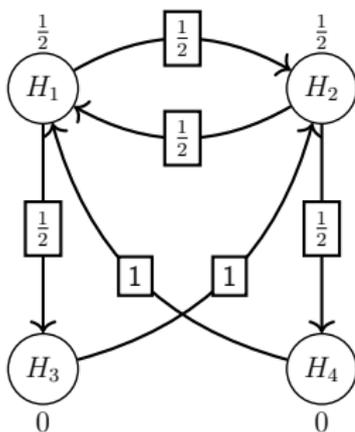


Decompose graph into 15 weighted intersection hypotheses

Intersection Hypothesis	Weights		
H_J	W_J		
H_1	1		
H_2	1		
H_3	1		
H_4	1		
$H_1 \cap H_2$	0.5, 0.5		
$H_1 \cap H_3$	1.0, 0.0		
$H_1 \cap H_4$	0.75, 0.25		
$H_2 \cap H_3$	0.75, 0.25		
$H_2 \cap H_4$	1.0, 0.0		
$H_3 \cap H_4$	0.5, 0.5		
$H_1 \cap H_2 \cap H_3$	0.5, 0.5, 0.0		
$H_1 \cap H_2 \cap H_4$	0.5, 0.5, 0.0		
$H_1 \cap H_3 \cap H_4$	0.75, 0.0, 0.25		
$H_2 \cap H_3 \cap H_4$	0.75, 0.25, 0.0		
$H_1 \cap H_2 \cap H_3 \cap H_4$	0.5, 0.5, 0.0, 0.0		

Bretz, Maurer, Brannath, Posch. SiM, 2009

Stage One Analysis (at $\alpha = 0.00153$)



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$H_2 \cap H_4$	1.0, 0.0		
$H_3 \cap H_4$	0.5, 0.5		
$H_1 \cap H_2 \cap H_3$	0.5, 0.5, 0.0		
$H_1 \cap H_2 \cap H_4$	0.5, 0.5, 0.0		
$H_1 \cap H_3 \cap H_4$	0.75, 0.0, 0.25		
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$H_1 \cap H_2 \cap H_3 \cap H_4$	0.5, 0.5, 0.0, 0.0		

Bretz, Maurer, Brannath, Posch. SiM, 2009

- Unadjusted (raw) Stage One p-values = $\{0.00045, 0.0952, 0.0225, 0.1104\}$

Aside: Computing Multiplicity Adjusted P-values

$$\{p_1 = 0.00045, p_2 = 0.0952, p_3 = 0.0225, p_4 = 0.1104\}$$

- Use raw p-values as building blocks for adjusted p-values
- Adjustment may be parametric or nonparametric

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- Adjustment may be parametric or nonparametric

Nonparametric (Bonferroni): Test $H_2 \cap H_3$ with weights

$$w_2 = 0.75, w_3 = 0.25$$

$$p_{\{1,2\}} = \min\left\{\frac{p_2}{w_2}, \frac{p_3}{w_3}\right\} = \min\left\{\frac{0.0952}{0.75}, \frac{0.0225}{0.25}\right\} = 0.09$$

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Nonparametric (Bonferroni): Test $H_2 \cap H_3$ with weights

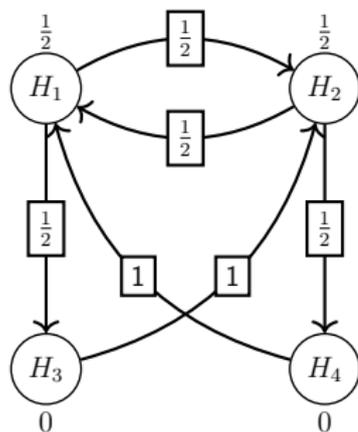
$$w_2 = 0.75, w_3 = 0.25$$

$$p_{\{1,2\}} = \min\left\{\frac{p_2}{w_2}, \frac{p_3}{w_3}\right\} = \min\left\{\frac{0.0952}{0.75}, \frac{0.0225}{0.25}\right\} = 0.09$$

Parametric (Dunnett): Test $H_1 \cap H_2$ with weights $w_1 = 0.5, w_2 = 0.5$

$$p_{\{2,3\}} = \Pr\left\{\min\left[\frac{P_1}{w_1}, \frac{P_2}{w_2}\right] \leq \min\left[\frac{0.00045}{0.5}, \frac{0.0952}{0.5}\right]\right\} = 0.00088$$

Stage One Analysis (at $\alpha = 0.00153$)



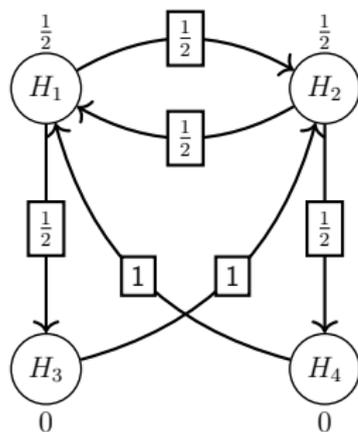
Decompose graph into 15 weighted intersection hypotheses

Intersection Hypothesis	Weights	Adjusted p-value	Adjustment Method
H_J	W_J	$p_{J,1}$	
H_1	1	0.00045	NA
H_2	1	0.0952	NA
H_3	1	0.0225	NA
H_4	1	0.1104	NA
$H_1 \cap H_2$	0.5, 0.5	0.00088	Parametric
$H_1 \cap H_3$	1.0, 0.0	0.00045	Bonferroni
$H_1 \cap H_4$	0.75, 0.25	0.0006	Bonferroni
$H_2 \cap H_3$	0.75, 0.25	0.0900	Bonferroni
$H_2 \cap H_4$	1.0, 0.0	0.0952	Bonferroni
$H_3 \cap H_4$	0.5, 0.5	0.0410	Parametric
$H_1 \cap H_2 \cap H_3$	0.5, 0.5, 0.0	0.00088	Mixed
$H_1 \cap H_2 \cap H_4$	0.5, 0.5, 0.0	0.00088	Mixed
$H_1 \cap H_3 \cap H_4$	0.75, 0.0, 0.25	0.0006	Mixed
$H_2 \cap H_3 \cap H_4$	0.75, 0.25, 0.0	0.0900	Mixed
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Bretz, Maurer, Brannath, Posch. SiM, 2009

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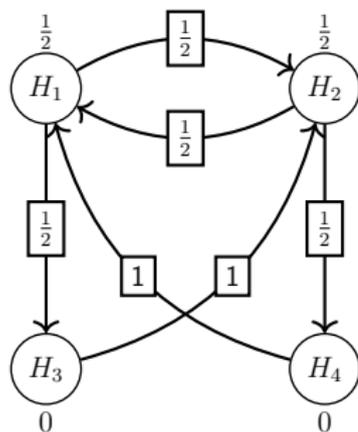
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Bretz, Maurer, Brannath, Posch. SiM, 2009

- Unadjusted (raw) Stage One p-values = $\{0.00045, 0.0952, 0.0225, 0.1104\}$
- Reject any H_J for which $p_{J,1} \leq 0.00153$ (Lan-DeMets)

Stage One Analysis (at $\alpha = 0.00153$)



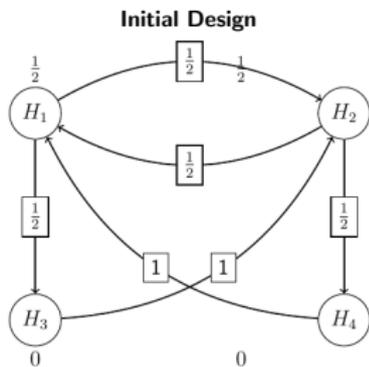
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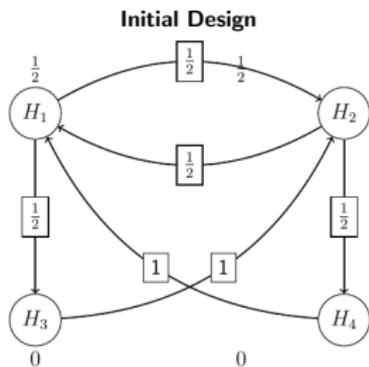
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- Unadjusted (raw) Stage One p-values = $\{0.00045, 0.0952, 0.0225, 0.1104\}$
- Reject any H_J for which $p_{J,1} \leq 0.00153$ (Lan-DeMets)
- H_1 is rejected under closed testing. H_2, H_3, H_4 are retained

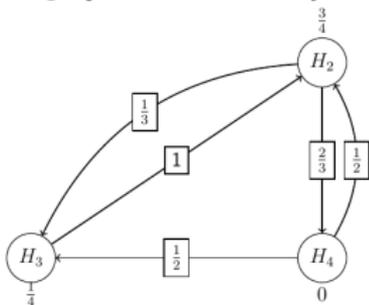
Modify Graph as Desired for Stage Two



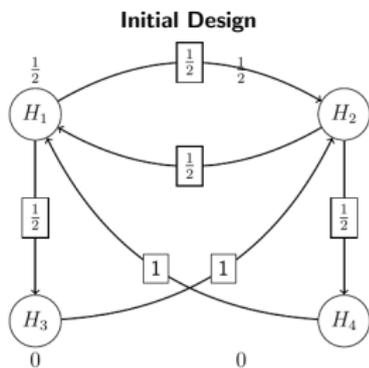
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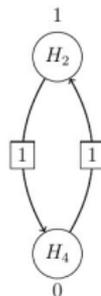
H_1 rejected at interim analysis



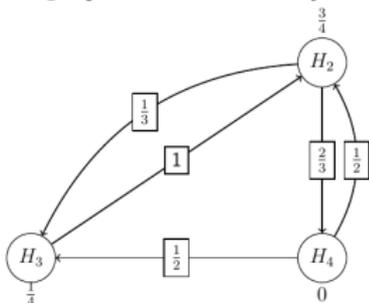
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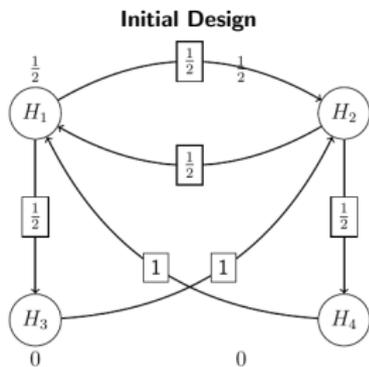
H_1 rejected, H_3 dropped



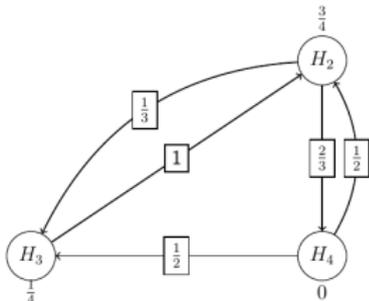
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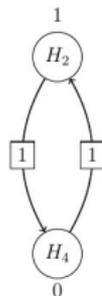
Modify Graph as Desired for Stage Two



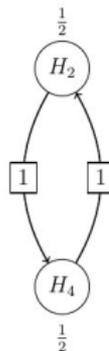
H_1 rejected at interim analysis



H_1 rejected, H_3 dropped



H_1 rejected, H_3 dropped, weights altered



Two Methods for Stage Two Testing

P-value Combination Method (PVcombo)

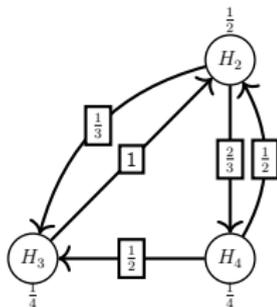
- Combine incremental multiplicity adjusted p-values
- Pre-specify the combination function
- Use two-arm group sequential cut-off to reject hypotheses
- Use closed testing of individual hypotheses

Conditional Error Rate Method (CER)

- Use unadjusted cumulative p-values from the two stages
- Use multi-arm group sequential cut-off to reject hypotheses
- Adjust cut-off by preserving CER if design is adapted

Stage Two Testing by PVcombo Method

- Suppose we proceed with a modified stage two graph



- Decompose into 7 weighted intersection hypothesis tests

Index Set $J \in J^+$	Intersection Hypothesis H_J	Weights W_J	Adjusted p-value $p_{J,(2)}$ (incremental)	Adjustment Method
$\{2\}$	H_2	1	0.1121	NA
$\{3\}$	H_3	1	0.0112	NA
$\{4\}$	H_4	1	0.0448	NA
$\{2, 3\}$	$H_2 \cap H_3$	0.625, 0.375	0.0299	Bonferroni
$\{2, 4\}$	$H_2 \cap H_4$	0.75, 0.25	0.1495	Bonferroni
$\{3, 4\}$	$H_3 \cap H_4$	0.417, 0.583	0.0249	Parametric
$\{2, 3, 4\}$	$H_2 \cap H_3 \cap H_4$	0.5, 0.25, 0.25	0.0418	Mixed

Stage Two Testing by PVcombo Method

- Combine **incremental** stagewise adjusted p-values $p_{J,1}$ and $p_{J,(2)}$
- Utilize a **pre-specified** combination function

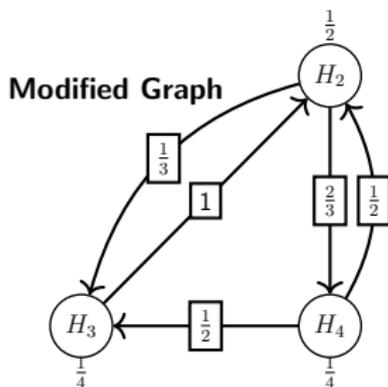
$$C(p_{J,1}, p_{J,(2)}) = 1 - \Phi\left[\sqrt{\frac{1}{2}}\Phi^{-1}(1 - p_{J,1}) + \sqrt{\frac{1}{2}}\Phi^{-1}(1 - p_{J,(2)})\right]$$

- Reject H_J if $C(p_{J,1}, p_{J,(2)}) \leq 0.0245$ (Lan-DeMets Boundary)

Index Set $J \in J^+$	Intersection Hypothesis H_J	Stage-wise Adjusted p-values		Combined p-value $C_J(p_{J,1}, p_{J,(2)})$
		$p_{J,1}$	$p_{J,(2)}$	
{2}	H_2	0.0952	0.1121	0.0371
{3}	H_3	0.0225	0.0112	0.0012
{4}	H_4	0.1104	0.0448	0.0194
{2, 3}	$H_2 \cap H_3$	0.0900	0.0299	0.0113
{2, 4}	$H_2 \cap H_4$	0.0952	0.1495	0.0484
{3, 4}	$H_3 \cap H_4$	0.0410	0.0249	0.0044
{2, 3, 4}	$H_2 \cap H_3 \cap H_4$	0.0900	0.0418	0.0149

Reject H_3 by the closed test

Stage Two Testing by CER Method



Intersection H_J	Modified Weights W_J	Multiplicity Adjustment
H_2	1	NA
H_3	1	NA
H_4	1	NA
$H_2 \cap H_3$	0.625, 0.375	Nonparametric
$H_2 \cap H_4$	0.75, 0.25	Nonparametric
$H_3 \cap H_4$	0.417, 0.583	Parametric
$H_2 \cap H_3 \cap H_4$	0.5, 0.25, 0.25	Mixed

Example: Stage Two Adaptive Test of $H_3 \cap H_4$

- Pre-specify level- α multivariate group sequential boundaries (C_1, C_2) :

$$P \left\{ \min_{\{j \in (3,4)\}} [p_{j,1} \leq w_j C_1] \text{ or } \min_{\{j \in (3,4)\}} [p_{j,2} \leq w_j C_2] \right\} = \alpha$$
- If trial adapts, recompute the stage two cut-off C_2 such that
 CER of adaptive test \leq CER of pre-specified test

Stage Two Testing by CER Method

Example: Stage Two Adaptive Test of $H_3 \cap H_4$

- Notation:
 - $(p_{3,1}, p_{4,1})$: stage one **unadjusted** p-values
 - $(p_{3,2}, p_{4,2})$: stage two **cumulative, unadjusted** p-values if no adaptation
 - $(p_{3,2*}, p_{4,2*})$: stage two **cumulative, unadjusted** p-values if trial adapts

Stage Two Testing by CER Method

Example: Stage Two Adaptive Test of $H_3 \cap H_4$

- Notation:
 - $(p_{3,1}, p_{4,1})$: stage one **unadjusted** p-values
 - $(p_{3,2}, p_{4,2})$: stage two **cumulative, unadjusted** p-values if no adaptation
 - $(p_{3,2*}, p_{4,2*})$: stage two **cumulative, unadjusted** p-values if trial adapts
- **If no adaptation.** Reject $H_3 \cap H_4$ at stage two if

$$\min\left(\frac{p_{3,2}}{w_3}, \frac{p_{4,2}}{w_4}\right) \leq C_2$$

where C_2 is the group sequential cut-off for **2-arms vs control**

Stage Two Testing by CER Method

Example: Stage Two Adaptive Test of $H_3 \cap H_4$

- Notation:
 $(p_{3,1}, p_{4,1})$: stage one **unadjusted** p-values
 $(p_{3,2}, p_{4,2})$: stage two **cumulative, unadjusted** p-values if no adaptation
 $(p_{3,2^*}, p_{4,2^*})$: stage two **cumulative, unadjusted** p-values if trial adapts
- **If no adaptation.** Reject $H_3 \cap H_4$ at stage two if

$$\min\left(\frac{p_{3,2}}{w_3}, \frac{p_{4,2}}{w_4}\right) \leq C_2$$

where C_2 is the group sequential cut-off for **2-arms vs control**

- **If adaptation.** Reject $H_3 \cap H_4$ if

$$\min\left(\frac{p_{3,2}^*}{w_3^*}, \frac{p_{4,2}^*}{w_4^*}\right) \leq C_2^*$$

Stage Two Testing by CER Method

C_2^* satisfies the CER condition

$$\begin{aligned} P_0\left\{\min\left(\frac{P_{3,2}^*}{w_3^*}, \frac{P_{4,2}^*}{w_4^*}\right) \leq C_2^* | p_{3,1}, p_{4,1}\right\} \\ \leq P_0\left\{\min\left(\frac{P_{3,2}}{w_3}, \frac{P_{4,2}}{w_4}\right) \leq C_2 | p_{3,1}, p_{4,1}\right\} \end{aligned}$$

Key Idea of the CER Method

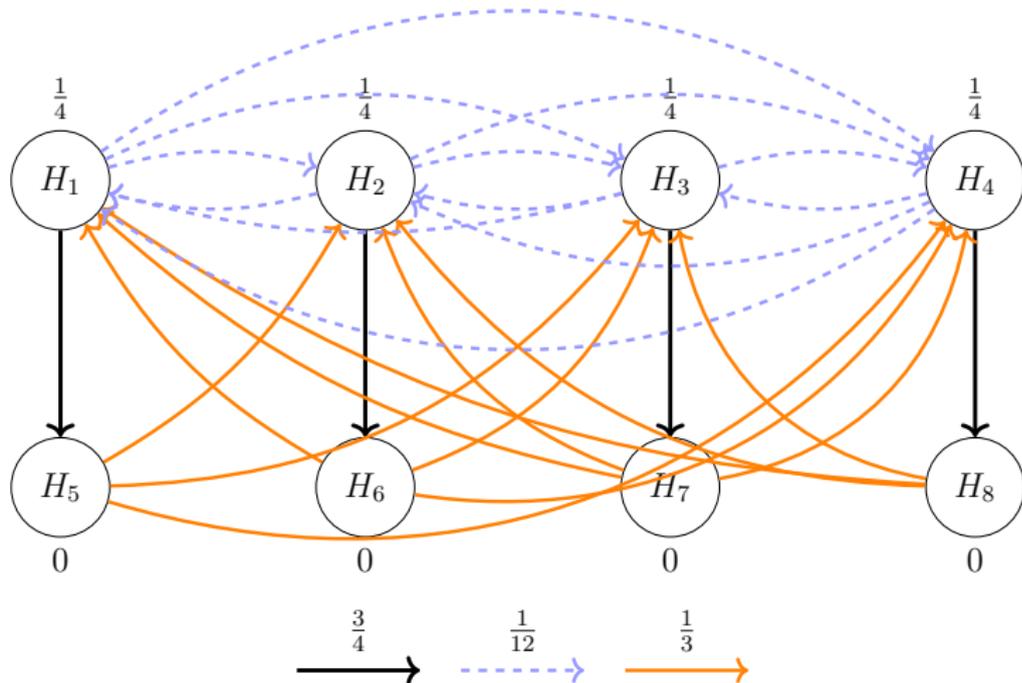
A procedure that bounds the conditional type-1 error of the adapted test, by the conditional type-1 error of the original unadapted test, **over all possible stage one results**, also bounds its unconditional type-1 error

Stage Two Testing by CER Method

Intersection	Adapted Weights	Weighted Pvalues	Adjusted Cut-Off (C_2^*)
H_J	$w_j^*, j \in J$	$\frac{p_{j,2}^*}{w_j^*}, j \in J$	
H_2	1	0.0371	0.0245
H_3	1	0.0012	0.0245
H_4	1	0.0195	0.0245
$H_2 \cap H_3$	0.625, 0.375	0.0594, 0.0032	0.0208
$H_2 \cap H_4$	0.75, 0.25	0.0495, 0.0780	0.0277
$H_3 \cap H_4$	0.417, 0.583	0.0029, 0.0334	0.0296
$H_2 \cap H_3 \cap H_4$	0.5, 0.25, 0.25	0.0742, 0.0048, 0.0780	0.0275

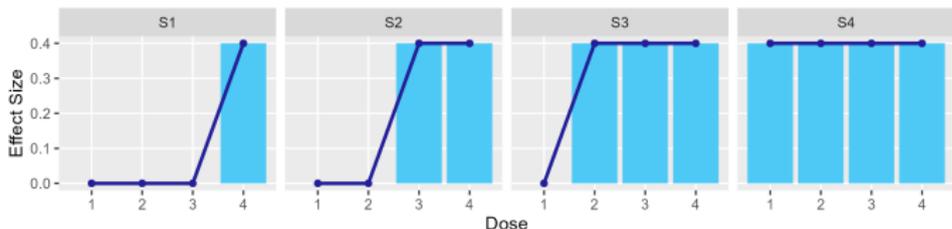
- Cumulative stage two p-values:
 $\{p_{2,2}^* = 0.0371, p_{3,2}^* = 0.0012, p_{4,2}^* = 0.0195\}$
- H_3 is rejected by the closed test

Simulation Study of the Two Methods



Scenarios and Adaptive Decision Rules

- 100 subjects/arm; 90% power at $\delta_j = 0.4, \sigma_j = 1$, for $j = 1, \dots, 8$
- Four alternative hypothesis scenarios



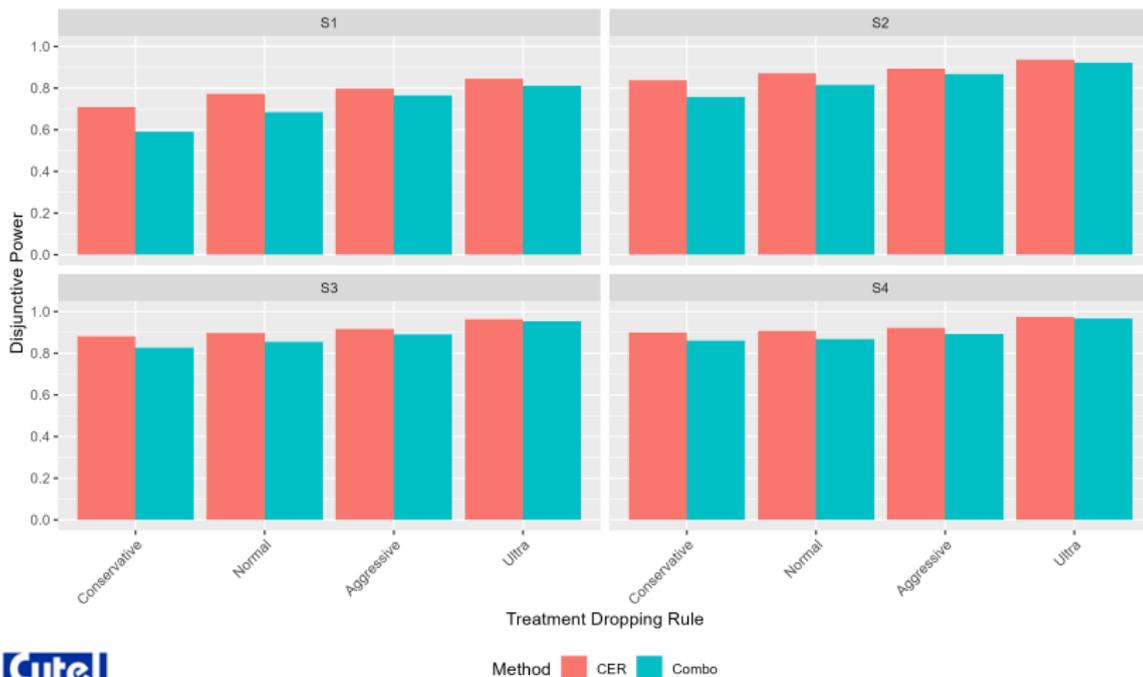
- Four decision rules for dropping non-performing doses at stage one

Conservative rule	Drop doses with p-value > 0.75
Normal rule	Drop doses with p-value > 0.5
Aggressive rule	Drop doses with p-value > 0.25
Ultra Aggressive rule	Select dose with smallest p-value

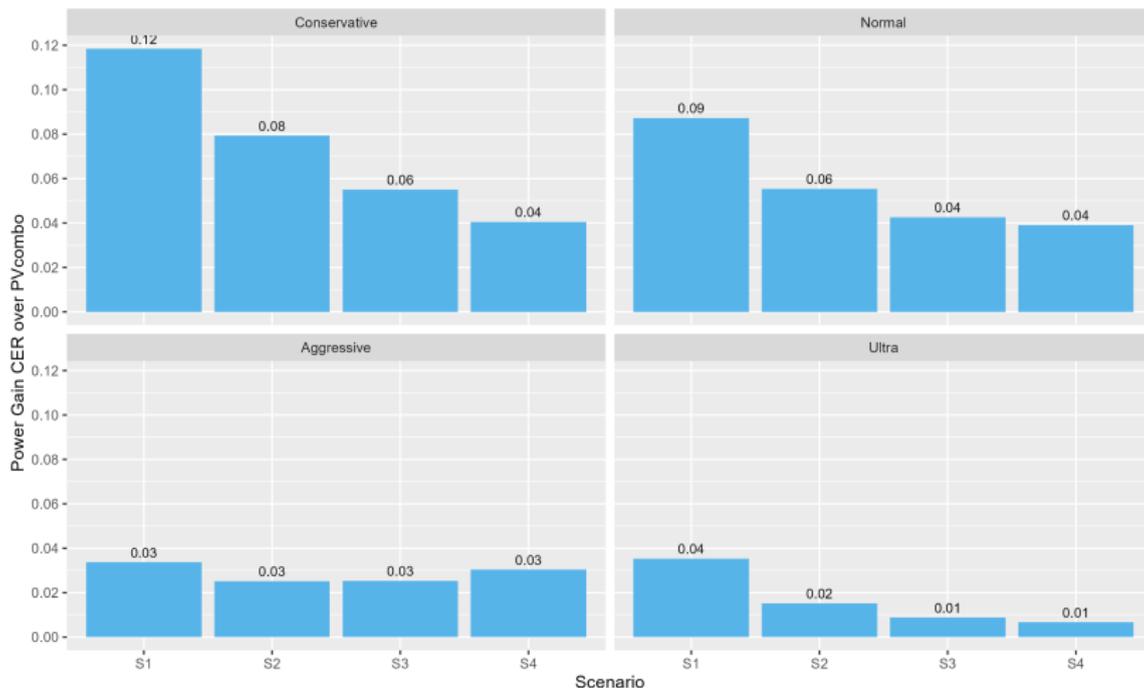
- Subjects re-assigned from dropped doses to continuing doses

Disjunctive Power: CER vs PVcombo

Results from 10,000 Simulated Trials

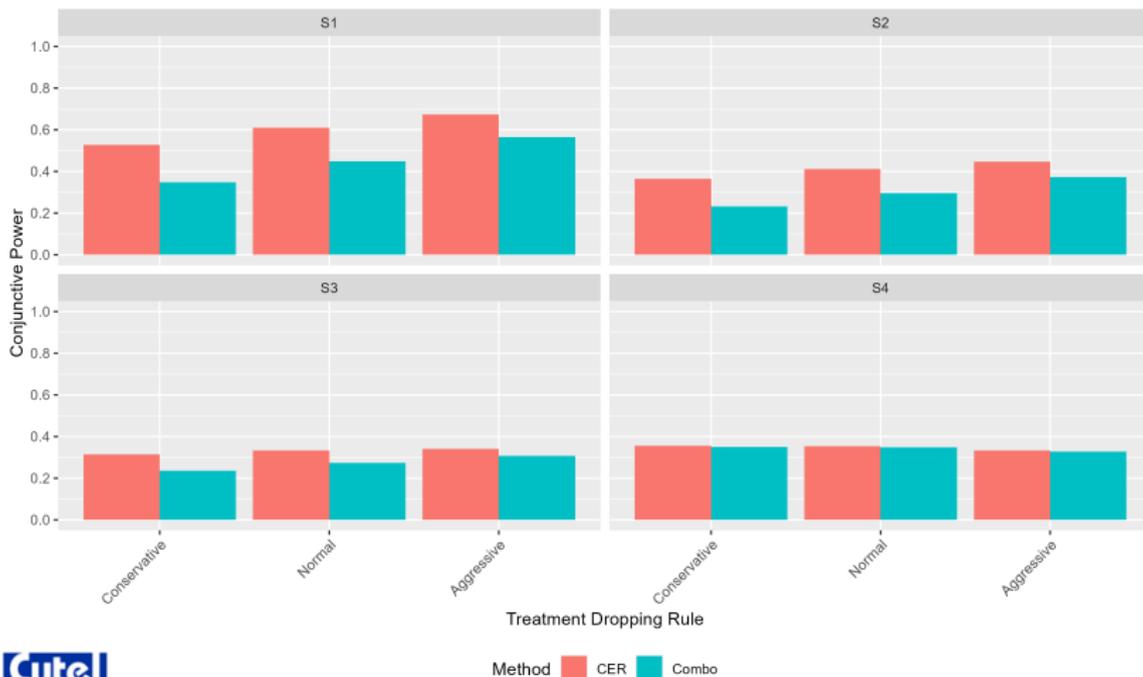


Gain in Disjunctive Power: CER - PVcombo

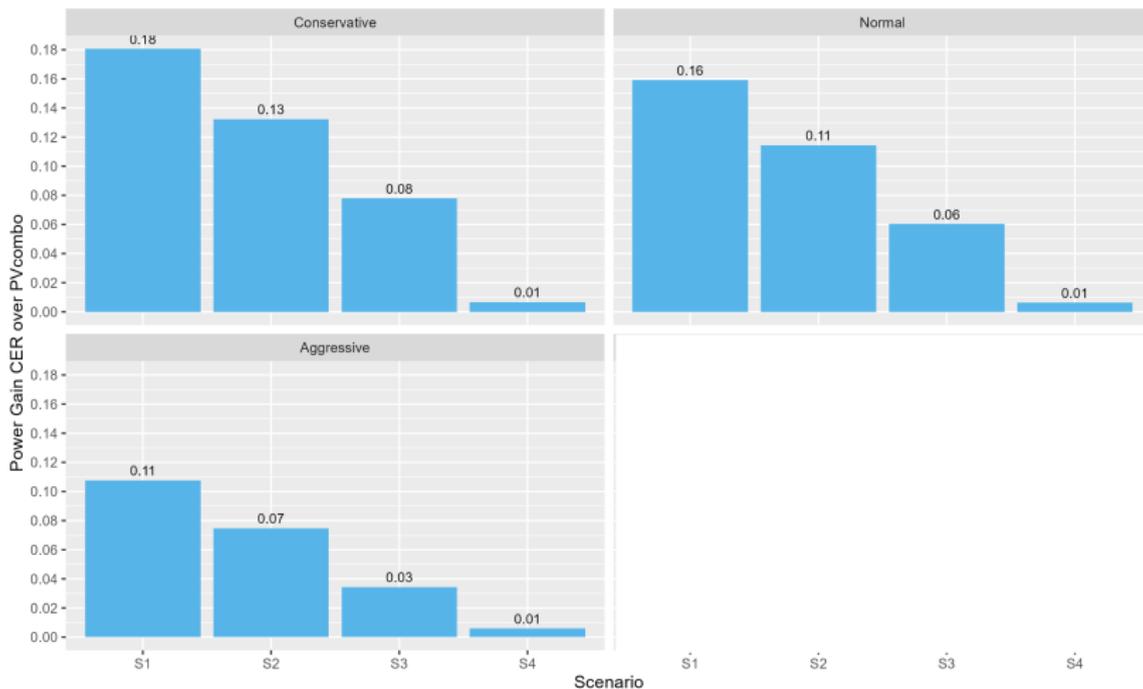


Conjunctive Power: CER vs PVcombo

Results from 10,000 Simulated Trials

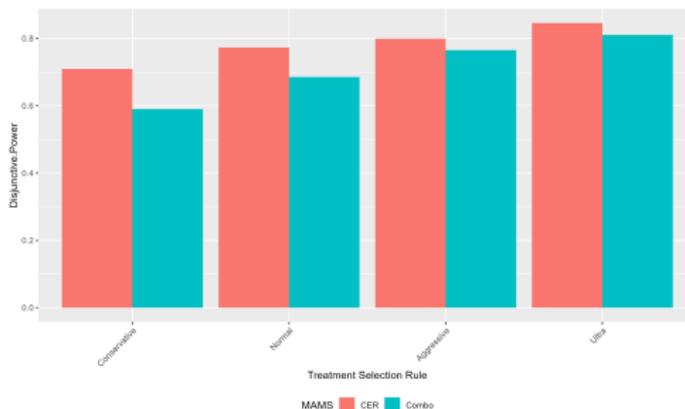


Gain in Conjunctive Power: CER - PVcombo



Conclusions from Simulation Results

1. Power of CER exceeds that of PVcombo everywhere
 - Up to 12% excess disjunctive and 18% excess conjunctive
2. Power gain of CER over PVcombo decreases with increasing aggressiveness for dropping doses
3. For both methods, absolute power increases with increasing aggressiveness for dropping doses



Plausible Explanation for Greater Power of CER

Consonance (Hommel, Bretz, Maurer, SiM 2007)

- In a consonant MTP, rejection of the global intersection hypothesis implies rejection of at least one individual hypothesis
- It follows that consonant MTPs have greater power for rejecting individual hypotheses than non-consonant ones
- In our example, PVcombo is not consonant whereas CER is consonant if doses are not dropped. This explains:
 - greater power of CER over PVcombo
 - decline in power gain with increasingly aggressive dose dropping rules
- In general CER tests lose consonance less often than PVcombo tests

Summary

- Graphs are a natural and intuitive way to assign weights to multiple hypotheses in a MTP
- Developed initially by Bretz et al (SiM 2009) for single stage designs with Bonferroni based tests
- Extended to adaptive two-stage adaptive designs that allow **early stopping, dropping of hypotheses, alteration of graphs, sample size re-assessment**
- Utilize nonparametric, parametric and mixed tests depending on knowledge of correlations among the hypotheses
- Established that CER method dominates over PVcombo method over wide range of scenarios and decision rules

Publication

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Graph Based, Adaptive, Multiarm, Multiple Endpoint, Two-Stage Designs

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