

# Clinical trials with multiple objectives – optimal rejection regions based on Neyman-Pearson tests

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# General Framework

- Interested in testing two elementary null hypotheses  $H_i : \mu_i \leq 0$  ( $i = 1, 2$ )
- Associated with two (correlated) bivariate normal Z-statistics

$$Z_1, Z_2 \sim N\left((\mu_1, \mu_2), \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right)$$

- Directly applicable to common testing scenarios, e.g.:
  - Comparison of two treatment arms against a common control with equal sample sizes for all 3 groups gives  $\rho = 0.5$ , i.e. “Dunnett Situation” ( $\rho$  will depend on the allocation ratio)
  - When testing the full population and a subgroup ( $\rho$  will depend on size of subgroup)
  - Correlated co-primary endpoints (here  $\rho$  usually is unknown)
- Type I error inflation when each hypothesis is tested naively at  $\alpha$

# Objectives

- How can we test an elementary null hypothesis  $H_i : \mu_i \leq 0$  ( $i = 1, 2$ )
  - while controlling Familywise Error Rate (FWER) at level  $\alpha$ ?
  - and maximising the power?

FWER: probability of incorrectly rejecting at least one null hypothesis

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  - while controlling Familywise Error Rate (FWER) at level  $\alpha$ ?
  - and maximising the power?
- Use closed testing principle and define test for the intersection hypothesis
  - Reject  $H_i$  if  $Z_i \geq z_{1-\alpha}$  **and** a test for the intersection  $H_{12}$  can be rejected at level  $\alpha$
  - Intersection point null  $H_{12} : (\mu_1, \mu_2) = (0, 0)$
  - **Maximising power** at  $(\mu_1, \mu_2) = (\theta'_1, \theta'_2)$
  - **Controlling Type I Error Rate** under the point null at level  $\alpha$

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  - **Maximising power** at  $(\mu_1, \mu_2) = (\theta'_1, \theta'_2)$
  - **Controlling Type I Error Rate** under the point null at level  $\alpha$
- Apply Neyman-Pearson Lemma

FWER: probability of incorrectly rejecting at least one null hypothesis

# Optimising The Intersection Hypothesis $H_{12}$ Test

- According to Neyman-Pearson Lemma the most powerful test for testing  $H_{12}$  against point alternative has the rejection region in a  $Z_1$  and  $Z_2$  plane

$$R = \{(Z_1, Z_2) | w_1 Z_1 + w_2 Z_2 \geq c\},$$

where  $w_1 = \frac{\theta'_1 - \rho\theta'_2}{(1-\rho^2)}$ ,  $w_2 = \frac{\theta'_2 - \rho\theta'_1}{(1-\rho^2)}$ , and

$$c = \Phi^{-1}(1 - \alpha) \sqrt{w_1^2 + w_2^2 + 2w_1 w_2 \rho}$$

- For a proof see BITTMAN ET AL (2009)

# Optimal Rejection Regions

The rejection region boundary  $w_1 Z_1 + w_2 Z_2 = c$  has a negative slope if

- $\rho \leq 0$
- $\rho > 0$  and  $\theta'_1/\theta'_2 > \rho$
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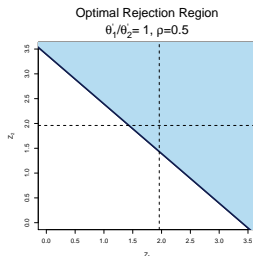


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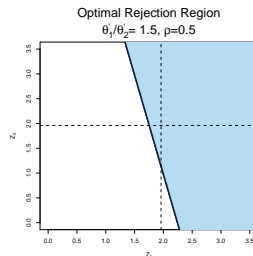
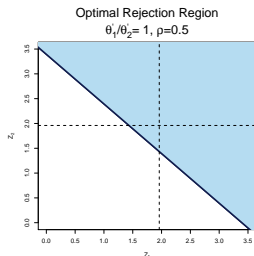


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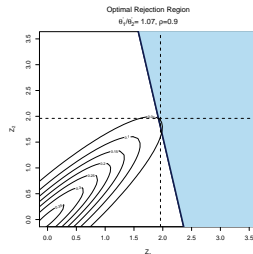
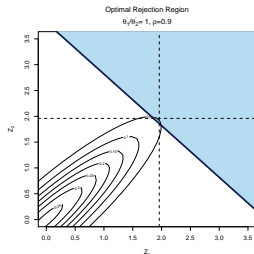


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$\rho = 0.9$ :

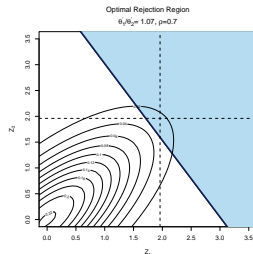
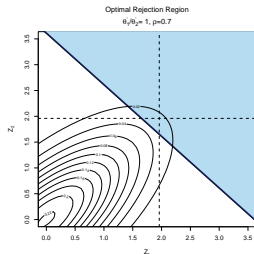


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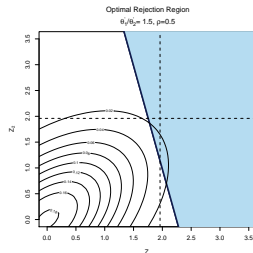
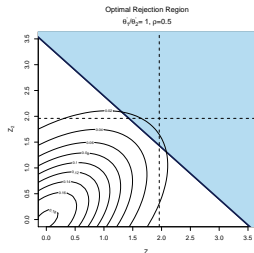


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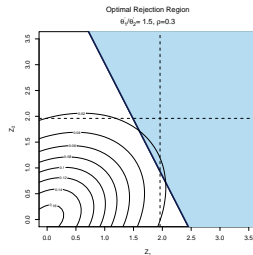
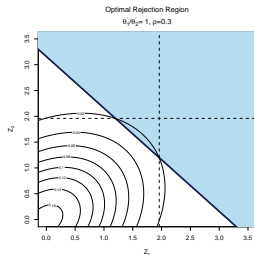


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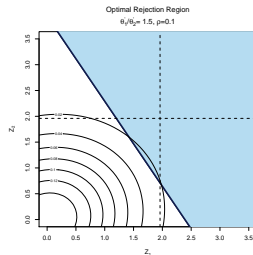
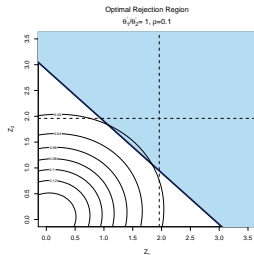


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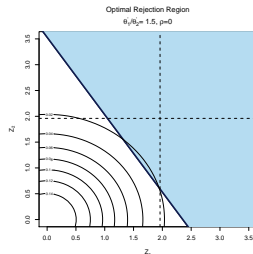
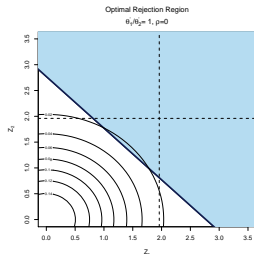


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$$\rho = 0:$$



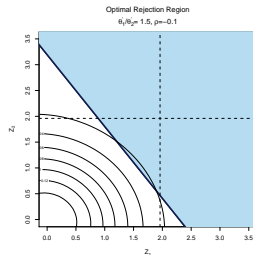
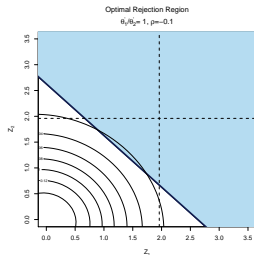


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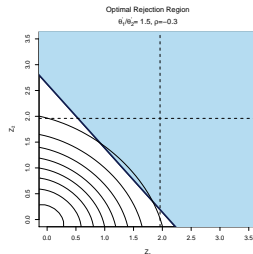
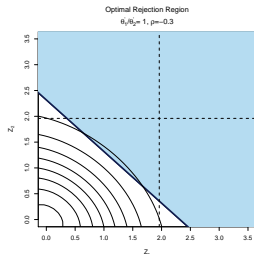


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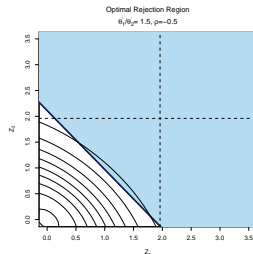
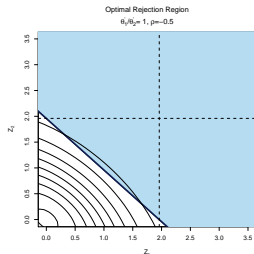


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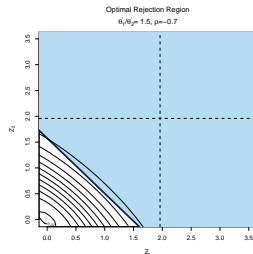
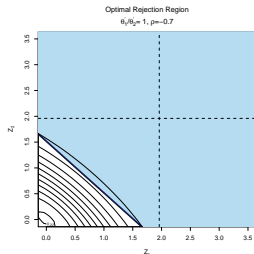


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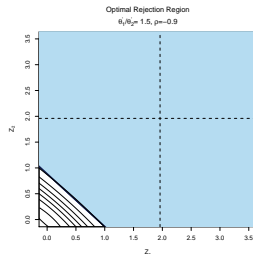
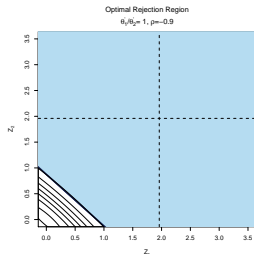


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# Optimal Rejection Regions

The rejection region boundary

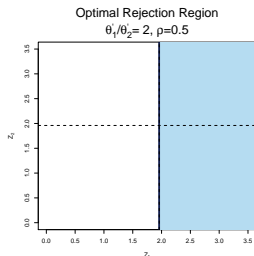
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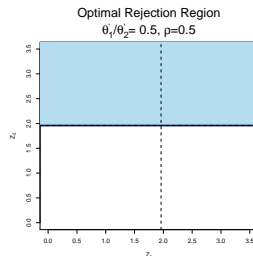
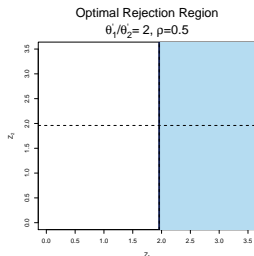


# Optimal Rejection Regions

The rejection region boundary

- Is a vertical line if  $\theta'_1/\theta'_2 = 1/\rho$  for  $\rho \geq 0$ 
  - Optimal test depends on  $Z_1$  only
- Is a horizontal line if  $\theta'_1/\theta'_2 = \rho$  for  $\rho \geq 0$ 
  - Optimal test depends on  $Z_2$  only

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# Optimal Rejection Regions

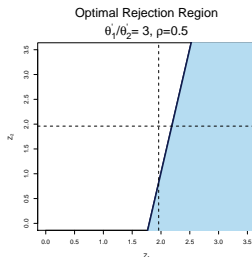
The rejection region boundary has a positive slope if

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The rejection region boundary has a positive slope if

- $\theta'_1/\theta'_2 > 1/\rho$  for  $\rho > 0$

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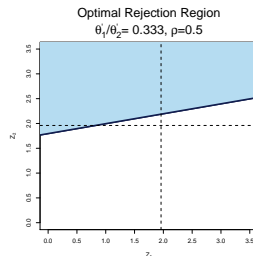
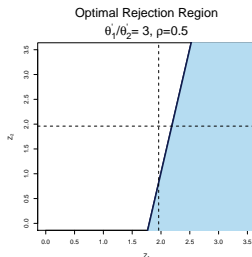


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The rejection region boundary has a positive slope if

- $\theta'_1/\theta'_2 > 1/\rho$  for  $\rho > 0$
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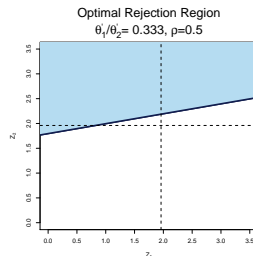
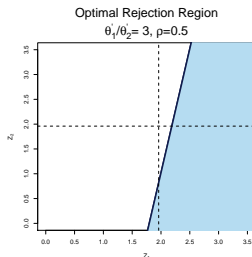
- $\theta'_1/\theta'_2 > 1/\rho$  for  $\rho > 0$
- $\theta'_1/\theta'_2 < \rho$  for  $\rho > 0$

Under these configurations Type I Error of point null hypothesis  $H_{12}$  is controlled, but **NOT** of the composite null hypothesis

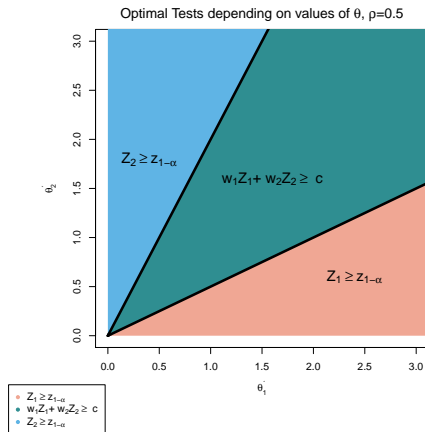
$$H_{12} = \{(\mu_1, \mu_2) | \mu_1 \leq 0 \wedge \mu_2 \leq 0\}$$

- E.g. Type I Error when  $(\mu_1 = 0, \mu_2 \rightarrow -\infty) = 1!$

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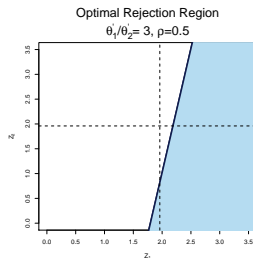


# Testing Composite Intersection Null Hypothesis

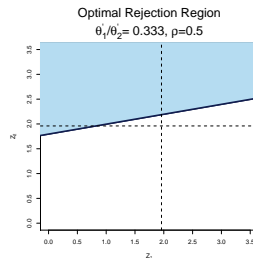


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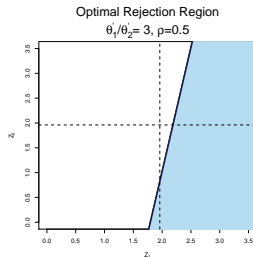
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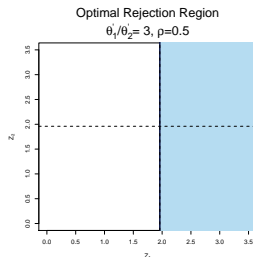
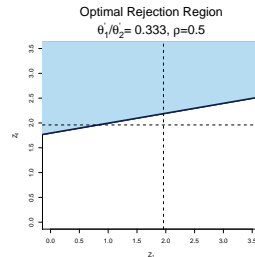
Rejection  
Region for  
The Point  
Null  $H_{12}$



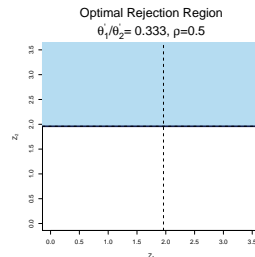
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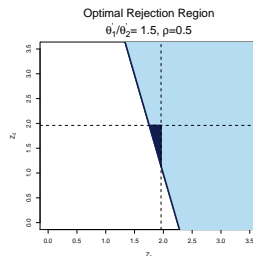
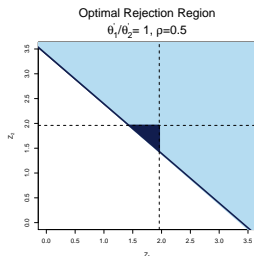


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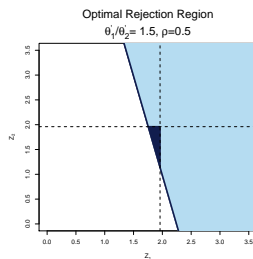
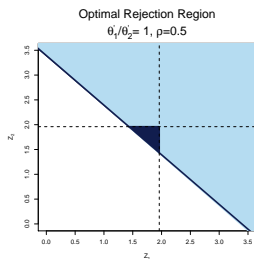


## NON-CONSONANT TESTS



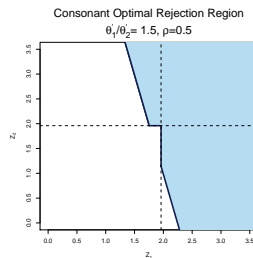
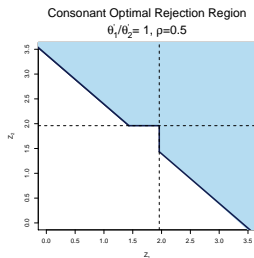
# Consonant Rejection Regions

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  - For some outcomes the intersection hypothesis is rejected but none of the elementary hypotheses  $H_i$  ( $i = 1, 2$ ) can be rejected



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  - Exclusion of the region where  $H_1$  and  $H_2$  cannot be rejected

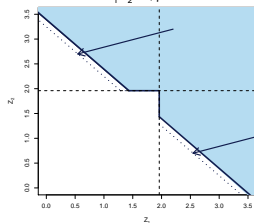


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  - Exclusion of the region where  $H_1$  and  $H_2$  cannot be rejected
  - Shift of the rejection line

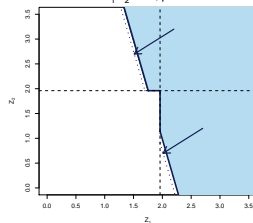
Truncated Consonant Optimal Rejection Region

$$\theta_1/\theta_2 = 1, \rho = 0.5$$



Truncated Consonant Optimal Rejection Region

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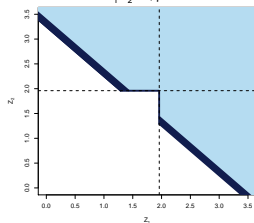


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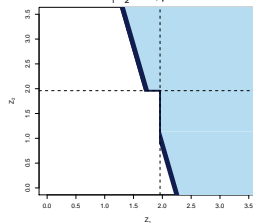
Truncated Consonant Optimal Rejection Region

$$\theta'_1/\theta'_2 = 1, \rho = 0.5$$



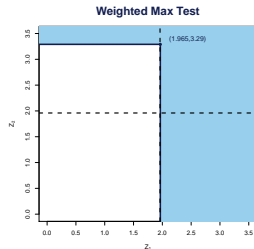
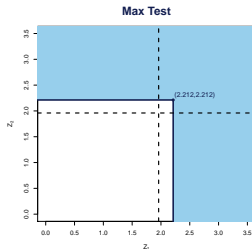
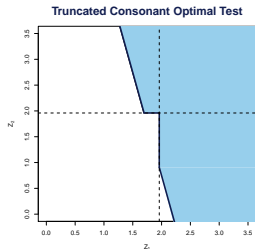
Truncated Consonant Optimal Rejection Region

$$\theta'_1/\theta'_2 = 1.5, \rho = 0.5$$



# Power Considerations Within Closed Testing:

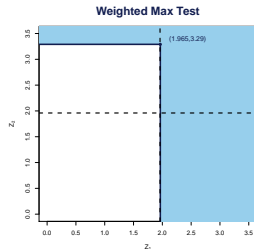
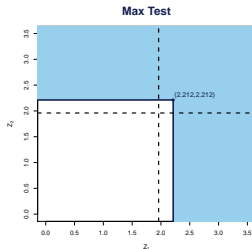
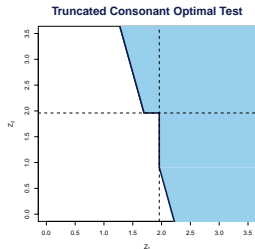
$$\rho = 0.5, \theta'_1 = 3, \theta'_2 = 2$$



True Effect	Disjunctive Power	
$\mu_1 = 3.0, \mu_2 = 2.0$	0.86151	0.85117

# Power Considerations Within Closed Testing:

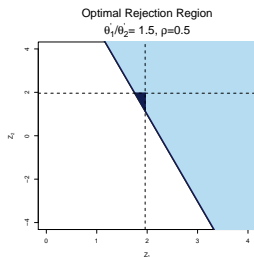
$$\rho = 0.5, \theta'_1 = 3, \theta'_2 = 2$$



True Effect	Disjunctive Power	
$\mu_1 = 3.0, \mu_2 = 2.0$	0.86151	0.85117
$\mu_1 = 1.5, \mu_2 = 3.0$	0.51703	0.50952

# How to make optimal tests more robust?

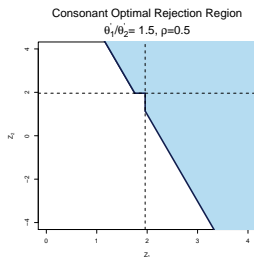
- Alternative approaches
  - Instead of shifting the line, bound the region with horizontal and vertical lines while fully exhausting  $\alpha$





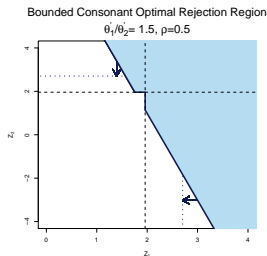
# How to make optimal tests more robust?

- Alternative approaches
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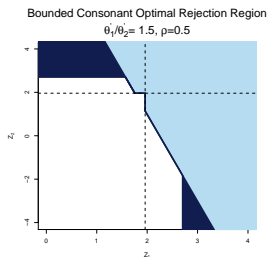
# How to make optimal tests more robust?

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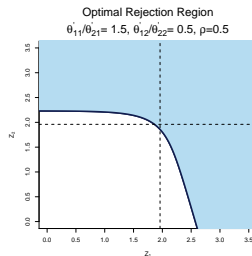
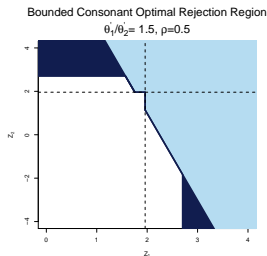
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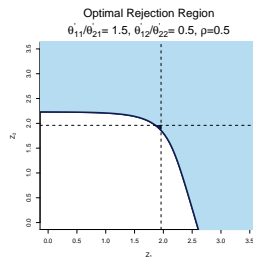
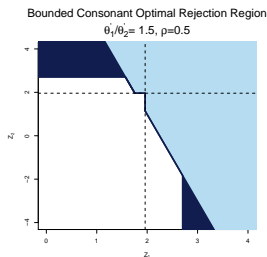
# How to make optimal tests more robust?

- Alternative approaches
  - Instead of shifting the line, bound the region with horizontal and vertical lines while fully exhausting  $\alpha$
  - Use a two-point alternative, each with assigned probability



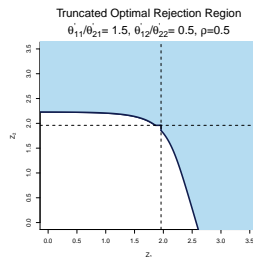
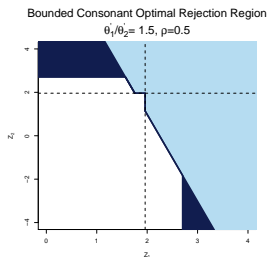
# How to make optimal tests more robust?

- Alternative approaches
  - Instead of shifting the line, bound the region with horizontal and vertical lines while fully exhausting  $\alpha$
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# How to make optimal tests more robust?

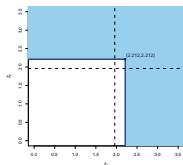
- Alternative approaches
  - Instead of shifting the line, bound the region with horizontal and vertical lines while fully exhausting  $\alpha$
  - Use a two-point alternative, each with assigned probability



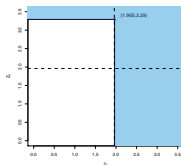
# How to make optimal tests more robust?

- Alternative approaches
  - Instead of shifting the line, bound the region with horizontal and vertical lines while fully exhausting  $\alpha$
  - Use a two-point alternative, each with assigned probability
- In the following we compare all 5 approaches:

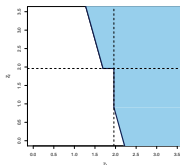
Max Test



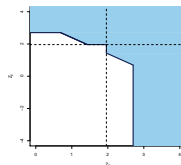
Weighted Max Test



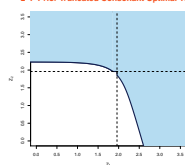
Truncated Consonant Optimal Test



Bounded Consonant Optimal Test



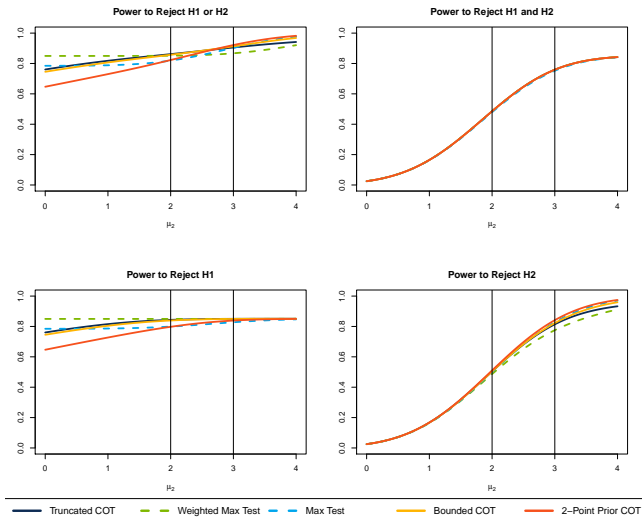
2-P Prior Truncated Consonant Optimal Test



# Robustness of approaches when $\mu$ is different than $\theta'$

Design parameters:  $\theta'_1 = 3.0$ ,  $\theta'_2 = 2.0$ , ( $\theta''_1 = 1.5$ ,  $\theta''_2 = 3.0$ )

True values:  $\mu_1 = 3.0$ ,  $\mu_2$ : shown on x-axis

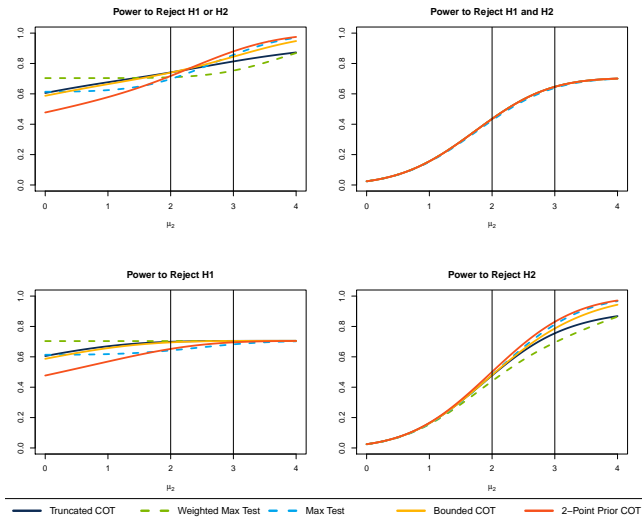




# Robustness of approaches when $\mu$ is different than $\theta'$

Design parameters:  $\theta'_1 = 3.0$ ,  $\theta'_2 = 2.0$ , ( $\theta''_1 = 1.5$ ,  $\theta''_2 = 3.0$ )

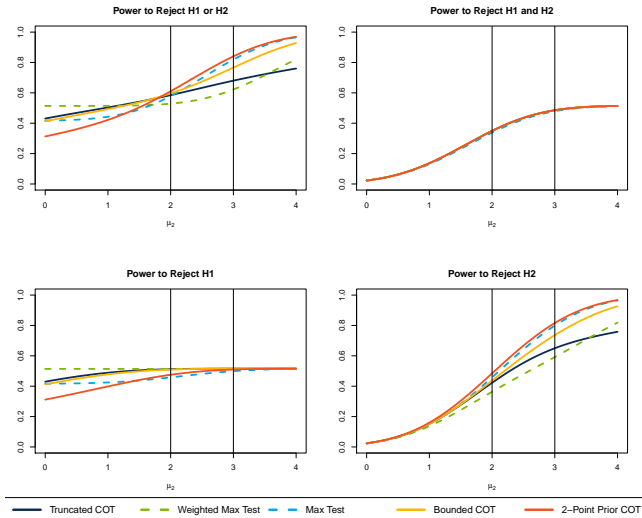
True values:  $\mu_1 = 2.5$ ,  $\mu_2$ : shown on x-axis



# Robustness of approaches when $\mu$ is different than $\theta'$

Design parameters:  $\theta'_1 = 3.0$ ,  $\theta'_2 = 2.0$ , ( $\theta''_1 = 1.5$ ,  $\theta''_2 = 3.0$ )

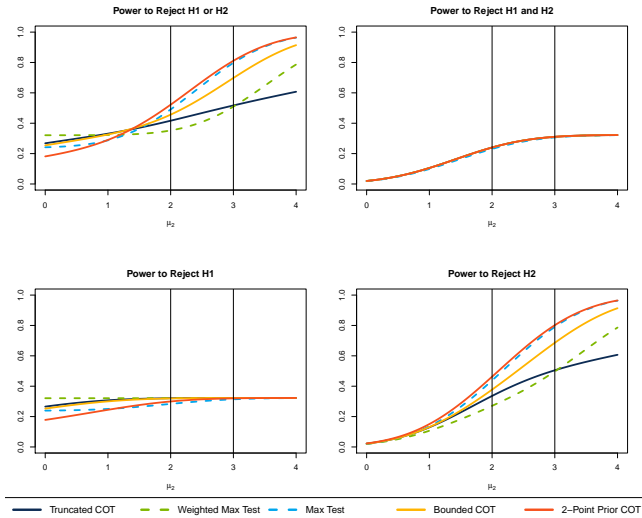
True values:  $\mu_1 = 2.0$ ,  $\mu_2$ : shown on x-axis



# Robustness of approaches when $\mu$ is different than $\theta'$

Design parameters:  $\theta'_1 = 3.0$ ,  $\theta'_2 = 2.0$ , ( $\theta''_1 = 1.5$ ,  $\theta''_2 = 3.0$ )

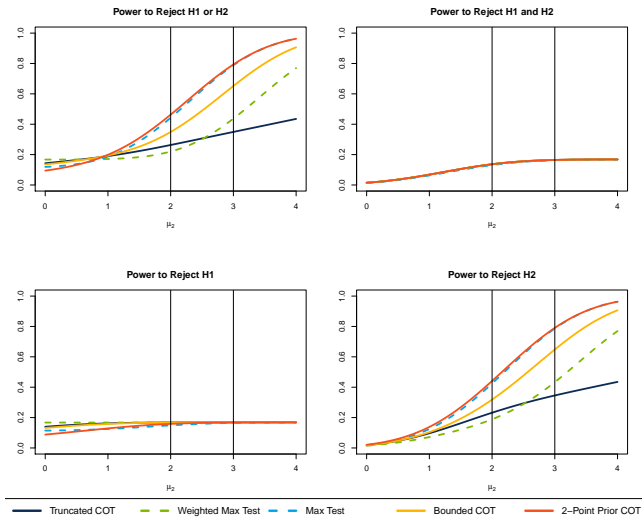
True values:  $\mu_1 = 1.5$ ,  $\mu_2$ : shown on x-axis



# Robustness of approaches when $\mu$ is different than $\theta'$

Design parameters:  $\theta'_1 = 3.0$ ,  $\theta'_2 = 2.0$ , ( $\theta''_1 = 1.5$ ,  $\theta''_2 = 3.0$ )

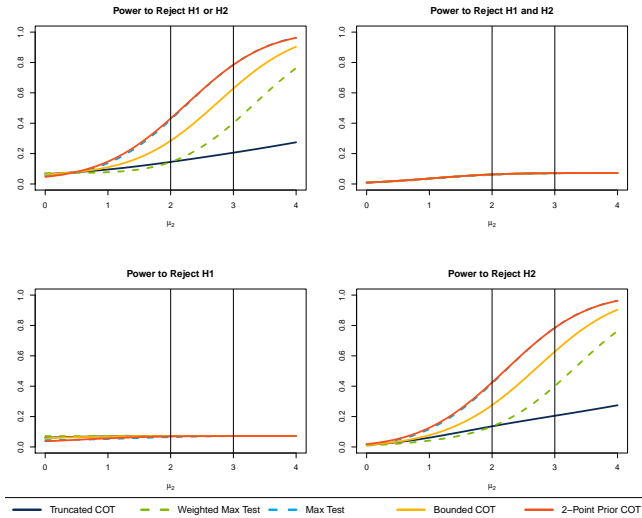
True values:  $\mu_1 = 1.0$ ,  $\mu_2$ : shown on x-axis



# Robustness of approaches when $\mu$ is different than $\theta'$

Design parameters:  $\theta'_1 = 3.0$ ,  $\theta'_2 = 2.0$ , ( $\theta''_1 = 1.5$ ,  $\theta''_2 = 3.0$ )

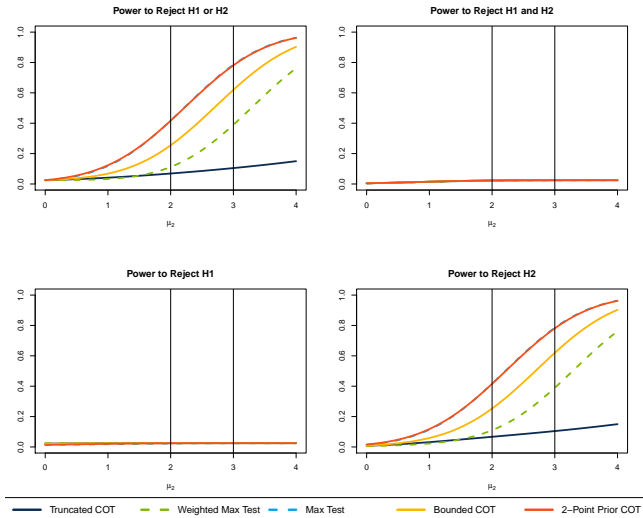
True values:  $\mu_1 = 0.5$ ,  $\mu_2$ : shown on x-axis



# Robustness of approaches when $\mu$ is different than $\theta'$

Design parameters:  $\theta'_1 = 3.0$ ,  $\theta'_2 = 2.0$ , ( $\theta''_1 = 1.5$ ,  $\theta''_2 = 3.0$ )

True values:  $\mu_1 = 0.0$ ,  $\mu_2$ : shown on x-axis



# Remarks on correlation

- (Consonant) Optimal test directly applicable if  $\rho$  is known. This is the case if correlation is induced by design (e.g., for many-one comparisons or subgroup testing)
- More problematic if  $\rho$  is unknown, e.g., for different endpoints.
  - good knowledge and/or conservative assumption on  $\rho$
  - plug-in observed correlation
  - plug-in boundary of a confidence interval for observed correlation (Berger and Boos, 1994)

# Conclusions

- We found optimal test for intersection hypothesis  $H_{12}$  with a composite null
- In a Dunnett Situation the Consonant Optimal Test achieves higher power than the (Weighted) Max Test under the target effects
- However, there might be a power loss if the true effect size differs from the pre-specified alternative
- More robust approaches such as Bounded Consonant Optimal Test or use of two-point alternatives can improve the power results
- Use of utility functions (e.g. more weight on one hypothesis, number of rejected hypotheses ...) can be another approach for finding optimal rejection regions (not discussed here)



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Romano, J., Shaikh, A., and Wolf, M. (2011).  
Consonance and the closure method in multiple testing.  
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Su, T., Glimm, E., Whitehead, J., and Branson, M. (2012).  
An evaluation of methods for testing hypotheses relating to two endpoints in a single clinical trial.  
*Statistics in Medicine*, 11:107–117.

# Are there any questions?



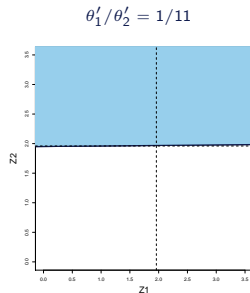
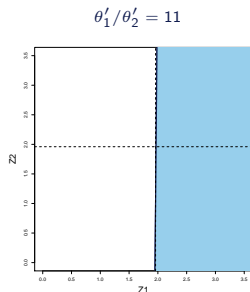
# BACK-UP

# Optimal Rejection Regions

The rejection region boundary has a positive slope if

- $\theta'_1/\theta'_2 > 1/\rho$  for  $\rho > 0$
- $\theta'_1/\theta'_2 < \rho$  for  $\rho > 0$

$\rho = 0.1$ :

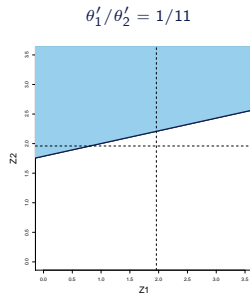
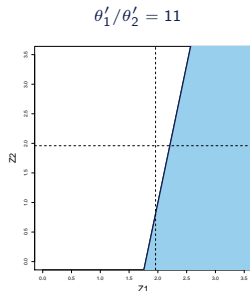


# Optimal Rejection Regions

The rejection region boundary has a positive slope if

- $\theta'_1/\theta'_2 > 1/\rho$  for  $\rho > 0$
- $\theta'_1/\theta'_2 < \rho$  for  $\rho > 0$

$\rho = 0.3$ :

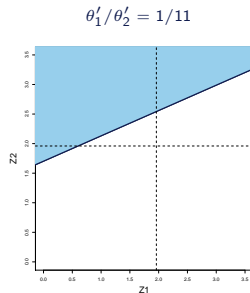
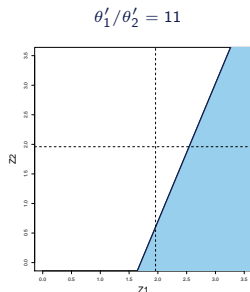


# Optimal Rejection Regions

The rejection region boundary has a positive slope if

- $\theta'_1/\theta'_2 > 1/\rho$  for  $\rho > 0$
- $\theta'_1/\theta'_2 < \rho$  for  $\rho > 0$

$\rho = 0.5$ :

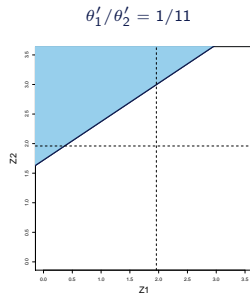
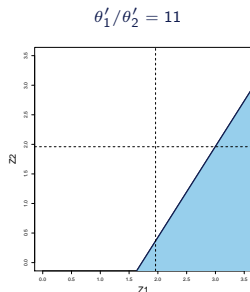


# Optimal Rejection Regions

The rejection region boundary has a positive slope if

- $\theta'_1/\theta'_2 > 1/\rho$  for  $\rho > 0$
- $\theta'_1/\theta'_2 < \rho$  for  $\rho > 0$

$\rho = 0.7$ :

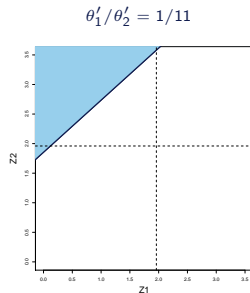
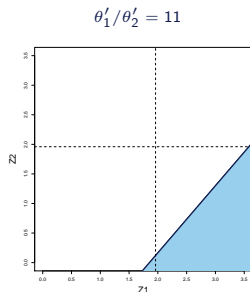


# Optimal Rejection Regions

The rejection region boundary has a positive slope if

- $\theta'_1/\theta'_2 > 1/\rho$  for  $\rho > 0$
- $\theta'_1/\theta'_2 < \rho$  for  $\rho > 0$

$\rho = 0.9$ :



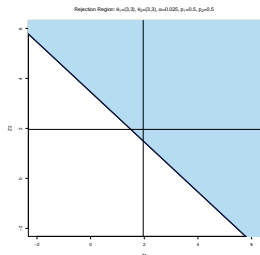


# Two-point alternative

Two sets of alternatives considered such that:

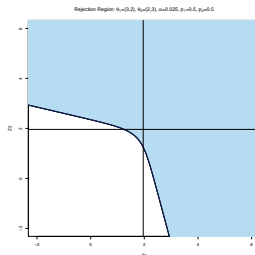
- $ALR = \frac{f_{H'}(Z_1, Z_2)}{f_H(Z_1, Z_2)} = \frac{\sum_{i=1}^2 p_i f_{H'_i}(Z_1, Z_2)}{f_H(Z_1, Z_2)}$
- Rejection region cannot be found analytically. Numerical approximation instead
- Rejection regions change depending on  $\theta'_{1i}/\theta'_{2i}$

# Two-point Alternative Rejection Regions



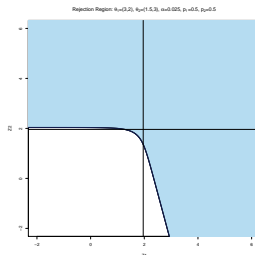
- Rejection regions change depending on  $\theta'_{1i}/\theta'_{2i}$ 
  - If none of the alternatives has  $\theta'_1/\theta'_2 > 1/\rho$ , then the shape does not cross the lines  $Z_{1-\alpha}$

# Two-point Alternative Rejection Regions



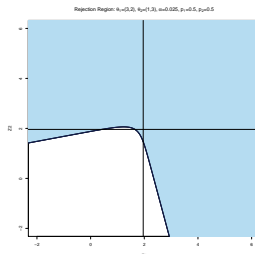
- Rejection regions change depending on  $\theta'_{1i}/\theta'_{2i}$ 
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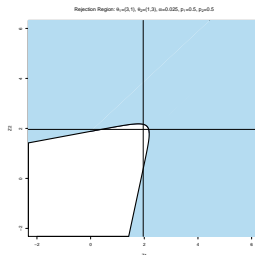
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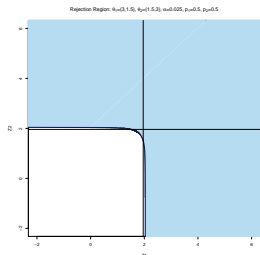
- Rejection regions change depending on  $\theta'_1/\theta'_2$ 
  - If none of the alternatives has  $\theta'_1/\theta'_2 > 1/\rho$ , then the shape does not cross the lines  $Z_{1-\alpha}$
  - If one of the alternatives has  $\theta'_1/\theta'_2 > 1/\rho$ , then the rejection region boundary crosses  $Z_{1-\alpha}$

# Two-point Alternative Rejection Regions



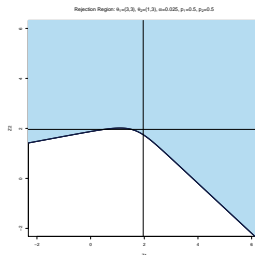
- Rejection regions change depending on  $\theta'_{1i}/\theta'_{2i}$ 
  - If none of the alternatives has  $\theta'_1/\theta'_2 > 1/\rho$ , then the shape does not cross the lines  $Z_{1-\alpha}$
  - If one of the alternatives has  $\theta'_1/\theta'_2 > 1/\rho$ , then the rejection region boundary crosses  $Z_{1-\alpha}$
  - If the alternatives have  $\theta'_1/\theta'_2 > 1/\rho$  and  $\theta'_2/\theta'_1 > 1/\rho$ , then the rejection region boundary crosses the lines  $Z_i = Z_{1-\alpha}$

# Two-point Alternative Rejection Regions



- Rejection regions change depending on  $\theta'_{1i}/\theta'_{2i}$ 
  - If none of the alternatives has  $\theta'_1/\theta'_2 > 1/\rho$ , then the shape does not cross the lines  $Z_{1-\alpha}$
  - If one of the alternatives has  $\theta'_1/\theta'_2 > 1/\rho$ , then the rejection region boundary crosses  $Z_{1-\alpha}$
  - If the alternatives have  $\theta'_1/\theta'_2 > 1/\rho$  and  $\theta'_2/\theta'_1 > 1/\rho$ , then the rejection region boundary crosses the lines  $Z_i = Z_{1-\alpha}$

# Two-point Alternative Rejection Regions



- Rejection regions change depending on  $\theta'_{1i}/\theta'_{2i}$ 
  - If none of the alternatives has  $\theta'_1/\theta'_2 > 1/\rho$ , then the shape does not cross the lines  $Z_{1-\alpha}$
  - If one of the alternatives has  $\theta'_1/\theta'_2 > 1/\rho$ , then the rejection region boundary crosses  $Z_{1-\alpha}$
  - If the alternatives have  $\theta'_1/\theta'_2 > 1/\rho$  and  $\theta'_2/\theta'_1 > 1/\rho$ , then the rejection region boundary crosses the lines  $Z_i = Z_{1-\alpha}$



# Two- and N-Point Priors

- Conjecture that rejection boundary of optimal test is concave for any prior
- For consonant test, truncation has to be performed
- For smaller values of z-statistics, the rejection region would be bounded by  $z_{1-\alpha}$ .

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