

## 2 Adaptive FWER control

### 2.1 known dependence

Gaussian case with known  $\Sigma$ , but arbitrary with  $\tau_{ii} = 1$  for all:

Let us work with test statistics  $T_j(X) = \begin{cases} X_j & \text{(one sided)} \\ |X_j| & \text{(two sided)} \end{cases}, 1 \leq j \leq m$

Consider the threshold  $S_\alpha(\Sigma) = \min \{ x \in \mathbb{R} : \mathbb{P}_{Z \sim \mathcal{N}(0, \Sigma)} \left( \max_{1 \leq j \leq m} T_j(Z) \leq x \right) \geq 1 - \alpha \}$   
↑ quantile computed under the full null.

**Proposition:** In the Gaussian setting (either one-sided or two-sided)

$$\forall P \in \mathcal{D}, \text{FWER}(S_\alpha(\Sigma), P) \leq \alpha$$

And there exists  $P_0$  with  $\text{FWER}(S_\alpha(\Sigma), P_0) = \alpha$ .

**Proof:** 
$$\begin{aligned} \text{FWER}(S_\alpha(\Sigma), P) &= \mathbb{P}(\exists j \in \mathcal{H}_0(P) : T_j(X) > S_\alpha(\Sigma)) \\ &= \mathbb{P}\left(\sup_{j \in \mathcal{H}_0(P)} T_j(X) > S_\alpha(\Sigma)\right) \end{aligned}$$

Since  $\forall j \in \mathcal{H}_0(P), T_j(X) \leq T_j(X - \mu)$  (both one-sided or two-sided)

$$\text{The latter is } \leq \mathbb{P}\left(\sup_{j \in \mathcal{H}_0(P)} T_j(X - \mu) > S_\alpha(\Sigma)\right) \leq \mathbb{P}\left(\sup_{1 \leq j \leq m} T_j(X - \mu) > S_\alpha(\Sigma)\right) \leq \alpha$$

=  $Z \sim \mathcal{N}(0, \Sigma)$

Moreover, for  $P_0$  such that  $\mu = 0$  (full null)

$$\text{FWER}(S_\alpha(\Sigma), P) = \mathbb{P}\left(\sup_{1 \leq j \leq m} T_j(X - \mu) > S_\alpha(\Sigma)\right) = \alpha \text{ because } \sup_j T_j(X - \mu) \text{ has a continuous distribution}$$

**Examples:** ①  $\Sigma = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$   $\rho$ -equi correlated with  $\rho \geq 0$ , say one-sided □

$Z \sim \mathcal{N}(0, \Sigma)$  can be realized as  $Z_j = \sqrt{\rho} W + \sqrt{1-\rho} \xi_j$  where  $W, \xi_1, \dots, \xi_m$  iid  $\mathcal{N}(0, 1)$

Hence we can compute  $S_\alpha(\Sigma)$  more explicitly via:

$$\mathbb{P}_{Z \sim \mathcal{N}(0, \Sigma)} \left( \max_{1 \leq j \leq m} T_j(Z) \leq x \right) = \mathbb{P}\left(\sqrt{1-\rho} \max_j \xi_j \leq x - \sqrt{\rho} W\right) = \begin{cases} \int \left[ \Phi\left(\frac{x - \sqrt{\rho} w}{\sqrt{1-\rho}}\right) \right]^m \phi(w) dw & \text{if } \rho < 1 \\ \Phi(x) & \text{if } \rho = 1 \end{cases}$$

② Linear model:  $Y = M\beta + \varepsilon$ ,  $\varepsilon \sim \mathcal{N}(0, I_n)$ ,  $M$  full rank ( $n \geq p$ )  
 (standard)  $n \times 1$   $n \times p$   $p \times 1$   $n \times 1$ ,  $[(M^t M)^{-1}]_{jj} = 1 \quad \forall j$

OLS  $\hat{\beta} = (M^t M)^{-1} M^t Y \sim \mathcal{N}(\underbrace{\beta}_{=\mu}, \underbrace{(M^t M)^{-1}}_{=\Sigma})$   
 $= X$

for  $Z \sim \mathcal{N}(0, (M^t M)^{-1})$ , distribution of  $\max_{1 \leq j \leq m} Z_j$  can be approached by Monte-Carlo algorithm

2.2 unknown dependence: the randomization trick

[Westfall and Young (1993)]  
 [Romano and Wolf (2006)]

Consider the two-group model and Student statistics  $T_j(X) = \frac{1}{\sqrt{1/n_0 + 1/n_1}} \frac{|\hat{\mu}_{0j} - \hat{\mu}_{1j}|}{\hat{\sigma}_j}$   
 although we do not assume that  $Q$  is Gaussian nor known

An essential property here is called the randomization property

$(T_j(X))_{j \in \mathcal{H}_0} \sim (T_j(X^\sigma))_{j \in \mathcal{H}_0}$  for any  $\sigma \in \mathcal{L}_n$  true here!

Generate  $\sigma_1 \dots \sigma_B$  iid uniform on  $\mathcal{L}_n$

Consider the threshold  $S_\alpha(X) = \min \left\{ x \in \mathbb{R} : \frac{1}{B+1} \left( 1 + \sum_{b=1}^B \mathbb{1} \left\{ \max_{1 \leq j \leq m} T_j(X^{\sigma_b}) \leq x \right\} \right) \geq 1 - \alpha \right\}$

(also called 'maxT' procedure)

→ mimics the distribution of the max under the null

**Proposition:** In the two-group setting  $\forall P \in \mathcal{P}$ ,  $\text{FWER}(S_\alpha(X), P) \leq \alpha$

**Proof:** first, let us consider the 'ideal threshold'

$S_\alpha^\circ(X) = \min \left\{ x \in \mathbb{R} : \frac{1}{B+1} \left( 1 + \sum_{b=1}^B \mathbb{1} \left\{ \max_{j \in \mathcal{H}_0(P)} T_j(X^{\sigma_b}) \leq x \right\} \right) \geq 1 - \alpha \right\}$

Obviously  $S_\alpha^\circ(X) \leq S_\alpha(X)$

First,  $\forall t > S_\alpha(X)$ ,  $t > S_\alpha^\circ(X)$ , and thus by def of the quantile  $S_\alpha^\circ(X)$ ,

$$\frac{1}{B+1} \left( 1 + \sum_{b=1}^B \mathbb{1} \left\{ \max_{j \in \mathcal{H}_b(P)} T_j(X^{\sigma_b}) \geq t \right\} \right) \leq \frac{1}{B+1} \left( 1 + \sum_{b=1}^B \mathbb{1} \left\{ \max_{j \in \mathcal{H}_b(P)} T_j(X^{\sigma_b}) > S_\alpha(X) \right\} \right) \leq \alpha$$

Hence,

$$\text{FWER}(S_\alpha, P) = \mathbb{P} \left( \max_{j \in \mathcal{H}(P)} T_j(X) > S_\alpha(X) \right) = \mathbb{P} \left( \frac{1}{B+1} \sum_{b=0}^B \mathbb{1} \{ Y_b \geq Y_0 \} \leq \alpha \right)$$

where  $Y_0 = \max_{j \in \mathcal{H}(P)} T_j(X)$  and  $Y_b = \max_{j \in \mathcal{H}_b(P)} T_j(X^{\sigma_b})$

Now, by the **randomization hypo**, we can show that  $(Y_0, \dots, Y_B)$  is exchangeable

We can conclude the proof by the same argument as in Part I (2) □

### ③ Step down refinement

[Westfall and Young (1993)] [Romano and Wolf (2005)]

Remember:  $\text{FWER}(R^{\text{Bonf}}, P) \leq \alpha \frac{m_0(P)}{m}$  may be not close to  $\alpha$

In fact: same phenomenon with the previous  $S_\alpha(\Gamma)$  or  $S_\alpha(X)$

because the max is taken under the full null, as if  $\mathcal{H}_0(P) = \{1, \dots, m\}$

**Idea**: if  $A_0$  is the set accepted nulls, apply the same method in restriction to  $A_0$ . This gives a new set of rejection. Iterate until convergence.

**Formally** consider  $R_\mathcal{G}$  rejected set and  $A_\mathcal{G} = \{1, \dots, m\} \setminus R_\mathcal{G}$  for some arbitrary  $\mathcal{G} \subset \{1, \dots, m\}$

**SD algorithm**: \* step 0: let  $\mathcal{G}_0 = \mathcal{H}$

\* step  $j \geq 1$ : let  $\mathcal{G}_j = A_{\mathcal{G}_{j-1}}$  if  $\mathcal{G}_j = \mathcal{G}_{j-1}$  stop and let  $\hat{\mathcal{G}} = \mathcal{G}_j$   
otherwise go to step  $j+1$

**Proposition**: In a multiple testing framework consider a family  $(R_\mathcal{G})_{\mathcal{G} \subset \mathcal{H}}$  of multiple testing procedures satisfying (i)  $\forall P \in \mathcal{P}$ , for  $\mathcal{G} = \mathcal{H}_0(P)$ ,  $\text{FWER}(R_\mathcal{G}, P) \leq \alpha$   
(ii)  $\forall \mathcal{G}, \mathcal{G}' \subset \mathcal{H}$ ,  $\mathcal{G} \subset \mathcal{G}' \Rightarrow A_\mathcal{G} \subset A_{\mathcal{G}'}$

Then  $\forall P \in \mathcal{P}$ ,  $\text{FWER}(R_{\hat{\mathcal{G}}}, P) \leq \alpha$

**Proof:** On an event with proba  $\geq 1 - \alpha$  we have  $\mathcal{H}_0(P) \subset A_{\mathcal{H}_0(P)}$  by (i)

On this event, we can show that  $\mathcal{H}_0(P) \subset A_{\hat{\rho}}$  by the following argument:

for all  $j \geq 0$ ,  $\mathcal{H}_0(P) \subset \mathcal{C}_j$  implies  $A_{\mathcal{H}_0(P)} \subset A_{\mathcal{C}_j} = \mathcal{C}_{j+1}$  by (ii) and thus  $\mathcal{H}_0(P) \subset \mathcal{C}_{j+1}$   
 since  $\mathcal{H}_0(P) \subset \mathcal{C}_0 = \mathcal{H}$  we have  $\mathcal{H}_0(P) \subset \mathcal{C}_j$  for all  $j$  □

**Application 1:** Bonferroni type  $R_{\rho} = \{1 \leq j \leq m : p_j(X) \leq \frac{\alpha}{|B|}\}$  satisfies (i) and (ii)

This provides the Holm procedure (= SD version of Bonferroni)

**Application 2:** Gaussian model with known covariance  $\Upsilon$

(i) and (ii) satisfied with the RW-type  $R_{\rho} = \{1 \leq j \leq m : T_j(X) > S_{\rho}(\tau)\}$

where  $S_{\rho}(\tau) = \min \{x \in \mathbb{R} : \mathbb{P}(\max_{Z \sim N(0, \Upsilon)} \{T_j(Z)\}_{j \in \mathcal{C}} \leq x) \geq 1 - \alpha\}$

This provides a step down procedure that incorporates the knowledge of  $\Upsilon$ .

This improves the 'single step' procedure of section 2.1

**Exercise:** simplified formulation

Let us define the step down procedure with critical values  $\tau_{\ell}$ ,  $1 \leq \ell \leq m$  as rejecting the nulls corresponding to  $p_{(1)} \leq \dots \leq p_{(m)}$

for the stopping rule  $\hat{e} = \max \{\ell \in \{0, \dots, m\} : \forall \ell' \leq \ell, p_{(\ell')} \leq \tau_{\ell'}\}$  (#)

(mind the conventions  $p_{(0)} = 0, \tau_0 = 0$ )

① Show that the Holm procedure corresponds to the step down procedure with critical values  $\tau_{\ell} = \frac{\alpha}{m - \ell + 1}$ ,  $1 \leq \ell \leq m$

② In the Gaussian equicorrelated with known equi-correlation  $\rho \in [0, 1]$  (say two-sided) show that the RW step down procedure corresponds to the step down procedure with the critical values

$\tau_{\ell}(\tau) = \min \{x \in \mathbb{R} : \mathbb{P}(\min_{1 \leq j \leq m - \ell + 1} \{2 \Phi(|X_j|)\} \leq x) \geq 1 - \alpha\}$ ,  $1 \leq \ell \leq m$

### Application 3 Two-group case with unknown dependence

(i) and (ii) satisfied with the RW-type  $R_g = \{ 1 \leq j \leq m : T_j(X) > S_g(X) \}$

$$S_g(X) = \min \left\{ x \in \mathbb{R} : \frac{1}{B+1} \left( 1 + \sum_{b=1}^B 1 \right) \max_{j \in \mathcal{G}} T_j(X^{(b)}) \leq x \right\} \geq 1 - \alpha$$

This improves the 'single-step' procedure found in (2.2) especially when many signal