### 1 Simultaneous vs Selective Inference

**Last time**: Solve all inference problems at once, guarantee 0 type I errors (w.p.  $1 - \alpha$ ) **Logic**: Then, ok to cherrypick "interesting" results

**Example 1.1.**  $X_i = \mu_i + \varepsilon_i$ ,  $\varepsilon_i \stackrel{\text{iid}}{\sim} N(0,1)$ ,  $i = 1, \ldots, n$ 

- 1. Select  $i^* = \arg \max X_i$
- 2. Report a CI for  $\mu_{i^*}$ . Note  $\mu_{i^*}$  not necessarily equal to  $\max_i \mu_i$ .

## 1.1 Simultaneous approach

Construct intervals  $C_i = X_i \pm z_{\tilde{\alpha}_n/2}$  where

$$\tilde{\alpha}_n = 1 - (1 - \alpha)^{1/n} \approx \alpha/n \tag{1.1}$$

$$z_{\tilde{\alpha}_n/2} \approx \sqrt{2\log n} \tag{1.2}$$

Report  $C_{i^*(X)(X)}$ .

$$\mathbb{P}_{u}[\mu_{i^*} \notin C_{i^*}] \le \mathbb{P}_{u}[\mu_{i} \notin C_{i}, \text{ any } i] = \alpha \tag{1.3}$$

Two issues:

- 1) We expect  $X_{i^*} > \mu_{i^*}$  So why inflate symmetrically?
- 2) What if  $\mu_1 \gg \max_{i>1} \mu_i$   $\mathbb{P}[i^* = 1] \approx 1$   $\mathbb{P}[\mu_{i^*} \notin C_{i^*}] \approx P[\mu_1 \notin C_1] \approx \alpha/n$

# 1.2 Selective approach

**Idea**: Design  $C_i$  to guarantee

$$\mathbb{P}_{\mu}[\mu_i \not\in C_i \mid i^* = i] = \alpha \tag{1.4}$$

Then we have

$$\mathbb{P}_{\mu}[\mu_{i^*} \notin C_{i^*}] = \mathbb{E}_{\mu}[\mathbb{P}_{\mu}[\mu_i^* \notin C_{i^*} \mid i^*]] = \alpha \tag{1.5}$$

The conditional distribution

$$P(X \mid i^*(x) = i) \propto e^{-\frac{1}{2}||x - \mu||^2} 1_{\underset{j \neq i}{\underbrace{x_i > \max_{j \neq i} x_j}}}$$
(1.6)

$$\propto e^{\mu' x} e^{-\|x\|^2/2} 1_{x \in A_i} \tag{1.7}$$

$$= e^{\mu_i x_i + \mu'_{-i} x_{-i}} e^{-\|x\|^2 / 2} \mathbf{1}_{x \in A_i}$$
(1.8)

UMPU test of  $H_0: \mu_i = c$  condition on  $x_i$ 

Reduced the problem to same case as when we had nuisance parameters.

TODO: Fig 28.1

**Note**: Interval for  $\mu_i$  only defined as  $A_i$ .

Suppose  $\mu_1 \gg \max_{i>1} \mu_i$ .

Then  $X_1 \gg \max_{i>1} X_i$  (whp) and conditional inference  $\approx$  marginal inference. So  $C_{i^*} \stackrel{whp}{=} C_1 \approx X_1 \pm z_{\alpha/2}.$ 

#### False Discovery Rate (FDR) 2

In 19951988 Benjamini & Hochberg proposed controlling a more liberal error criterion for multiple testing: False Discovery Rate.

**Idea**: Test 500k hypothesis and make 100 rejections, of which 5 are false.

Let V = # false rejections and R = # total rejections.

**Definition 2.1.** The False Discovery Proportion (FDP)

$$FDP = \frac{V}{R} \quad \left[ \frac{0}{0} = 0 \right] \tag{2.1}$$

The FDP is a random variable, so the False Discovery Rate (FDR)

$$FDR = \mathbb{E}[FDP] \tag{2.2}$$

Proposal: control  $FDR \leq \alpha$ 

#### **BH Procedure** 2.1

**Setup**:  $p_1, \ldots, p_n$  *p*-values for  $H_{0,1}, \ldots, H_{0,n}$  independent [uniform if null].

Let  $p_{(1)} \le p_{(2)} \le \cdots \le p_{(n)}$ ,  $H_{0,(i)} =$  hypothesis corresponding to  $p_{(i)}$ . Select  $R = \{r : p_{(r)} \le \frac{\alpha r}{n} \text{ (or 0)}\}.$ 

Reject  $H_{0,(1)}, ..., H_{0,(R)}$  (or none if R = 0).

TODO: Fig 28.2

**Intuition**: Consider the rule rejecting all  $p_i \le t$  for fixd  $t \in [0,1]$ .

$$FDP(t) = \frac{\#\{i \in \mathcal{H}_0 : p_i \le t\}}{1 \vee \#\{i : p_i \le t\}} = \frac{V_t}{1 \vee R_t}$$
 (2.3)

But  $\mathbb{E}V_t = t | \mathcal{H}_0 rvert \leq tn$  and

$$\widehat{FDP}(t) = \frac{nt}{1 \vee R_t} \tag{2.4}$$

**Idea**: Could take  $t^* = \sup\{t : \widehat{FDP}(t) \le \alpha\}$ . Reject all  $H_{0,i}$  with  $p_i \le t^*$ .

*Remark* 2.2. If *R* is BH procedure, then  $p_{(R)} \le t^* \le p_{(R+1)} \implies$  BH-procedure equivalent to " $t^*$  procedure"

*Proof.* Consider  $t = p_{(i)}$ .

$$\widehat{FDP}(p_{(i)}) \le \alpha \iff \frac{np_{(i)}}{i} \le \alpha \iff p_{(i)} \le \alpha \tag{2.5}$$

Also  $\widehat{FDP}(t) \uparrow$  in t between order statistics (jumps at order statistics) TODO: Fig 28.3

**Theorem 2.3** (Storey, Taylor, & Siegmund). *BH-procedure controls FDR*.

Define  $M_t = \frac{V_t}{nt}$ .  $M_t$  is a MG as t goes from  $1 \to 0$  wrt  $\mathcal{F} = \sigma(p_i : i \notin \mathcal{H}_0 \text{ or } p_i > t)$ For s < t,  $V_s \mid \mathcal{F}_t \sim Binom(V_t, \frac{s}{t})$ .

$$\mathbb{E}[M_s \mid \mathcal{F}_t] = \frac{1}{ns} \mathbb{E}[V_s \mid \mathcal{F}_t]$$
 (2.6)

$$=\frac{1}{ns}V_t\cdot\frac{s}{t}\tag{2.7}$$

$$=\frac{1}{ns}(M_tnt)\frac{s}{t}=M_t \tag{2.8}$$

 $t^*$  is a stopping time wrt  $(\mathcal{F}_t)$ .

$$FDR = \mathbb{E}[FDP(t^*)] = \mathbb{E}[\widehat{FDP}(t^*M_{t^*})] = \mathbb{E}[\alpha M_{t^*}] = \alpha \mathbb{E}[M_1] = \alpha \frac{|\mathcal{H}_0|}{TODO: ??} \le \alpha \quad (2.9)$$