1 Multiple Testing

A multiple testing problem is one where we test > 1 hypotheses using same data set.

Example 1.1.
$$X_i \stackrel{\text{iid}}{\sim} N(\mu_i, 1), i = 1, ..., n$$
 $H_{0,i}: \mu_i = 0, H_{1,i}: \mu_i \neq 0$

Common setup:

- Measuring crop yields / patient outcomes under different treatments
- Gene expression of n genes in cancer vs controls / FMRI meas. in n voxels

Example 1.2.
$$p_i \in [0,1], i = 1,...,n \ (i \in \mathcal{I})$$

 $H_{0,i}: p_i \sim U[0,1]$ [or p_i stoch. larger than U[0,1]]

 $H_{1,i}: p_i$ "smaller"

Genome-wide association study (GWAS), for SNP i

	healthy	diseased
wild-type	•	•
mutant	•	•

Observe $X \sim P \in \mathcal{P}$, return set of rejected hypotheses.

[Ex. 1] Suppose n = 100, $\mu_i = 0$, $\forall i = 1, ..., n$,

 $\mathbb{E}[\text{\# Rejections}] = n\alpha = 5 \ (\alpha = 0.05)$

 $\mathbb{P}[\text{at least one false rejection}] \approx 1$

Classic proposal: control familywise error rate (FWER)

$$FWER = \sup_{P \in \mathcal{P}} \mathbb{P}_P[\text{any true } H_{0,i} \text{ rejected}]$$
 (1.1)

1.1 Bonferroni / Šídák Correction

First rule (Bonferroni): Reject $H_{0,i}$ if $p_i \leq \frac{\alpha}{n}$

$$\mathbb{P}[\text{any false rejection}] = \mathbb{P}\left[\bigcup_{i \in \mathcal{H}_0} H_{0,i} \text{ reject}\right]$$
 (1.2)

$$\leq \sum_{i \in \mathcal{H}_0} \mathbb{P}\left[H_{0,i} \text{ rejected}\right] \leq |\mathcal{H}_0| \frac{\alpha}{n} \leq \alpha$$
 (1.3)

where \mathcal{H}_0 : { $i : H_{0,i}$ true}.

More liberal (Ŝidák): If p_i independent, can use the rule: Reject $H_{0,i}$ if $p_i \leq \tilde{\alpha}_n$ where $\tilde{\alpha}_n = 1 - (1 - \alpha)^{1/n} \approx \frac{\alpha}{n}$. Improvement in power over Bonferroni: $\tilde{\alpha}_n > \frac{\alpha}{n}$

1.2 Correlated Statistics

Often test stats are dependent

Example 1.3 (Pairwise comparisons). $X_i \stackrel{\text{ind.}}{\sim} N(\mu_i, 1) = \mu_i + \varepsilon_i$.

 $H_{0,ij}: \mu_1 = \mu_j, H_{1,ij}: \mu_i \neq \mu_j$ $\binom{n}{2}$ hypotheses.

$$X_i - X_j = \mu_i - \mu_j + (\varepsilon_i - \varepsilon_j) \sim N(\mu_i - \mu_2, 2)$$

Could use Bonferroni: Reject if $\frac{|X_i - X_j|}{\sqrt{2}} > z_{\frac{\alpha}{2\binom{n}{2}}}$

More powerful: Reject $H_{0,ij}$ if $|X_i - X_j| > r_{\alpha}$ where

$$\mathbb{P}\left[\max_{i,j}|\varepsilon_i - \varepsilon_j| > r_\alpha\right] = \alpha \tag{1.4}$$

This is less conservative than the Bonferroni correction: apply the union bound to get

$$\mathbb{P}\left[\max_{i,j}|\varepsilon_{i}-\varepsilon_{j}|>z_{\frac{\alpha}{2\binom{n}{2}}}\sqrt{2}\right] \leq \binom{n}{2}\mathbb{P}\left[|\varepsilon_{i}-\varepsilon_{j}|>z_{\frac{\alpha}{2\binom{n}{2}}}\sqrt{2}\right] \tag{1.5}$$

$$= \binom{n}{2} \frac{\alpha}{\binom{n}{2}} = \alpha \tag{1.6}$$

This is called Tukey's Honestly Significant Difference procedure

Example 1.4. Comparing all linear combos, $X_i \sim \text{ind.} N(\mu_i, 1)$.

 $H_{0,\nu}: \nu'\mu = 0, \nu \in \mathbb{R}^n$

Reject when $\frac{|X'\nu|}{\|v\|} > \chi_n(\alpha)$.

This is because

$$\mathbb{P}[\text{any false rej.}] = \mathbb{P}\left[\frac{|X'\nu|}{\|\nu\|} > \chi_n(\alpha), \text{ any } \nu \text{ s.t. } \nu'\mu = 0\right]$$
 (1.7)

$$\leq \mathbb{P}\left[\max_{\|\nu\|=1}|\varepsilon'\nu| > \chi_n(\alpha)\right] \tag{1.8}$$

$$= \mathbb{P}\left[\|\varepsilon\| > \chi_n(\alpha)\right] = \alpha \tag{1.9}$$

called Scheffé's S-method

$$\chi_n(\alpha) \approx \sqrt{n} \gg z_{\frac{alpham}{2\binom{n}{2}}} \sqrt{2}$$
(1.10)

$$\approx \sqrt{2 \cdot 2 \log \binom{n}{2}} \approx 2\sqrt{2 \log n} \tag{1.11}$$

More generally $X_i \sim N(\mu_i, \sigma^2)$ where σ^2 is unknown, $\hat{\sigma}^2 \sim \sigma^2 \chi_d^2 \perp X$.

Test $H_{0,\nu}: \mu'\nu = 0, \forall \nu \in \Xi \subset \mathbb{R}^n$.

Reject $H_{0,\nu}A$ if $\frac{|X_i'\nu|}{\hat{\sigma}||\nu||} \geq c_{\alpha}$

$$\mathbb{P}\left[\sup_{\nu\in\Xi}\frac{|\varepsilon_i'\nu|}{\hat{\sigma}\|\nu\|}>c\right]=\tag{1.12}$$

2 Simultaneous Intervals

Construct CI for ...