Lecture 18 11/16/2020

The entire set of m tests is called a "family" is "any logical collection of inferences for which it is meaningful to take into account some combined measure of "error" or a set of tests where you wish to prevent "data dredging" (e.g. the spurious correlations in 342) or to "ensure a correct 'overall' decision in the collection of tests".

We'll discuss two error properties/metrics for a family of tests.

The first is called "familywise error rate" (FWER) defined as:

$$FWER := P(V>0) \leq FWER_0 \leftarrow \text{this is the level of control that I choose e.g. } 5\%$$

If you can show that $FWER \leq FWER_0$ for any $m_0 \leq m$ subset of the m tests, this is called "strong FWER control". We won't study it. If you can show that $FWER \leq FWER_0$ for $m_0 = m$ then this called "weak FWER control" which we will study. If $m_0 = m$ ...

		Decision: Retain H_0	Decision: Reject H_0	
Truth	H_0	U	V	m_0
	H_a	0	0	0
		F	R	m

$\Rightarrow V = R \Rightarrow FWER = P(R>0)$

Our goal is weak FWER control under the most general settings.

$R_1 = 1$ if H_{0_1} is rejected, $R_1 = 0$ if H_{0_1} is retained.

$R_2 = 1$ " H_{0_2} " " $R_2 = 0$ " H_{0_2} " "

$R_m = 1$ " H_{0_m} " " $R_m = 0$ " H_{0_m} " "

$$FWER = P(R>0) = P(R_1 = 1 \cup R_2 = 1 \cup \dots \cup R_m = 1)$$
$$\leq \sum_{i=1}^{m} P(R_i = 1) = m\alpha.$$

recall from Math 241, $P(A \cup B) = P(A) + P(B) - P(A \cap B)$
the principle of inclusion - exclusion:

$$P(A_1 \cup A_2 \cup \dots \cup A_n) = \sum P(A_i) - \sum P(A_i \cap A_j) + \sum P(A_i \cap A_j \cap A_k) - \dots + \dots - \dots +$$

and from here you can prove "Boole's Inequality":

$$P(A_1 \cup A_2 \cup \dots \cup A_n) \leq \sum P(A_i)$$

$$\Rightarrow FWER \leq FWER_0 \Rightarrow m\alpha = FWER_0 \Rightarrow \alpha = \frac{FWER_0}{m}.$$

this is called the Bonferroni correction (1936)

$\Rightarrow$ a pval for an individual test must be less than $FWER_0 / m$. Equivalently, you can multiple the p-values by $m / FWER_0$ and compare each to alpha = 5%.

$$pval \leq \frac{FWER_0}{m} = \alpha \Rightarrow \underbrace{\frac{m}{FWER_0} \, pval}_{\text{Adjusted P-value}} \leq \alpha.$$

e.g. if $m = 30$, $FWER_0 = 5\%$ $\Rightarrow$ $alpha = FWER_0 / m$
$= 0.00167$

The obvious problem with this correction is... it gives you really bad power! Because it is ultra-conservative.

We can do a bit better if we assume the tests are independent. Then, $R_1, R_2, \ldots, R_m \overset{iid}{\sim} Bern(\alpha) \Rightarrow R \sim Bin(m, \alpha)$

$$FWER = P(R>0) = 1 - P(R=0) = 1-(1-\alpha)^m \leq FWER_0$$

$$\Rightarrow 1 - FWER_0 = (1-\alpha)^m \Rightarrow 1-\alpha = (1-FWER_0)^{1/m}$$

$$\Rightarrow \alpha = 1-(1-FWER)^{1/m} \Rightarrow 1-\alpha = (1-FWER_0)^{1/m}.$$

$$\Rightarrow \alpha = 1-(1-FWER_0)^{1/m}$$ Dann - Sidak Correction (1967)

e.g. if $m = 30$, $FWER_0 = 5\%$

$$\Rightarrow \alpha = 1-(95\%)^{1/30} = 0.00171 > 0.00167.$$
(the Bonferroni)

Thus, you get slightly higher power with Sidak.

$1-(1-x)^{1/c} \approx x/c$ (1st order Taylor series)

There are other methods e.g. the "Holm step-down" procedure (1979) but we won't study it it is similar to the Simes' procedure (1986) which we talk about now.

Bonferroni and Sidak never looked at the p-values and there's a lot of information there. Remember, Fisher created the p-val to gauge the "strength" of a rejection. Rejecting with a p-value of 0.00001 is much stronger than rejecting with a p-value of 0.01. Holm and Simes used this. For the m tests, you get p-values $p_1, p_2, \ldots p_m$ but don't retain / reject anything yet!! Order them from smallest to largest.

$p(1) \leq p(2) \leq \ldots \leq p(m)$ (order statistics)

min pval ↑ max pval ↑

"liner step-up"

Then locate the following: $a_* := \max\{a : p_{(a)} \leq \frac{a}{m} FWER_0\}$

$\in \{\text{Bonferroni}, \ldots, \alpha(\text{naive})\}$

or let $a_* = 0$ if max doesn't exist

Then set $\text{alpha} = \frac{a_*}{m} FWER_0$

You can prove that this gives you weak FWER control. It is rare that this is not more powerful than Bonferroni / Sidak.

By construction you reject all tests up to the a_* th test (if the tests are in order of p-value). Then you retain all the other $m - a_*$ tests

The problem with FWER in general is maybe it's too conservative. What if you want to trade some false rejections for more power? Let's consider another metric of familywise control (not FWER), called "False Discovery Rate" (FDR). First, define the "False Discovery Proportion" (FDP),

$$FDP := \begin{cases} V/R & \text{if } R>0 \\ 0 & \text{if } R=0 \end{cases}$$, the random proportion of rejections that are Type I errors

$FDR := E[FDP]$, the expected proportion of rejections that are Type I errors.

Now we wish to control FDR so we want:

$FDR \leq FDR_0$, a constant you set. For example if $FDR_0 = 5\%$ and I run m tests and get 100 rejections, then I expect ≤ 5 of the rejections to be Type I errors and ≥ 95 of the rejections to be real discoveries.

Note: if $m = m_0$ then $FWER = FDR$. Proof.

$$m = m_0 \implies V = R \implies FDP = \begin{cases} 1 & \text{if } R>0 \\ 0 & \text{if } R=0 \end{cases} = Bern(P(R>0))$$

$$\implies FDR = E[FDP] = P(R>0) = FWER.$$

Not on test

Note: the FDR procedure is more powerful than the FWER procedure.

$\mathbb{1}_{V\geq 1} \geq V/R$ if $V=0 \Rightarrow 0 \geq 0$ ✓

$V=1 \Rightarrow 1 \geq 1$ or $1/2$ or $1/3$ ... $1/R$

$V \geq 1 \Rightarrow 1 \geq 1$ or $\frac{V}{V+1}$ or ... V/R.

$$\Rightarrow E[\mathbb{1}_{V\geq 1}] \geq E[V/R]$$

$$P(V \geq 1) \geq FDR$$

$$\|$$

$$FWER \geq FDR \checkmark$$

Benjamini and Hochberg (1995) proved the Simes procedure controls FDR for any m_0 subset of the m tests. In fact $FDR = m_0/m\ FDR_0 \leq FDR_0$ thus for a small m_0 (which don't observe), the FDR control is much better than FDR_0.