

## Lec 8 MATH 341 / 691

$m$ : # of hypothesis tests

$m_0$ : # of tests s.t.  $H_0$  is true,  $m_0 \leq m$

$r$ : # of rejections,  $r \leq m$ ,  $R$  is its r.v.

$v$ : # of Type I error,  $v \leq r$ ,  $V$  is its r.v.

If  $m = m_0 = 1$ ,  $P(R=1) = P(V=1) \geq \alpha$ , <sup>the level which is</sup> set by you

If  $m = m_0$

$$V = R = \text{Binom}(m, \alpha)$$

$$P(V \geq 1) = 1 - P(V=0) = 1 - (1-\alpha)^m$$

for  $\alpha = 5\%$ ,  $m = 30$ ,  $P(V \geq 1) = 76\%$

for any  $\alpha > 0$ ,  $m \rightarrow \infty$ ,  $P(V \geq 1) \rightarrow 1$

(FWER)  
Family-wise error control

$$\text{FWER} := P(V \geq 1)$$

A family of tests is a logical collection of tests where its meaningful to talk about a notion of error on the collection.

Not well-defined!

The analogue of  $\alpha$  is now denoted  $\text{FWER}_0$ , the value you control e.g.  $\text{FWER}_0 = 5\%$

If  $FWER \leq FWER_0$  for any  $m_0 \leq m$ , this is called "Strong control of FWER".

If  $FWER \leq FWER_0$  for all  $m_0 = m$ , this is called "weak control of FWER".

$m = m_0$

We will focus on weak control of FWER. The r.v.s of interest are

$$\begin{aligned} R_1 &:= \begin{cases} 1 & \text{if first test } H_0 \text{ is rejected} \\ 0 & \text{if first test } H_0 \text{ is retained} \end{cases} \\ R_2 &:= \begin{cases} 1 & \text{if second test } H_0 \text{ is rejected} \\ 0 & \text{if second test } H_0 \text{ is retained} \end{cases} \\ \vdots \\ R_m &:= \begin{cases} 1 & \text{if } m\text{-th test } H_0 \text{ is rejected} \\ 0 & \text{if } m\text{-th test } H_0 \text{ is retained} \end{cases} \end{aligned}$$

no knowledge of the dependence structure of these Bernoullis

$R = R_1 + R_2 + \dots + R_m$ , the total # of rejections  
Assume level  $\alpha$  for each of the  $m$  tests

$$FWER := P(R \geq 1) = P(R_1 = 1 \cup R_2 = 1 \cup \dots \cup R_m = 1) \leq \sum_{l=1}^m P(R_l = 1) = m\alpha$$

Boole's Inequality

$\downarrow m$

set  $FWER_0 = m\alpha$  and solve for  $\alpha$

$$\Rightarrow FWER \leq m\alpha, \Rightarrow \text{if } \alpha = \frac{FWER_0}{m} \Rightarrow FWER \leq FWER_0$$

e.g.  $FWER_0 = 5\%, m = 100 \Rightarrow \alpha = 0.0005$

This called the Bonferroni Correction (1936).

It always works but it's extremely conservative i.e. it's very difficult to reject  $H_0$  if  $H_0$  is false i.e. Power is very low!

Let's assume  $R_1, R_2, \dots, R_m \stackrel{iid}{\sim} \text{Bern}(\alpha)$

3

$$\text{FWER} = P(R \geq 1) = 1 - P(R = 0) = 1 - (1 - \alpha)^m$$

Set  $\text{FWER}_0 = 1 - (1 - \alpha)^m$  and solve for  $\alpha$

$$1 - \text{FWER}_0 = (1 - \alpha)^m \Rightarrow 1 - \alpha = (1 - \text{FWER}_0)^{1/m} \Rightarrow \alpha = 1 - (1 - \text{FWER}_0)^{1/m}$$

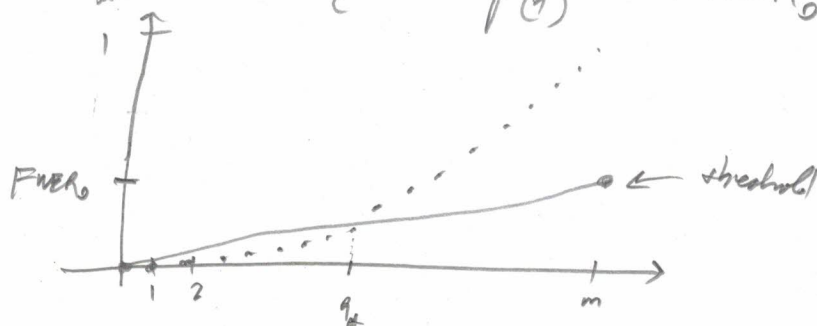
This is called the Dunn-Sidak correction (1967).

if  $\text{FWER}_0 = 5\%$ ,  $m = 100 \Rightarrow \alpha = .000513 > \text{Bonferroni } \alpha$   
but not by much.

There needs to be a better way! Note that Neither Bonferroni nor Dunn examined the p-values themselves, which gauge "strength of rejection". A p-value of .0001 is much stronger than a p-value of .01. Simon in 1986 decided to use this idea. For all  $m$  <sup>independent</sup> tests, there are  $m$  p-values:

$p_1, p_2, \dots, p_m$ . Sort them from smaller to larger  $p_{(1)}, p_{(2)}, \dots, p_{(m)}$ .

Let  $q_{\#} := \max \left\{ q; p(q) \leq \text{FWER}_0 \frac{q}{m} \right\}$  "linear step-up" or Qif max doesn't exist



Then reject all hypotheses corresponding to  $p_{(q)} \leq \text{FWER}_0 \frac{q_{\#}}{m}$   
Proof comes after we do order statistics in 3.40.

Maybe... FWER is not the metric to care about...

$FWER = P(R \geq 1)$  is really conservative. 5% that any rejection happens at all?

How about the following. Let the false discovery proportion, be:

$$FDP := \begin{cases} \frac{V}{R}, & R > 0 \\ 0, & R = 0 \end{cases} \text{ the prop. of all rejections that are Type I errors}$$

Since you need to control a scalar quantity, define the false discovery rate (FDR) to be  $FDR := E[FDP]$

which we control to be no more than  $FDR_0$  e.g.

$FDR \leq FDR_0 = 5\%$  we say the FDR is controlled at 5%.

$\Rightarrow$  If you get  $n=100$ , you expect  $v=5$ , i.e. 5% and 95 to be true discoveries (i.e.  $H_0$  is true).

If  $m=m_0$ ,  $FWER = FDR$ . Proof:

$$\text{Since } m=m_0, V=R \Rightarrow FDP = \begin{cases} 1 & \text{if } R \geq 1 \\ 0 & \text{if } R=0 \end{cases} = \text{Bern}(P(R \geq 1)) = \text{Bern}(FWER)$$

$$\Rightarrow E[FDP] = FWER$$

So FDR only makes sense if  $m_0 < m$ , i.e. there are some discoveries to be made. This makes FDR control realistic unlike controlling with FWER.

Benjamini & Hochberg, 1995

5

Then: the Simes procedure controls FDR, i.e.

if you let  $q_k := \max \{ q : p(q) \leq FDR_0 \frac{q}{m} \}$  or  $\infty$  if no max  
and reject all tests whose  $p_{\text{val}} < FDR_0 \frac{q_k}{m}$ , Proof too difficult.

This result is the most cited result in the entire field of statistics.

FDR is less conservative than FWER

$$\frac{V}{R} \leq \mathbb{1}_{V \geq 1}$$

if  $V=0$ ,  $0 \leq 0$

if  $V=1$ ,  $1 \leq 1$ ,  $\frac{1}{2} \leq 1$ ,  $\frac{1}{3} \leq 1$ , ...

if  $V=2$ ,  $1 \leq 1$ ,  $\frac{2}{3} \leq 1$ ,  $\frac{2}{4} \leq 1$ , ...

if  $V \geq 1$ ,  $\frac{V}{R} \leq 1$

$$\Rightarrow E\left[\frac{V}{R}\right] \leq E[\mathbb{1}_{V \geq 1}]$$

$$\Rightarrow FDR \leq FWER.$$

to get the same # of false discoveries, you need a higher FWER  
to get the same FWER, you have to be okay with much less false discoveries.



Totally different type of test. Called Goodness-of-Fit.

Usually we assume  $DBP: X_1, \dots, X_n \stackrel{iid}{\sim} f(x; \theta)$

And we want to test  $\theta$ .

Now, we flip things to reverse. We begin with data

e.g. 1.73, -0.91, 0.93, 2.16, 0.03 and want to show

"is the DBP different from  $X_1, \dots, X_n \stackrel{iid}{\sim} f(x; \theta)$ "?

e.g.

↓ note: needs full specification. There cannot be any unknown parameters

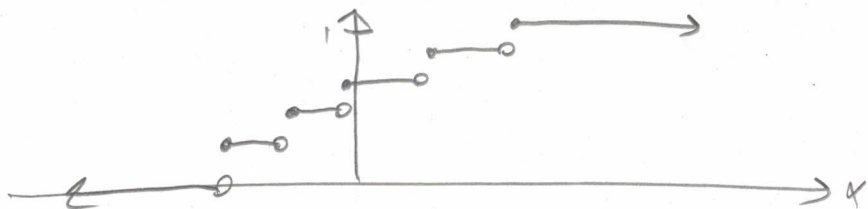
$H_0: X_1, \dots, X_n \stackrel{iid}{\sim} N(0,1)$  i.e.  $F_X(x) = \Phi(x)$  param's

$H_a: DBP$  is anything else

If the  $H_0$  is a continuous DBP, we can use the Kolmogorov-Smirnov Test. We first compute

the estimate of  $F(x)$ ,  $\hat{F}_n(x)$  called the empirical CDF (ECDF).

$$\hat{F}_n(x) := \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{X_i \leq x} \quad \text{e.g.}$$



this is a function estimator for the true CDF.

Under  $H_0$ ,  $F_{H_0}$  is assumed. Now we need to measure difference between  $F_{H_0}$  and  $\hat{F}_n$ . We need a test statistic and we need its distr under  $H_0$ .

$$D_n = \text{scalar diff}(\hat{F}_n, F_{H_0})$$

One possibility is the largest absolute difference between the two functions.

$$D_n := \sup_x \{ |\hat{F}_n(x) - F_{H_0}(x)| \} \quad \text{"Supremum norm difference"}$$

Glivenko-Cantelli

Then:  $D_n \rightarrow 0$  if  $H_0$  is true  $\Rightarrow \lim_{n \rightarrow \infty} \hat{F}_n(x) = F(x)$   
 of 1933  $D_n \rightarrow c \neq 0$  if  $H_0$  not true  $\Rightarrow \text{Power} \rightarrow 1$  as  $n \rightarrow \infty$ .

What's the scaling distr of  $D_n$ ?

Kolmogorov in 1933 proved that

$\sqrt{n} D_n \xrightarrow{d} K$ , the Kolmogorov Distr. (Show it on wikipedia)

Amazing result which is completely distr.-free like the CLT.

Tables of critical values are tabulated. Recommended to have  $n > 50$ .

(Show values)