

DSO 699: Statistics Theory

Special Topics in Data Sciences and Operations

Week 5

Adel Javanmard

USC Marshall

Department of Data Sciences and Operations

September 22, 2023

Announcements

- HW1 is due next week (Sep 29)
- Midterm exam is in two weeks (Oct 6)
 - ✓ in-class exam
 - ✓ you can have access to slides
 - ✓ no internet

Recap from the previous class

We talked about:

- Connection/difference between global testing and multiple hypotheses testing
- Family-wise Error Rate (FWER): $\mathbb{P}(V \geq 1)$
 - ✓ Strong control
 - ✓ Weak control
- Methods for controlling FWER
 - ✓ Bonferroni's method
 - ✓ Šidák's method
 - ✓ Holm's step-down procedure
- The closure principle (valid global testing \rightarrow FWER control in multiple hypotheses testing)

Outline for today

- 1 False Discovery Rate (FDR) and Benjamini-Hochberg (BH) Procedure
- 2 BH under Dependence
- 3 Storey's Procedure

False Discovery Rate and Benjamini-Hochberg (BH) Procedure

False discovery proportion (FDP)

Outcomes in multiple testing:

	Fail to reject	Rejected	Total
True null	U	V	n_0
False null	T	S	$n - n_0$
Total	$n - R$	R	n

- We learned that FWER becomes too stringent in large scale hypothesis testing (With $\text{FWER} \leq \alpha$ the power goes down as # hypotheses grows)
- **False discovery proportion (FDP):**

$$\text{FDP} = \frac{V}{\max(R, 1)} = \begin{cases} \frac{V}{R} & R \geq 1 \\ 0 & R = 0 \end{cases}$$

- FDP is unobservable. Why?
- FDP is a random quantity
- $0 \leq \text{FDP} \leq 1$.

False discovery rate (FDR)

V, R are usually correlated
controlling expected ratio of correlated can be challenging

- We can try to control expectation of FDP:

$$\text{FDR} = \mathbb{E}[\text{FDP}] = \mathbb{E}\left[\frac{V}{\max(R, 1)}\right]$$

FWER control implies FDR control

[Benjamini-Hochberg '95]

- FDR is a weaker condition than FWER and allows for more powerful tests. Why?

$$\mathbb{I}(V \geq 1) \geq \frac{V}{\max(R, 1)}$$

$0 \text{ or } 1$ $\text{rate, so from } 0 \text{ to } 1.$

$=0$ implies rhs 0, if $=1$ then the ratio is less or equal to 1.

- FDR gives us control *on average* across many repetitions of an experiment. Sometimes, FDP may have large variation (sizably larger than its expectation)
- False discovery exceedance:

$$\text{FDX}_\gamma = \mathbb{P}(\text{FDP} \geq \gamma).$$

by markov inequality, we can show this is stringent than FDR

Benjamini-Hochberg (BH) procedure

1. Sort p-values $p_{(1)} \leq p_{(2)} \leq \dots \leq p_{(n)}$
2. Let $i_0 := \max\{i \in [n] : p_{(i)} \leq \frac{i}{n}\alpha\}$
3. Reject all p-values $p_{(i)}$ for $i \leq i_0$ (or $p_j \leq p_{(i_0)}$)

R is random, cutoff is function of R so

1) cut off is random

2) cutoff and R are correlated

Some observations:

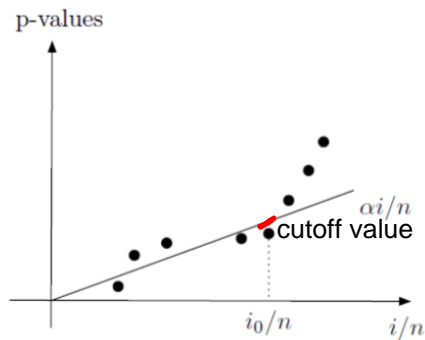
- BH cutoff depends on all p-values
- The cutoff and the total number of rejections are explicitly related:
 i_0 : total # of rejections
cutoff := $\frac{\alpha i_0}{n}$ explicit expression for cutoff cannot avoid dependence on i_0
- BH cutoff is a “random” quantity!

loop? this makes proof difficult

but positive feedback.

reject more (by randomness of data) -> higher cutoff -> reject more encourage more rejection

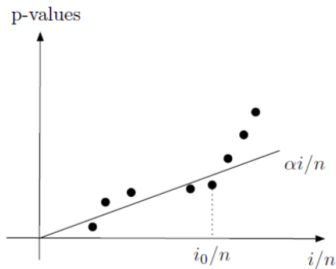
An illustration



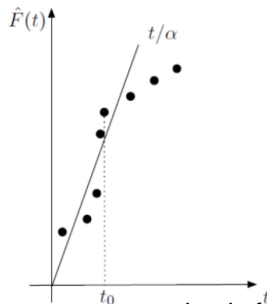
BH cutoff is shown by dashed line.

we use last index,
so we have to check all p-value

The Empirical Process Viewpoint of BH



(a) P-values on the y axis, indices on x



(b) P-values on the x axis, indices on y

moving along cutoff, check if cdf is over me

Recall the empirical CDF $\hat{F}(t) = \frac{1}{n} \sum_{i=1}^n \mathbb{I}(p_i \leq t)$. support = $[0,1]$

We then have $\hat{F}(p_{(i)}) = \frac{i}{n}$.

The Empirical Process Viewpoint of BH (cont'd)

Recall that BH procedure rejects $p_{(1)}, \dots, p_{(i_0)}$ where

$$i_0 = \max \left\{ i : p_{(i)} \leq \frac{\alpha i}{n} \right\}$$

The critical p-value $p^* = p_{(i_0)}$ can alternatively be written as

$$\begin{aligned} p^* &= \max \left\{ p_{(i)} : p_{(i)} \leq \frac{\alpha i}{n} \right\} \\ &= \max \left\{ p_{(i)} : p_{(i)} \leq \alpha \hat{F}(p_{(i)}) \right\} \\ &= \max \left\{ t \in \{p_1, \dots, p_n\} : t \leq \alpha \hat{F}(t) \right\} \end{aligned}$$

So the BH cutoff can be written as

or $\max_t t/\alpha < F(t)$
max cdf that goes over the
linear line

$$\tau_{BH} = \max \left\{ t : \frac{t}{\hat{F}(t)} \leq \alpha \right\}$$

t need not be discrete, rejection results are the same

Is it a natural choice? anyway empirical cdf is step function

The Empirical Process Viewpoint of BH (cont'd)

Is it a natural choice for cutoff? n_0 is fixed constant

For given $t \in (0, 1)$ consider a rule that rejects H_i iff $p_i \leq t$.

$$\begin{aligned} \text{FDR}(t) &= \mathbb{E} \left[\frac{V(t)}{R(t)} \right] \overset{\text{cheating}}{\approx} \frac{E[V(t)]}{R(t)} && \text{linearity of E. dependence} \\ &= \frac{n_0 t}{n \widehat{F}(t)} && \text{doesn't matter for E} \\ &\leq \frac{nt}{n \widehat{F}(t)} := \widehat{\text{FDR}}(t) && \text{E indicator = prob} \\ &&& \text{prob of rejecting null = t} \\ &&& \text{how many null? } n_0 \\ &&& \text{loose upper bound} \end{aligned}$$

Fhat: proportion of p-values less than t
n Fhat = number of ...

So the BH cutoff can be written as

$$\begin{aligned} \tau_{BH} &= \max \left\{ t : \frac{t}{\widehat{F}(t)} \leq \alpha \right\} \\ &= \max \left\{ t : \widehat{\text{FDR}}(t) \leq \alpha \right\}. \end{aligned}$$

control loose upper bound by alpha
which then controls FDR

BH procedure controls FDR

wrong proof:

$E(V/R) = E(V) / E(R)$ (first mistake)

$E \mathbb{I}(p_i < a R/n) = a R/n$ (second mistake - R is r.v. correlated with p_i
so it's not uniform prob. even conditioning on R does not make it uniform)

Theorem

If $\{p_1, \dots, p_n\}$ are mutually independent then the BH procedure at level α satisfies

$$\text{FDR} = \frac{n_0}{n} \alpha \leq \alpha$$

There are several elegant proofs for this theorem:

- Induction (Very first proof by Benjamini-Hochberg '95)
- Martingale theory
- **Leave-one-out**

idea: p_i and R is correlated but not highly correlated
e.g. if p_i is not the boundary, its value does not matter to R

This technique is useful for weak correlation situation

Proof of FDR control

Here i is not ordered i.e. not (i)

Let \mathcal{H}_0 be the set of null p-values.

$$\text{FDP} = \frac{V}{\max(R, 1)} = \sum_{i \in \mathcal{H}_0} \frac{V_i}{\max(R, 1)},$$

V_i is random variable

$$V_i = \mathbb{I}(p_i \leq \alpha R/n).$$

Let's think for individual term

$$(2) V_i = \mathbb{I}[i \text{ reject}] =$$

- *Challenge:* V_i and R are correlated. $\mathbb{I}[i \text{ rej}, R \leq k] \cup \mathbb{I}[i \text{ rej}, R = k] \cup \mathbb{I}[i \text{ rej}, R > k]$

(1) somehow randomness moved to numerator = sum of 1

$$\frac{V_i}{\max(R, 1)} = \sum_{k=1}^n \frac{V_i \mathbb{I}(R = k)}{k} = \sum_{k=1}^n \frac{\mathbb{I}(p_i \leq \alpha k/n) \mathbb{I}(R = k)}{k}$$

transform this three times

only one term is true (nonzero)

We still have correlation between R and p_i (but a weak correlation!)

possible values:

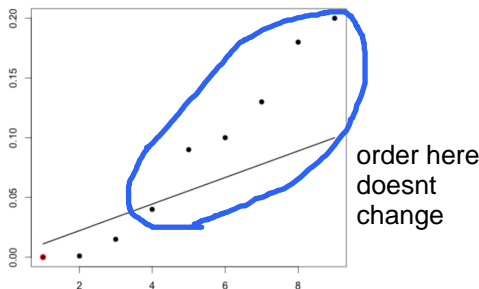
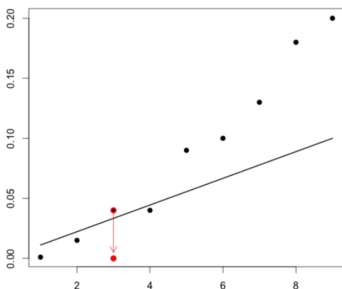
0, 1, 1/2, 1/3, ... 1/n

Proof of FDR control (cont'd)

Leave-one-out technique:

If p_i is **rejected** its **actual value is not relevant to R** as far as it is under the cutoff. i.e. number of the rejection doesn't change

(How about setting it to zero?)



this is random variable. we have i number of this kind of thing

Define $R(p_i \rightarrow 0)$ the number of rejection if you set p_i to zero and keep the others intact

Let \mathcal{F}_i be (the σ -algebra) generated by $\{p_1, \dots, p_{i-1}, p_{i+1}, \dots, p_n\}$.

Proof of FDR control (cont'd)

conditional expectation
is a random variable

$$\begin{aligned}
 \mathbb{E} \left(\frac{V_i}{\max(R, 1)} \middle| \mathcal{F}_i \right) &= \sum_{k=1}^n \left(\frac{\mathbb{I}(p_i \leq \alpha k/n) \mathbb{I}(R = k)}{k} \middle| \mathcal{F}_i \right) \\
 &= \sum_{k=1}^n \left(\frac{\mathbb{I}(p_i \leq \alpha k/n) \mathbb{I}(R(p_i \rightarrow 0) = k)}{k} \middle| \mathcal{F}_i \right) \\
 &= \sum_{k=1}^n \frac{\mathbb{I}(R(p_i \rightarrow 0) = k)}{k} \mathbb{P}(p_i \leq \alpha k/n) \\
 &= \frac{\alpha}{n} \sum_{k=1}^n \mathbb{I}(R(p_i \rightarrow 0) = k) \\
 &= \frac{\alpha}{n} .
 \end{aligned}$$

independence

$\rightarrow E(XY) = E(X)E(Y)$

& conditioned on \mathcal{F}_i , right term is constant

& p_i is indep of other p-values

so conditioning meaningless

only one indicator
is 1

(where did we use independence of p_i 's?)

The proof is completed by taking another expectation (w.r.t \mathcal{F}_i) and summing over $i \in [n]$.

A few remarks

- BH cutoff is adaptive! (it depends on all p -values and not just a function of α and n)
- There is an inherent positive feedback: cutoff $\Rightarrow R$
(Burden of proof decreases if you make more rejections)
- Under global null we have FDR = FWER (why?)

any rejection is false rejection. $V=R$. Then FDP = 0 ($V=0$) or 1 ($V>1$) i.e. indicator random variable.
so E indicator = prob.

Comparison with Sime's: Under global null:

$$\text{FWER} = \text{FDR} = \frac{\alpha n_0}{n} = \alpha$$

By description of BH cutoff: BH make at least one rejection \Leftrightarrow simes test

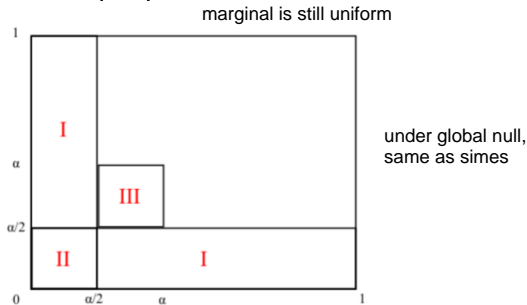
$$\text{FWER} = \mathbb{P}(V \geq 1) = \mathbb{P}(\exists i : p_{(i)} n/i \leq \alpha)$$

Putting together, it proves validity of Simes' procedure for global testing!

BH under Dependence

A toy example

Consider $n = 2$, $p_1, p_2 \sim \text{Unif}(0, 1)$ (arbitrarily correlated).



under global null, =prob of having at least one rejection (since it's global null)

$$\text{FDR} = \text{FWER} = \mathbb{P}(\text{I}) + \mathbb{P}(\text{II}) + \mathbb{P}(\text{III})$$

$$\begin{aligned} a &= (I+II) + (I+II) \\ \text{so subtract II once} \end{aligned} \quad \begin{aligned} &= \alpha + \mathbb{P}(\text{III}) - \mathbb{P}(\text{II}) \leq \alpha + \mathbb{P}(\text{III}) \end{aligned} \quad \begin{aligned} &\text{this is not 0, due to dependence} \end{aligned}$$

Also,

don't think as ith rejection, think of as global testing

so all we can do
is upper bounding
by removing - II

$$\mathbb{P}(\text{III}) = \mathbb{P}(\alpha/2 \leq p_1, p_2 \leq \alpha) \leq \mathbb{P}(\alpha/2 \leq p_1 \leq \alpha) = \alpha/2$$

So $\text{FDR} \leq 3\alpha/2$.

under general dependence

upper bounding by marginal

we can calculate marginal

because marginal is uniform

Two theorems

Recall the harmonic sum

$$h_n := 1 + \frac{1}{2} + \dots + \frac{1}{n} \approx \log n$$

Theorem (Benjamini and Yekutieli 2001)– upper bound

Under **arbitrarily dependence** among p -values, BH procedure at level α has the following control of FDR:

$$\text{FDR} \leq \alpha h_n \frac{n_0}{n} \leq \alpha h_n.$$

still controlled, but less performance

Theorem (Guo and Rao 2008)– lower bound which means that the above bound is tight

For any $n \geq 1$, there **exists a joint distribution of p -values** such that the FDR of BH at level α satisfies

$$\text{FDR} \geq \min(1, \alpha h_n).$$

Proof: (Whiteboard)

Storey's Procedure

Improving BH

Recall the empirical process view point of BH:

$$\tau_{BH} = \max \left\{ t : \frac{t}{\widehat{F}(t)} \leq \alpha \right\}.$$

We were to able to exactly characterize FDR of BH(α) procedure as

$$\text{FDR} = \frac{\alpha n_0}{n}$$

What if we could estimate n_0 ?

we can set larger threshold; by replacing n with n_0

An estimate of π_0

what we have:

if null, p-values are uniform

if not null, p-value would be generally small

Let $\pi_0 = n_0/n$ be the fraction of nulls.

Pick $\lambda \in (0, 1)$ and compute

usually large λ to get many samples

large p-values i.e. nulls

$$\hat{\pi}_0^\lambda = \frac{\sum_{i=1}^n \mathbb{I}(p_i > \lambda)}{n(1 - \lambda)} \quad (1)$$

Why is this estimate sensible?

$n_0 (1 - \lambda)$ parameter
~~ $\sum 1(p_i > \lambda)$ estimate

Storey's procedure

1. Pick $\lambda \in (0, 1)$ (typically $\lambda = 1/2$)
2. Estimate null proportions:

$$\hat{\pi}_0^\lambda = \frac{1 + \sum_{i=1}^n \mathbb{I}(p_i > \lambda)}{n(1 - \lambda)} \quad (2)$$

3. Similar to BH construct the cutoff:

$$\tau_{\text{storey}} = \max \left\{ 0 \leq t \leq \lambda : \frac{\hat{\pi}_0^\lambda t}{\hat{F}(t)} \leq \alpha \right\}.$$

- We only consider $0 \leq t \leq \lambda$ because in the estimate $\hat{\pi}_0^\lambda$ we implicitly assume p -values above λ are null.

Storey's procedure

Theorem (Storey 2004)

If the p -values are independent, then for $\lambda \in (0, 1)$ the Storey's procedure controls FDR as

$$\text{FDR} \leq (1 - \lambda^{n_0})\alpha \leq \alpha.$$

Recap

We talked about

- False discovery rate (FDR), false discovery proportion (FDP) and false discovery exceedance
- Benjamini-Hochberg procedure
 - ✓ for dependent p -values
 - ✓ for arbitrarily correlated p -values
- Storey's procedure

Don't forget about:

- HW1 (due next week)
- In-class midterm (in two weeks)

