

Introduction to multiple Testing

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Introduction

Multiple univariate statistical tests

- easy way to explore data: (many) **univariate** tests
e.g. between each explanatory variable and the outcome
- can be a (bad) way to select variables for a small(er) multivariate model
⇒ *screening method*
- when multivariate models do not make sense or are not feasible

One statistical test

| Your decision/Reality | H_0 is true | H_0 is false |
|--------------------------------------------|------------------|------------------|
| Do not reject H_0 (test non-significant) | Correct decision | Wrong decision |
| Reject H_0 (test significant) | Wrong decision | Correct decision |

20 statistical tests

If we repeat the procedure 20 times, that is, *if we perform 20 univariate tests without changing anything*: \implies great chance of having false positive detections...

How many tests do we expect will be false positive detection ?

m statistical tests

- How do we adapt to the fact that we have many (*m*) tests ?
- Can we **adjust** the level of significance α accordingly ?

Russian roulette



Assume that a gun has 20 locations and contains one bullet.

- *pull the trigger 1 time*: gun fires with **5%** probability
- *pull the trigger 10 times*: gun fires with **40%** probability
- *pull the trigger 25 times*: gun fires with **72%** probability
- *pull the trigger 100 times*: gun fires with **99%** probability

Probability

The probability of no undesirable event (false positive or gun firing) is:

$$(1 - \alpha)^m$$

Type-I error for multiple tests

Multiple testing notations

- m : total number of tests
- \mathcal{M}_0 : the set of true null hypotheses
- V : number of false positive (null hypotheses wrongly rejected)
- R : number of null hypotheses rejected

| Null hypotheses | True | False | Total |
|-----------------|-------|-----------|-------|
| Non-rejected | U | T | W |
| Rejected | V | S | R |
| Total | m_0 | $m - m_0$ | m |

Family Wise Error Rate (FWER)

$$FWER = P(V > 0 | \mathcal{M}_0)$$

\implies the probability to get at least one false positive, knowing the true null hypotheses.

- we want to stricly control the number of false positives
- m is “not so large”

Often for confirmatory analyses

False Discovery Rate (FDR)

$$FDR = E[V/R | \mathcal{M}_0]$$

⇒ the expected number of false positives on average among rejected null hypotheses, knowing the true null hypotheses.

- m is “really large”
- the FWER is too conservative
(we do not reject any null hypothesis)

Often for exploratory/hypothesis generating analyses

Multiple testing correction

Correction for multiple tests

When we take into account the number of tests, we can either:

- Correct p-values (called **adjusted p-values**) and keep the significance level α fixed
- Keep raw p-values and correct significance level α

\implies Both ways are equivalent *but software usually use adjusted p-values*

Correction to control the FWER (1)

Bonferroni correction:

Compare p-values to α/m instead of α

\implies adjusted p-values: $q = \min(1, mp)$

- **Controls the FWER**
(playing *Russian roulette* 10 times with a gun with 200 slots is "safer")
- Too conservative as soon as m get large

Correction to control the FWER (2)

Holm correction:

1. Compare the smallest p-value to α/m . If the associated null hypothesis is not rejected **stop**, otherwise **continue**
 2. Compare the second smallest p-value to $\alpha/(m - 1)$
If the associated null hypothesis is not rejected **stop**, otherwise **continue**
 3. ...
 4. Compare the largest p-value to $\alpha/1$ and **conclude**
- ⇒ also **controls the FWER** but a bit less conservative than Bonferonni
(more null hypotheses could be rejected, if m is not too large)

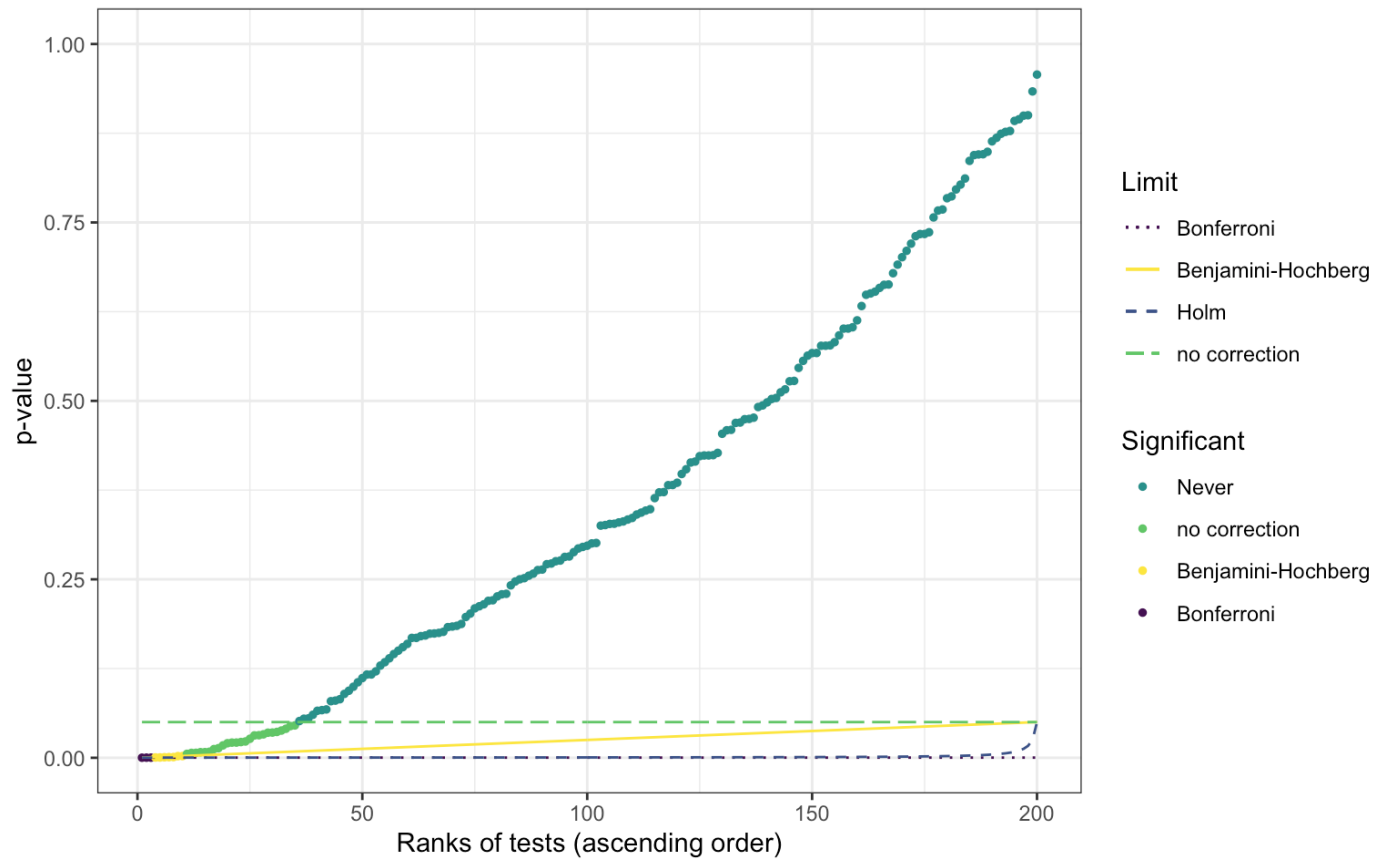
Correction to control the FDR

1. Compare the smallest p-value to α/m , the second smallest p-value to $2\alpha/m$, ..., and the largest p-value to α .
2. Find the largest p-value that is strictly less than its associated threshold. We note this p-value p^* .
3. Reject all null hypotheses associated to p-values smaller than p^* .

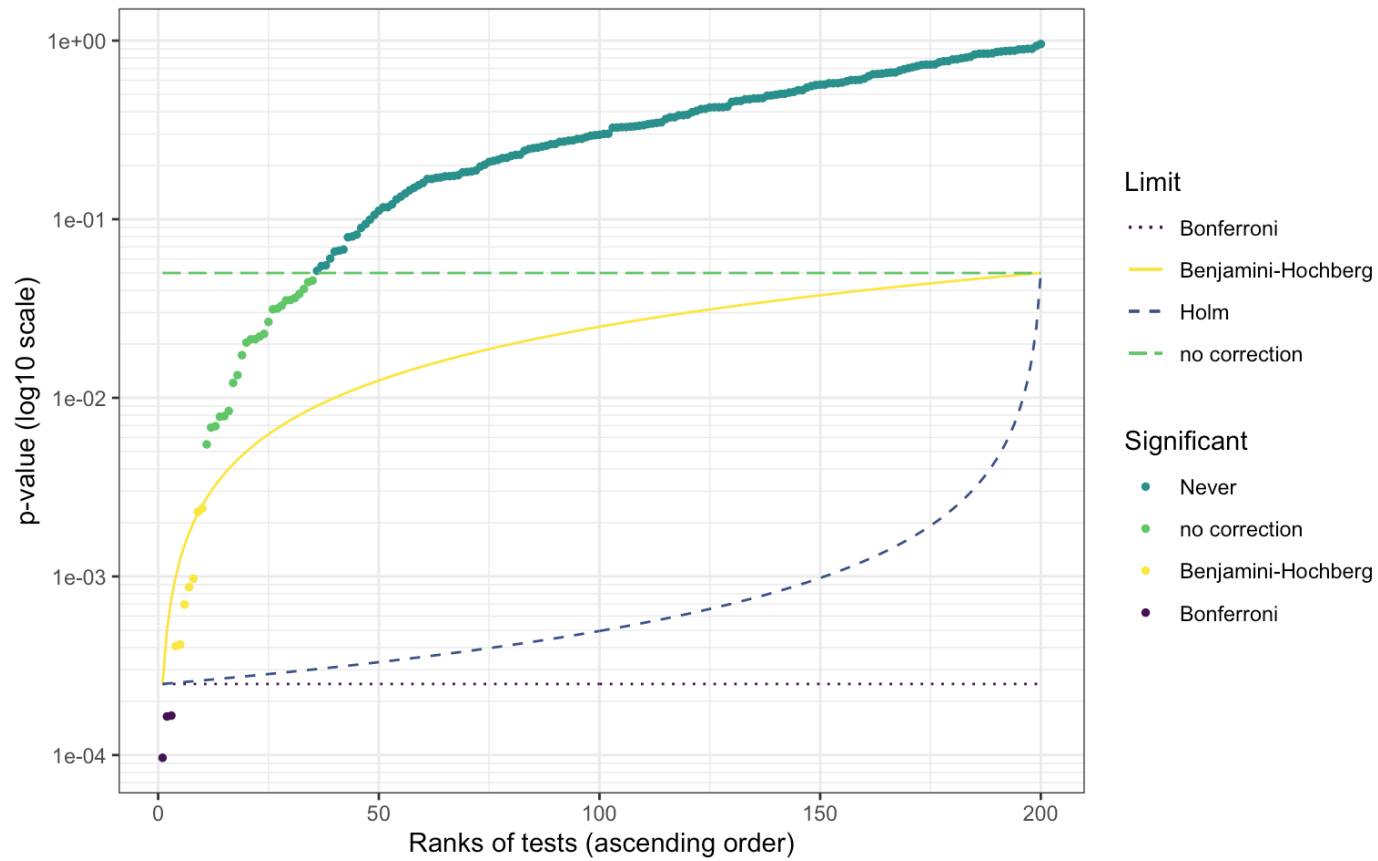
⇒ controls the FDR (but not the FWER)

Hence, even more flexible than Holm correction and usually used when m is very large

Vizualizing an example



Vizualizing an example – log-scale



Conclusion

Take home message

Multiple testing must be taken into account:

- \implies p-values must be adjusted !
- choose the correction method according to your scientific objectives
- **NEVER** play at Russian roulette (seriously) !

Further reading

- Dudoit, S & van der Laan, J. *Multiple Testing Procedures with Applications to Genomics*. Springer Series in Statistics (2008).
- Foulkes, AS. *Applied statistical genetics with R: for population-based association studies*. Springer Verlag (2009).
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- Holm, S. A simple sequentially rejective multiple test procedure. *Scandinavian journal of statistics*. (1979).
- Phipson B & Smyth GK. Permutation p-values should never be zero: calculating exact p-values when permutations are randomly drawn. *Statistical Applications in Genetics and Molecular Biology*. 31;9(1):1544–6115 (2010).