# 单因素方差分析&多重检验矫正

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问题描述

水平	A1	A2	A2	
	$X_{11}$	$X_{12}$	• • •	$X_{1s}$
加索体	$X_{21}$	$X_{22}$	• • •	$X_{2s}$
观察值		• • •	• • •	. • . • .
	$X_{n_1 1}$	$X_{n_22}$	• • •	$X_{n_s s}$
样本总和	$T_1$	$T_2$	• • •	$T_{s}$
样本均值	$\overline{X_{\cdot 1}}$	$\overline{X_{\cdot 2}}$	• • •	$\overline{X_{\cdot_S}}$
总体均值	$\mu_1$	$\mu_2$	• • •	$\mu_{\scriptscriptstyle S}$

假定在水平  $A_j$ 下的多次观察的结果为 $X_{1j}, X_{2j} \cdots X_{n_j j}$ ,视为来自正态总体 N  $(\mu_j, \sigma^2)$  的一个简单随机样本。

#### 变量定义

水平	A1	A2		As
	$X_{11}$	$X_{12}$	•••	$X_{1s}$
加索体	$X_{21}$	$X_{22}$	•••	$X_{2s}$
观察值				
	$X_{n_11}$	$X_{n_22}$		$X_{n_s s}$
样本总和	$T_1$	$T_2$		$T_s$
样本均值	$\overline{X_{\cdot 1}}$	$\overline{X_{\cdot 2}}$		$\overline{X_{\cdot_S}}$
总体均值	$\mu_1$	$\mu_2$	•••	$\mu_{\scriptscriptstyle S}$

$$\overline{X} = \frac{1}{n} \sum_{j=1}^{s} \sum_{i=1}^{n_j} X_{ij}$$

$$\overline{X}_{\cdot j} = \frac{1}{n_j} \sum_{i=1}^{n_j} X_{ij} = \mu + \alpha_j + \varepsilon_{\cdot j}$$

记 $\varepsilon_{ij} = X_{ij} - \mu_j$  为随机误差,则 $\varepsilon_{ij} \sim N(0, \sigma^2)$ 上述单因素模型可表示为  $\begin{cases} X_{ij} = \mu_j + \varepsilon_{ij} \\ \varepsilon_{ij} \sim N(0, \sigma^2) \end{cases}$ 

ANOVA的任务是检验在各水平下的均值是否相等,即 $H_0: \mu_1 = \mu_2 = ... = \mu_s$  ,  $H_1: \mu_1, \mu_2 \dots \mu_s$  不全相同

上述单因素模型可表示为  $\begin{cases} X_{ij} = \mu + \alpha_j + \varepsilon_{ij} \\ \varepsilon_{ij} \sim N(0, \sigma^2) \end{cases}$ 

ANOVA的任务是检验在各水平下的均值是否相等,即 $H_0: \alpha_1 = \alpha_2 = ... = \alpha_s$ ,  $H_1: \alpha_1, \alpha_2 \dots \alpha_s$  不全相同

平方和分解

$$S_T = \sum_{j=1}^{s} \sum_{i=1}^{n_j} (X_{ij} - \overline{X})^2$$

$$= \sum_{j=1}^{s} \sum_{i=1}^{n_j} (X_{ij} - \overline{X}_{.j})^2 + \sum_{j=1}^{s} \sum_{i=1}^{n_j} (X_{.j} - \overline{X})^2$$

$$= S_E + S_A$$

$$S_E = \sum_{j=1}^{s} \sum_{i=1}^{n_j} (X_{ij} - \overline{X}_{.j})^2 = \sum_{j=1}^{s} \sum_{i=1}^{n_j} (\varepsilon_{ij} - \overline{\varepsilon}_{.j})^2$$

$$S_A = \sum_{j=1}^s \sum_{i=1}^{n_j} (\overline{X_{\cdot j}} - \overline{X})^2 = \sum_{j=1}^s n_j (\alpha_j + \overline{\varepsilon}_{\cdot j} - \overline{\varepsilon})^2$$

$$E(S_E) = (n - s)\sigma^2$$

$$E(S_A) = \sum_{j=1}^{s} n_j \alpha_j^2 + (s-1)\sigma^2$$

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无条件

当且仅当H0成立时

$$E(\frac{S_E}{n-s}) = \sigma^2$$

$$E(\frac{S_A}{s-1}) = \sigma^2$$

$$F = \frac{\frac{S_A}{(s-1)}}{\frac{S_E}{(n-s)}}$$

F分布

$$E(S_E) = (n - s)\sigma^2$$

无条件

$$E(\frac{S_E}{n-s}) = \sigma^2$$

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$$E(\frac{S_A}{s-1}) = \sigma^2$$

$$F = \frac{\frac{S_A}{(s-1)}}{\frac{S_E}{(n-s)}}$$

$$\frac{S_E}{\sigma^2} \sim \chi^2(n-2)$$

$$\frac{S_A}{\sigma^2} \sim \chi^2(s-1)$$

#### 方差分析表

方差来源	平方和	自由度	均方	F值
因素A	$S_{\!A}$	s — 1	$\overline{S_A} = \frac{S_A}{s-1}$	$F = \frac{\overline{S}_A}{\overline{S}_E}$
误差	$S_E$	n-s	$\overline{S_E} = \frac{S_E}{n - s}$	
总和	$S_T$	<i>n</i> − 1		

#tell where the data come from
datafilename= "http://personalityproject.org/R/datasets/R.appendix1.data"

#read the data into a table
data.ex1=read.table(datafilename, header=T)

Dosage	Alertness
a	30
a	38
a	35
a	41
a	27
a	24
b	32
b	26
b	31
b	29
b	27
b	35
b	21
b	25
С	17
С	21
С	20
С	19

```
#do the analysis of variance
aov.ex1 = aov(Alertness~Dosage, data=data.ex1)
#show the summary table
summary(aov.ex1)
```

```
> summary(aov.ex1)

Df Sum Sq Mean Sq F value Pr(>F)

Dosage 2 426.2 213.12 8.789 0.00298 **

Residuals 15 363.8 24.25

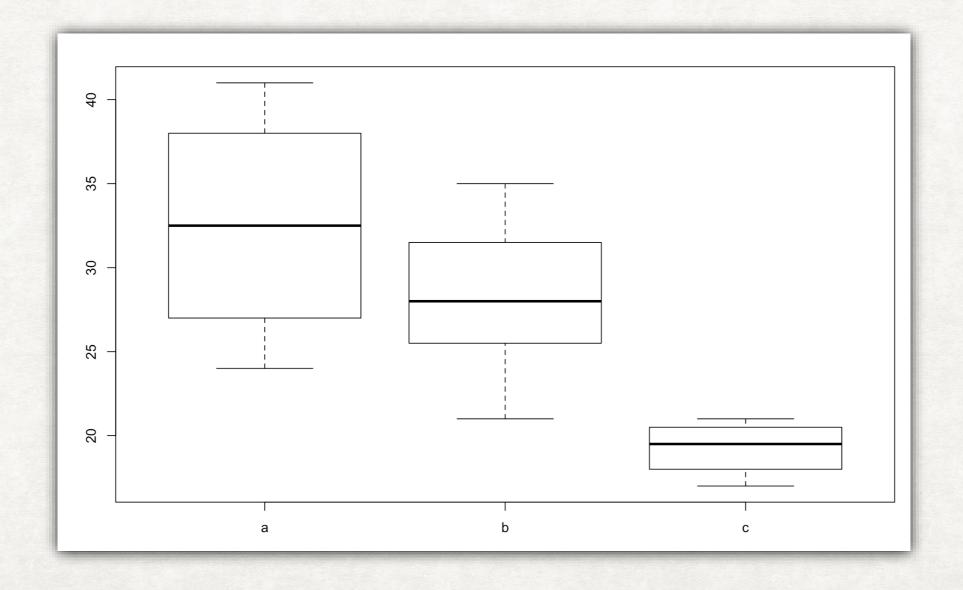
---

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

#report the means and the number of subjects/cell
print(model.tables(aov.ex1, "means"), digits=3)

#graphical summary

boxplot (Alertness Dosage, data=data. ex1)



## 3. 多重检验矫正

- Suppose the treatment is a new way of teaching writing to students, and the control is the standard way of teaching writing.
   Students in the two groups can be compared in terms of grammar, spelling, organization, content, and so on. As more attributes are compared, it becomes increasingly likely that the treatment and control groups will appear to differ on at least one attribute due to random sampling error alone.
- Suppose we consider the efficacy of a drug in terms of the reduction of any one of a number of disease symptoms. As more symptoms are considered, it becomes increasingly likely that the drug will appear to be an improvement over existing drugs in terms of at least one symptom.

$$ar{lpha} = 1 - ig(1 - lpha_{ ext{\{per comparison}\}}ig)^m.$$

Let  $H_1,\ldots,H_m$  be a family of hypotheses and  $p_1,\ldots,p_m$  their corresponding p-values. Let m be the total number of null hypotheses and  $m_0$  the number of true null hypotheses. The familywise error rate (FWER) is the probability of rejecting at least one true  $H_i$ , that is, of making at least one type I error. The Bonferroni correction rejects the null hypothesis for each  $p_i \leq \frac{\alpha}{m}$ , thereby controlling the FWER at  $\leq \alpha$ . Proof of this control follows from Boole's inequality, as follows:

$$ext{FWER} = P\left\{igcup_{i=1}^{m_0}\left(p_i \leq rac{lpha}{m}
ight)
ight\} \leq \sum_{i=1}^{m_0}\left\{P\left(p_i \leq rac{lpha}{m}
ight)
ight\} = m_0rac{lpha}{m} \leq mrac{lpha}{m} = lpha.$$

This control does not require any assumptions about dependence among the p-values or about how many of the null hypotheses are true.<sup>[6]</sup>

```
pairwise.t.test (x, A, p.adjust.method =
    "Bonferroni")
p.adjust(p, method = "Bonferroni")
```

#### Bonferroni

```
e.g. > height <- data.frame(
        X<-c(
         176,178,159,165,167,
     + 180,177,169,165,172,
     + 168,174,162,156,167,
         189,185,179,178,179
     + ),
     + A<-g1(4,5)
     + )
     > pairwise.t.test(height$x,height$A,p.adjust.method = "bonferroni")
             Pairwise comparisons using t tests with pooled SD
     data: height$x and height$A
     2 1.0000 -
     3 1.0000 0.5864 -
     4 0.0352 0.2131 0.0055
     P value adjustment method: bonferroni
```

The method is as follows:

- ullet Let  $H_1,\ldots,H_m$  be a family of hypotheses and  $P_1,\ldots,P_m$  the corresponding P-values.
- ullet Start by ordering the p-values (from lowest to highest)  $P_{(1)} \dots P_{(m)}$  and let the associated hypotheses be  $H_{(1)} \dots H_{(m)}$
- ullet For a given significance level lpha, let k be the minimal index such that  $P_{(k)}>rac{lpha}{m+1-k}$
- ullet Reject the null hypotheses  $H_{(1)} \ldots H_{(k-1)}$  and do not reject  $H_{(k)} \ldots H_{(m)}$
- ullet If k=1 then do not reject any of the null hypotheses and if no such k exist then reject all of the null hypotheses.

The Holm–Bonferroni method ensures that this method will control the  $FWER \leq \alpha$ , where FWER is the familywise error rate

- 1. Order the p-values  $P(1), P(2), \ldots, P(n)$  and their associated hypotheses  $H(1), \ldots, H(n)$
- 2. Reject all hypotheses H(k) having  $P(k) \leq rac{lpha}{n+1-k}$  where  $k=1,\ldots,n$

# 4. p. adjust 函数 HOMMEL

Let j be the largest integer for which

$$p_{n-j+k}>rac{klpha}{j}$$

for all  $k=1,\ldots,j$ .

If no such j exists, reject all hypotheses; otherwise, reject all  $H_i$  with  $p_i \leq \frac{\alpha}{j}$ . Both j and i, btw, go from 1 to n.

# 4. p. adjust 函数 BH / BY

### FDR

The Benjamini–Hochberg procedure (BH step-up procedure) controls the FDR at level  $\alpha$ . [1] It works as follows:

- 1. For a given  $\alpha$ , find the largest k such that  $P_{(k)} \leq \frac{k}{m} \alpha$ .
- 2. Reject the null hypothesis (i.e., declare discoveries) for all  $H_{(i)}$  for  $i=1,\ldots,k$  .
- The *Benjamini-Hochberg-Yekutieli* procedure controls the false discovery rate under positive dependence assumptions. [13] This refinement modifies the threshold and

$$P_{(k)} \leq rac{k}{m \cdot c(m)} lpha$$

- ullet If the tests are independent or positively correlated: c(m)=1
- ullet Under arbitrary dependence:  $c(m) = \sum_{i=1}^m rac{1}{i}$

In the case of negative correlation, c(m) can be approximated by using the Euler-Mascheroni constant.

$$\sum_{i=1}^m rac{1}{i} pprox \ln(m) + \gamma + rac{1}{2m}.$$

#### SUMMARY

#### Adjust P-values for Multiple Comparisons

#### Description

Given a set of p-values, returns p-values adjusted using one of several methods.

#### Usage

```
p.adjust(p, method = p.adjust.methods, n = length(p))
p.adjust.methods
# c("holm", "hochberg", "hommel", "bonferroni", "BH", "BY",
# "fdr", "none")
```

#### Arguments

p numeric vector of p-values (possibly with <u>NAs</u>). Any other R is coerced by <u>as.numeric</u>.

method correction method. Can be abbreviated.

n number of comparisons, must be at least length (p); only set this (to non-default) when you know what you are doing!

#### Q1:

A large randomized trial compared an experimental drug and 9 other standard drugs for treating motion sickness. An ANOVA test revealed significant differences between the groups. The investigators wanted to know if the experimental drug ("drug 1") beat any of the standard drugs in reducing total minutes of nausea, and, if so, which ones. The p-values from the pairwise t tests (comparing drug 1 with drugs 2-10) are below.

Drug I vs. drug	2	3	4	5	6	7	8	9	10
p-value	.05	.3	.25	.04	.001	.006	.08	.002	.01

a. Which differences would be considered statistically significant using a Bonferroni correction? or Holm-Hochberg correction?

#### **Q2:**

In the grade three of high school X, there are four kinds of classes using various teaching methods to teach mathematics. To identify whether the teaching method makes sense, five students' math scores are randomly chosen from the classes after the final exam.

Class 1	75	77	70	88	72
Class 2	83	80	85	90	84
Class 3	65	67	77	68	65
Class 4	72	70	71	65	82

· Answer:

```
> P_set<-data.frame(row.names =c(1:9),p_value=c(0.05,0.3,0.25,0.04,0.001,0.006,0.08,0.002,0.01))
> ordered_set<-data.frame(row.names = order(P_set$p_value),original_p = P_set[order(P_set$p_value),])
> ordered_set$bonferroni<-p.adjust(ordered_set$original_p,method = "bonferroni" )
> ordered_set$holm<-p.adjust(ordered_set$original_p,method = "holm" )
> ordered_set$hochberg<-p.adjust(ordered_set$original_p,method = "hochberg" )
> ordered set
  original_p bonferroni holm hochberg
5
      0.001
                 0.009 0.009
                                0.009
8
      0.002
                 0.018 0.016
                                0.016
                                0.042
6
      0.006
                 0.054 0.042
9
      0.010
                0.090 0.060
                                0.060
4
      0.040
              0.360 0.200
                                0.200
1
                                0.200
      0.050
                0.450 0.200
7
      0.080
                 0.720 0.240
                                0.240
3
      0.250
                 1.000 0.500
                                0.300
      0.300
                 1.000 0.500
                                0.300
```

• Answer:

# Our question 1 p. adjust

Input = ("Raw. p Food Blue\_fish . 34 Bread . 594 Butter . 212 Carbohydrates . 384 Cereals and pasta . 074 Dairy products . 275 Eggs . 696 Fats . 269 Fruit . 341 Legumes . 06 Nuts Olive oil .008 Potatoes . 569 Processed meat . 986 Proteins . 042 Red meat . 251

You need to order the data by their p value and adjust their p value with Bonferroni, BH, Holm, Hochberg, Hommel, BY.

- a) Save your result in a table (see format below)
- b) Plot new p old p for all the methods in the same coordinate.

Food	raw.p	Beferroni	ВН	Ho1m	Hochberg	Homme1	ВҮ

# Our question 2 anova

Using the following data, perform a oneway analysis of variance using  $\alpha = .05$ . Write up the results in the following format.

Group1	Group2	Group3
51	23	56
45	43	76
33	23	74
45	43	87
67	45	56

