

Two-way ANOVA

(68)

$$y_{ijk} = \mu_{ij} + \varepsilon_{ijk} \quad \text{means model}$$

$$= \mu_{..} + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \varepsilon_{ijk} \quad \begin{array}{l} \text{main effect} \\ \text{interaction model} \end{array}$$

$$\alpha_i = \mu_{i.} - \mu_{..} \quad \text{effect due to factor A}$$

$$\beta_j = \mu_{.j} - \mu_{..} \quad \text{effect due to factor B}$$

$$\mu_{..} \quad \text{overall effect}$$

$$i = 1, \dots, a, \quad j = 1, \dots, b, \quad k = 1, \dots, n_{ij}$$

$$n_T = \sum_i \sum_j n_{ij}$$

If none levels of factor A interact the levels of factor

$$B \quad \mu_{ij} - \mu_{im} = \mu_{.j} - \mu_{.m} \quad \text{for all } i, j, l, m$$

no interaction

If factors A and B have no interaction, then

$$\mu_{ij} = \mu_{..} + \alpha_i + \beta_j \quad \text{for all } i, j$$

proof: $\mu_{ij} - \mu_{..} - \alpha_i - \beta_j = \mu_{ij} - \mu_{i.} - \mu_{.j} + \mu_{..}$

(69)

$$\begin{aligned}
&= \mu_{ij} - \frac{1}{b} \sum_{m=1}^b \mu_{im} - \frac{1}{a} \sum_{k=1}^a \mu_{kj} + \frac{1}{ab} \sum_k \sum_m \mu_{km} \\
&= \frac{1}{ab} \sum_k \sum_m \mu_{ij} - \frac{1}{ab} \sum_{k=1}^a \sum_{m=1}^b \mu_{im} - \frac{1}{ab} \sum_k \sum_m \mu_{kj} + \frac{1}{ab} \sum_k \sum_m \mu_{km} \\
&= \frac{1}{ab} \sum_k \sum_m (\underbrace{\mu_{ij} - \mu_{im} - \mu_{kj} + \mu_{km}}_0) \\
&= 0
\end{aligned}$$

Fixed effects Model

$$y_{ijk} = \mu_{..} + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \varepsilon_{ijk}$$

$$E \varepsilon_{ijk} = 0,$$

$$\text{Normal, } \text{Var}(\varepsilon_{ijk}) = \sigma^2, \quad \text{Cov}(\varepsilon_{ijk}, \varepsilon_{lmn}) = 0$$

Estimation

$$\begin{aligned}
&\text{Least square: } \sum_i \sum_j \sum_k (y_{ijk} - \mu_{ij})^2 \rightarrow \min \{ \mu_{ij} \} \\
&\Rightarrow \hat{\mu}_{ij} = \bar{y}_{ij}
\end{aligned}$$

$$\text{or } \sum_i \sum_j \sum_k (y_{ijk} - \mu_{..} - \alpha_i - \beta_j - (\alpha\beta)_{ij})^2$$

$$\text{subject to } \sum_i \alpha_i = \sum_j \beta_j = \sum_i \sum_j (\alpha\beta)_{ij} = \sum_i \sum_j (\alpha\beta)_{ij} = 0$$

$$\begin{aligned}
 \Rightarrow \hat{\mu}_{...} &= \bar{y}_{...} \\
 \hat{\alpha}_i &= \bar{y}_{i..} - \bar{y}_{...} \\
 \hat{\beta}_j &= \bar{y}_{.j.} - \bar{y}_{...} \\
 (\alpha\beta)_{ij} &= \bar{y}_{ij.} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{...} \\
 &= \bar{y}_{ij.} - \hat{\alpha}_i - \hat{\beta}_j + \hat{\mu}_{...}
 \end{aligned}$$

Fitted value

$$\hat{y}_{ijk} = \bar{y}_{ij.}$$

ANOVA (Balanced case) ($n_{ij} = n$)

$$SSTO = SSTR + SSE \quad \text{where}$$

$$SSTO = \sum_i \sum_j \sum_k \frac{n_{ij}}{k} (y_{ijk} - \bar{y}_{...})^2 \quad (n_T - 1) \text{ df}$$

$$\begin{aligned}
 SSTR &= \sum_i \sum_j \frac{n_{ij}}{j} (\bar{y}_{ij.} - \bar{y}_{...})^2 \\
 &= \sum_i \sum_j \frac{n_{ij}}{j} (\bar{y}_{ij.} - \bar{y}_{...})^2
 \end{aligned}$$

with 1 constraint $\sum_i \sum_j \frac{n_{ij}}{j} (\bar{y}_{ij.} - \bar{y}_{...}) = 0$
 $(ab - 1) \text{ df}$

(71)

$$\begin{aligned}
 SSE &= \sum_i \sum_j \sum_k \frac{n_{ijk}}{n_{ij}} (y_{ijk} - \bar{y}_{ij\cdot})^2 \\
 &= \sum_i \sum_j \sum_k \frac{(n_{ij} - 1)}{n_{ij}} S_{ij\cdot}^2 \quad (n_T - ab) \text{ df}
 \end{aligned}$$

Proof:
$$\begin{aligned}
 SSTO &= \sum_i \sum_j \sum_k \sum_l \frac{1}{n_{ij}} (y_{ijk} - \bar{y}_{ij\cdot} + \bar{y}_{ij\cdot} - \bar{y}_{i\cdot\cdot})^2 \\
 &= \sum_i \sum_j \sum_k \sum_l \frac{1}{n_{ij}} (y_{ijk} - \bar{y}_{ij\cdot})^2 + \sum_i \sum_j \sum_l \frac{1}{n_{ij}} (\bar{y}_{ij\cdot} - \bar{y}_{i\cdot\cdot})^2 \\
 &\quad + 2 \sum_i \sum_j \sum_k \sum_l \frac{1}{n_{ij}} (y_{ijk} - \bar{y}_{ij\cdot}) (\bar{y}_{ij\cdot} - \bar{y}_{i\cdot\cdot})
 \end{aligned}$$

Note
$$\begin{aligned}
 &\sum_i \sum_j \sum_k \sum_l \frac{1}{n_{ij}} \underbrace{(y_{ijk} - \bar{y}_{ij\cdot}) (\bar{y}_{ij\cdot} - \bar{y}_{i\cdot\cdot})}_{=0} \\
 &= \sum_i \sum_j \sum_k \frac{1}{n_{ij}} (\bar{y}_{ij\cdot} - \bar{y}_{i\cdot\cdot}) \underbrace{\sum_l (y_{ijk} - \bar{y}_{ij\cdot})}_0 \\
 &= 0
 \end{aligned}$$

• Partition of SSTO (balanced $n_{ij} = n$)

$$\begin{aligned}
 SSTO &= \sum_i \sum_j \sum_k \frac{1}{n} n (y_{ijk} - \bar{y}_{i\cdot\cdot})^2 \\
 &= n \sum_i \sum_j \left\{ (y_{i\cdot\cdot} - \bar{y}_{i\cdot\cdot}) + (\bar{y}_{ij\cdot} - \bar{y}_{i\cdot\cdot}) + (\bar{y}_{ij\cdot} - \bar{y}_{i\cdot\cdot} - \bar{y}_{j\cdot\cdot} + \bar{y}_{i\cdot\cdot}) \right\}^2 \\
 &= n \sum_i \sum_j \left\{ b (y_{i\cdot\cdot} - \bar{y}_{i\cdot\cdot})^2 + n a \sum_j (\bar{y}_{ij\cdot} - \bar{y}_{i\cdot\cdot})^2 \right. \\
 &\quad \left. + n \sum_j \frac{1}{b} (\bar{y}_{ij\cdot} - \bar{y}_{i\cdot\cdot} - \bar{y}_{j\cdot\cdot} + \bar{y}_{i\cdot\cdot})^2 + \text{cross products} \right\}
 \end{aligned}$$

(72)

$$\begin{aligned}
 &= nb \sum_i (\bar{y}_{i..} - \bar{y}_{...})^2 + na \sum_j (\bar{y}_{.j.} - \bar{y}_{...})^2 \\
 &\quad + n \sum_i \sum_j (\bar{y}_{ij.} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{...})^2 \\
 &= SSA + SSB + SSAB
 \end{aligned}$$

Cross products part.

$$\begin{aligned}
 (1) \sum_i \sum_j (\bar{y}_{i..} - \bar{y}_{...}) (\bar{y}_{.j.} - \bar{y}_{...}) &= 0 \\
 (2) \sum_i \sum_j (\bar{y}_{i..} - \bar{y}_{...}) (\bar{y}_{ij.} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{...}) & \\
 &= \sum_i (\bar{y}_{i..} - \bar{y}_{...}) \sum_{j=1}^b (\bar{y}_{ij.} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{...}) \\
 &= b (\bar{y}_{i..} - \bar{y}_{...} - \bar{y}_{i..} - \bar{y}_{...} + \bar{y}_{...}) = 0
 \end{aligned}$$

= 0

(3) Similarly = 0

Expected Mean Square (balanced)

$$MSE = \frac{\sum_i \sum_j \sum_k (\bar{y}_{ijk.} - \bar{y}_{ij.})^2}{n_T - ab} = \frac{\sum_i \sum_j (n_{ij} - 1) S_{ij}^2}{\sum_i \sum_j (n_{ij} - 1)}$$

$$E MSE = \sigma^2$$

$$MSA = \frac{\sum \sum \sum (\bar{y}_{i..} - \bar{y}_{...})^2}{a-1} = \frac{bn \sum \hat{\alpha}_i^2}{a-1}$$

Consider a 1-way ANOVA model

$$\bar{y}_{i:k} = \mu_i^* + \varepsilon_{i:k}^*, \quad \varepsilon_{i:k}^* \sim N(0, \frac{\sigma^2}{b})$$

$$Y \sim N(0, \sigma^2)$$

$$\bar{Y} \sim N(0, \frac{\sigma^2}{n})$$

$$SSTR = SSA + SSB + SSAB$$

$$= nb \sum_i (\bar{y}_{i..} - \bar{y}_{...})^2 + na \sum_j (\bar{y}_{.j.} - \bar{y}_{...})^2 + n \sum_i \sum_j (\bar{y}_{ij.} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{...})^2$$

$$(ab-1) = a-1 + b-1 + (a-1)(b-1)$$

two way ANOVA data

$$\rightarrow \begin{Bmatrix} \begin{matrix} y_{111} & \dots & y_{1b1} \\ \vdots & & \vdots \\ y_{a11} & \dots & y_{ab1} \end{matrix} \\ \begin{matrix} y_{11n} & \dots & y_{1bn} \\ \vdots & & \vdots \\ y_{a1n} & \dots & y_{abn} \end{matrix} \end{Bmatrix}$$

$$y_{ij:k} = \mu_{i:j} + \varepsilon_{i:j:k}$$

$$\bar{y}_{i:k} = \mu_{i.} + \bar{\varepsilon}_{i:k}$$

$$\bar{\varepsilon}_{i:k} \sim N(0, \frac{\sigma^2}{b})$$

$$SS_{TR}^* = \sum_i n (\bar{y}_{i..} - \bar{y}_{...})^2$$

$$E MS_{TR}^* = \frac{\sigma^2}{b} + \frac{n \sum_i (\mu_{i.} - \mu_{..})^2}{a-1}$$

$$E SS_{TR}^* = (a-1) \frac{\sigma^2}{b} + n \sum_i (\mu_{i.} - \mu_{..})^2$$

$$SS_{TR}^* = \sum_j n (\bar{y}_{.j.} - \bar{y}_{...})^2$$

$$E SS_{TR}^* = (b-1) \frac{\sigma^2}{a} + n \sum_j (\mu_{.j} - \mu_{..})^2$$

$$SS_{TR}^* = \sum_j n (\bar{y}_{ij.} - \bar{y}_{i..})^2$$

$$i=1, \dots, a$$

$$E SS_{TR}^* = (b-1) \sigma^2 + n \sum_j (\mu_{.j} - \mu_{..})^2$$

Two way ANOVA

$$E MSA = \frac{1}{a-1} E nb \sum_i (\bar{y}_{i..} - \bar{y}_{...})^2$$

$$= \frac{b}{a-1} \left[(a-1) \frac{\sigma^2}{b} + n \sum_i (\mu_{i.} - \mu_{..})^2 \right] = \sigma^2 + nb \frac{\sum_i (\mu_{i.} - \mu_{..})^2}{a-1}$$

$$E MSB = \sigma^2 + na \frac{\sum_j (\mu_{.j} - \mu_{..})^2}{b-1}$$

(75)

$$\begin{aligned}
 E MSAB &= \frac{1}{(a-1)(b-1)} E n \sum_j \sum_i (\bar{y}_{ij} - \bar{y}_{i..} - \bar{y}_{.j} + \bar{y}_{...})^2 \\
 &= \frac{1}{(a-1)(b-1)} E \left\{ n \sum_i \sum_j (\bar{y}_{ij} - \bar{y}_{i..})^2 + n a \sum_j (\bar{y}_{.j} - \bar{y}_{...})^2 \right. \\
 &\quad \left. - 2 n \sum_i \sum_j (\bar{y}_{ij} - \bar{y}_{i..})(\bar{y}_{.j} - \bar{y}_{...}) \right\} \\
 &= \frac{1}{(a-1)(b-1)} E \left\{ n \sum_i \sum_j (\bar{y}_{ij} - \bar{y}_{i..})^2 - n a \sum_j (\bar{y}_{.j} - \bar{y}_{...})^2 \right\} \\
 &= \frac{1}{(a-1)(b-1)} \left[\sum_i \left\{ (b-1) \sigma^2 + n \sum_j (\mu_{ij} - \mu_{i.})^2 \right\} - a \underbrace{(b-1) \frac{\sigma^2}{a} - a n \sum_j (\mu_{.j} - \mu_{...})^2}_{\sigma^2} \right] \\
 &= \frac{1}{(a-1)(b-1)} \left[(a-1)(b-1) \sigma^2 + n \sum_i \sum_j (\mu_{ij} - \mu_{i.})^2 - a n \sum_j (\mu_{.j} - \mu_{...})^2 \right] \\
 &\stackrel{(*)}{=} \sigma^2 + \frac{n}{(a-1)(b-1)} \sum_i \sum_j (\mu_{ij} - \mu_{i.} - \mu_{.j} + \mu_{...})^2 \\
 &= \sigma^2 + \frac{n \sum_i \sum_j (\alpha \beta)_{ij}^2}{(a-1)(b-1)}
 \end{aligned}$$

(*) because $\sum_i \sum_j (\mu_{ij} - \mu_{i.} - \mu_{.j} + \mu_{...})^2$

$$= \sum_i \sum_j (\mu_{ij} - \mu_{i.})^2 + \sum_i \sum_j (\mu_{.j} - \mu_{...})^2$$

(76)

$$\begin{aligned}
 & -2 \sum_i \sum_j (\mu_{ij} - \mu_{i.}) (\mu_{ij} - \mu_{..}) \\
 & = \sum_i \sum_j \{ (\mu_{ij} - \mu_{i.})^2 - (\mu_{ij} - \mu_{..})^2 \}
 \end{aligned}$$

Testing A effects, B effects, and interaction

So we test $H_0: \alpha_i = 0$, with $F_A = \frac{MSA}{MSE}$

$H_0: \beta_j = 0$ with $F_B = \frac{MSB}{MSE}$

$H_0: (\alpha\beta)_{ij} = 0$ with $F_{AB} = \frac{MSAB}{MSE}$

H_0 all \sim F distr. with suitable d.f.

But: Multiple comparisons (3 test at the same stage)

(1). Bonferroni, if 3 tests are done with sig.

levels $\alpha_1, \alpha_2, \alpha_3$, then

$$FWER = \alpha \leq \alpha_1 + \alpha_2 + \alpha_3$$

(2). Improvement, Kimball inequality

$$\text{FWER } \alpha \leq 1 - (1 - \alpha_1)(1 - \alpha_2)(1 - \alpha_3)$$

$$\text{If } \alpha_1 = \alpha_2 = \alpha_3 = .1, \quad \alpha_{\text{Bonf}} \leq .3$$

$$\alpha_{\text{Kimball}} \leq .271$$

$$\alpha_1 = \alpha_2 = \alpha_3 = .05, \quad \alpha_{\text{Bonf}} \leq .15$$

$$\alpha_{\text{Kimball}} \leq .1426$$

So if $\alpha_1 = \alpha_2 = \alpha_3$, then

$$\text{FWER } \alpha \leq 1 - (1 - \alpha_i)^3$$

$$\text{We choose } \alpha_i = 1 - (1 - \alpha)^{1/3}$$

Kimball inequality

Let $\xi_0, \xi_1, \xi_2, \xi_3$ independent, > 0

(There are MSE, MSA, MSB, MSAB under H_0)
 F_1, F_2, F_3 are some positive numbers

(critical values).

$$\text{Then: } P\left(\bigcap_{k=1}^3 \left(\frac{\xi_k}{\xi_0} \leq F_k\right)\right) \geq \prod_{k=1}^3 P\left(\frac{\xi_k}{\xi_0} \leq F_k\right)$$

(78)

Pf: Let $Z_k := P\left(\frac{Z_k}{Z_0} \leq F_k \mid Z_0\right)$; $Y_k = 1\left(\frac{Z_k}{Z_0} \leq F_k\right)$

all Z_k are non-decreasing functions of Z_0 .

If both f, g monotone in the same direction

$$(f(x_2) - f(x_1))(g(x_2) - g(x_1)) \geq 0$$

Then $E(f(x)g(x)) \geq E f(x) E g(x)$

or $\text{Cov}(f(x), g(x)) \geq 0$ (positively correlated)

Pf: X_1, X_2 iid r.v.s. of X

$$0 \leq E\left[\{f(X_2) - f(X_1)\}\{g(X_2) - g(X_1)\}\right]$$

$$= E\{f(X_2)g(X_2) - f(X_1)g(X_2) - f(X_2)g(X_1) + f(X_1)g(X_1)\}$$

$$= 2\{E(f(X)g(X)) - E f(X) E g(X)\}$$

Conditional on Z_0 , $\{Y_k\}$ are indep.

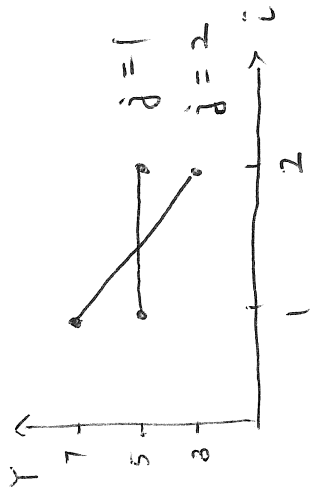
$$\begin{aligned}
 \text{Then } E(Y_1 Y_2 Y_3) &= P\left\{\bigcap_{k=1}^3 \left(\frac{Z_k}{Z_0} \leq F_k\right)\right\} \\
 &= E\left(E(Y_1 | Z_0) E(Y_2 | Z_0) E(Y_3 | Z_0)\right) \\
 &= E(Z_1 Z_2 Z_3) \\
 &\geq E(Z_1) E(Z_2 Z_3) \geq E Z_1 E Z_2 E Z_3 \\
 &= \prod_{k=1}^3 P\left\{\frac{Z_k}{Z_0} \leq F_k\right\}
 \end{aligned}$$

Ex: A clinical trial is used to find the optimal combination of 2 antibiotics A & B. Each antibiotic can be in 2 forms: powder or liquid. Each combination was given to 2 patients as following

Y_{ijk}	i	
	1	2
j	4	4
2	6	8
	2	4

\bar{Y}_{ij}	i	
	1	2
j	5	5
2	7	3

a). plot the data to show the interaction.



b) Test on the interaction. $(H_0: (\alpha\beta)_{ij} = 0)$

$$F = \frac{SSAB/1}{SSE/4} = \frac{8}{8/4} = 4 \quad \text{with d.f. (1, 4)}$$

$$P\text{-value} > .1$$

Fail to reject H_0 . no significant interaction