What to do today (March 7, 2023)? Part 1. Introduction and Review (Chp 1-5) Part 2. Basic Statistical Inference (Chp 6-9) Part 3. Important Topics in Statistics (Chp 10-13)

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§3.1. Analysis of Variance (ANOVA, Chp 10-11)
§3.1.1 Introduction
§3.1.2 One-Factor ANOVA (Chp 10)
§3.1.3 Multi-Factor ANOVA (Chp 11)
§3.1.4 Further Topics on ANOVA
§3.2 Introduction to Regression Analysis (Chp 12-13)
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Part 4. Further Topics (Selected from Chp 14-16)

Some Logistics.

- ▶ Homework 7 has been assigned. It's due on Monday March 13.
- ▶ Midterm 2 will be on Friday March 10, to cover Chp 6-10.

§3.1.2B More on Multiple Comparisons

(i) Tukey's Procedure

After One-factor ANOVA answers yes/no difference among I groups, Tukey's procedure identifies which two groups are different, using simultaneous CI of $\mu_i - \mu_j$, for any i,j

• Constructing CI: $\mu_i - \mu_j$'s $1 - \alpha$ CI is

$$(\bar{X}_{i.}-\bar{X}_{j.})\pm W_{ij}$$

 $W_{ij} = Q_{\alpha}(I, n_T - I) \sqrt{\frac{MSS_e}{2}(\frac{1}{n_i} + \frac{1}{n_j})}$ with $Q_{\alpha}(I, n_T - I)$ the upper-tail α critical value of the studentized range distn.

▶ Making inference: If $|\bar{X}_{i.} - \bar{X}_{j.}| > W_{ij}$, conclude μ_i and μ_j are significantly different at level α

§3.1.2B More on Multiple Comparisons

(ii). CI of Other Parameters in one-factor ANOVA

For example,

 \blacktriangleright to estimate $\theta = \sum_{i=1}^{I} c_i \mu_i$?

$$\hat{\theta} = \sum_{i=1}^{I} c_i \hat{\mu}_i = \sum_{i=1}^{I} c_i \bar{X}_{i.}$$

$$var(\hat{\theta}) = \sum_{i=1}^{I} c_i^2 var(\hat{\mu}_i) = \sum_{i=1}^{I} c_i^2 \frac{\sigma^2}{n_i} = \sum_{i=1}^{I} \frac{c_i^2}{n_i} \hat{\sigma}^2$$

$$\implies (1-\alpha)100\%$$
 CI of $\theta = \sum_{i=1}^{I} c_i \mu_i$:

$$\hat{ heta} \mp ME(\hat{ heta}) = \sum_{i=1}^{I} c_i \bar{X}_{i.} \mp t_{lpha/2} (n_T - I) \sqrt{\sum_{i=1}^{I} \frac{c_i^2}{n_i} MSE}$$

§3.1.3 Two-Factor ANOVA (Chp 11)

Setting.

- (i) A study is concerned with two factors A, B with I, J levels, to answer whether the outcomes are closely associated with the factors, jointly or individually.
 e.g., body weights according to gender (F,M: I=2) and age (E,M,Y: J=3)?
- (ii) Observations: kth obs in (i,j)th group X_{ijk} , $k=1,\ldots,n_{ij}$ and $i=1,\ldots,I$, $j=1,\ldots,J$ with $n_T=\sum_i\sum_j n_{ij}$. $(n_{ij}\equiv n,$ balanced study)

► Formulation (I).

$$X_{ijk} = \mu_{ij} + \epsilon_{ijk}, \quad \epsilon_{ijk} \sim N(0, \sigma^2)$$
 iid

To test $H_0: \mu_{ii} = \mu$ for all i, j vs $H_1:$ otherwise

 \implies one-factor ANOVA: when $n_T > IJ$ (at least one $n_{ii} > 1$)

Source of Variation	df	SS	MSS	F-value
treatment	IJ-1	SS_{tr}	$\frac{SS_{tr}}{(IJ-1)}$	$F = \frac{MSS_{tr}}{MSS_e}$
error	$n_T - IJ$	SS_e	$\frac{SS_e}{(n_T-IJ)}$	
total	n_T-1	SS_T	$\frac{SS_T}{(n_T-1)}$	

$$SS_{T} = SS_{tr} + SS_{e}$$

$$SS_{T} = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{n_{ij}} (X_{ijk} - \bar{X}_{...})^{2} = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{n_{ij}} X_{ijk}^{2} - n_{T} \bar{X}_{...}^{2}$$

$$SS_{e} = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{n_{ij}} (X_{ijk} - \bar{X}_{ij.})^{2} = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{n_{ij}} X_{ijk}^{2} - \sum_{i=1}^{I} \sum_{j=1}^{J} n_{ij} \bar{X}_{ij.}^{2}$$

How about factor A's (or B's) individual effect? How about factors A and B's interaction?

► Formulation (II). Consider

$$\mu_{ij} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij}$$

 α_i : factor A's main effect with $\sum_{j=1}^{I} \alpha_i = 0$, β_j : factor B's main effect with $\sum_{j=1}^{J} \beta_j = 0$, $(\alpha\beta)_{ij}$: factors A and B's interaction with $\sum_{i=1}^{I} (\alpha\beta)_{ij} = \sum_{j=1}^{J} (\alpha\beta)_{ij} = 0$.

Two-factor ANOVA model.

$$X_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}, \quad \epsilon_{ijk} \sim N(0, \sigma^2) \text{ iid}$$

 $k = 1, \dots, n_{ij} \text{ and } i = 1, \dots, I, j = 1, \dots, J.$

To test the following 3 sets of hypotheses: $H_{0A}: \alpha_i = 0$ for all i vs $H_{1A}:$ otherwise $H_{0B}: \beta_j = 0$ for all j vs $H_{1B}:$ otherwise $H_{0AB}: (\alpha\beta)_{ii} = 0$ for all i, j vs $H_{1AB}:$ otherwise

To consider individual variation:

$$X_{ijk} - \bar{X}_{...} = (\bar{X}_{i..} - \bar{X}_{...}) + (\bar{X}_{.j.} - \bar{X}_{...}) + (\bar{X}_{ij.} - \bar{X}_{i...} - \bar{X}_{.j.} + \bar{X}_{...}) + (X_{ijk} - \bar{X}_{ij.})$$

How about total variation decomposition?

► Sum of Squares.

 $n_T = \sum_{i=1}^{J} \sum_{j=1}^{J} n_{ij}$, the total number of study observations.

[a]. Sum squares total: (Variation total)

$$SS_T = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{n_{ij}} (X_{ijk} - \bar{X}_{...})^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{n_{ij}} X_{ijk}^2 - n_T \bar{X}_{...}^2$$

[b]. Sum squares error: (Variation due to individual fluctuation)

$$SS_e = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{n_{ij}} (X_{ijk} - \bar{X}_{ij.})^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{n_{ij}} X_{ijk}^2 - \sum_{i=1}^{I} \sum_{j=1}^{J} n_{ij} \bar{X}_{ij.}^2$$

[c]. Sum squares factor A/B: (Variation due to factor A/B's diff levels)

$$SS_A = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{n_{ij}} (\bar{X}_{i..} - \bar{X}_{...})^2 = \sum_{i=1}^{I} (\sum_{j=1}^{J} n_{ij}) \bar{X}_{i..}^2 - n_T \bar{X}_{...}^2$$

$$SS_B = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{n_{ij}} (\bar{X}_{.j.} - \bar{X}_{...})^2 = \sum_{j=1}^{J} (\sum_{i=1}^{I} n_{ij}) \bar{X}_{.j.}^2 - n_T \bar{X}_{...}^2$$

[d]. Sum squares A,B interaction: (Variation due to factors A and B's interaction)

$$extit{SS}_{AB} = \sum_{I}^{I} \sum_{j}^{J} \sum_{i,j}^{n_{ij}} (ar{X}_{ij.} - ar{X}_{i..} - ar{X}_{.j.} + ar{X}_{...})^2$$

with

$$ar{X}_{ij.} - ar{X}_{i..} - ar{X}_{.j.} + ar{X}_{...}$$

$$= [ar{X}_{ij.} - ar{X}_{...}] - [ar{X}_{i..} - ar{X}_{...}] - [ar{X}_{.j.} - ar{X}_{...}]$$

$$\approx (\mu_{ii} - \mu) - \alpha_{i} - \beta_{i} = (\alpha \beta)_{ii}$$

i=1 i=1 k=1

Relationships: Only in a balanced study $(n_{ii} \equiv n)$ $SS_T = SS_A + SS_B + SS_{AB} + SS_{AB}$

with
$$SS_{tr} = SS_A + SS_B + SS_{AB}$$
 (Otherwise, no such decomposition and a different method needed)

Further

Further
$$E \big\{ \textit{MSS}_{\rm e} \big\} = E \big\{ \frac{\textit{SS}_{\rm e}}{\textit{n}_T - \textit{IJ}} \big\} = \sigma^2$$

with $n_T = \sum_{i=1}^{J} \sum_{j=1}^{J} n_{ij}$: it's nIJ if $n_{ij} \equiv n$.

with
$$n_T = \sum_{i=1}^{J} \sum_{j=1}^{J} n_{ij}$$
: it's nIJ if $n_{ij} \equiv n$.

$$F(MSS_i) - F(SS_{tr}) - \sigma^2 + \sum_{i=1}^{J} \sum_{j=1}^{J} \sum_{j=1}^{J} \sum_{i=1}^{J} \sum_{j=1}^{J} \sum_{i=1}^{J} \sum_{j=1}^{J} \sum_{i=1}^{J} \sum_{j=1}^{J} \sum_{i=1}^{J} \sum_{j=1}^{J} \sum_{i=1}^{J} \sum_{j=1}^{J} \sum_{j=1}^$$

$$E\{MSS_{tr}\} = E\{\frac{SS_{tr}}{IJ - 1}\} = \sigma^2 + \frac{\sum_{i=1}^{I} \sum_{j=1}^{J} n_{ij} (\mu_{ij} - \mu)^2}{IJ - 1}$$

$$E\{MSS_{tr}\} = E\{\frac{SS_{tr}}{IJ-1}\} = \sigma^2 + \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} n_{ij} (\mu_{ij} - \mu)^2}{IJ-1}$$

$$E\{MSS_A\} = E\{\frac{SS_A}{IJ-1}\} = \sigma^2 + \frac{nJ}{IJ-1} \sum_{i=1}^{l} \alpha_i^2$$

$$E\{MSS_{tr}\} = E\{\frac{SS_{tr}}{IJ - 1}\} = \sigma^{2} + \frac{\sum_{i=1}^{I} \sum_{j=1}^{J} n_{ij} (\mu_{ij} - \mu_{ij})}{IJ - 1}$$

$$E\{MSS_{tr}\} = E\{\frac{SS_{A}}{IJ - 1}\} = \sigma^{2} + \frac{nJ}{IJ} \sum_{j=1}^{I} n_{ij} (\mu_{ij} - \mu_{ij})$$

$$E\{MSS_A\} = E\{\frac{SS_A}{I-1}\} = \sigma^2 + \frac{nJ}{I-1} \sum_{i=1}^{I} \alpha_i^2$$

$$E\{MSS_B\} = E\{\frac{SS_B}{J-1}\} = \sigma^2 + \frac{nI}{J-1} \sum_{i=1}^{J} \beta_j^2$$

$$E\{MSS_A\} = E\{\frac{SS_A}{I-1}\} = \sigma^2 + \frac{nJ}{I-1} \sum_{i=1}^{I} \alpha_i^2$$

$$E\{MSS_A\} = E\{\frac{SS_A}{I-1}\} = \sigma^2 + \frac{nJ}{I-1} \sum_{i=1}^{J} \alpha_i^2$$

$$E\{MSS_A\} = E\{\frac{SS_B}{I-1}\} = \sigma^2 + \frac{nJ}{I-1} \sum_{i=1}^{J} \alpha_i^2$$

$$E\{MSS_A\} = E\{\frac{1-\alpha}{l-1}\} = \sigma^2 + \frac{1}{l-1}\sum_{i=1}^{l}\alpha_i^2$$

$$E\{MSS_A\} = E\{\frac{1}{I-1}\} = \sigma^2 + \frac{1}{I-1}\sum_{i=1}^{J}\alpha_i^2$$

$$E\{MSS_A\} = E\{\frac{SS_B}{I-1}\} = \frac{1}{I-1}\sum_{i=1}^{J}\alpha_i^2$$

$$E\{NSSA\} = E\{\frac{1}{I-1}\} = 0 + \frac{1}{I-1}\sum_{i=1}^{J} \alpha_i$$

 $E\{MSS_{AB}\} = \sigma^2 + \frac{n}{(I-1)(J-1)} \sum_{i=1}^{J} \sum_{i=1}^{J} (\alpha \beta)_{ij}^2$

Two-factor ANOVA Table. (in a balanced study: $n_T = IJn$)

Source of Variation	df	SS	MSS	F-value
А	l-1	SS_A	$\frac{SS_A}{(I-1)}$	$F_A = \frac{MSS_A}{MSS_e}$
В	J-1	SS_B	$\frac{SS_B}{(J-1)}$	$F_B = \frac{MSS_B}{MSS_a}$
AB	(I-1)(J-1)	SS_{AB}	$\frac{SS_{AB}}{(I-1)(J-1)}$	$F_{AB} = \frac{MSS_{AB}}{MSS_e}$
error	$n_T - IJ$	SS_e	$\frac{\dot{S}\dot{S}_e}{(n_T - IJ)}$	
total	n_T-1	SS_T	,	

► F-Test (on Factor A).

 H_{0A} : $\alpha_i = 0$ vs H_{1A} : otherwise

$$F_A = \frac{SS_A/(I-1)}{SS_e/(n_T - IJ)} \sim F(I-1, n_T - IJ)$$

under H_{0A} .

At α -significance level, $c_A = f_{\alpha}(I-1, n_T-IJ)$ such that $P_{H_{0A}}(F_A > c_A) = \alpha$; reject H_{0A} if $F_{A,obs} > c_A$.

► F-Test (on Factor B).

 $H_{0B}: \beta_j = 0$ vs $H_{1B}:$ otherwise

$$F_B = \frac{SS_B/(J-1)}{SS_e/(n_T - IJ)} \sim F(J-1, n_T - IJ)$$

under H_{0B} .

At α -significance level, $c_B = f_{\alpha}(J-1, n_T-IJ)$ such that $P_{H_{0B}}(F_B > c_B) = \alpha$; reject H_{0B} if $F_{B,obs} > c_B$.

F-Test (on Factors A,B interaction).

$$H_{0AB}:(lphaeta)_{ij}=0$$
 vs $H_{1AB}:$ otherwise

under H_{0AB} .

At α -significance level, $c_{AB} = f_{\alpha}((I-1)(J-1), n_T - IJ)$ such that $P_{H_{0AB}}(F_{AB} > c_{AB}) = \alpha$; reject H_{0AB} if $F_{AB,obs} > c_{AB}$.

 $F_{AB} = \frac{SS_{AB}/(I-1)(J-1)}{SS_{AB}/(I-1)(J-1)} \sim F((I-1)(J-1), n_T - IJ)$

Example 6.3

- ▶ **Study.** to compare yields of 3 different tomato varieties and 4 different plant densities, each combination of variety is used in 3 plots
- **Formulation.** two-factor ANOVA model; to test H_{0A} , H_{0B} , H_{0AB} at level $\alpha = 5\%$
- ▶ **Data.** I = 3, J = 4 and n = 3: x_{ijk}

	В					
Α	1	2	3	4	X _i	\bar{x}_{i}
1	X ₁₁₁ , X ₁₁₂ , X ₁₁₃					
2	$X_{211}, X_{212}, X_{213}$					
3						
<i>X</i> . <i>j</i> .					$x_{} = 500$	
$\bar{x}_{.i.}$						$\bar{x}_{} = 13.89$

► ANOVA table.

Source of Variation	df	SS	MSS	F-value
A	3 – 1	327.60	163.8	$F_{A,obs} = 103.02$
В	4 - 1	86.69	28.9	$F_{B,obs} = 18.18$
AB	(3-1)(4-1)	8.03	1.34	$F_{AB,obs} = .84$
error	24	38.04	1.59	
total	35	460.36		

Making inference.

$$f_{0.01}(2,24) = 5.61 < F_{A,obs} \Longrightarrow \text{reject } H_{0A}.$$

 $f_{0.01}(3,24) = 4.72 < F_{B,obs} \Longrightarrow \text{reject } H_{0B}.$
 $f_{0.01}(6,24) = 3.67 > F_{AB,obs} \Longrightarrow \text{don't reject } H_{0AB}.$

Note that roughly $\mu_{ij} = \mu + \alpha_i + \beta_j$: e.g. $\mu_{1j} - \mu_{2j} = \alpha_1 - \alpha_2$; $\mu_{i2} - \mu_{i3} = \beta_2 - \beta_3$.

What if $n \geqslant 1$ (i.e. n = 1)?

Example 6.4 (p438)

- ▶ **Study.** to remove marks on fabrics from erasable pens with A: brand of pen and B: wash treatment.
- ▶ **Data.** overall specimen color change (lower, better): I = 3, I = 4 and n = 1

		В				
Α	1	2	3	4	total	average
1	.97				2.39	.598
2	.77				1.38	.345
3	.67				1.82	.455
total	2.41	1.01	1.27	.90	5.59	
average						.466

▶ **To test on** H_{0A} , H_{0B} and H_{0AB} ? two factor study but n = 1: in 2-factor ANOVA table $n_T = IJ$ \implies consider $\mu_{ij} = \mu + \alpha_i + \beta_i$.

► ANOVA table.

Source of Variation	df	SS	MSS	F-value
A	3-1	0.128		$F_{A,obs} = 4.43$
В	4-1	0.480		$F_{B,obs} = 11.05$
error	(3-1)(4-1)	0.087		,
total	12-1	0.695		

► Making inference.

$$f_{\alpha}(2,6) = 5.14 > F_{A,obs} \Longrightarrow \text{don't reject } H_{0A}.$$

 $f_{\alpha}(3,6) = 4.76 > F_{B,obs} \Longrightarrow \text{reject } H_{0B}.$

How about 3-factor ANOVA? How about multi-factor ANOVA?

To be discussed next

What will we study next?

- Part 1. Introduction and Review (Chp 1-5)
- Part 2. Basic Statistical Inference (Chp 6-9)
- Part 3. Important Topics in Statistics (Chp 10-13)
 - 3.1A One-Factor Analysis of Variance (Chp 10)
 - 3.1B Multi-Factor ANOVA (Chp 11)
 - 3.2A Simple Linear Regression Analysis (Chp 12)
 - 3.2B More on Regression (Chp 13)

Part 4. Further Topics (Selected from Chp 14-16)