

Random Effects Model

(Eisenhart ~ 1997)

fixed vs random effects in Anova

Example: Sodium Content in Beer (USA data set)

Experiment {
- Six brands
- Each brand 8 12 ounce bottles were sampled
& Sodium Content in mg were measured.

Questions:

- ① Expected value of sodium content for a given brand?
- ② Does sodium content differ significantly between brands?
- ③ What is expected value of sodium content in Beer?
- ④ What is the variability of sodium content between different Beer brands?

Data - (2005) kutner et al

Random effects model

One way
Anova

Y_{ij} - j^{th} observation in factor level i

$$Y_{ij} = \mu + \alpha_i + \epsilon_{ij} \quad j=1, \dots, n_i; i=1, \dots, I$$

α_i - fixed effect

$\epsilon_{ij} \sim N(0, \sigma^2)$ independent

Random effects model

Y_{ij} - j^{th} observation in factor level i

$$Y_{ij} = \mu + \alpha_i + \epsilon_{ij} \quad j=1, \dots, n_i; i=1, \dots, I$$

$$\epsilon_{ij} \sim N(0, \sigma^2)$$

$$\alpha_i \sim N(0, \sigma_\alpha^2)$$

independent

In R we used library(lme4) and applied lmer function:

$$\hat{\mu} = 17.629$$

$$\hat{\sigma}^2 = 0.716$$

$$\hat{\sigma}_\alpha^2 = 26.274$$

REML: restricted maximum likelihood

- Predict random effects
- Estimate fixed effects & variance parameters
- Parameters: $\mu, \sigma^2, \sigma_\alpha^2$

Usage:-

- Model has less parameters
- (preferred) # of bands is large ($I \gg$)
of repetitions is small ($n_i \ll$)

i.e. if # $\alpha_i \gg$ and # $n_i \ll$ -- is sufficient data to estimate α_i

Differences between fixed effect & Random effect

one way
Anova

Random
effects
model

- $E[Y_{ij}] = \mu + \alpha_i$
- $Cov[Y_{ij}, Y_{ik}]$
 $= Cov(\mu + \alpha_i + \epsilon_{ij}, \mu + \alpha_i + \epsilon_{ik})$
 $= Cov(\epsilon_{ij}, \epsilon_{ik}) = 0$

All responses are independent
(\therefore normality)

- $E[Y_{ij}] = \mu$
- $Var[Y_{ij}] = \sigma_\alpha^2 + \sigma^2$
- $Cov(Y_{ij}, Y_{ik})$

$$E_\mu = \sigma_\alpha^2$$

(observations within
group/factor are not
statistically independent)

Intra class Correlation

$$\rho = \frac{Cov(Y_{ik}, Y_{ij})}{\sqrt{Var(Y_{ik}) Var(Y_{ij})}}$$

$$E_\mu = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma^2}$$

Hypothesis Testing:

• $H_0: \sigma_\alpha^2 = 0$ (no variability in the factor levels)
 \Downarrow
 $\alpha_i = 0, E[\alpha_i] = 0 \forall i$

• $H_A: \sigma_\alpha^2 > 0$

Use F-test:

(Recall: same as
one way Anova
F-test)

$$\frac{SS_\alpha / I - 1}{RSS / n - I} \sim F_{I-1, n-I}$$

- $E[\bar{y}_{..}] = \mu$

$\hat{\mu} := \bar{y}_{..}$ is unbiased for μ estimate

- $\text{Var}[\bar{y}_{..}] = \frac{1}{n} \sigma^2 + \frac{\left(\sum_{i=1}^I n_i^2 \right)}{n^2} \sigma_\alpha^2$

$\frac{SS_\alpha}{(I-1)n}$ is an estimate of $\text{var}(\bar{y}_{..})$

- Confidence Interval $100(1-\alpha)\%$ for μ is

$$\left(\bar{y}_{..} - t_{I-1, (1-\frac{\alpha}{2})} \sqrt{\frac{SS_\alpha}{(I-1)n}}, \bar{y}_{..} + t_{I-1, (1-\frac{\alpha}{2})} \sqrt{\frac{SS_\alpha}{(I-1)n}} \right)$$

- $\hat{\sigma}^2 = \frac{RSS}{n-I}$

- $n \hat{\sigma}^2 + \frac{\sum_{i=1}^I n_i^2}{(I-1)} \hat{\sigma}_\alpha^2 = \frac{SS_\alpha}{(I-1)}$