

Model: $Y_{ij} = \mu + \alpha_i + \varepsilon_{ij}$, $\varepsilon_{ij} \stackrel{iid}{\sim} N(0, \sigma_e^2)$

ANOVA Assumptions

- the t populations are normally distributed
- the t populations are independent
- the t populations have equal variance
- we have a SRS from each population (treatments randomly assigned to EUs)

A test is robust with respect to an assumption if violating the assumption does not greatly affect the properties of the test.

$Y_{ij} = \mu + \alpha_i + \varepsilon_{ij}$, $\varepsilon_{ij} \stackrel{iid}{\sim} N(0, \sigma_e^2) \rightarrow \hat{\varepsilon}_{ij} = e_{ij} = Y_{ij} - \hat{Y}_{ij} = Y_{ij} - \bar{Y}_i$

Assessing ANOVA Assumptions

- SRS: the F -test is not robust to violations of independence within groups
 - positive correlation \rightarrow Standard Errors are under estimated
 - randomization helps guard against correlated observations
- Independence: the F -test is not robust to violations of independence between groups
 - violations can seriously affect Type I & Type II Errors rates
- Normality: the F -test is robust to departures from normality

Tests:

 - Shapiro-Wilk Test
 - Anderson-Darling Test
 - Kolmogorov-Smirnov Test
 - Q-Q plot: plot observed quantiles vs. expected quantiles from a Normal Dist
- HOV: the F -test is not robust to violations (Standard Errors are inflated)

Tests:

 - $F_{\max,s} = s_{\max}^2 / s_{\min}^2$ $df = n^* - 1$ where $n^* = \max(n_1, n_2)$
 - * Quick and easy, but not robust to non-normal data
 - Brown & Forsythe's Test (a.k.a. "Levene's median")
 - * Robust test of HOV
 - * Equivalent to an ANOVA test on recoded data $z_{ij} = |y_{ij} - \tilde{y}_i|$
 - Residual – Predicted Plots
 - Standardized Residuals: $w_{ij} = e_{ij} / \sqrt{MSE}$
 - Studentized Residuals: $w_{ij}^* = e_{ij} / \sqrt{MSE(1 - 1/r_i)}$

Variance Stabilizing Transformations

Several scenarios lead to data where the SD is related to the mean

$$Y \sim \chi_k^2 \quad \rightarrow \quad E(Y) = k \quad \text{Var}(Y) = 2k$$

$$Y \sim \text{Bin}(n, p) \quad \rightarrow \quad E(Y) = np \quad \text{Var}(Y) = np(1-p)$$

$$Y \sim \text{Poisson}(\lambda) \quad \rightarrow \quad E(Y) = \lambda \quad \text{Var}(Y) = \lambda$$

Goal: Find a transformation $W=g(Y)$ so that $\text{Var}(W)$ is constant across groups

Claim: If Y is a RV with $E(Y)=\mu$ and $SD(Y)=\sigma_y$ and $W=g(Y)$, where g is differentiable
Then $\sigma_w = |g'(\mu)|\sigma_y$

Box-Cox Power Transformation for a Completely Randomized Design (CRD)

Suppose the data, Y_{ij} , satisfy the following conditions: $E(Y) = \mu$ and $\sigma_y = c\mu^m$

Let $W = Y^p$ and choose p so that σ_w does not depend on μ .

P	Transformation
2	y^2
1	none
$\frac{1}{2}$	\sqrt{y}
0	$\log(y)$
$-\frac{1}{2}$	$1/\sqrt{y}$
-1	$1/y$
-2	$1/y^2$

Recall from Calculus:

Taylor Series approximation for a differentiable function $g(x)$ about $x=a$

- Approximates $g(x)$ with the polynomial $T_n(x)$

$$\bullet \quad T_n(x) = g(a) + g'(a)(x-a) + \frac{g''(a)}{2!}(x-a)^2 + \dots + \frac{g^{(n)}(a)}{n!}(x-a)^n$$

Claim: If Y is a RV with $E(Y)=\mu$ and $SD(Y)=\sigma_y$ and $W=g(Y)$, where g is differentiable
Then $\sigma_w = |g'(\mu)|\sigma_y$

Let Y be a RV with a finite mean and SD

$$W = g(y) \stackrel{(T)}{=} g(\mu) + (Y - \mu)g'(\mu) + \text{HigherOrderTerms}$$

$$\begin{aligned} E(W) &= g(\mu) + E(Y - \mu)g'(\mu) + E[\text{H.O.T.}] \\ &\approx g(\mu) \end{aligned}$$

$$\text{Var}(W) = E[W - E(W)]^2$$