Random Latex Notes

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Studying for ST703 Exam 1

$$\overline{X - \bar{x}} = \sum (x_i - \bar{x}) = 0$$

$$Cov(X,Y) = E\Big((X - E(X)) \cdot (Y - E(Y))\Big)$$

for $\theta = \beta_1 - \beta_2$

$$Var(\hat{\beta}_1 - \hat{\beta}_2) = Var(\hat{\beta}_1) + Var(\hat{\beta}_2) - 2Cov(Var(\hat{\beta}_1), Var(\hat{\beta}_2))$$

$$stderr = \frac{\sigma}{\sqrt{n}}$$

$$stderr(\hat{\beta_0}) = \sqrt{s^2\Big(\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{\sum (x_i - \bar{x})^2}\Big)}$$

$$stderr(\hat{\beta}_1) = \sqrt{\frac{s^2}{\sum (x_i - \bar{x})^2}}$$

$$s^2 = MSE$$

$$\text{Covariance Matrix} = \sigma^2 \cdot (X^T X)^{-1}$$

$$\sigma = \sqrt{MSE} \quad \forall x = x_i$$

$$T = \frac{\hat{\theta} - \theta_0}{SE(\hat{\theta})}$$

$$SSRegn = \sum (\hat{y_i} - \bar{y})^2$$

$$SSE = \sum (y_i - \hat{y_i})^2$$

$$SST = \sum (y_i - \bar{y})^2$$

$$R(\beta_1, \beta_2 | \beta_0) = \text{full model SSE of ANOVA}$$

$$R(\beta_2 | \beta_0) = \text{full model SSE - Type II SS } \beta_1$$

We are 90

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Studying for ST520 midterm

$$E[\hat{\theta}] = \theta$$

$$P[D|E] \approx 0 \ \wedge \ P[D|\bar{E}] \approx 0 \Rightarrow \theta \approx \psi$$

In a prospective study, n_{1+} and n_{2+} are fixed.

$$[(X_1 > r_1) \wedge (X_1 + X_2 > r)] \vee (X_1 > r)$$

We will estimate Δ using $\hat{\Delta} = \bar{Y_1} - \bar{Y_2}$, where $\bar{Y_1}$ is the sample average response of the n_1 patients receiving treatment A, and $\bar{Y_2}$ is the sample average response of the n_2 patients receiving treatment B. Notice $\hat{\Delta}$ is most efficient when $\pi = 0.5$.

Start with m balls labeled A and m balls labeled B. Randomly pick a ball for the first patient and assign the treatment indicated by the ball. If the patient recieves A, then replace that A ball with a B.

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Studying for ST703 Exam 2

Source	DF	SS	MS	F
Model	$t-1$	$\sum_{i-1}^{t} \sum_{j=1}^{n_1} \left(\bar{y}_{i+} - \bar{y}_{++} \right)^2$	$\frac{SSM}{df_M}$	$\frac{MSM}{MSE}$
Error	$\sum_{i=1}^{t}(n_i) - t$	$\sum_{i=1}^{t} \sum_{j=1}^{n_i} \left(y_{ij} - \bar{y}_{i+} \right)^2$	$\frac{SSE}{df_E}$	
Total	$\sum_{i=1}^{t}(n_i) - 1$	$\sum_{i=1}^{t} \sum_{j=1}^{n_1} \left(y_{ij} - \bar{y}_{++} \right)^2$		

$$\hat{\beta}$$

$$X\hat{\beta}$$

	Partial SS (III) used in t-test	Sequential SS (I) incremental
X_1	$R(\beta_1\|\beta_0, \beta_2, \beta_3)$	$R(\beta_1\|\beta_0)$
X_2	$R(\beta_2\|\beta_0, \beta_1, \beta_3)$	$R(\beta_2\|\beta_0, \beta_1)$
X_3	$R(\beta_3\|\beta_0, \beta_1, \beta_2)$	$R(\beta_3\|\beta_0, \beta_1, \beta_2)$

$$Var(a_1\hat{\beta}_1 + a_2\hat{\beta}_2) = a_1^2 Var(\hat{\beta}_1) + a_2^2 Var(\hat{\beta}_2) + 2a_1a_2Cov(\hat{\beta}_1, \hat{\beta}_2)$$

$$\begin{aligned}
|\hat{\theta}| &\geq t_{df_{error},\alpha/2} SE(\hat{\theta}); \text{ Fisher} \\
&\geq t_{df_{error},\frac{1}{k}\frac{\alpha}{2}} SE(\hat{\theta}); \text{ Bonferroni} \\
&\geq q_{t,df_{error},\alpha} \cdot \sqrt{\frac{1}{2}} SE(\hat{\theta}); \text{ Tukey-Kramer} \\
&\geq \sqrt{(t-1)F^{t-1}_{df_{error},\alpha}} SE(\hat{\theta}); \text{ Scheffe}
\end{aligned}$$

ν is the df used to estimate σ^2. W_i is the sample mean for group i.

$$\mu_P - \mu = 3$$

$$\mu_T - \mu = 3$$

$$\mu_S - \mu = -6$$

$$\mu_E - \mu = 0$$

$$\mu_C - \mu = 0$$

if null is true this subtraction is 0 so $MSModel = \sigma^2 = MSE$
Pooled variance = MSE
Sample Variance = $\frac{1}{N-1}\sum(y_i - \bar{y})^2 = \frac{SSTotal}{N-1}$
Remember

$$t = \frac{\hat{\theta} - \theta_0}{SE(\hat{\theta_0})} \Rightarrow \frac{\hat{\mu}_1 - \hat{\mu}_2 - \theta_0}{\sqrt{MSE(1/n_1 + 1/n_2)}}$$

2-sided F p-value = $2\Big[1 - F_{t_{n-1}}(|t_{obs}|)\Big]$

Interpretation Example: β_0 is the effect from location 5 for initial weight = 0, β_{1-4} are the differences in effects between locations 1-4 and 5 for fixed initial weight.

$E_{ij} \sim N(0, \sigma^2)$ where σ^2 is the population variance of the response