Random Latex Notes

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2019-10-08

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

2019-10-11

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.

2019-10-08

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

2019-11-18

Studying for 701 midterm 2

$$1 - \frac{u}{u+v} = \frac{v}{u+v}$$

$$\begin{aligned}
M_X(t) &= \int_0^\infty e^{tx} \frac{1}{\Gamma(p/2)2^{p/2}} \cdot x^{p/2-1} e^{-x/2} dx \\
&= \int_0^\infty \frac{1}{\Gamma(p/2)2^{p/2}} x^{p/2-1} \cdot e^{-x/2+tx} dx \\
&= \int_0^\infty \frac{1}{\Gamma(p/2)2^{p/2}} x^{p/2-1} \cdot e^{-x/2(1-2t)} dx \\
&= (1-2t)^{-(p/2-1)} \int_0^\infty \frac{1}{\Gamma(p/2)2^{p/2}} \cdot x^{p/2-1} e^{-x/2(1-2t)} (1-2t)^{p/2-1} dx \\
&= (1-2t)^{-(p/2-1)} \int_0^\infty \frac{1}{\Gamma(p/2)2^{p/2}} \cdot (x(1-2t))^{p/2-1} e^{-x/2(1-2t)} dx
\end{aligned}$$

$$\begin{aligned}
u &= x(1-2t) \\
du &= (1-2t)dx
\end{aligned}$$

$$\begin{aligned}
&= (1-2t)^{-(p/2-1)} \int_0^\infty \frac{1}{\Gamma(p/2)2^{p/2}} \cdot (u)^{p/2-1} e^{-u/2} \frac{1}{1-2t} du \\
&= \frac{(1-2t)^{-p/2+1}}{1-2t} \cdot 1 \\
&= (1-2t)^{-p/2}
\end{aligned}$$

2019-11-19

Clinical trials homework 5

$$1 - m(x)\hat{S}(t)$$

2019-12-06

dots

$\cdots - - - - - - \ldots - - - - - - - \cdots$

2019-12-07

ST703 final cheat sheet

Source	df	SS
A	$a-1$	$\sum_i \sum_j \sum_k (\overline{y}_{i++} - \overline{y}_{+++})^2$
B	$b-1$	$\sum_i \sum_j \sum_k (\overline{y}_{+j+} - \overline{y}_{+++})^2$
AB	$(a-1)(b-1)$	$\sum_i \sum_j \sum_k (\overline{y}_{ij+} - \overline{y}_{i++} - \overline{y}_{+j+} + \overline{y}_{+++})^2$
Error	$N-ab$	$\sum_i \sum_j \sum_k (y_{ijk} - \overline{y}_{ij+})^2$
Total	$N-1$	$\sum_i \sum_j \sum_k (y_{ijk} - \overline{y}_{+++})^2$

$$\frac{1}{2}[1, 1, -1, -1]$$

$$\frac{1}{2}[1, -1, 1, -1]$$

$$[1, 0, -1, 0]$$

$$[0, 1, 0, -1]$$

$$[1, -1, 0, 0]$$

$$[0, 0, 1, -1]$$

$$[1, -1, -1, 1]$$

σ_T accounts for variability among treatment effects; this component contributes to the variance of the observed response because the observed response depends on the effect of a randomly selected treatment

σ accounts for the variability of the replicate measurements for the same treatment

$$\begin{aligned}
E(Y_{ij}) &= \mu \\
Var(Y_{ij}) &= \sigma_T^2 + \sigma^2 \\
Cov(Y_{ij}, Cov(Y_{il})) &= Cov(T_i + E_{ij}, T_i + E_{il}) = \sigma_T^2 \text{ for} j \neq l \\
Cov(Y_{ij}, Y_{kl}) &= 0 \text{ for } i \neq k
\end{aligned}$$

$$\sigma_T^2 = 0$$

if $SE = \sqrt{c_1 MS_1 + \cdots + c_k MS_k}$ then

$$\begin{aligned}
E(Y_{ijk}) &= 0 \\
Var(Y_{ijk}) &= \sigma_A^2 + \sigma_B^2 + \sigma_{AB}^2 + \sigma^2 \\
Cov(Y_{ijk}, Y_{ijl}) &= \sigma_A^2 + \sigma_B^2 + \sigma_{AB}^2 \\
Cov(Y_{ijk}, Y_{iml}) &= \sigma_A^2 \\
Cov(Y_{ijk}, Y_{qjl}) &= \sigma_B^2
\end{aligned}$$

$$
\begin{aligned}
E(Y_{ijk}) &= \mu + \alpha_i \\
Var(Y_{ijk}) &= \sigma_B^2 + \sigma_{\alpha B}^2 + \sigma^2 \\
Cov(Y_{ijk}, Y_{ijl}) &= \sigma_B^2 + \sigma_{\alpha B}^2 \text{ for } k \neq l \\
Cov(Y_{ijk}, Y_{iml}) &= 0 \text{ for } j \neq m \\
Cov(Y_{ijk}, Y_{qjl}) &= \sigma_B^2 \text{ for } i \neq q
\end{aligned}
$$

if assuming $b_i = b$ and $n_{ij} = n$, $DFB(A) = a(b-1)$ and $DFE = nab - ab$

$$
\begin{aligned}
E(Y_{ijk}) &= \mu \\
Var(Y_{ijk}) &= \sigma_A^2 + \sigma_{B(A)}^2 + \sigma^2 \\
Cov(Y_{ijk}, Y_{ijl}) &= \sigma_A^2 + \sigma_{B(A)}^2 \text{ for } k \neq l \\
Cov(Y_{ijk}, Y_{iml}) &= \sigma_A^2 \text{ for } j \neq m \\
Cov(Y_{ijk}, Y_{qjl}) &= 0 \text{ for } i \neq q
\end{aligned}
$$

$$
\begin{aligned}
E(Y_{ijk}) &= \mu + \alpha_i \\
Var(Y_{ijk}) &= \sigma_{B(A)}^2 + \sigma^2 \\
Cov(Y_{ijk}, Y_{ijl}) &= \sigma_{B(A)}^2 \text{ for } k \neq l \\
Cov(Y_{ijk}, Y_{iml}) &= 0 \text{ for } j \neq m \\
Cov(Y_{ijk}, Y_{qjl}) &= 0 \text{ for } i \neq q
\end{aligned}
$$

2019-12-08

ST520 final cheat sheet

$$T_n = \frac{\overline{Y}_1 - \overline{Y}_2}{\sqrt{\frac{\sigma_1}{n_1} + \frac{\sigma_2}{n_2}}}$$

$$\phi(n, \Delta_A, \theta) = \frac{\Delta_A}{\sqrt{\frac{\sigma_1}{n_1} + \frac{\sigma_2}{n_2}}}$$

$$SE\Big[KM(t)\Big] = KM(t)\left[\sum_{deathtimes \;\; u \leq t} \frac{d(u)}{n(u)(n(u) - d(u))}\right]^{1/2}$$

Notice that $\lambda_1(t) \leq \lambda_0(t) \Rightarrow S_1(t) > S_0(t)$
Compare T_n to $\mathcal{Z}_\alpha$

$$b_j = c(\alpha, K, \Phi) \times j^{(\Phi - 0.5)}$$

$$
\begin{aligned}
\Phi = 0 &: \text{ O'Brien Fleming} \\
\Phi = 0.5 &: \text{ Pocock}
\end{aligned}
$$

$$E_{\Delta^\star}(V_k) = \sum_{j=1}^{k} j \cdot P_{\Delta^\star}(|T(t_1)| < b_1 \wedge \cdots \wedge |T(T_{j-1})| < b_{j-1} \wedge |T(T_j)| > b_j)$$

$$AI = \frac{IF(\alpha, \beta, K, \Phi)}{K} \cdot I^{FS} \cdot E_{\Delta^\star}(V)$$

δ_i unknown b/c inclusion and exclusion principles and whether or not the patient wants to be in the study So sampling is unknown. Thus, this is a biased sample of the target population

2019-12-10

ST701 Final Exam cheat sheet

Convergence in distribution

$X_n \xrightarrow{d} X$ if $F_{X_n}(x) \to F_X(x)$ for all x such that F_X is continuous

If c is a constant $X_n \xrightarrow{d} c \Leftrightarrow X_n \xrightarrow{p} c$

$$M_{X_n}(t) \to M_X(t) \Rightarrow X_n \xrightarrow{d} X$$

If $X_n \xrightarrow{d} X$ and $Y_n \xrightarrow{p} c$

$$aX_n + bY_n \xrightarrow{d} aX + bc$$
$$X_nY_n \xrightarrow{d} cX$$
$$X_n/Y_n \xrightarrow{d} X/c \ (c \neq 0)$$

$$X_N \xrightarrow{as} X \Rightarrow X_n \xrightarrow{p} X$$
$$X_N \xrightarrow{L_2} X \Rightarrow X_n \xrightarrow{p} X$$
$$X_N \xrightarrow{d} X \Rightarrow X_n \xrightarrow{d} X$$
$$X_N \xrightarrow{d} c \Leftrightarrow X_n \xrightarrow{p} c$$

CLT

Let X_i iid RV with $E(X_i) = \mu$ and $V(X_i) = \sigma^2$ and $\overline{X} = 1/n \sum X_i$.

$$\frac{\sqrt{n}(\overline{X} - \mu)}{\sigma} \xrightarrow{d} N(0, 1)$$

2019-12-11

520 Final

$$\overline{\pi} = \frac{\pi_1 \cdot n_1}{n_1 + n_2} + \frac{\pi_2 \cdot n_2}{n_1 + n_2}$$

2012-12-12

703 Final

$$\mathcal{Z}_{\alpha/2} \cdot SE(\theta) \leq \frac{length}{2}$$

$$\mathcal{Z}_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}} \leq \frac{length}{2}$$

$$\mathcal{Z}_{\alpha/2} \cdot \sqrt{\frac{p(1-p)}{n}} \leq \frac{2 \cdot 0.02}{2}$$

2020-03-04

pfrac command

\newcommand{\pfrac}[2]{\frac{ \partial #1 }{\partial #2 }}

$$\frac{\partial^2 \ell}{\partial \theta^2}$$