



Oppgave 1

a)

Man benyttet randomisert blokkdesign.

I situasjonen har man $k = 5$, $b = 15$, $n = kb = 75$.

ANOVA-tabellen blir

Kilde	df	SS	MS	F	P-verdi
Instrument	$k - 1 = 4$	0.20219	$\frac{0.20219}{4} = 0.0505$	$\frac{0.0505}{0.004818} = 10.48$	0
Objekt	$b - 1 = 14$	45.48159	$\frac{45.48159}{14} = 3.2487$	$\frac{3.2487}{0.004818} = 674.3$	0
Error	$74 - 4 - 14 = 56$	0.26981	$\frac{0.26981}{56} = 0.004818$		
Total	$n - 1 = 74$	45.95359			

der

$$SSTR = 45.95359 - 0.26981 - 45.48159 = 0.20219.$$

Modellen er:

$$Y_{ij} = \mu_j + \beta_i + \epsilon_{ij}; \quad \epsilon_{ij} \sim N(0, \sigma^2),$$

hvor

μ_j : effekten av instrument nr. j

β_i : effekten av objekt nr. i

ϵ_{ij} : tilfeldig feil

b)

 H_0 for p -verdi i første linje:

$$H_0 : \mu_1 = \mu_2 = \dots = \mu_5$$

 H_0 for p -verdi i andre linje:

$$H_0 : \beta_1 = \beta_2 = \dots = \beta_{15}$$

Forskningsinstitusjonen er interessert i den første p -verdien, dvs. er det forskjell mellom instrumentene.

P -verdien er (avrundet til) null, så konklusjon blir **forkast** H_0 , dvs. det er forskjell mellom måleinstrumentene.

Oppgave 2

Teoretiske momenter er

$$E[X] = \frac{r}{\lambda}$$

$$E[X^2] = \text{Var}[X] + (E[X])^2 = \frac{r}{\lambda^2} + \left(\frac{r}{\lambda}\right)^2 = \frac{r(1+r)}{\lambda^2}$$

Momentestimatorene er dermed gitt ved

$$\frac{1}{n} \sum_{i=1}^n X_i = \frac{\hat{r}}{\hat{\lambda}}, \quad \frac{1}{n} \sum_{i=1}^n X_i^2 = \frac{\hat{r}(1+\hat{r})}{\hat{\lambda}^2},$$

Dette gir

$$\hat{r} = \frac{\hat{\lambda}}{n} \sum_{i=1}^n X_i.$$

Dermed

$$\begin{aligned} \hat{\lambda}^2 \cdot \frac{1}{n} \sum_{i=1}^n X_i^2 &= \hat{\lambda} \cdot \frac{1}{n} \sum_{i=1}^n X_i \left(1 + \hat{\lambda} \cdot \frac{1}{n} \sum_{i=1}^n X_i\right) \\ \Rightarrow \hat{\lambda} \cdot \left[\frac{1}{n} \sum_{i=1}^n X_i^2 - \left(\frac{1}{n} \sum_{i=1}^n X_i\right)^2 \right] &= \frac{1}{n} \sum_{i=1}^n X_i \\ \Rightarrow \hat{\lambda} &= \frac{\frac{1}{n} \sum_{i=1}^n X_i}{\frac{1}{n} \sum_{i=1}^n X_i^2 - \left(\frac{1}{n} \sum_{i=1}^n X_i\right)^2} \quad \text{og} \quad \hat{r} = \frac{\left(\frac{1}{n} \sum_{i=1}^n X_i\right)^2}{\frac{1}{n} \sum_{i=1}^n X_i^2 - \left(\frac{1}{n} \sum_{i=1}^n X_i\right)^2}. \end{aligned}$$

Oppgave 3

a)

Rimelighetsfunksjonen blir

$$L(\theta) = \prod_{i=1}^n f_X(x_i, \theta) = \prod_{i=1}^n \left[\frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{\theta}} e^{-\frac{1}{2\theta}(x_i-1)^2} \right];$$

log-rimelighetsfunksjonen blir

$$l(\theta) = \sum_{i=1}^n \left[-\frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln \theta - \frac{1}{2\theta} (x_i - 1)^2 \right] = -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln(\theta) - \frac{1}{2\theta} \sum_{i=1}^n (x_i - 1)^2.$$

Deriverer for å finne maksimumspunkt,

$$l'(\theta) = -\frac{n}{2\theta} + \frac{1}{2\theta^2} \sum_{i=1}^n (x_i - 1)^2.$$

Finner SME ved å sette de partiellderiverte lik null,

$$l'(\theta) = 0 \quad \Rightarrow \quad -n = \frac{1}{\theta} \sum_{i=1}^n (x_i - 1)^2 \quad \Rightarrow \quad \theta = \frac{1}{n} \sum_{i=1}^n (x_i - 1)^2.$$

Dermed

$$\hat{\theta} = \frac{1}{n} \sum_{i=1}^n (X_i - 1)^2.$$

For at

$$\frac{n\hat{\theta}}{\theta} = \sum_{i=1}^n \left(\frac{X_i - 1}{\sqrt{\theta}} \right)^2,$$

vet man at

$$\begin{aligned} X_i &\sim N(1, \theta) \quad \Rightarrow \quad \frac{X_i - 1}{\sqrt{\theta}} \sim N(0, 1) \\ \Rightarrow \quad \left(\frac{X_i - 1}{\sqrt{\theta}} \right)^2 &\sim \chi_1^2, \quad \text{og dermed} \quad \sum_{i=1}^n \left(\frac{X_i - 1}{\sqrt{\theta}} \right)^2 \sim \chi_n^2, \end{aligned}$$

fordi X_i -ene er uavhengige.

b)

Vet fra a) at $\frac{n\hat{\theta}}{\theta} \sim \chi_n^2$.

Dette gir

$$E\left(\frac{n\hat{\theta}}{\theta}\right) = n \Leftrightarrow \frac{n}{\theta} E[\hat{\theta}] = n \Rightarrow \underline{\underline{E[\hat{\theta}] = \theta}},$$

$$\text{Var}\left(\frac{n\hat{\theta}}{\theta}\right) = n \Leftrightarrow \frac{n^2}{\theta^2} \text{Var}[\hat{\theta}] = 2n \Rightarrow \underline{\underline{\text{Var}[\hat{\theta}] = \frac{2\theta^2}{n}}}.$$

Benytter Cramer-Rao:

$$f_X(x; \theta) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{\theta}} e^{-\frac{1}{2\theta}(x-1)^2}$$

$$\ln f_X(x; \theta) = -\frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln \theta - \frac{1}{2\theta} (x-1)^2$$

$$\frac{\partial}{\partial \theta} \ln f_X(x; \theta) = -\frac{1}{2\theta} + \frac{1}{2\theta^2} (x-1)^2$$

$$\frac{\partial^2}{\partial \theta^2} \ln f_X(x; \theta) = \frac{1}{2\theta^2} - \frac{2}{2\theta^3} (x-1)^2$$

$$E\left[\frac{\partial^2}{\partial \theta^2} \ln f_X(X; \theta)\right] = E\left[\frac{1}{2\theta^2} - \frac{2}{2\theta^3} (X-1)^2\right] = \frac{1}{2\theta^2} - \frac{1}{\theta^3} \text{Var}[X] = \frac{1}{2\theta^2} - \frac{1}{\theta^3} \cdot \theta = -\frac{1}{2\theta^2}$$

$$\left\{-nE\left[\frac{\partial^2}{\partial \theta^2} \ln f_X(X; \theta)\right]\right\}^{-1} = \frac{2\theta^2}{n} = \text{Var}[\hat{\theta}]$$

Enhver forventningsrett estimator $\tilde{\theta}$, for θ har $\text{Var}[\tilde{\theta}] \geq \text{Var}[\hat{\theta}]$.Derfor er $\hat{\theta}$ en beste estimator.

c)

Vet at $V = \frac{n\hat{\theta}}{\theta} \sim \chi_n^2$ slik at

$$P\left(\chi_{1-\frac{\alpha}{2}, n}^2 \leq \frac{n\hat{\theta}}{\theta} \leq \chi_{\frac{\alpha}{2}, n}^2\right) = 1 - \alpha$$

Men

$$\chi_{1-\frac{\alpha}{2}, n}^2 \leq \frac{n\hat{\theta}}{\theta} \Leftrightarrow \theta \leq \frac{n\hat{\theta}}{\chi_{1-\frac{\alpha}{2}, n}^2}$$

$$\frac{n\hat{\theta}}{\theta} \leq \chi_{\frac{\alpha}{2}, n}^2 \Leftrightarrow \frac{n\hat{\theta}}{\chi_{\frac{\alpha}{2}, n}^2} \leq \theta$$

dvs.

$$P\left(\frac{n\hat{\theta}}{\chi_{\frac{\alpha}{2}, n}^2} \leq \theta \leq \frac{n\hat{\theta}}{\chi_{1-\frac{\alpha}{2}, n}^2}\right) = 1 - \alpha,$$

og $(1 - \alpha)100\%$ konfidensintervall for θ blir: $\left[\frac{n\hat{\theta}}{\chi_{\frac{\alpha}{2}, n}^2}; \frac{n\hat{\theta}}{\chi_{1-\frac{\alpha}{2}, n}^2} \right]$.

d)

Det er rimelig å forkaste H_0 dersom $\hat{\theta} \leq k_l$ eller $\hat{\theta} \geq k_r$.
Bestemmer k_l og k_r fra kravene:

$$P(\hat{\theta} \leq k_l | H_0) = \frac{\alpha}{2}, \quad P(\hat{\theta} \geq k_r | H_0) = \frac{\alpha}{2}$$

som er det samme med

$$P\left(\frac{n\hat{\theta}}{\theta} \leq \frac{nk_l}{1} | H_0\right) = \frac{\alpha}{2}, \quad P\left(\frac{n\hat{\theta}}{\theta} \geq \frac{nk_r}{1} | H_0\right) = \frac{\alpha}{2}$$

dvs.

$$nk_l = \chi_{1-\frac{\alpha}{2}, n}^2 \quad \text{og} \quad nk_r = \chi_{\frac{\alpha}{2}, n}^2 \\ \Rightarrow k_l = \frac{1}{n} \chi_{1-\frac{\alpha}{2}, n}^2, \quad k_r = \frac{1}{n} \chi_{\frac{\alpha}{2}, n}^2$$

Derfor, er beslutningsregelen som

$$\text{“Forkast } H_0 \text{ dersom } \hat{\theta} \leq \frac{1}{n} \chi_{1-\frac{\alpha}{2}, n}^2 \text{ eller } \hat{\theta} \geq \frac{1}{n} \chi_{\frac{\alpha}{2}, n}^2 \text{”}$$

Styrkefunksjonen blir

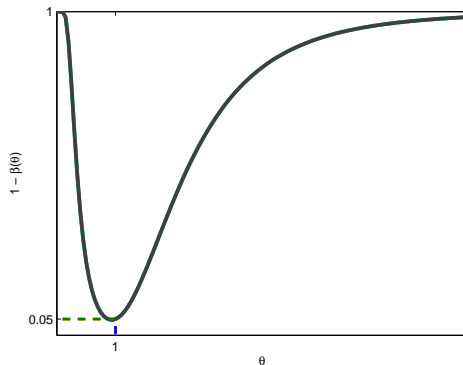
$$1 - \beta(\theta) = P(\text{Forkast } H_0 | \theta) = P\left(\hat{\theta} \leq \frac{1}{n} \chi_{1-\frac{\alpha}{2}, n}^2 \mid \theta\right) + P\left(\hat{\theta} \geq \frac{1}{n} \chi_{\frac{\alpha}{2}, n}^2 \mid \theta\right) \\ = P\left(\frac{n\hat{\theta}}{\theta} \leq \frac{\chi_{1-\frac{\alpha}{2}, n}^2}{\theta} \mid \theta\right) + P\left(\frac{n\hat{\theta}}{\theta} \geq \frac{\chi_{\frac{\alpha}{2}, n}^2}{\theta} \mid \theta\right) \\ \underline{\underline{1 - \beta(\theta) = P\left(V \leq \frac{\chi_{1-\frac{\alpha}{2}, n}^2}{\theta}\right) + P\left(V \geq \frac{\chi_{\frac{\alpha}{2}, n}^2}{\theta}\right), \quad \text{når } V \sim \chi_n^2.}}$$

Med $\alpha = 0.05$ og $n = 10$ blir

$$\chi_{1-\frac{\alpha}{2}, n}^2 = 3.247, \quad \chi_{\frac{\alpha}{2}, n}^2 = 20.483$$

$$1 - \beta(\theta) = P\left(V \leq \frac{3.247}{\theta}\right) + P\left(V \geq \frac{20.483}{\theta}\right).$$

Kvalitativ oppførsel



e)

Her

$$L(\theta) = \frac{1}{(2\pi)^{n/2}} \cdot \frac{1}{\theta^{n/2}} e^{-\frac{1}{2\theta} \sum_{i=1}^n (x_i - 1)^2}$$

$$\omega = \{\theta | \theta = 1\} = \{1\}$$

$$\Omega = \{\theta | \theta \neq 1\}$$

$$L(\hat{\omega}) = L(1) = \frac{1}{(2\pi)^{n/2}} \cdot \frac{1}{1^{n/2}} e^{-\frac{1}{2} \sum_{i=1}^n (x_i - 1)^2} = \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} \sum_{i=1}^n (x_i - 1)^2}$$

$$L(\hat{\Omega}) = L(\hat{\theta}) = \frac{1}{(2\pi)^{n/2}} \cdot \frac{1}{(\hat{\theta})^{n/2}} e^{-\frac{1}{2\hat{\theta}} \sum_{i=1}^n (x_i - 1)^2} = \frac{1}{(2\pi\hat{\theta})^{n/2}} e^{-\frac{n}{2}}, \quad \text{fordi } \hat{\theta} = \frac{1}{n} \sum_{i=1}^n (x_i - 1)^2$$

Dermed

$$\lambda = \frac{L(\hat{\omega})}{L(\hat{\Omega})} = (\hat{\theta})^{n/2} e^{-\frac{1}{2}[\sum_{i=1}^n (x_i - 1)^2 - n]} = (\hat{\theta})^{n/2} e^{-\frac{1}{2}[n\hat{\theta} - n]} = \underline{\underline{(\hat{\theta})^{n/2} e^{-\frac{1}{2}(\hat{\theta} - 1)}}}.$$

Testen i d) er **ikke** en GLRT fordi $\lambda(\theta) = \theta^{n/2} e^{-\frac{n}{2}(\theta-1)}$ er **ikke** en monoton funksjon av θ . Dette kan man for eksempel se ved å observere at

$$\frac{\partial}{\partial \theta} \left(\ln \lambda(\theta) \right) > 0 \quad \text{for } \theta < 1$$

$$\frac{\partial}{\partial \theta} \left(\ln \lambda(\theta) \right) < 0 \quad \text{for } \theta > 1.$$