

7.34 The group is given by $g_1(x) = n-x$, $g_2(x) = x$. Under this group.

If $Y = n-X$, then

$$Y = g_1(X) \sim B(n, 1-\theta) \quad \text{i.e.} \quad \bar{y} = 1-\theta$$

The invariant estimator T must satisfy

a)
$$T(x) = 1 - T(n-x)$$

(5)

b) The Bayes estimator is

$$\hat{p}_B = \frac{y + \alpha}{\alpha + \beta + n}$$

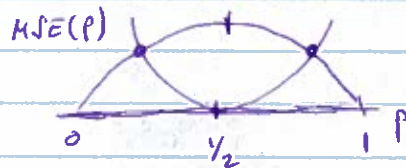
For this to be invariant we must have

$$\begin{aligned} \frac{y + \alpha}{\alpha + \beta + n} &= 1 - \frac{n - y + \alpha}{\alpha + \beta + n} \\ &= \frac{y + \beta}{\alpha + \beta + n} \end{aligned}$$

i.e. $\alpha = \beta$

c)
$$MSE = E \left[\hat{p}_B - p \right]^2 = E \left[\frac{y}{\alpha + \beta + n} - \frac{np}{\alpha + \beta + n} \right]^2 + \left[\frac{n\alpha + \alpha}{\alpha + \beta + n} - p \right]^2$$

$$= \frac{np(1-p)}{(2\alpha + n)^2} + \left(\frac{\alpha(1-2p)}{2\alpha + n} \right)^2$$



Consider the rule which has constant MSE for all p . Then at $p = \frac{1}{2}$,
$$MSE\left(\frac{1}{2}\right) = \frac{n}{4(2\alpha + n)^2}$$

at $p = 0$,
$$MSE(0) = \frac{\alpha^2}{(2\alpha + n)^2}$$

Equating we have that $\alpha = \sqrt{n}/2$

Hence,
$$\frac{y + \sqrt{n}/2}{\left[\frac{\sqrt{n}}{2} + n \right]}$$
 Alternatively
$$\frac{\partial MSE(p)}{\partial p} = \frac{(1-2p)(n-4\alpha^2)}{(2\alpha+n)^2} = 0$$

falls a minimum $\Rightarrow \alpha = \sqrt{n}/2$

7.39

$$\int f(x; \theta) dx = 1$$

Differentiate with respect to θ $\int \frac{\partial}{\partial \theta} f(x; \theta) dx = 0$

i.e. $\int \left[\frac{1}{f(x; \theta)} \cdot \frac{\partial f(x; \theta)}{\partial \theta} \right] \cdot f(x; \theta) dx = 0$

$$(2) \quad \int \left[\frac{\partial \log f}{\partial \theta} \right] \cdot f(x; \theta) dx = 0$$

Differentiate again $\int \left[\frac{\partial^2 \log f}{\partial \theta^2} \right] f(x; \theta) dx + \int \frac{\partial \log f}{\partial \theta} \cdot \frac{\partial f(x; \theta)}{\partial \theta} dx = 0$

$$\int \frac{\partial^2 \log f}{\partial \theta^2} \cdot f dx + \int \left(\frac{\partial \log f}{\partial \theta} \right)^2 f dx = 0$$

$$7.41 \text{ a) } E[\sum a_i X_i] = [\sum a_i] \mu = \mu \text{ if } \sum a_i = 1$$

$$\text{b) } \text{Var}[\sum a_i X_i] = \sigma^2 \sum a_i^2$$

$$(2) \quad U = \sum a_i^2 + \lambda (\sum a_i - 1)$$

$$\frac{\partial U}{\partial a_i} = 2a_i + \lambda = 0 \Rightarrow a_i = -\lambda/2 \text{ for all } i$$

Hence all the a_i are equal to $\frac{1}{n}$

7.48 a) The Fisher information for the binomial was shown in class to be

$$\frac{n}{p(1-p)}$$

(4) \therefore the CR lower bound is $\frac{p(1-p)}{n}$ which is attained by \bar{X}_n

b) We know by independence $E \prod X_i = p^n$; also $\sum X_i$ is complete and sufficient for p , Hence $E[\prod X_i | \sum X_i]$ is better by Rao-Blackwell.

Since $X_i = \begin{cases} 1 \\ 0 \end{cases}$, $\phi(t) = E[\prod X_i | T = \sum X_i] = P(X_1 = \dots = X_n = 1 | T = t)$

$$= p^n P\left[\sum_{i=1}^n X_i = t - t\right] / P\left[\sum_{i=1}^n X_i = t\right] = \binom{n-t}{t} / \binom{n}{t} \quad \text{Hilroy}$$