

1a) $\frac{L(X, \theta)}{L(Y, \theta)} = (1-\theta)^{\sum_{i=1}^n X_i - \sum_{i=1}^n Y_i}$ which does not depend on θ iff $\sum_{i=1}^n X_i = \sum_{i=1}^n Y_i$. Hence $T = \sum_{i=1}^n X_i$ is minimal sufficient. It is also complete (see one-par. expon. argument below)

1b) $EX_1 = \sum_{x=1}^{\infty} x \theta (1-\theta)^{x-1} = \theta \sum_{x=1}^{\infty} x (1-\theta)^{x-1} = \theta \frac{d}{d\theta} \left(-\sum_{x=1}^{\infty} (1-\theta)^x \right)$
 $= -\theta \frac{d}{d\theta} \left[(1-\theta)(1 + (1-\theta) + (1-\theta)^2 + \dots) \right] = -\theta \frac{d}{d\theta} \left(\frac{1-\theta}{1+\theta-\theta} \right) =$
 $= -\theta \frac{d}{d\theta} \left(\frac{1-\theta}{\theta} \right) = \frac{1}{\theta} \quad (\text{Note: } \theta \in (0,1))$

1c) $\ln L(X, \theta) = n \ln \theta + \left(\sum_{i=1}^n X_i - n \right) \ln(1-\theta)$
 $\frac{\partial}{\partial \theta} \ln L(X, \theta) = \frac{n}{\theta} - \frac{\sum_{i=1}^n X_i - n}{1-\theta}$; $\frac{\partial^2}{\partial \theta^2} \ln L(X, \theta) = -\frac{n}{\theta^2} - \frac{\sum_{i=1}^n X_i - n}{(1-\theta)^2}$
 $E\left(-\frac{\partial^2}{\partial \theta^2} \ln L\right) = \frac{n}{\theta^2} + \frac{n/\theta - n}{(1-\theta)^2} = \frac{n}{\theta^2} + \frac{n(1-\theta)}{\theta(1-\theta)^2} = \frac{n}{\theta^2(1-\theta)} = I_X(\theta)$
BUT: $I_T(\theta) = I_X(\theta)$ because T is sufficient! Hence $I_T(\theta) = \frac{n}{\theta^2(1-\theta)}$

1d) We want the n th success to happen at trial t .

Immediately before the t -th trial we must have had $(n-1)$ successes (with a probability for this being $\binom{t-1}{n-1} \theta^{n-1} (1-\theta)^{t-n}$) and, independently of this event, the last trial must be a success (with a probability θ). Multiply the two expressions due to independence.

We have an unbiased estimator of θ : $W = I_{\{X_1=1\}}(X)$ is unbiased since $EW = P(X_1=1) = \theta$

T is a function of sufficient, but also a complete statistic since $f(x; \theta) = \theta(1-\theta)^{x-1}$ belongs to a one-parameter exponential family with (for example) $a(\theta) = \frac{\theta}{1-\theta}$, $b(x) = 1$, $c(\theta) = \ln(1-\theta)$, $d(x) = x$

Hence UMVUE: $E(I_{\{X_1=1\}}(X) | T=t) = \frac{P(X_1=1 \cap \sum_{i=1}^n X_i = t)}{P(\sum_{i=1}^n X_i = t)}$
 $= \frac{P(X_1=1 \cap \sum_{i=1}^n X_i = t-1)}{P(\sum_{i=1}^n X_i = t-1)} = \frac{\theta \binom{t-2}{n-2} \theta^{n-2} (1-\theta)^{t-n}}{\binom{t-1}{n-1} \theta^n (1-\theta)^{t-n}} = \frac{(t-2)!(n-1)!}{(n-2)!(t-1)!} = \boxed{\frac{n-1}{t-1}}$

$$e) f(X|\theta)\pi(\theta) = \theta^n (1-\theta)^{\sum_{i=1}^n x_i - n} \theta^2 (1-\theta) = \theta^{n+2} (1-\theta)^{\sum_{i=1}^n x_i - n + 1}$$

This implies that $h(\theta|X) \propto f(X|\theta)\pi(\theta)$ must be a Beta density with parameters $(n+3, \sum_{i=1}^n x_i - n + 2)$

Since $\hat{\theta}_{\text{Bayes}} = E(\theta|X)$, $\hat{\theta}_{\text{Bayes}}$ must be the conditional expected value of $h(\theta|X)$, i.e.

$$\frac{n+3}{n+3 + \sum_{i=1}^n x_i - n + 2} = \frac{n+3}{\sum_{i=1}^n x_i + 5}$$

f) We use again the fact that $f(x; \theta)$ belongs to one-parameter exponential but denote: $a(\theta) = \frac{\theta}{\theta-1}$, $b(x) = 1$, $c(\theta) = -\ln(1-\theta)$, $d(x) = -x$ (since we need $c(\theta)$ to be monotonically increasing in θ). Then, using the BGE theorem, we know that an UMP α test for $H_0: \theta \leq \theta_0$ vs $H_1: \theta > \theta_0$ exists and has the structure

$$\varphi^* = \begin{cases} 1 & -\sum x_i > \tilde{K} \\ \gamma & -\sum x_i = \tilde{K} \\ 0 & -\sum x_i < \tilde{K} \end{cases}$$

This is the same as $\varphi^* = \begin{cases} 1 & \text{if } \sum_{i=1}^n x_i < K \\ \gamma & \text{if } \sum_{i=1}^n x_i = K \\ 0 & \text{if } \sum_{i=1}^n x_i > K \end{cases}$ (by renaming the constant).

Since $n=5$, possible realisations of $T = \sum_{i=1}^5 x_i$ are 5, 6, 7, ... Using the formula we have for $\theta_0 = .3$:

$$P_{\theta_0}(T=5) = .3^5 = 0.00243; \quad P_{\theta_0}(T=6) = \binom{5}{4} .3^5 .7 = 0.0085$$

$$P_{\theta_0}(T=7) = \binom{6}{4} .3^5 (.7)^2 = 0.01786 \text{ and we see that}$$

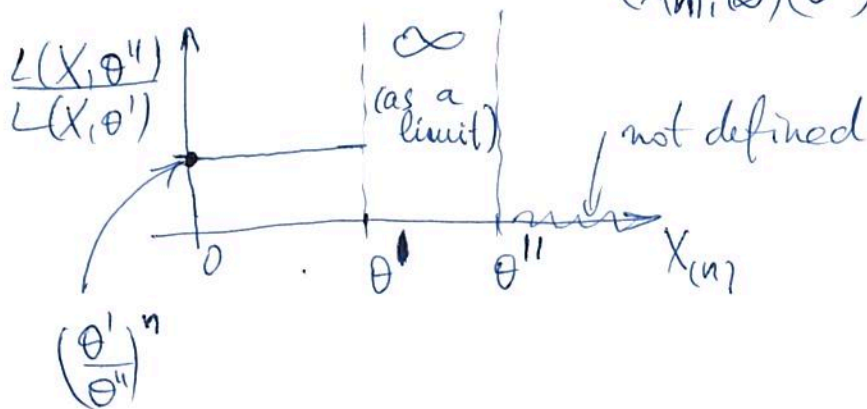
$P_{\theta_0}(T < 7) < 0.02$ but $P_{\theta_0}(T \leq 7) > 0.02$. Hence

$$K = 7. \quad \gamma = \frac{0.02 - P(T < 7)}{P(T = 7)} = \frac{0.02 - (0.00243 + 0.0085)}{0.01786}$$

Hence $\gamma = .5078 \approx 0.5$

2 a) $L(X, \theta) = \frac{1}{\theta^n} I_{(X_{(n)}, \infty)}(\theta)$. Fix $0 < \theta' < \theta''$:

$$\frac{L(X, \theta'')}{L(X, \theta')} = \left(\frac{\theta'}{\theta''}\right)^n \frac{I_{(X_{(n)}, \infty)}(\theta'')}{I_{(X_{(n)}, \infty)}(\theta')}$$



Hence we have
MLR in $T = X_{(n)}$

b) We know that $F_{X_{(n)}}(y) = P(X_{(n)} \leq y) = P(X_1 \leq y \cap X_2 \leq y \cap \dots \cap X_n \leq y)$
 $= (F_{X_1}(y))^n = \left(\frac{y}{\theta}\right)^n$ when $0 < y < \theta$

(and, of course, $F_{X_{(n)}}(y) = 0$ for $y < 0$, $F_{X_{(n)}}(y) = 1$ for $y > \theta$.)

BG theorem tells us that aUMP α test exists with the structure

$$\varphi^* = \begin{cases} 1 & X_{(n)} > K \\ 0 & X_{(n)} \leq K \end{cases}$$

To find K , we need $E_{\theta=3} \varphi^* = \alpha = P_{\theta=3}(X_{(n)} > K) =$
 $= 1 - \left(\frac{K}{3}\right)^n$. Hence $K = 3(1-\alpha)^{1/n}$

The powerfunction is $P_{\theta}(X_{(n)} > K) = \begin{cases} 1 - \left(\frac{K}{\theta}\right)^n, & 0 < K < \theta \\ 0 & K > \theta \end{cases}$

i.e. $P_{\theta}(X_{(n)} > K) = \begin{cases} 1 - (1-\alpha)\left(\frac{3}{\theta}\right)^n & 0 < K < \theta \\ 1 & K > \theta \end{cases} \Rightarrow$



c) $P_{\theta}(Y_n < y) = P_{\theta}\left(\frac{Y_n}{n} < \frac{y}{n}\right) = P_{\theta}\left(1 - \frac{X_{(n)}}{\theta} < \frac{y}{n}\right)$

$$= P_{\theta}(\theta(1 - \frac{y}{n}) < X_{(n)}) = 1 - P_{\theta}(X_{(n)} \leq \theta(1 - \frac{y}{n})) = 1 - \left(1 - \frac{y}{n}\right)^n \rightarrow 1 - e^{-y}$$

This means that $P_{\theta}\left(\frac{y}{n} \rightarrow 0\right)_{n \rightarrow \infty} \rightarrow 1$ i.e. $P\left(1 - \frac{X_{(n)}}{\theta} \rightarrow 0\right) \rightarrow 0 \Rightarrow X_{(n)} \xrightarrow{P} \theta$