

Stat 611—Practice Midterm Solution

(1) **(a)** Since $x_1 + x_2 + x_3 = n$, the joint mass function is

$$\begin{aligned} & \binom{n}{x_1, x_2, x_3} \theta^{x_1} \theta^{x_2} (1 - 2\theta)^{x_3} \\ &= \binom{n}{x_1, x_2, x_3} \exp\{(x_1 + x_2) \log(\theta/(1 - 2\theta)) + n \log(1 - 2\theta)\}, \end{aligned}$$

an exponential family with sufficient statistic $T = X_1 + X_2$. Then $L'(\theta) = (T - 2n\theta)/(\theta(1 - 2\theta))$, and the MLE is $\hat{\theta} = T/(2n)$. **(b)** Since $T \sim \text{Bin}(n, 2\theta)$, $\text{Var}(T) = 2n\theta(1 - 2\theta)$, and $I(\theta) = \text{Var}(L'(\theta)) = 2n/(\theta(1 - 2\theta))$. **(c)** By the Central Limit Theorem, $\sqrt{n}(\delta - \theta) \Rightarrow N(0, \theta(1 - \theta))$ and $\sqrt{n}(\hat{\theta} - \theta) \Rightarrow N(0, \theta(1 - 2\theta)/2)$. So the asymptotic relative efficiency is $(1 - 2\theta)/(2 - 2\theta)$. **(d)** $\sqrt{n}(\hat{\theta}^2 - \theta^2) \Rightarrow N(0, 2\theta^3(1 - 2\theta))$.

(2) The maximum likelihood estimators of p and q based on the full data X are $\hat{p} = (N_{11} + N_{12})/n$ and $\hat{q} = (N_{11} + N_{21})/n$. Next, letting $n_{21} = n - n_{11} - n_{12} - n_{22}$,

$$\begin{aligned} & P(N_{12} = n_{12} | N_{11} = n_{11}, N_{22} = n_{22}) \\ &= \frac{P(N_{11} = n_{11}, N_{12} = n_{12}, N_{22} = n_{22})}{P(N_{11} = n_{11}, N_{22} = n_{22})} \\ &= \frac{\binom{n}{n_{11}, n_{12}, n_{21}, n_{22}} p^{n_{11} + n_{12}} (1 - p)^{n_{21} + n_{22}} q^{n_{11} + n_{21}} (1 - q)^{n_{12} + n_{22}}}{\binom{n}{n_{11}, n_{22}, n - n_{11} - n_{22}} p^{n_{11}} q^{n_{11}} (1 - p)^{n_{22}} (1 - q)^{n_{22}} (p + q - 2pq)^{n_{12} + n_{21}}} \\ &= \binom{n_{12} + n_{21}}{n_{12}} \left(\frac{p - pq}{p + q - 2pq} \right)^{n_{12}} \left(\frac{q - pq}{p + q - 2pq} \right)^{n_{21}}. \end{aligned}$$

This is a binomial mass function, and so $E[N_{12} | N_{11}, N_{22}] = (n - N_{11} - N_{22})(p - pq)/(p + q - 2pq)$. Similarly, $E[N_{21} | N_{11}, N_{22}] = (n - N_{11} - N_{22})(q - pq)/(p + q - 2pq)$. If \hat{p}_k and \hat{q}_k are approximations for the maximum likelihood estimates after k iterations, then revised estimates after $k + 1$ iterations (obtained approximating N_{12} and N_{21} by their conditional expectations treating \hat{p}_k and \hat{q}_k as true values of the parameters) are

$$\begin{aligned} \hat{p}_{k+1} &= \frac{N_{11}}{n} + \frac{(n - N_{11} - N_{22})(\hat{p}_k - \hat{p}_k \hat{q}_k)}{n(\hat{p}_k + \hat{q}_k - 2\hat{p}_k \hat{q}_k)}, \\ \hat{q}_{k+1} &= \frac{N_{11}}{n} + \frac{(n - N_{11} - N_{22})(\hat{q}_k - \hat{p}_k \hat{q}_k)}{n(\hat{p}_k + \hat{q}_k - 2\hat{p}_k \hat{q}_k)}. \end{aligned}$$

- (3) **(a)** For $x \geq 0$, $P(M - \theta \leq x) = P(X_i - \theta \leq x, \text{ for some } i) = P(\epsilon_i \leq x, \text{ for some } i) = 1 - e^{-nx}$. So $M - \theta$ is pivotal. **(b)** The upper and lower $\alpha/2$ -quantiles for $M - \theta$ are $\log(2/\alpha)/n$ and $\log(2/(2 - \alpha))/n$. Since $M - \theta$ lies between these values if and only if $\theta \in (M - \log(2/\alpha)/n, M - \log(2/(2 - \alpha))/n)$, this interval is a $1 - \alpha$ confidence interval for θ . **(c)** The limiting distribution is standard exponential, since this is the distribution for $n(M_n - \theta)$, regardless the sample size n .
- (4) **(a)** The indicators averaged to form \hat{p}_n have mean $h(\theta) = e^{-1/\theta}$ and variance $e^{-1/\theta}(1 - e^{-1/\theta})$. By the Central Limit Theorem $\sqrt{n}(\hat{p}_n - h(\theta)) \Rightarrow Z_1 \sim N(0, e^{-1/\theta}(1 - e^{-1/\theta}))$. **(b)** By the Central Limit Theorem, $\sqrt{n}(\bar{X} - \theta) \Rightarrow N(0, \theta^2)$. By the delta method, $\sqrt{n}(h(\bar{X}) - h(\theta)) \Rightarrow Z_1 \sim N(0, e^{-2/\theta}/\theta^2)$. **(c)** The ARE is $1/[\theta^2(e^{1/\theta} - 1)]$.
- (5) **(a)** With $T(x) = \sum \log x_i$, the joint density is $\exp\{\theta T - T + n \log \theta\}$ and $\hat{\theta} = -n/T$. **(b)** The Fisher information for a single observation is $1/\theta^2$, so $\sqrt{n}(\hat{\theta} - \theta) \Rightarrow N(0, \theta^2)$. **(c)** Since $EX_i = \xi = \theta/(\theta + 1)$ and $\text{Var}(X_i) = \sigma^2 = \theta/[(\theta + 1)^2(\theta + 2)]$, by the Central Limit Theorem, $\sqrt{n}(\bar{X} - \xi) \Rightarrow N(0, \sigma^2)$. Since $\delta_n = h(\bar{X})$ with $h(\xi) = \xi/(1 - \xi) = \theta$, by the delta method, $\sqrt{n}(h(\bar{X}) - \theta) \Rightarrow N(0, \theta(\theta + 1)^2/(\theta + 2))$. **(d)** The ARE is $\theta(\theta + 2)/(\theta + 1)^2$.
- (6) $E|Y_n| = n(n + 1)/4$, and by Markov's inequality

$$P(|Y_n| > Kn^\alpha) \leq \frac{1}{4K} \frac{n(n + 1)}{n^\alpha}.$$

If $\Lambda(\alpha) \stackrel{\text{def}}{=} \sup_{n \geq 1} n(n + 1)/n^\alpha$, then

$$\sup_{n \geq 1} P|Y_n| > Kn^\alpha \leq \frac{\Lambda(\alpha)}{4K}.$$

If $\alpha \geq 2$, $\Lambda(\alpha) < \infty$ and this expression tends to zero as $K \rightarrow \infty$, and hence $Y_n = O_p(n^\alpha)$. Although this is all I expected when I set this problem, to be complete we should also show that Y_n is not $O_p(n^\alpha)$ if $\alpha < 2$. To see this, note that since

$U_k < k$ almost surely, $Y_n < n(n+1)/2$ almost surely. So

$$\frac{n(n+1)}{4} = EY_n$$

$$\begin{aligned} &\leq E \left[Kn^\alpha I\{Y_n \leq Kn^\alpha\} + \frac{n(n+1)}{2} I\{Y_n > Kn^\alpha\} \right] \\ &= Kn^\alpha + \left[\frac{n(n+1)}{2} - Kn^\alpha \right] P(Y_n > Kn^\alpha). \end{aligned}$$

Solving, for n sufficiently large,

$$P(Y_n > Kn^\alpha) \geq \frac{n(n+1) - 4Kn^\alpha}{2n(n+1) - 4Kn^\alpha}.$$

Since this bound tends to $1/2$ as $n \rightarrow \infty$, Y_n is not $O_p(n^\alpha)$.

- (7) **(a)** Let $\bar{W}_n(t) = \frac{1}{n} \sum_{i=1}^n e^{tX_i}$, with mean $\mu(t) = E\bar{W}_n(t) = 1/(1-t)$. Since $\mu(1/3) = 3/2$ and T_n solves $\bar{W}_n(T_n) = 3/2$, $T_n \xrightarrow{p} 1/3$ as $n \rightarrow \infty$. **(b)** Since $\text{Var}(e^{X_i}/3) = 3/4$,

$$\sqrt{n}(\bar{W}_n(1/3) - 3/2) \Rightarrow N(0, 3/4).$$

By Taylor expansion,

$$\sqrt{n}(T_n - 1/3) = \frac{\sqrt{n}(\bar{W}_n(1/3) - 3/2)}{-\bar{W}'_n(T_n^*)},$$

with T_n^* and intermediate value between T_n and $1/3$. Since $T_n^* \xrightarrow{p} 1/3$, $\bar{W}'_n(T_n^*) - \bar{W}'_n(1/3) \xrightarrow{p} 0$ (by our law of large numbers for random functions). But $\bar{W}'_n(1/3) \xrightarrow{p} E\bar{W}'_n(1/3) = 9/4$, and so $\bar{W}'_n(T_n^*) \xrightarrow{p} 9/4$. Hence

$$\sqrt{n}(T_n - 1/3) \Rightarrow N(0, 4/27).$$