

STAT6201: Theoretical Statistics I

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Homework 2

1. Let $\mathcal{P}_0 \subseteq \mathcal{P}$, such that $P(A) = 0$ for all $P \in \mathcal{P}_0$ implies that $P(A) = 0$ for all $P \in \mathcal{P}$. Furthermore, let T be sufficient for \mathcal{P} , and complete for \mathcal{P}_0 . We claim that T is complete sufficient for \mathcal{P} . Indeed, let f be a measurable function such that $\mathbb{E}_P[f(T)] = 0$ for all $P \in \mathcal{P}$. By completeness of T for \mathcal{P}_0 , we have $f(T) = 0$, P almost surely for all $P \in \mathcal{P}_0$. Set $A = \{x \in \mathcal{X} : f(T(x)) \neq 0\}$, so we have $P(A) = 0$ for all $P \in \mathcal{P}_0$; by assumption, we have $P(A) = 0$ for all $P \in \mathcal{P}$, i.e. $f(T) = 0$, P almost surely for all $P \in \mathcal{P}$. It follows that T is complete sufficient for \mathcal{P} .
2. (a) Let U be minimal sufficient, and T be complete sufficient for some family of distributions \mathcal{P} . Minimality of U means that $U = g(T)$ for some measurable g . Define

$$h: T(\mathcal{X}) \rightarrow g \circ T(\mathcal{X}), \quad t \mapsto \mathbb{E}_P[T \mid U = g(t)] - t.$$

Note that this is well defined; sufficiency of U guarantees that the conditional expectation $\mathbb{E}_P[T \mid U = u]$ is a function of u independent of $P \in \mathcal{P}$! With this, observe that

$$\mathbb{E}_P[h(T)] = \mathbb{E}_P[\mathbb{E}_P[T \mid U]] - \mathbb{E}_P[T] = \mathbb{E}_P[T] - \mathbb{E}_P[T] = 0.$$

Completeness of T forces $h(T) = 0$, P almost surely for all $P \in \mathcal{P}$. This immediately gives

$$T = \mathbb{E}_P[T \mid U] := \tilde{g}(U),$$

whence T is a function of U . It follows that T is minimal sufficient for \mathcal{P} , being in bijection with the minimal sufficient statistic U . Alternatively, note that for any sufficient statistic V , we have $U = g_V(V)$ for some measurable g_V , so $T = \tilde{g} \circ g_V(V)$, whence T is minimal sufficient for \mathcal{P} .

- (b) First, observe that (measurable) functions of complete sufficient statistics are complete. Indeed, if T is complete sufficient and g is a measurable function, then for measurable f , we have $\mathbb{E}_P[f(g(T))] = 0$ for all $P \in \mathcal{P}$, which gives $f \circ g(T) = 0$ for all $P \in \mathcal{P}$ via completeness of T , whence $g(T)$ is complete for \mathcal{P} .

With this, let $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Uniform}(\theta - 1/2, \theta + 1/2)$. Then,

$$\begin{aligned} f(\mathbf{x}; \theta) &= \prod_{i=1}^n \mathbf{1}(\theta - 1/2 < x_i < \theta + 1/2) \\ &= \mathbf{1}(\theta - 1/2 < x_{(1)} \leq x_{(n)} < \theta + 1/2), \end{aligned}$$

so

$$\frac{f(\mathbf{x}; \theta)}{f(\mathbf{y}; \theta)} = \frac{\mathbf{1}(\theta - 1/2 < x_{(1)} \leq x_{(n)} < \theta + 1/2)}{\mathbf{1}(\theta - 1/2 < y_{(1)} \leq y_{(n)} < \theta + 1/2)}$$

is independent of θ if and only if the indicator functions describe precisely the same intervals, i.e. $(x_{(1)}, x_{(n)}) = (y_{(1)}, y_{(n)})$. Thus, $T(\mathbf{X}) = (X_{(1)}, X_{(n)})$ is minimal sufficient for $\theta \in \mathbb{R}$.

Now, suppose that a complete sufficient statistic U for $\theta \in \mathbb{R}$ exists; then, $T = g(U)$ for some measurable function g by minimality of T , whence T is complete minimal sufficient for $\theta \in \mathbb{R}$. By setting $h(\mathbf{t}) = t_2 - t_1$, we have

$$\begin{aligned}\mathbb{E}_\theta[h(T)] &= \mathbb{E}_\theta[X_{(n)} - X_{(1)}] \\ &= \mathbb{E}_\theta[(X_{(n)} - \theta) - (X_{(1)} - \theta)] \\ &= \mathbb{E}_0[X_{(n)} - X_{(1)}] \\ &= C, \end{aligned} \quad (= (n-1)/(n+1))$$

using the fact that $\{X_i - \theta\}_{i=1}^n$ are iid $\text{Uniform}(-1/2, 1/2)$ random variables. But we certainly do not have $h(T) = X_{(n)} - X_{(1)} = C$, P_θ almost surely! This is a contradiction, whence no complete sufficient statistic for $\theta \in \mathbb{R}$ exists.

3. We have $X_1, \dots, X_n \stackrel{iid}{\sim} f_\theta$, with density $f(x; \theta) = e^{-(x-\theta)} \mathbf{1}(\theta \leq x)$. It follows that

$$f(\mathbf{x}; \theta) = e^{-(\sum_{i=1}^n (x_i - \theta))} \prod_{i=1}^n \mathbf{1}(\theta \leq x_i) = e^{-n(\bar{x} - \theta)} \mathbf{1}(\theta \leq x_{(1)}).$$

(a) We immediately have $T = X_{(1)}$ sufficient for $\theta \in \mathbb{R}$ via Neyman-Fisher factorization. Also,

$$\frac{f(\mathbf{x}; \theta)}{f(\mathbf{y}; \theta)} = \frac{e^{-n\bar{x}} \mathbf{1}(\theta \leq x_{(1)})}{e^{-n\bar{y}} \mathbf{1}(\theta \leq y_{(1)})}$$

becomes independent of θ if and only if $x_{(1)} = y_{(1)}$, whence $T = X_{(1)}$ is minimal sufficient for $\theta \in \mathbb{R}$.

Now, compute

$$\begin{aligned}P_\theta(T \geq t) &= P_\theta(X_{(1)} \geq t) \\ &= P_\theta(X_{(1)} - \theta \geq t - \theta) \\ &= P_0(X_{(1)} \geq t - \theta) \\ &= \prod_{i=1}^n P_0(X_i \geq t - \theta) \\ &= \prod_{i=1}^n e^{-(t-\theta)} \\ &= e^{-n(t-\theta)}\end{aligned}$$

for $t \geq \theta$. It follows that the density of $T = X_{(1)}$ is given by

$$f_T(t) = ne^{-n(t-\theta)} \mathbf{1}(\theta \leq t).$$

Suppose that g is measurable, and that $\mathbb{E}_\theta[g(T)] = 0$ for all $\theta \in \mathbb{R}$. This means that

$$\int_{\theta}^{\infty} g(t) e^{-nt} e^{n\theta} dt = 0, \quad \text{for all } \theta \in \mathbb{R}.$$

Thus, for any $\alpha, \beta \in \mathbb{R}$, we have

$$\int_{(\alpha, \beta]} g(t) e^{-nt} dt = \left(\int_{\alpha}^{\infty} - \int_{\beta}^{\infty} \right) g(t) e^{-nt} dt = 0.$$

Indeed, the Monotone Convergence Theorem gives

$$\int_{\mathbb{R}} g(t) e^{-nt} dt = 0.$$

This is sufficient to show that $g = 0$ almost everywhere; the collection

$$\mathcal{E} = \left\{ E \in \mathcal{B}(\mathbb{R}) : \int_E g(t) e^{-nt} dt = 0 \right\}$$

is a λ -system containing the π -system of intervals of the form $(-\alpha, \beta]$ which generates the Borel σ -algebra $\mathcal{B}(\mathbb{R})$, hence must be equal to $\mathcal{B}(\mathbb{R})$ by Dynkin's Lemma. It follows that

$$\int_E g(t) e^{-nt} dt = 0$$

for all Borel sets E . From this, we may conclude that $g(t) e^{-nt} = 0$, hence $g = 0$ almost everywhere.

Remark: If f is $(\Omega, \mathcal{M}, \mu)$ measurable and

$$\int_E f d\mu = 0, \quad \text{for all } E \in \mathcal{M},$$

then setting $E_k = \{\omega \in \Omega : f(\omega) > 1/k\}$ gives

$$0 = \int_{E_k} f d\mu \geq \int_{E_k} \frac{1}{k} d\mu = \frac{1}{k} \mu(E_k),$$

whence all $\mu(E_k) = 0$, so $\mu(\{\omega : f(\omega) > 0\}) = 0$ via continuity from below. Similarly, $\mu(\{\omega : f(\omega) < 0\}) = 0$, whence $f = 0$, μ -almost everywhere.

Remark: We have shown that the signed Borel measure ν described by $d\nu(t) = g(t) e^{-nt} dt$ agrees with the zero measure on all intervals (θ, ∞) , hence must be zero.

(b) Now suppose that our family is restricted to $\theta \in (-\infty, 0)$. Set

$$c_1 = \int_0^1 e^{-nt} dt > 0, \quad c_2 = \int_1^\infty e^{-nt} dt > 0,$$

and

$$g(t) = c_2 \mathbf{1}_{(0,1]}(t) - c_1 \mathbf{1}_{(1,\infty)}(t).$$

Then, for $\theta < 0$,

$$\begin{aligned} \mathbb{E}_\theta[g(T)] &= \int_\theta^\infty g(t) e^{-nt} e^{n\theta} dt \\ &= e^{n\theta} \int_0^1 c_2 e^{-nt} dt - e^{n\theta} \int_1^\infty c_1 e^{-nt} dt \\ &= e^{n\theta} (c_2 c_1 - c_1 c_2) \\ &= 0. \end{aligned}$$

However, we do not have $g(T) = 0$, P_{-1} -everywhere! Thus, T cannot be complete for $\theta \in (-\infty, 0)$.

4. Consider an exponential family $\{P_\theta\}_{\theta \in \Theta}$ on \mathcal{X} , with densities

$$f(x; \theta) = \frac{dP_\theta}{d\nu} = e^{\eta(\theta)T(x) - B(\theta)} h(x),$$

where ν is σ -finite. Furthermore, let Θ be an open interval in \mathbb{R} , on which η, B are infinitely differentiable, $\eta' \neq 0$, and we have sufficient regularity to interchange differentiation with respect to θ and integration with respect to ν .

(a) Set $\tau(\theta) = \mathbb{E}_\theta[T(X)]$, and observe that

$$\int_{\mathcal{X}} e^{\eta(\theta)T(x)-B(\theta)} h(x) d\nu(x) = \int_{\mathcal{X}} f(x; \theta) d\nu(x) = 1$$

for all $\theta \in \Theta$ gives

$$\int_{\mathcal{X}} (\eta'(\theta)T(x) - B'(\theta)) e^{\eta(\theta)T(x)-B(\theta)} h(x) d\nu(x) = \frac{\partial}{\partial \theta} \int_{\mathcal{X}} f(x; \theta) d\nu(x) = 0.$$

Rearranging, we have

$$\eta'(\theta) \int_{\mathcal{X}} T(x) f(x; \theta) d\nu(x) = B'(\theta) \int_{\mathcal{X}} f(x; \theta) d\nu(x), \quad (\star)$$

which is precisely $\eta'(\theta)\mathbb{E}_\theta[T(X)] = B'(\theta)$, whence $\tau(\theta) = B'(\theta)/\eta'(\theta)$.

(b) Differentiating (\star) after dividing by $\eta'(\theta)$, we have

$$\int_{\mathcal{X}} T(x)(\eta'(\theta)T(x) - B'(\theta)) f(x; \theta) d\nu(x) = \tau'(\theta),$$

which means that

$$\eta'(\theta)\mathbb{E}_\theta[(T(X))^2] - B'(\theta)\mathbb{E}_\theta[T(X)] = \tau'(\theta).$$

This simplifies to

$$\mathbb{E}_\theta[(T(X))^2] = \frac{\tau'(\theta)}{\eta'(\theta)} + (\tau(\theta))^2.$$

It follows that

$$\text{Var}_\theta(T(X)) = \mathbb{E}_\theta[(T(X))^2] - (\mathbb{E}_\theta[T(X)])^2 = \frac{\tau'(\theta)}{(\eta'(\theta))}.$$

5. We will prove the Lehmann-Scheffé Theorem. Let U be unbiased for $g(\theta)$ in the family $\{P_\theta\}_{\theta \in \Theta}$, and let T be a complete sufficient statistic for $\theta \in \Theta$. Set

$$h(t) = \mathbb{E}_\theta[U \mid T = t],$$

whence $\delta = h(T)$ is a well-defined statistic; this is free of θ by sufficiency of T ! Now, δ is unbiased for $g(\theta)$ since $\mathbb{E}_\theta[\mathbb{E}_\theta[U \mid T]] = \mathbb{E}_\theta[U] = g(\theta)$. Furthermore, the Blackwell-Rao Theorem guarantees that for any competing unbiased estimator S of $g(\theta)$, we have

$$\text{Var}_\theta(\delta) \leq \text{Var}_\theta(S), \quad \text{for all } \theta \in \Theta,$$

since these variances evaluate to precisely the risks under the convex squared error loss $\ell(\cdot, \theta) = (\cdot - g(\theta))^2$. Thus, δ is Uniformly Minimum Variance Unbiased (UMVU) for $g(\theta)$.

It remains to show that δ is unique. Let $\tilde{\delta} = \tilde{h}(T)$ also be unbiased for $g(\theta)$, whence

$$\mathbb{E}_\theta[(h - \tilde{h})(T)] = \mathbb{E}_\theta[\delta] - \mathbb{E}_\theta[\tilde{\delta}] = 0$$

via unbiasedness. Then, $(h - \tilde{h})(T) = 0$, i.e. $\delta = \tilde{\delta}$, P_θ almost surely, via completeness of T .

Remark: We have shown that any unbiased function of a complete sufficient statistic is UMVU.

6. Let $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Exp}(\theta)$ for $\theta > 0$, so \mathbf{X} has density

$$f(\mathbf{x}; \theta) = \prod_{i=1}^n \theta e^{-\theta x_i} \mathbf{1}_{(0, \infty)}(x_i) = \theta^n e^{-n\theta \bar{x}} \mathbf{1}_{(0, \infty)}(x_{(1)}).$$

- (a) Observe that we have a 1-parameter exponential family, with natural parameter $\eta(\theta) = -\theta$, and $T(\mathbf{X}) = n\bar{X} = \sum_{i=1}^n X_i$. Since our natural parameter space $(-\infty, 0)$ has non-empty interior, T is complete minimal sufficient for $\theta \in (0, \infty)$.
- (b) Let $a > 0$, and let $\phi(\theta) = e^{-\theta a}$. Define

$$\hat{\phi}(T) = \left(1 - \frac{a}{T}\right)^{n-1} \mathbf{1}(T \geq a).$$

Since this is a function of the complete sufficient statistic T , we need only check that $\hat{\phi}$ is unbiased for ϕ for us to conclude that $\hat{\phi}$ is UMVU, via uniqueness in the Lehmann-Scheffé Theorem!

Note that $T \sim \Gamma(n, \theta)$; the characteristic function of an exponential random variable is simply

$$\varphi_{X_1}(t) = \mathbb{E}_\theta [e^{itX_1}] = \int_0^\infty \theta e^{-(\theta - it)x} dx = \frac{\theta}{\theta - it} = \left(1 - \frac{it}{\theta}\right)^{-1}.$$

Thus, the characteristic function of T satisfies

$$\varphi_T(t) = \varphi_{\sum_{i=1}^n X_i}(t) = \prod_{i=1}^n \varphi_{X_i}(t) = \left(1 - \frac{it}{\theta}\right)^{-n},$$

from which the claim follows. This means that T has density

$$f_T(t; \theta) = \frac{\theta^n}{\Gamma(n)} t^{n-1} e^{-\theta t} \mathbf{1}_{(0, \infty)}(t).$$

Finally,

$$\begin{aligned} \mathbb{E}_\theta[\hat{\phi}] &= \frac{\theta^n}{\Gamma(n)} \int_a^\infty \left(1 - \frac{a}{t}\right)^{n-1} t^{n-1} e^{-\theta t} dt \\ &= \frac{\theta^n}{\Gamma(n)} \int_a^\infty (t - a)^{n-1} e^{-\theta t} dt \\ &= \frac{\theta^n}{\Gamma(n)} \int_0^\infty t^{n-1} e^{-\theta(t+a)} dt \\ &= \frac{\theta^n}{\Gamma(n)} \int_0^\infty t^{n-1} e^{-\theta t} dt \cdot e^{-\theta a} \\ &= e^{-\theta a} \\ &= \phi(\theta). \end{aligned}$$