

1 Review

1.1 Sufficiency

$T(X)$ is *sufficient* if $P_\theta(X|T)$ does not depend on θ i.e. $(p_\theta(X) = g_\theta(T(x))h(x))$

$T(X)$ is *minimal sufficient* if:

- T is sufficient
- $T(X) \stackrel{\text{a.s.}}{=} f(S(X))$ for any S sufficient

Theorem: T is minimal sufficient if $p_\theta(x) \propto_\theta p_\theta(y) \implies T(x) = T(y)$

$T(X)$ is *complete sufficient* if:

- T is sufficient
- $\mathbb{E}_\theta[g(T(X))] = 0 \quad \forall \theta \implies g(T) \stackrel{\text{a.s.}}{=} 0$

Proposition 1.1. If T is complete, then it is independent of all ancillary statistics.

1.2 Exponential families

$p_\theta(x) = e^{\eta(\theta)'T(x) - B(\theta)}h(x)$ for $\theta \in \Theta$, $\eta(\theta) \in \Xi \subset \mathbb{R}^s$.

If $\text{span}(\{\eta(\theta_1) - \eta(\theta) : \theta_1, \theta \in \Theta\}) = \mathbb{R}^s$, then T is minimal sufficient.

If $\eta(\Theta)$ contains an open set, we say η is *full-rank*. $\implies T(X)$ is complete sufficient.

A *curved* exponential family is one which is not full rank.

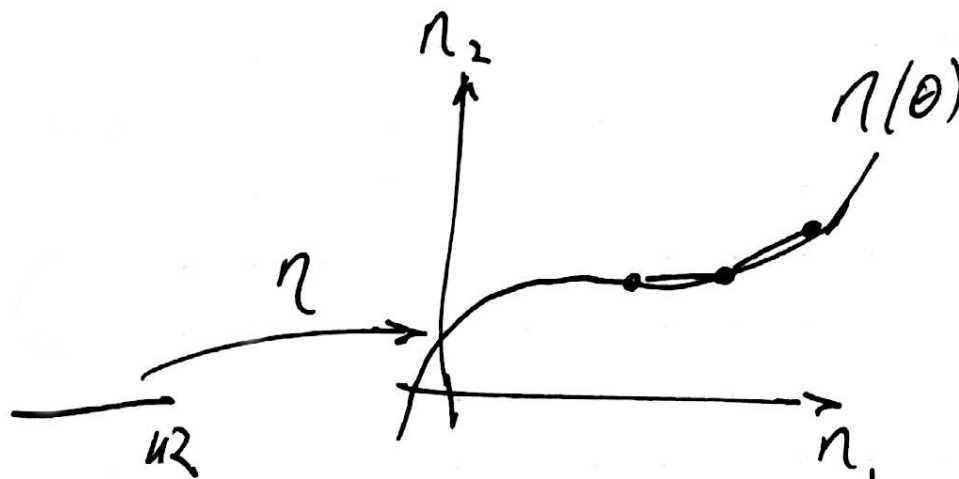


Figure 1: Example of curved exponential family, not full rank because closed in $\mathbb{R}^s = \mathbb{R}^2$

1.3 Rao-Blackwell

Theorem 1.2. If T is sufficient, $\tilde{\delta}(X)$ some estimator, $L(\theta, \cdot)$ convex loss, then the estimator

$$\delta(X) = \mathbb{E}[\tilde{\delta}(X)|T] \quad (1.1)$$

is better i.e. $L(\theta, \delta) \leq L(\theta, \tilde{\delta})$

2 Unbiased estimators

Example 2.1 (Bias-Variance Tradeoff).

$$\text{MSE}(\theta; \delta) = \mathbb{E}_\theta[(\delta(X) - g(\theta))^2] \quad (2.1)$$

$$= \mathbb{E}_\theta[(\delta(X) - \mathbb{E}_\theta \delta + \mathbb{E}_\theta \delta - g(\theta))^2] \quad (2.2)$$

$$= \mathbb{E}_\theta[(\delta - \mathbb{E}_\theta \delta)^2] + (\mathbb{E}_\theta(\delta) - g(\theta))^2 + 2(\mathbb{E}_\theta(\delta) - g(\theta))\mathbb{E}_\theta[(\delta(X) - \mathbb{E}_\theta[\delta])] \quad (2.3)$$

$$= \text{Var}_\theta(\delta) + \text{Bias}_\theta(\delta)^2 \quad (2.4)$$

Definition 2.2. $\delta(X)$ is an *unbiased* estimator of g if $\text{Bias}_\theta(\delta) = \mathbb{E}_\theta[g(\theta) - \mathbb{E}_\theta \delta] = 0$.

Definition 2.3. A statistic g is *U-estimable* if there exists an unbiased estimator.

Definition 2.4. $\delta(X)$ is *UMVU* (uniform minimum variance unbiased estimator) if δ is unbiased and $\text{Var}_\theta(\delta) \leq \text{Var}_\theta(\tilde{\delta})$ for all $\theta \in \Theta$ and any other unbiased $\tilde{\delta}$.

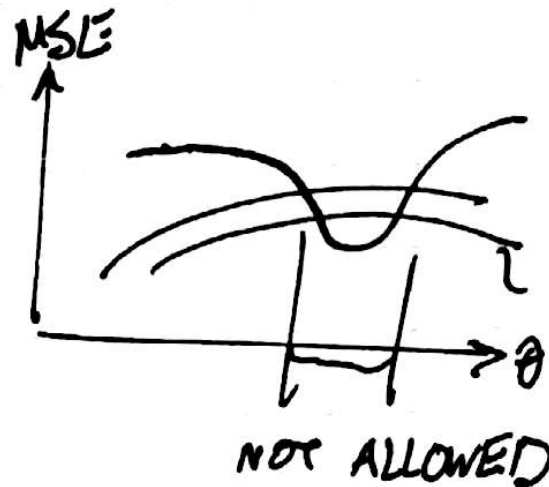


Figure 2: No estimator in this figure is UMVU; the bold estimator is not minimum variance in the indicated region

Theorem 2.5. If $g(\theta)$ is U-estimable and T is complete sufficient, $\exists!$ UMVU estimator $\delta(T(X))$.

Proof. Let $\delta_0(X)$ be unbiased (\exists since g is U -estimable) and consider the Rao-Blackwellized estimator $\delta(T) = \mathbb{E}_\theta[\delta_0|T]$.

We first show δ is unbiased:

$$\mathbb{E}_\theta \delta(T) = \mathbb{E}_\theta \mathbb{E}_\theta[\delta_0|T] \quad (2.5)$$

$$= \mathbb{E}_\theta[\delta_0] \quad \text{Tower property} \quad (2.6)$$

$$= g(\theta) \quad \delta_0 \text{ unbiased} \quad (2.7)$$

We next show essential uniqueness of δ . Suppose $\tilde{\delta}(T)$ unbiased. As both are unbiased, $\mathbb{E}_\theta[\delta - \tilde{\delta}] = 0$ for all θ so by completeness $\delta \stackrel{\text{a.s.}}{=} \tilde{\delta}$.

By Rao-Blackwell, no other $\delta^*(X)$ could be better. \square

2 ways to find UMVUE:

(1) Directly

(2) Find any unbiased $\delta(T)$, Rao-Blackwellize

Example 2.6. $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Pois}(\theta)$. $p_\theta(x) = \frac{\theta^x e^{-\theta}}{x!}$ for $\theta \geq 0, x \in \mathbb{N}^*$. Complete sufficient statistic $T = \sum X_i \sim \text{Pois}(n\theta)$. $p_\theta^T(t) = \frac{(n\theta)^t e^{-n\theta}}{t!}$. Estimate θ^2 .

One way:

$$\theta^2 = \mathbb{E}[X_1]^2 \quad (2.8)$$

$$= \mathbb{E}[X_1 X_2] = \delta_0 \quad (2.9)$$

and Rao-Blackwellize.

Another way: Any unbiased $\delta(T)$ must satisfy

$$\sum_{t=1}^{\infty} \delta(t) p_\theta^T(t) = \theta^2 \quad \forall \theta \quad (2.10)$$

$$\sum_{t=1}^{\infty} \delta(t) \frac{n^t \theta^t}{t!} = e^{n\theta} \theta^2 \quad \forall \theta \quad (2.11)$$

$$= \sum_{k \geq 0} \frac{n^k}{k!} \theta^{k+2} \quad (2.12)$$

Matching coefficients implies

$$\delta(T) = \left(\frac{T(T-1)}{n^2} \right)_+ \approx (T/n)^2 \quad (2.13)$$

(Note: this shows that $\mathbb{E}[X_1 X_2 | X_1 + X_2 = T] = (T(T-1))/n^2$ **TODO: really?**)

Example 2.7. In Keener. $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} U[0, \theta]$. $T = X_{(n)}$ complete sufficient.

$$p_\theta^T(t) = \frac{\partial}{\partial t} P_\theta[T = t] \quad (2.14)$$

$$= \frac{\partial}{\partial t} \left(\frac{t}{\theta} \right)^n = \frac{n}{\theta^n} t^{n-1} \quad (2.15)$$

$$\mathbb{E}_\theta T = \frac{n}{n+1}\theta \implies \frac{n+1}{n}T \text{ is UMVU} \quad (2.16)$$

Example 2.8 (Nonparametric Problem). $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} p(X)$ wrt Leb. s.t. $\mathbb{E}_p[|X|] < \infty$. Estimate $\mu(p) = \int_{-\infty}^{\infty} xp(x)dx = \mathbb{E}_p X$.

Know $T = (X_{(1)}, \dots, X_{(n)})$ is sufficient (because iid), can show it is also complete.

X_1 is unbiased, so Rao-Blackwellizing

$$\mathbb{E}_p[X_1 | X_{(1)}, \dots, X_{(n)}] = \frac{1}{n} \sum_{i=1}^n X_{(i)} \quad \text{Data exchangeable} \quad (2.17)$$

$$= \bar{X} \quad (2.18)$$

So \bar{X} is UMVU.

2.1 U-statistics (U for Unbiased)

Suppose we want to estimate

$$g(p) = \mathbb{E}_p[|X_1 - X_2|] \quad (2.19)$$

(Gini's mean difference)

Or more generally

$$g(p) = \mathbb{E}_p[h(X_1, \dots, X_m)] \quad m \leq n \quad (2.20)$$

First of all

$$\delta_0 = h(X_1, \dots, X_m) \quad (2.21)$$

is an unbiased estimator obtained by just taking the first m observations. But we can do better by Rao-Blackwellizing

$$\delta(X) = \frac{n!}{(n-m)!} \sum_{\substack{i_1, \dots, i_m \\ \text{distinct}}} h(X_{i_1}, \dots, X_{i_m}) \quad (2.22)$$

This is called a *U-statistic*.