STA732
Statistical Inference

Lecture 04: Completeness and Ancillarity

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https://www2.stat.duke.edu/courses/Spring22/sta732.01/

Recap from Lecture 03

- **Sufficient statistic T:** when T is known, we have enough information to estimate θ.
- **Factorization theorem:** if we can factor the likelihood, then we prove T is sufficient

$$p_\theta(x) = g_\theta(T(x))h(x)$$

- **Minimal sufficiency:** we can order the sufficient statistics and define the minimal (intuitively it is the most compressed version of sufficient statistics)

Goal of Lecture 04

1. Define ancillarity and completeness
2. Complete statistics in exponential family
3. Basu's theorem

Chap. 3.5 in Keener or Chap. 1.6 in Lehmann and Casella

Ancillarity and Completeness

Definition. Ancillarity

Suppose X has distribution from a family $\mathscr{P} = \{P_\theta, \theta \in \Omega\}$. A statistics $V(X)$ is called ancillary if its distribution does not depend on θ. So $V(X)$ by itself provides no information about θ.

Examples

- In the Laplace location family example of Lecture 3, the joint density is

$$p_\theta(x) = \frac{1}{2^n} \exp\left\{ -\sum_{i=1}^{n} |x_i - \theta| \right\}$$

  We showed that the order statistics is minimal sufficient. But $X_{(1)} - X_{(3)}$ is ancillary. The distribution of $(X_{(1)} - \theta) - (X_{(3)} - \theta)$ does not depend on θ
- Similarly for $X_1, \ldots, X_n \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\theta, 1)$. $X_1 - X_2$ is ancillary

Definition. First-order ancillary

A statistics $V(X)$ is called first-order ancillary if $\mathbb{E}_\theta[V(X)]$ does not depend on θ.

Example:
$X_1, \ldots, X_n \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma^2)$, X_1 is first-order ancillary but it is not ancillary.

Definition. Completeness

Suppose X has distribution from a family $\mathscr{P} = \{P_\theta, \theta \in \Omega\}$. A statistics $T(X)$ is complete if no non-constant function of T is first-order ancillary. In other words,

$$\mathbb{E}_\theta[f(T(X))] = 0,\ \forall\theta \Rightarrow f(T(X)) = 0, \text{a.s.},\ \forall\theta$$

Remark:

- In some sense, the complete + sufficient formalizes our **ideal** notion of "optimal data compression"
- The minimal sufficiency is our **achievable** notion of "optimal data compression"

Example 1: minimal sufficient statistics is not necessarily complete

In the Laplace location family example with joint density

$$p_\theta(x) = \frac{1}{2^n} \exp\left\{ -\sum_{i=1}^{n} |x_i - \theta| \right\}$$

$S = (X_{(1)}, \dots X_{(n)})$ is minimal sufficient statistics. But it is not complete! Consider

$$\text{median}(X_{(i)}) - \text{mean}(X_{(i)})$$

why is its expectaion 0? symmetry

Example 2: a minimal sufficient complete statistics

$X_1, \ldots, X_n \overset{\text{i.i.d.}}{\sim} \text{Unif}[0, \theta], \theta \in (0, \infty)$. Show that $T(X) = X_{(n)}$ is minimal sufficient and complete.

proof:

Example 3: a complete statistics that is not sufficient

$X_1, \dots, X_{10} \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\theta, 1)$.

- X_1 is not sufficient
- X_1 is complete

proof:

Complete sufficient implies minimal sufficient

Theorem 3.17 in Keener

If T is complete and sufficient, then T is minimal sufficient.

proof:

Complete statistics in exponential family

Definition. Full-rank exponential family

An exponential family $\mathscr{P}$ with densities $p_\theta(x) = \exp\left\{\eta(\theta)^\top T(x) - B(\theta)\right\} h(x)$, $\theta \in \Omega$ is said to be full rank if the interior of $\eta(\Omega)$ is not empty and if $T_1, \ldots, T_s$ do not satisfy a linear constraint of the form $v^\top T \overset{\text{a.s.}}{=} c$.

Otherwise, we say the family $\mathscr{P}$ is curved

Examples

Which of the following exponential family is full rank?

- $p_\theta(x) = \exp\left(\begin{pmatrix}\theta_1 \\ \theta_2\end{pmatrix}^\top \begin{pmatrix}x_1 \\ x_2\end{pmatrix} - B(\theta)\right) h(x)$
- $p_\theta(x) = \exp\left(\begin{pmatrix}\theta_1 \\ \theta_1^2\end{pmatrix}^\top \begin{pmatrix}x_1 \\ x_2\end{pmatrix} - B(\theta)\right) h(x)$
- $p_\theta(x) = \exp\left(\begin{pmatrix}\theta_1 \\ \theta_2\end{pmatrix}^\top \begin{pmatrix}x_1 \\ -2x_1\end{pmatrix} - B(\theta)\right) h(x)$

$T(X)$ in full-rank exponential family is complete sufficient

Theorem 3.19 in Keener

In an exponential family of full rank, $T(X)$ is complete sufficient.

proof in Lehmann & Romano, Thm 4.3.1

Key proof ideas:

- W.L.O.G., assume the parameter space contain the rectangle $I = \left\{\theta \mid \left|\theta_j\right| \leq a\right\}$
- For $f = f^+ - f^-$ satisfying $\mathbb{E}_\theta f(T) = 0$, we have for $\theta \in I$

$$\int e^{\theta^\top t} f^+(t) d\nu(t) = \int e^{\theta^\top t} f^-(t) d\nu(t)$$

- We can normalize both sides to make appear moment generating functions on both sides. Equality by moment generating functions implies $f^+ = f^-$

Basu’s theorem

Basu's Theorem

Theorem 3.21 in Keener

If T is complete and sufficient for $\mathscr{P} = \{P_\theta, \theta \in \Omega\}$, and if V is ancillary, then T and V are independent under P_θ for any $\theta \in \Omega$.

Basu's Theorem

Theorem 3.21 in Keener

If T is complete and sufficient for $\mathscr{P} = \{P_\theta, \theta \in \Omega\}$, and if V is ancillary, then T and V are independent under P_θ for any $\theta \in \Omega$.

Remark

- Ancillarity, completeness, sufficiency are all properties of a statistics with respect to a family $\mathscr{P}$
- Independence is a property with respect to a particular distribution P_θ

proof of Basu's theorem:

To show independence, we have to show $\forall \theta, A, B$ that

$$P_\theta(V \in A, T \in B) = P_\theta(V \in A) P_\theta(T \in B)$$

Define

$$q_A(t) = P_\theta(V \in A \mid T = t)$$
$$\rho_A = P_\theta(V \in A)$$

- First, show that they do no depend on θ.
- Second, show that they are equal by completeness

Application to independence of normal sample mean and variance

$X_1, \dots, X_n \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, \sigma^2)$. Consider the subfamily $\mathscr{P}_{\sigma^2} = \{\mathcal{N}(\mu, \sigma^2)^n : \mu \in \mathbb{R}\}$.

- $\bar{X} = \frac{1}{n} \sum X_i$ is complete sufficient for $\mathscr{P}_{\sigma^2}$.
- $S^2 = \frac{1}{n-1} \sum (X_i - \bar{X})^2$ is ancillary why?

Apply Basu's theorem

Review of basics of conditional expectations

Let X, Z be random variables with joint density $p(x, z) = p(z \mid x)p(x)$. Let h be a measurable function with $\int \int |h(x, z)|\, p(x, z) dx dz < \infty$. The conditional expectation of h given X is

$$\mathbb{E}\left[h(X, Z) \mid X = x\right] = \int h(x, z) p(z \mid x) dz$$

Basic properties of conditional expectation

- Pull-out property: if $h(x, z) = h_1(x)h_2(z)$, then

$$\mathbb{E}[h(X, Z) \mid X = x] = h_1(x)\mathbb{E}[h_2(Z) \mid X = x]$$

- Tower property:

$$\mathbb{E}[\mathbb{E}[h(X, Z) \mid X]] = \mathbb{E}[h(X, Z)]$$

- Conditional expectation under independence: if $p(x, z) = p(x)p(z)$, then

$$\mathbb{E}[h(Z) \mid X = x] = \mathbb{E}[h(Z)]$$

Summary

- V is **ancillary** if its distribution does not depend on θ
- **Completeness + sufficiency** as the ideal notion of optimal data compression
- **Basu's theorem** is useful to prove independence

What is next?

- Rao-Blackwell Theorem
- UMVU

Thank you for attending

See you on Monday in Old Chem 025