

# STAT 611-600

## Theory of Statistics - Inference Lecture 3: Minimal Sufficiency

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# Sufficient Statistics: Transformation

- If  $T$  is sufficient for  $\theta$  and  $T = c(U)$ , a mathematical function of some other statistic  $U$ , then  $U$  is also sufficient.
- If  $T$  is sufficient for  $\theta$ , and  $U = r(T)$  with  $r$  being **one-to-one**, then  $U$  is also sufficient.
- Remark: When one statistic is a function of the other statistic and vice versa, then they carry exactly the same amount of information.

# Transformed Sufficient Statistics: Examples

## Examples:

- If  $\sum_{i=1}^n X_i$  is sufficient, so is  $\bar{X}$
- If  $(\sum_{i=1}^n X_i, \sum_{i=1}^n X_i^2)$  are sufficient, so are  $(\bar{X}, S^2)$
- If  $\sum_{i=1}^n X_i$  is sufficient, then  $(\sum_{i=1}^m X_i, \sum_{i=m+1}^n X_i)$  are sufficient, and so are  $(\sum_{i=1}^n X_i, \sum_{i=1}^n X_i^2)$
- Examples of non-sufficiency  
Ex.  $X_1, X_2$  iid  $Poi(\lambda)$ .  $T = X_1 - X_2$  is not sufficient  
Ex.  $X_1, \dots, X_n$  iid with pmf  $f(x; \theta)$ .  $T = (X_1, \dots, X_{n-1})$  is not sufficient.

# Minimal Sufficient Statistics

It is seen that different sufficient statistics are possible. **Which one is the best?**

(Of course, equivalent statistics need not be separately considered)  
Naturally, the one with maximum possible reduction.

- For  $N(\theta, 1)$ ,  $\bar{X}$  is a better sufficient statistic for  $\theta$  than  $(\bar{X}, S^2)$ .

## Definition

$T$  is a *minimal sufficient statistic* if, given any other sufficient statistic  $T'$ , there is a function  $c(\cdot)$  such that  $T = c(T')$ .

# Minimal Sufficient Statistics

- Minimal sufficient statistic has the smallest dimension among possible sufficient statistics. Often the dimension is equal to the number of free parameters (exceptions do exist).
- Partition interpretation of minimal sufficient statistics
  - Any sufficient statistic introduces a partition on the sample space.
  - The partition of a minimal sufficient statistic is the *coarsest*.

## How to Check Minimal Sufficiency?

### Theorem

*A statistic  $T$  is minimal sufficient if the following property holds: For any two sample points  $\mathbf{x}$  and  $\mathbf{y}$ ,  $f(\mathbf{x}; \theta)/f(\mathbf{y}; \theta)$  does not depend on  $\theta$  (i.e.  $f(\mathbf{x}; \theta)/f(\mathbf{y}; \theta)$  is a constant function of  $\theta$ ) if and only if  $T(\mathbf{x}) = T(\mathbf{y})$*

### Examples.

- $X_i$  iid Uniform $[\theta, \theta + 1]$ .
- $X_i$  iid  $N(\mu, \sigma^2)$ .

# Minimal Sufficient Statistics: Exponential families

For iid observations from an exponential family with the probability density  $f(x; \theta) = c(\theta)h(\mathbf{x}) \exp\{\sum_{j=1}^k w_j(\theta)t_j(\mathbf{x})\}$ , where  $\theta$  is  $d$  dimensional, if  $w_j(\theta)$ 's are **linearly independent**, then the statistic

$$T(\mathbf{X}) = (\sum_{i=1}^n t_1(\mathbf{X}_i), \dots, \sum_{i=1}^n t_k(\mathbf{X}_i))$$

is minimal sufficient for  $\theta$ .

- In particular, for full-rank exponential family (i.e.  $d = k$ ),  $T$  is always minimal sufficient. For the distribution with multiple parameters  $\theta = (\theta_1, \dots, \theta_s)$ , the minimal sufficient statistic is also a vector  $T = (T_1(\mathbf{X}), \dots, T_r(\mathbf{X}))$ .
- Often  $r = s$ , but not always.
- For curved exponential families, we can have  $r > s$ .  
Example:  $X_i$  iid  $N(\mu, \mu^2)$ .

# Minimal Sufficient Statistics

## Remarks:

- Minimal sufficient statistic is not unique. Any two are in one-to-one correspondence, so are equivalent.
- If  $T(\mathbf{X})$  is minimal sufficient for  $\mathcal{P}_0$ , and  $T(\mathbf{X})$  is sufficient for  $\mathcal{P}$ , and  $\mathcal{P}_0 \subset \mathcal{P}$ , then  $T(\mathbf{X})$  is minimal sufficient for  $\mathcal{P}$ .

Examples:  $\mathcal{P} = \{\text{all distributions with pdf}\}$ ,  
 $\mathcal{P}_0 = \{\text{Cauchy distribution}\}$ ,  $T(\mathbf{X}) = (X_{(1)}, \dots, X_{(n)})$



## Definition

A statistic  $T$  is *ancillary* if its distribution does not depend on  $\theta$ .

- Induced family is completely known, contains no information about  $\theta$
- Opposite of sufficiency.

# Ancillary Statistic: Location family

## General Results for Location Family with pdf $f(x - \theta)$

- $T$  is a location invariant statistic, i.e.,  
 $T(x_1 + b, \dots, x_n + b) = T(x_1, \dots, x_n)$ . Then  $T$  is ancillary.
- Sample std  $S$  is ancillary (and so are other estimates of scale).
- Examples: iid  $N(\theta, 1)$ . Show  $S^2$  is ancillary.
- Examples: Location family, iid pdf  $f(x - \theta)$ . Consider  
 $R = X_{(n)} - X_{(1)}$ .

# Ancillary Statistic: Location-scale family

General Results for Location-scale Family with pdf  $\frac{1}{\sigma} f\left(\frac{x - \mu}{\sigma}\right)$

- $T$  is a location-scale invariant statistic, i.e.,  
 $T(ax_1 + b, \dots, ax_n + b) = T(x_1, \dots, x_n)$ . Then  $T$  is ancillary.
- If  $T_1$  and  $T_2$  are two location-scale invariant statistics (see above), then  $T_1/T_2$  is ancillary.
- Example:  $X_1, X_2 \text{ Ind } N(0, \sigma^2)$ . Show  $X_1/X_2$  is ancillary.
- Example: For iid  $N(\mu, \sigma^2)$ ,  $T = ((X_1 - \bar{X})/S, \dots, (X_n - \bar{X})/S)$  is ancillary.