# IE605: Engineering Statistics <br> Lecture 10 

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Previous Lecture:

- Data Reduction
- Sufficiency principle
- Sufficient Statistics
- Factorization theorem

This Lecture:

- Minimum statistics
- Ancillary statistics
- Complete statistics


## Factorization theorem

How to come up with a sufficient statistic for a parameter

- guess a statistics (required good intuition)
- find its pdf/pmf (expression can be tedious)
- find the ration to acertain

Factorization Theorem: For a random sample $X$ with pdf/pmf $f(x \mid \theta)$, let $T(X)$ is a statistic for $\theta$. Then $T(X)$ is sufficient statistic if and only if if there exists functions $g(t \mid \theta)$ and $h(x)$ such that, for all $x$ and parameters points $\theta$

$$
f(x \mid \theta)=g(T(x) \mid \theta) h(x)
$$

## Example 1:

Population distribution $\sim \mathcal{N}\left(\mu, \sigma^{2}\right)$, with $\mu$ unknown and $\sigma^{2}$ known

$$
\begin{aligned}
f(x \mid \mu) & =\frac{1}{\left(2 \pi \sigma^{2}\right)^{n / 2}} \exp \left\{-\sum_{i=1}^{2}\left(x_{i}-\mu\right)^{2} / 2 \sigma^{2}\right\} \\
f(x \mid \mu) & =\frac{1}{\left(2 \pi \sigma^{2}\right)^{n / 2}} \exp \left\{\left(-\sum_{i=1}^{n}\left(x_{i}-\bar{x}\right)^{2}-n(\bar{x}-\mu)^{2}\right) / 2 \sigma^{2}\right\} \\
& =\frac{1}{\left(2 \pi \sigma^{2}\right)^{n / 2}} \exp \left\{-\sum_{i=1}^{n}\left(x_{i}-\bar{x}\right)^{2} / 2 \sigma^{2}\right\} \exp \left\{-n(\bar{x}-\mu)^{2} / 2 \sigma^{2}\right\} \\
& =h(x) g(\bar{x} \mid \mu)
\end{aligned}
$$

Hence $T(x)=\bar{x}$ is a sufficient statistics.

## Example 2:

Population distribution $\sim \mathcal{N}\left(\mu, \sigma^{2}\right)$, both $\mu$ and $\sigma^{2}$ unknown

$$
\begin{aligned}
f(x \mid \mu) & =\frac{1}{\left(2 \pi \sigma^{2}\right)^{n / 2}} \exp \left\{-\sum_{i=1}^{2}\left(x_{i}-\mu\right)^{2} / 2 \sigma^{2}\right\} \\
f(x \mid \mu) & =\frac{1}{\left(2 \pi \sigma^{2}\right)^{n / 2}} \exp \left\{\left(-\sum_{i=1}^{n}\left(x_{i}-\bar{x}\right)^{2}-n(\bar{x}-\mu)^{2}\right) / 2 \sigma^{2}\right\} \\
& =\frac{1}{\left(2 \pi \sigma^{2}\right)^{n / 2}} \exp \left\{-\sum_{i=1}^{n}\left(x_{i}-\bar{x}\right)^{2} / 2 \sigma^{2}\right\} \exp \left\{-n(\bar{x}-\mu)^{2} / 2 \sigma^{2}\right\} \\
& =\frac{1}{\left(2 \pi \sigma^{2}\right)^{n / 2}} \exp \left\{(n-1) s^{2} / 2 \sigma^{2}\right\} \exp \left\{-n(\bar{x}-\mu)^{2} / 2 \sigma^{2}\right\} \\
& =h(x) g\left(\bar{x}, s^{2} \mid\left(\mu, \sigma^{2}\right)\right)
\end{aligned}
$$

Set $T_{1}(x)=\bar{x}$ and $T_{2}(x)=s^{2}$. Then $T(x)=\left(T_{1}(x), T_{2}(x)\right)$ is a sufficient statistics for $\theta=\left(\mu, \sigma^{2}\right)$

## Sufficient Statistics for Exponential Family

Recall that $f(x \mid \theta)$ is belongs to exponential family with parameter $\theta=\left(\theta_{1}, \theta_{2}, \ldots, \theta_{d}\right)$ if

$$
\begin{gathered}
f(x \mid \theta)=h(x) c(\theta) \exp \left\{\sum_{i=1}^{k} w_{i}(\theta) t_{i}(x)\right\} . \\
T(x)=\left(\sum_{j=1}^{n} t_{1}\left(x_{j}\right), \ldots, \sum_{j=1}^{n} t_{k}\left(x_{j}\right)\right)
\end{gathered}
$$

is a sufficient statistics for $\theta(d \leq k)$.

## Functions of Sufficient Statistics

- Can there be one sufficient statistic or multiple?
- The entire sample is always sufficient statistic. Set $T(x)=\left(x_{1}, x_{2}, \ldots, x_{n}\right)$ and $h(x)=1$, then

$$
f(x \mid \theta)=f(T(x) \mid \theta) h(x)
$$

- Any one-to-one function of a sufficient statistics is also a sufficient statistics.
- Let $T^{\star}(X)=r(T(X))$ for some invertible $r$ and $T(X)$ is a sufficient statistics

$$
\begin{aligned}
f(x \mid \theta) & =g(T(x) \mid \theta) h(x) \\
& =g\left(r^{-1}\left(T^{\star}(x) \mid \theta\right)\right) h(x) \\
& =g^{\star}\left(T^{\star}(x) \mid \theta\right) h(x)
\end{aligned}
$$

Hence $T^{\star}(x)$ is a sufficient statistics

## Minimal Sufficient Statistics

A sufficient Statistics $T(X)$ is called a minimal sufficient statistics, if for any sufficient statistics $T^{\prime}(X)$,

$$
T^{\prime}(x)=T^{\prime}(y) \Longrightarrow T(x)=T(y)
$$

- $\mathcal{T}=\{t: t=T(x), x \in \mathcal{X}\}$ and $A_{t}=\{x: T(x)=t\}$
- $\mathcal{T}^{\prime}=\left\{t^{\prime}: t^{\prime}=T^{\prime}(x), x \in \mathcal{X}\right\}$ and $B_{t^{\prime}}=\left\{x: T^{\prime}(x)=t^{\prime}\right\}$
- for any $t^{\prime} \in \mathcal{T}^{\prime}$, there exists $t \in \mathcal{T}$ such that $B_{t^{\prime}} \subset A_{t}$.


## Example: Minimal Sufficient Statistics

Samples are drawn from $\mathcal{N}\left(\mu, \sigma^{2}\right)$ with unknown $\mu$ and known $\sigma^{2}$.

- $T_{1}(x)=\bar{x}$ is a sufficient statistics for $\mu$
- $T_{2}(x)=\left(\bar{x}, s^{2}\right)$ is also a sufficinet statistics for $\mu$ (verify!)
- $T_{1}(x)=\bar{x}=r\left(\bar{x}, s^{2}\right)=r\left(T_{2}(x)\right)$
- As both $T_{1}$ and $T_{2}$ are sufficient statistic they contain same knowledge about $\mu$
- Additional knowledge of $s^{2}$ does not add any information about $\mu$.
- $T_{1}$ gives better data reductions!


## Test for Minimal Sufficient Statistics

Let $f(x \mid \theta)$ be the pmf/pdf of a sample. Suppose there exists a function $T(X)$ such that, for every sample pair $(x, y)$, the ratio $f(x \mid \theta) / f(y \mid \theta)$ is a constant iff $T(x)=T(y)$. Then $T(X)$ is a minimal sufficient statistics.

- Image of $\mathcal{X}$ under $T$ :
- Define partion set $\mathcal{X}$
- Select one element in each partition
- Pair each $x \in \mathcal{X}$ with partitions
- Argue $T$ is sufficient statistics using factorization theorem


## Test for Minimal Sufficient Statistic contd..

- $T^{\prime}$ is another sufficient statistics
- Apply factorization theorem
- Consider points $(x, y)$ such that $T^{\prime}(x)=T^{\prime}(y)$. Apply ratio
- Apply the assumption to $T$ is minimal.


## Example: Normal Minimal Statistics

Samples are drawn from $\mathcal{N}\left(\mu, \sigma^{2}\right) .\left(\mu, \sigma^{2}\right)$ unknown.

- Consider two sample points $(x, y)$ with statistics $\left(\bar{x}, s_{x}^{2}\right)$ and $\left(\bar{x}, s_{x}^{2}\right)$

$$
\frac{f(x \mid \theta)}{f(y \mid \theta)}=\frac{\left(2 \pi \sigma^{2}\right)^{n / 2}}{\left(2 \pi \sigma^{2}\right)^{n / 2}} \frac{\exp \left\{-\left(n(\bar{x}-\mu)^{2}+(n-1) s_{x}^{2}\right) / 2 \sigma^{2}\right\}}{\exp \left\{-\left(n(\bar{y}-\mu)^{2}+(n-1) s_{y}^{2}\right) / 2 \sigma^{2}\right\}}
$$

- The ratio is constant iff $\bar{x}=\bar{y}$ and $s_{x}^{2}=s_{y}^{2}$, i.e., statistics are same


## Example: Uniform Minimal Statistics

Samples are drawn from $\operatorname{Unif}(\theta, \theta+1)$, $\theta$ is unknown.
PDF of sample $x$ is

$$
f(x \mid \theta)= \begin{cases}1 & \text { if } \quad \theta<x_{i}<\theta+1 \quad i=1,2, \ldots, n \\ 0 & \text { otherwise }\end{cases}
$$

- It can be reorganized as

$$
f(x \mid \theta)= \begin{cases}1 & \text { if } \quad \max _{i} x_{i}-1<\theta<\min _{i} x_{i} \quad i=1,2, \ldots, n \\ 0 & \text { otherwise }\end{cases}
$$

- $f(x \mid \theta) / f(y \mid \theta)$ is constant provided

$$
\max _{i} x_{i}=\max y_{i} \quad \& \quad \min x_{i}=\min y_{i}
$$

- $T(X)=\left(\min _{i} X_{i}, \max _{i} X_{i}\right)=\left(X_{(1)}, X_{(n)}\right)$ is MSS
- $\left(\left(X_{(n)}-X_{(1)}\right),\left(X_{(n)}+X_{(1)}\right) / 2\right)$ is also a MSS.


## Ancillary Statistics

- Sufficient Statistics contains all the information about parameter $\theta$ available from sample
- Ancillary Statistics, has a complementary purpose.

A statistics $S(X)$ whose distribution does not depend on the parameter $\theta$ is called an ancillary statistics

- Alone ancillary statistics contains no information about $\theta$
- When used in conjuection with other statistics it may reveal information about $\theta$


## Example: Uniform Ancillary Statistics

$X=\left(X_{1}, X_{2}, \ldots, X_{n}\right)$ are iid and $\sim \operatorname{Unif}(\theta, \theta+1)$.

$$
f(x \mid \theta)= \begin{cases}1 & \text { if } \quad \theta<x<\theta+1 \\ 0 & \text { otherwise }\end{cases}
$$

Joint pdf of $\left(X_{(1)}, X_{(n)}\right)$ can be derived
$g\left(x_{(1)}, x_{(n)}\right)= \begin{cases}n(n-1)\left(x_{(n)}-x_{(1)}\right)^{n-2} & \theta<x_{(1)}<x_{(n)}<\theta+1 \\ 0 & \text { otherwise }\end{cases}$
Define $R=\left(X_{(n)}-X_{(1)}\right)$ and $R=\left(X_{(n)}+X_{(1)}\right) / 2$. Find joint distributions of $(R, M)$

$$
h(r \mid \theta)=n(n-1) r^{n-2}(1-r) \quad 0<r<1
$$

(Complete!)

