

IE605: Engineering Statistics

Lecture 09

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Previous Lecture:

- ▶ Generating Random Samples

This Lecture:

- ▶ Data reduction
- ▶ Sufficiency principle
- ▶ Sufficient statistics
- ▶ factorization theorem

Data Reduction

- ▶ A random sample $x := (x_1, x_2, \dots, x_n)$ is a long list of numbers hard to interpret
- ▶ We may wish to summarize the information in it by determining a few key features
 - ▶ sample mean
 - ▶ sample variance
 - ▶ smallest value
 - ▶ largest value
- ▶ Any statistic $T(\cdot)$ defines a data reduction or data summary
- ▶ When we have statistics $T(x)$ we treat sample x and y the same as long as $T(x) = T(y)$

- ▶ $T(x) = \sum_{i=1}^n x_i$ gives the sum of the sample x . There could be many other samples with the same sum of sample space
- ▶ Data reduction can be thought of partition
- ▶ For any t , $A_t = \{x : T(x) = t\}$
- ▶ What are advantages and consequences of data reduction?

Statistic are associated with parameters.

Principles of data reduction:

- ▶ **Sufficiency Principle:** Parameter information by summarization of data
- ▶ **Likelihood Principle:** function of parameter determined by observed sample
- ▶ **Equivariance Principle:** preserves important features of model

Sufficiency Principle

- ▶ A **sufficient statistic** for a parameter θ , captures all information about θ contained in the sample
- ▶ knowledge of individual samples does not contain any more information about θ
- ▶ $x = (x_1, x_2, \dots, x_n)$ and $T(x)$ is a statics. $T(x)$ contains all information about θ . Further knowing x_3 or x_4 or any other component provides no additional information

Sufficiency Principle: If $T(X)$ is a sufficient statistic for θ , then any inference about θ should depend on the sample X only through $T(X)$

If x and y are such that $T(x) = T(y)$, then the inference about θ should be the same whether $X = x$ or $X = y$ is observed.

Characterization of Sufficient Statistic

A statistic $T(X)$ is a sufficient statistic for θ , if the conditional distribution of X given $T(X)$ does not depend on θ .

- ▶ $P_{\theta}(X = x | T(X) = t)$ is independent of θ if $T(X)$ is sufficient
- ▶ Sufficient statistic captures all the information about θ

Example:

- ▶ Statistician 1: Generate sample x and computes $T(x)$
- ▶ Statistician 2: is informed about $T(x)$ only not x
- ▶ if T is a sufficient statistic for parameter θ , both the statistician have same amount of information about θ .

Sufficient Statistic contd..

Let $T(X)$ is a sufficient Statistic for parameter θ

- ▶ $P_{\theta}(X = x|T(X) = t)$ doesn't depend on θ for all t
- ▶ Probability is non zero for sample $T(x) = t$
- ▶ We consider $P_{\theta}(X = x|T(X) = T(x))$. Note $\{X = x\} \subset \{y : T(y) = T(x)\}$. Then

$$\begin{aligned}P_{\theta}(X = x|T(X) = T(x)) &= \frac{P_{\theta}(X = x, T(X) = T(x))}{P_{\theta}(T(X) = T(x))} \\ &= \frac{P_{\theta}(X = x)}{P_{\theta}(T(X) = T(x))} \\ &= \frac{p(x|\theta)}{q(T(x)|\theta)}\end{aligned}$$

- ▶ $p(x|\theta)$ is the joint pmf of sample X and $q(t|\theta)$ is the distribution of statistic $T(X)$.

Alternate definition of sufficient statistic

If $p(x|\theta)$ is a joint pdf/pmf of X and $q(t|\theta)$ is pdf/pmf of $T(X)$, then $T(X)$ is a sufficient statistic for θ if for every x , the ratio $p(x|\theta)/q(T(x)|\theta)$ does not depend on θ .

Example 1: Bernoulli sufficient statistics Let $X = (X_1, X_2, \dots, X_n)$ be iid $\sim \text{Ber}(\theta)$. $T(X) = \sum_{i=1}^n X_i$ is a sufficient statistic for θ . For $x = (x_1, x_2, \dots, x_n)$, define $t = \sum_{i=1}^n x_i$

$$\begin{aligned}\frac{p(x|\theta)}{q(T(x)|\theta)} &= \frac{\prod_{i=1}^n \theta^{x_i} (1-\theta)^{1-x_i}}{\binom{n}{t} \theta^t (1-\theta)^{n-t}} \\ &= \frac{\theta^{\sum x_i} (1-\theta)^{\sum(1-x_i)}}{\binom{n}{t} \theta^t (1-\theta)^{n-t}} \\ &= \frac{\theta^t (1-\theta)^{n-t}}{\binom{n}{t} \theta^t (1-\theta)^{n-t}} \\ &= \frac{1}{\binom{n}{t}} = \frac{1}{\binom{n}{\sum x_i}} \quad (\text{not a function of } \theta)\end{aligned}$$

Example 2: Normal sufficient statistics $X = (X_1, X_2, \dots, X_n)$ is iid $\sim \mathcal{N}(\mu, \sigma^2)$. Sample mean $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$, is a sufficient statistic for μ .

$$p(x|\mu) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp\{-(x_i - \mu)^2/2\sigma^2\}$$

We know $\bar{X} \sim \mathcal{N}(\mu, \sigma^2/n)$

$$q(\bar{X}|\mu) = \frac{\sqrt{n}}{\sqrt{2\pi\sigma^2}} \exp\{-n(\bar{x} - \mu)^2/2\sigma^2\}$$

$$\frac{p(x|\theta)}{q(\bar{x}|\theta)} = \frac{\sqrt{n}}{\sqrt{(2\pi\sigma^2)^{n-1}}} \exp\left\{-\sum_{i=1}^n (x_i - \bar{x})^2/2\sigma^2\right\}$$

(does not depend on μ)

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 ascertain

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

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

Proof of factorization theorem for discrete case

Assume $T(X)$ is a sufficient statistic (\implies).

- ▶ $P_\theta(X = x | T(X) = T(x))$ does not depend on θ
- ▶ Set $h(x) = P_\theta(X = x | T(X) = T(x))$ (valid!)
- ▶ Set $g(t|\theta) = P_\theta(T(X) = t)$ (valid!)

$$\begin{aligned}f(x|\theta) &= P_\theta(X = x) \\&= P_\theta(X = x, T(X) = T(x)) \\&= P_\theta(X = x | T(X) = T(x))P_\theta(T(X) = T(x)) \\&= h(x)g(T(x)|\theta)\end{aligned}$$

Proof of factorization theorem for discrete case contd..

Assume the factorization holds (\Leftarrow)

- ▶ We show that ratio $f(x|\theta)/q(T(x)|\theta)$ does not depend on θ
- ▶ Choose x . Let $t = T(x)$ and $A_t = \{y : T(y) = t\}$

$$\begin{aligned}\frac{f(x|\theta)}{q(T(x)|\theta)} &= \frac{g(T(x)|\theta)h(x)}{q(T(x)|\theta)} \\ &= \frac{g(T(x)|\theta)h(x)}{\sum_{y \in A_t} f(y|\theta)} \\ &= \frac{g(T(x)|\theta)h(x)}{\sum_{y \in A_t} g(T(y)|\theta)h(y)} \\ &= \frac{g(T(x)|\theta)h(x)}{g(T(x)|\theta) \sum_{y \in A_t} h(y)} \\ &= \frac{h(x)}{\sum_{y \in A_t} h(y)} \quad \text{does not depend on } \theta\end{aligned}$$

$T(X)$ is a sufficient statistic for θ