

Sufficient Statistic:

Definition \rightarrow ①: Let X_1, X_2, \dots, X_n be a random sample of size 'n' drawn from a population having an unknown parameter θ . Let $T = T(X_1, X_2, \dots, X_n)$ be a statistic that estimates the parameter θ . T will be said to be sufficient for θ if no other statistic can give any further information regarding θ .

Definition \rightarrow ② T will be said to be sufficient for the parameter θ , if the conditional distribution of any other statistic given a value of T is independent of the parameter θ .

Definition \rightarrow ③ T will be said to be sufficient for the parameter θ , if the conditional distⁿ of X_1, X_2, \dots, X_n given a value of T is independent of θ .

Let x_1, x_2, \dots, x_m be a sample from $N(\mu, 1)$, where μ is unknown. Suppose that we transform variables x_1, x_2, \dots, x_m to y_1, y_2, \dots, y_m with the help of an orthogonal transformation so that y_1 is $N(\sqrt{n}\mu, 1)$; y_2, \dots, y_m are iid $N(0, 1)$ & also, y_1, y_2, \dots, y_m are independent. [Taking $y_1 = \sqrt{n}\bar{x}$ & $\forall k \geq 2(1 \leq k \leq m)$, $y_k = [(k-1)x_k - (x_1 + x_2 + \dots + x_{k-1})] / \sqrt{k(k-1)}$]. To estimate μ , we can use ~~or~~ either the observed values of x_1, x_2, \dots, x_m or simply the observed value of $y_1 = \sqrt{n}\bar{x}$. The random variables y_2, y_3, \dots, y_m provide no information about μ . Clearly, y_1 is preferable since one need not keep a record of all the ~~obs~~ observations; it suffices to accumulate the observations & compute y_1 . Any analysis of the data based on y_1 is just as effective as any analysis that could be based on x_i 's.

Problem (2): $X_1 \sim \text{PC}(2)$, $X_2 \sim \text{PC}(2)$. & X_1 & X_2 are independent. Show that $(X_1 + 2X_2)$ is not sufficient for λ .

Proof: Let, $T = X_1 + 2X_2$

$$\therefore P(X_1=0, X_2=0 | T=0) = 1 ; P(X_1=1, X_2=0 | T=1) = 1.$$

$$\begin{aligned} P(X_1=0, X_2=1 | T=2) &= \frac{P(X_1=0, X_2=1)}{P(T=2)} = \frac{P(X=0) P(X_2=1)}{P(X_1=2, X_2=0) + P(X_1=0, X_2=1)} \\ &= \frac{P(X_1=0) P(X_2=1)}{P(X_1=2) P(X_2=0) + P(X_1=0) P(X_2=1)}, \text{ since } X_1 \text{ \& } X_2 \text{ are independent} \end{aligned}$$

$$\begin{aligned} &= \frac{e^{-\lambda} \cdot \frac{\lambda^0}{0!} \cdot e^{-\lambda} \cdot \frac{\lambda^1}{1!}}{e^{-\lambda} \cdot \frac{\lambda^2}{2!} \cdot e^{-\lambda} \cdot \frac{\lambda^0}{0!} + e^{-\lambda} \cdot \frac{\lambda^0}{0!} \cdot e^{-\lambda} \cdot \frac{\lambda^1}{1!}} = \frac{e^{-\lambda} \cdot e^{-\lambda} \lambda}{e^{-\lambda} \cdot e^{-\lambda} \lambda + e^{-\lambda} \cdot \frac{\lambda^2}{2} \cdot e^{-\lambda}} \end{aligned}$$

$$= \frac{\lambda}{\lambda + \frac{\lambda^2}{2}} = \frac{2\lambda}{2\lambda + \lambda^2} = \frac{2}{2 + \lambda}. \text{ \& this expression is dependent on } \lambda.$$

As such, $T = X_1 + 2X_2$ is not a sufficient statistic for λ .

Neyman - Fisher Factorisation Theorem

Let x_1, x_2, \dots, x_n be a random sample of size 'n' drawn from a population having an unknown parameter θ . Let, $f_\theta(x_1, x_2, \dots, x_n)$ be the joint p.m.f. or p.d.f. of x_1, x_2, \dots, x_n . A statistic T is said to be sufficient for the parameter θ iff we can write

$$f_\theta(x_1, x_2, \dots, x_n) = g(\theta, t) \cdot h(x_1, x_2, \dots, x_n),$$

where, $g(\theta, t)$ is a function of θ & t and $h(x_1, x_2, \dots, x_n)$ is independent of θ . Also, $t = T(x_1, x_2, \dots, x_n)$.

sufficient statistic for an unknown θ

Problem 2:

Theorem: (1) Let T be a sufficient statistic for an unknown θ .
~~Let $\psi(T)$ be a 1-1 function of T . Show that $\psi(T)$ is also sufficient for θ .~~

Proof: Let $T' = \psi(T)$.

$\Rightarrow T = \psi^{-1}(T')$ since $\psi(T)$ is a 1-1 function, so inverse also exists.

$\Rightarrow T = \phi(T')$, say.

Since, T is sufficient for θ , from Neyman-Fisher Factorisation theorem, we have

$$f_{\theta}(x_1, x_2, \dots, x_n) = g(T, \theta) h(x_1, x_2, \dots, x_n), \text{ where, } h(x_1, x_2, \dots, x_n) \text{ is independent of } \theta.$$
$$= g[\phi(T'), \theta] h(x_1, x_2, \dots, x_n).$$

$$\Rightarrow f_{\theta}(x_1, x_2, \dots, x_n) = k(T', \theta) h(x_1, x_2, \dots, x_n).$$

As such, $T' = \psi(T)$ is sufficient for θ . [Proved].

Theorem: (2) If T be sufficient for \mathcal{Q} & $T = \psi(T^*)$, then, T^* is sufficient for \mathcal{Q} .

Proof: $\therefore T$ is sufficient for \mathcal{Q} ; \therefore From Neyman-Fisher Factorisation theorem we have, $f_{\mathcal{Q}}(\underline{x}) = q(\underline{t}, \mathcal{Q}) L(\underline{x}) = q(\mathcal{Q}, \psi(T^*)) L(\underline{x}) = q^*(\mathcal{Q}, T^*) L(\underline{x})$.

$\therefore T^*$ is sufficient for \mathcal{Q} . [Proved]

1.3) For a random variable sample X_i ($i=1, \dots, n$) from an exponential distribution with p.d.f.

$$f_{\theta}(x) = \begin{cases} \frac{1}{\theta} e^{-x/\theta}, & \text{if } 0 < x < \infty \\ 0, & \text{otherwise.} \end{cases}$$

where, $0 < \theta < \infty$, show that $\sum_i X_i$ is a sufficient statistic for θ .

Ans/. By question, X_i follows exponential distribution with parameter θ & the p.d.f. of X_i is given by

$$f_{\theta}(x_i) = \begin{cases} \frac{1}{\theta} \cdot e^{-x_i/\theta}, & 0 < x_i < \infty, \forall i=1, \dots, n \\ 0, & \text{otherwise} \end{cases}$$

Being a random sample, X_i 's are mutually independent, $\forall i=1, \dots, n$.

Hence, the joint p.d.f. of X_1, X_2, \dots, X_n is given by

$$f_{\theta}(x_1, x_2, \dots, x_n) = \begin{cases} \frac{1}{\theta^n} \cdot e^{-\sum_i x_i/\theta}, & 0 < x_i < \infty \\ 0, & \text{o.w.} \end{cases}$$

$$\Rightarrow f_{\theta}(x_1, x_2, \dots, x_n) = g(T, \theta) h(x_1, x_2, \dots, x_n), \text{ where,}$$

$$g(T, \theta) = \frac{1}{\theta^n} e^{-\sum_i x_i/\theta} \text{ which is dependent on } \theta \text{ \& } h(x_1, x_2, \dots, x_n) = 1, \text{ which is independent of } \theta. \text{ Also } T = \sum_{i=1}^n x_i$$

As such, the Neyman-Fisher Factorisation Theorem is satisfied for the statistic $T = \sum_{i=1}^n X_i$ & hence, it is sufficient for θ . [Proved].

1.7) Let, $X_i, i=1, \dots, n$ be a random sample from a distribution ω with p.d.f.

$$f_{\omega}(x) = \begin{cases} \omega x^{\omega-1}, & \text{if } 0 < x < 1 \\ 0, & \text{o.w.} \end{cases} \quad \text{where, } 0 < \omega < \infty.$$

Find a sufficient statistic for ω .

A/ By question, X_i is a continuous r.v. with p.d.f.

$$f_{\omega}(x_i) = \begin{cases} \omega x_i^{\omega-1}, & \text{if } 0 < x_i < 1 \\ 0, & \text{o.w.} \end{cases}, \quad i=1, \dots, n.$$

Being a random sample, X_i 's, $i=1, \dots, n$, are mutually independent.

Hence, the joint p.d.f. of x_1, x_2, \dots, x_n is given by,

$$f_{\omega}(x_1, x_2, \dots, x_n) = \begin{cases} \omega^n \left(\prod_{i=1}^n x_i \right)^{\omega-1}, & 0 < x_i < 1 \\ 0, & \text{o.w.} \end{cases}$$

$$\Rightarrow f_{\omega}(x_1, x_2, \dots, x_n) = g(\tau(\omega)) h(x_1, x_2, \dots, x_n), \quad \text{where}$$

5
 $g(\theta) = \theta^m \cdot \left(\prod_{i=1}^n x_i \right)^{\theta-1}$ which is dependent on θ , & $t = \prod_{i=1}^n x_i$

& $h(x_1, x_2, \dots, x_n) = 1$, which is independent of θ .

\therefore The statistic $T = \prod_{i=1}^n x_i$ satisfies the Neyman-Fisher factorisation theorem
& hence it is sufficient for θ .

2) Let $\underline{X} = (X_1, X_2, \dots, X_n)$ be a sample from $N(\alpha, \sigma^2)$, where α is a known real number. Show that the statistic $T(\underline{X}) = \left(\sum_{i=1}^n X_i, \sum_{i=1}^n X_i^2 \right)$ is sufficient for σ .

A) The joint p.d.f. of X_1, X_2, \dots, X_n is given by

$$f(x_1, x_2, \dots, x_n) = \frac{1}{(\sigma\sqrt{2\pi})^n} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \alpha)^2} \quad -\infty < x_i < \infty, \quad \forall i=1, \dots, n.$$

$$\begin{aligned} &= \frac{1}{\sigma^n (2\pi)^{n/2}} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n x_i^2 + \frac{2\alpha}{2\sigma^2} \sum_{i=1}^n x_i - n \frac{\alpha^2}{2\sigma^2}} \\ &= \frac{1}{\sigma^n (2\pi)^{n/2}} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n x_i^2 + \frac{\alpha}{\sigma} \sum_{i=1}^n x_i - n \frac{\alpha^2}{2\sigma^2}} \end{aligned}$$

$$\Rightarrow f_{\sigma}(x_1, x_2, \dots, x_n) = \cancel{q(t_1, t_2, \sigma)} q(t_1, t_2) h(x_1, x_2, \dots, x_n),$$

$$\text{where, } q(t_1, t_2, \sigma) = \frac{1}{\sigma^n} e^{-\frac{t_1}{2\sigma^2} + \frac{\alpha}{\sigma} t_2}, \quad \text{where, } t_1 = \sum_{i=1}^n x_i^2 \quad \& \quad t_2 = \sum_{i=1}^n x_i \quad \&$$

$$h(x_1, x_2, \dots, x_n) = \frac{1}{(2\pi)^{n/2}} e^{-n\alpha^2/2}$$

$\therefore T_1 = \sum_{i=1}^n x_i^2 \quad \& \quad T_2 = \sum_{i=1}^n x_i$ jointly ~~follow~~ satisfy the Neyman-Fisher factorisation theorem & hence, they are jointly sufficient for σ .

Problem: $f(x) = \frac{1}{2\sigma} e^{-\frac{|x|}{\sigma}}$, $-\infty < x < \infty$
 $\sigma > 0$.

If X is a single obs. from the above distⁿ, then prove that $|X|$ is sufficient for σ .

Solⁿ: Method #1: $f_0(x) = \frac{1}{2\sigma} e^{-\frac{|x|}{\sigma}}$, $-\infty < x < \infty$
 $\sigma > 0$

$\Rightarrow f_0(x) = g(t, \sigma) L(x_1, x_2, \dots, x_n)$, where,

$g(t, \sigma) = \frac{1}{2\sigma} e^{-\frac{|t|}{\sigma}}$, $t = |x|$, $L(x_1, x_2, \dots, x_n) \geq 1$. \therefore The statistic $T = |X|$ satisfies the Neyman-Fisher factorisation theorem. Hence, it is sufficient for σ .