

② Sufficiency

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Def A statistic $T: \mathcal{X} \rightarrow \mathcal{S}$ is sufficient for M if $f_{\theta T}(T(x))$ is a likelihood function for $(M, \mathcal{X}) \forall \theta$

- recall: $f_{\theta T}(t) =$ marginal density
of T
$$\sum_{x \in \mathcal{X}: T(x)=t} f_{\theta}(x)$$

Lemma (Factorization) T is sufficient for M iff $f_{\theta}(x) = c(x) g_{\theta}(T(x)) \forall x$ for some fn $c: \mathcal{X} \rightarrow (0, \infty)$, $g_{\theta}: \mathcal{S} \rightarrow (0, \infty)$

Proof: \Rightarrow For each x , we $f_{\theta T}(T(x)) = c(x) f_{\theta}(x)$
since $c(x) > 0$ so $f_{\theta}(x) = \frac{1}{c(x)} f_{\theta T}(T(x))$ so take
 $c(x) = \frac{1}{c(x)}$, $g_{\theta}(T(x)) = f_{\theta T}(T(x))$.

\Leftarrow We have $f_{\theta T}(T(x)) = \left(\sum_{x: T(x)=T(x)} c(x) \right) g_{\theta}(T(x)) = \frac{1}{c(x)} f_{\theta}(x)$
so is a likelihood function.

eg $x = (x_1, \dots, x_n) \sim \text{Bernoulli}(\theta)$

$$f_{\theta}(x) = \prod_{i=1}^n \theta^{x_i} (1-\theta)^{1-x_i} = \theta^{n\bar{x}} (1-\theta)^{n(1-\bar{x})}$$

= by Factorization ($c(x) \equiv 1$) we have that \bar{x} is a sufficient statistic.

Lemma 2 T is sufficient if $T(x) = T(x')$ implies $L(x) \propto L(x')$

Lemma 3 T is a suff stat for M iff whenever $f_{\theta T}(T(x))$ is the conditional distribution $x|T(x)$ is independent of θ

Proof: \Rightarrow We have that the conditional density

of x given $T(x) = t$ equals

$$f_{\theta}(x) / f_{\theta T}(T(x)) = c(x) f_{\theta}(T(x)) / f_{\theta}(T(x)) = c(x)$$

\Leftarrow Put $c(x) = f_{\theta}(x) / f_{\theta T}(T(x))$. Then

$$f_{\theta T}(T(x)) = c(x) f_{\theta}(x)$$

as $f_{\theta T}(T(x))$ is a LF and so T is sufficient.

note - this result has implications for model checking

- since the distribution of $x|T(x)$ is known we can compare the observed value of x with this

① distribution to see if it is surprising
for $x = (x_1, \dots, x_n)$ iid Bernoulli share $x_i \sim \theta$
is uniform on values in $\{0, 1\}^n$ with $n \neq 1$'s.

- minimal sufficiency

- a sufficient statistic makes a reduction
in the dimension of the data

② $x = (x_1, \dots, x_n)$ iid Bernoulli(θ) $\theta \in [0, 1]$

- x is suff so we go from
 n dimensions to 1 dimension.

- in making the reduction no relevant
information in the data concerning the
true value of θ is lost (same LF's)

- we want to make the maximum
reduction possible.

Def A sufficient statistic T for M is a
minimal sufficient statistic for M if
for any other sufficient statistic T' of
function h s.t. $f(x) = h(T'(x))$

note - from the model $M_T = \{f_\theta : \theta \in \Theta\}$
for a sufficient statistic T and
the observed value $T(x)$ we can
form a likelihood fun for (M, x)
via $L(\theta|x) = f_{\theta T}(T(x))$

= define for $x_1, x_2 \in \mathcal{X}$ $x_1 \equiv x_2$ if $L(\cdot | x_1) = c L(\cdot | x_2)$ for some $c > 0$

Lemma Any sufficient statistic T that satisfies $T(x_1) = T(x_2)$ iff $x_1 \equiv x_2$ is a MSS and conversely.

Proof: \Rightarrow Suppose T' is a sufficient statistic. Then if $T'(x_1) = T'(x_2)$ we have $x_1 \equiv x_2$ which implies $T(x_1) = T(x_2)$. Therefore \exists a fn h s.t. $T(x) = h(T'(x))$, and so T is a MSS.

\Leftarrow Suppose T is a MSS and $x_1 \equiv x_2$. Now define $T''(x) = x_1$ if $x \in \{x_1, x_2\}$ and $T'(x) = x$ otherwise. Then $f_{\theta, T''}(x) = f_{\theta}(x)$ if $x \notin \{x_1, x_2\}$ and $f_{\theta, T''}(x) = f_{\theta}(x) + f_{\theta}(x_2)$ if $x = x_1$ since $f_{\theta}(x_1) = c f_{\theta}(x_2)$.

Therefore $f_{\theta, T''}(x)$ is an LP and so T'' is a sufficient statistic and so \exists h s.t.

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$T(x_1) = h(T(x_2))$ which implies $T(x_1) = T(x_2)$

Corollary IF T is a sufficient statistic
of family LF $L(\cdot|\theta)$ we can
compute $T(x)$ then T is a MS.

Proof: IF $L(\cdot|\theta_1) = c L(\cdot|\theta_2)$
 $x_1 = x_2$ then

then $T(x_1) = T(x_2)$. IF $T(x_1) = T(x_2)$

then $L(\cdot|\theta_1) = c L(\cdot|\theta_2)$ which implies,

$\theta_1 = \theta_2$.

Ex $x = (x_1, \dots, x_n) \sim \text{Bernoulli}(\theta)$
with $\theta \in (0,1)$

- $L(\theta|x) = \theta^{n\bar{x}} (1-\theta)^{n(1-\bar{x})}$ of
 $T(x) = \bar{x}$ is sufficient

- $\ln L(\theta|x) = n\bar{x} \ln \theta + n(1-\bar{x}) \ln(1-\theta)$

$\frac{\partial \ln L(\theta|x)}{\partial \theta} = \frac{n\bar{x}}{\theta} - \frac{n(1-\bar{x})}{1-\theta} = 0$

- so $(1-\theta)n\bar{x} = \theta n(1-\bar{x})$ or

$\theta (n(1-\bar{x}) + n\bar{x}) = n\bar{x}$

$\theta = \bar{x}$

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$\therefore \bar{x}$ is a MSS

note

$$\frac{\partial^2 \ln L(\theta|x)}{\partial \theta^2} \Big|_{\theta = \bar{x}}$$

$$= -\frac{n\bar{x}}{\theta^2} - \frac{n(1-\bar{x})}{(1-\theta)^2} = -\frac{n}{\bar{x}} - \frac{n}{1-\bar{x}}$$

$$= -\frac{n}{\bar{x}(1-\bar{x})} < 0$$

$$\therefore \theta_{MLE}(x) = \bar{x}$$