Rao-Blackwell and sufficiency

Recap: Rao-Blackwell

Let θ be a parameter of interest, and $\tau(\theta)$ some function of θ . Let $\hat{\tau}$ be some inbiased estimator of $\tau(\theta)$, and τ a sufficient statistic for θ .

Let $\tau^* = \mathbb{E}[\hat{\tau}] = \tau$ (unbiased)

(2) $Var(\tau^*) \leq Var(\hat{\tau})$

Reminder: if the conditional distribution of X,, Xn 1 T does not depend on O, then T is a sufficient statistic For O

O E(27) = E[E(2/17]] = E(2) - 26) (iterated expectation) 2 Var(2*) = Var(E[ÎIT]) 4 Var(E[21T]) + E[var(2(T)] = Var(2) (law of total variance) why down need sufficiency? If 2* is a function of O, we can't actually calculate 2*. But if T is a sufficient statistic for O, then (X1,111, Xn) IT does not depend on O

=> ÊIT does not depend on Θ => E[ÎIT] (annot involve Θ

Example: Rao-Blackwell

Let
$$X_1, \ldots, X_n \stackrel{iid}{\sim} Poisson(\lambda)$$
.

a sufficient statistic: $T = \mathcal{L}_i \times_i$

Consider $\hat{\lambda} = X_i$ $\mathbb{E}[\hat{\lambda}] = \lambda$ $\text{Var}(\hat{\lambda}) = \lambda$
 $T = \mathcal{L}_i \times_i$ $\chi^* = \mathbb{E}[\hat{\lambda}|T]$

Now, $\mathbb{E}[\mathcal{L}_i \times_i | T = t] = \mathbb{E}[T|T = t] = t$
 $\Rightarrow \mathcal{L}_i \mathbb{E}[X_i | T = t] = t$
 $\Rightarrow \mathbb{E}[X_1 | T = t] = \frac{t}{n}$
 $\Rightarrow \mathcal{L}_i \times_i = T = \hat{\mathcal{L}}_i \times_i$

Conditioning on an insufficient statistic: $x_1,...,x_n$ λ^{iid} $Poissen(\lambda)$ $\hat{\lambda} = x_1$ x_2 is not sufficient for λ $\lambda^* = E[x_1 \mid x_2]$ $= E[x_1] = \lambda$ not a valid estimator of λ

$$x_{1}, x_{2} \qquad P(x_{1}=1, x_{2}=3, x_{1}+x_{2}=4)$$
Example: sufficiency

$$= P(x_{1}=1, x_{2}=3)$$

Let $X_1, \ldots, X_n \stackrel{iid}{\sim} Bernoulli(p)$.

Find a sufficient statistic for p.

$$T = \pm \Sigma_i X_i$$
 or $T = \Sigma_i X_i$ ~ Binamial (n,p)

$$=$$
 $\pm 2iXi$ $\propto 1 = 2iXi$ ~ 15 $nomial(N,P)$

$$\frac{f(\Sigma_{i} \times i \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i} \times i \mid p)} = \frac{f(X_{i}, ..., X_{n} \mid p)}{f(\Sigma_{i}$$

Factorization theorem

Let $x_1,...,x_n$ be a sample with joint probability function $f(x_1,...,x_n \mid \theta)$. A statistic $T \equiv T(X_1,...,X_n)$ is sufficient for θ if and ally if there exist functions $g(t \mid \theta)$ and $h(x_1,...,x_n)$ such that, for all possible $x_1,...,x_n$ and all possible θ , $f(x_1,...,x_n \mid \theta) = g(T(x_1,...,x_n) \mid \theta) h(x_1,...,x_n)$ soint distribution only depends an θ through the sufficient statistic

Example

Suppose
$$x_1, \dots, x_n \stackrel{\text{iid}}{\sim} \text{Bernalli}(p)$$

$$f(x_1, \dots, x_n \mid p) = P \stackrel{\text{Zi}(x_i)}{(1-p)} - \text{Zi}(x_i)$$

$$= g(\text{Zi}(x_i) \mid p) \ln(x_1, \dots, x_n)$$

$$= \frac{g(\text{Zi}(x_i) \mid p)}{p^{\text{Zi}(x_i)}(1-p)} = \frac{1}{p^{\text{Zi}(x_i)}(1-p)}$$