## Repetition week 43

### **Score statistic**

$$S(X|\theta) = \frac{\partial}{\partial \theta} \log f(X|\theta)$$

$$E\left[S\left(X\left|\theta\right)\right]=0$$

$$Var\left[S\left(\boldsymbol{X}|\theta\right)\right] = I_{X}\left(\theta\right) = -E\left[\frac{\partial}{\partial\theta}S\left(\boldsymbol{X}|\theta\right)\right] = -E\left[\frac{\partial^{2}}{\partial\theta^{2}}\log f\left(\boldsymbol{X}|\theta\right)\right]$$

Let 
$$\tau(\theta) = E[W(X)]$$

### **Cramer-Rao**

$$Var[W(X)] \ge \frac{\left(\frac{\partial}{\partial \theta}\tau(\theta)\right)^2}{I_X(\theta)}$$

### Cramer-Rao iid

$$Var[W(X)] \ge \frac{\left(\frac{\partial}{\partial \theta}\tau(\theta)\right)^{2}}{nI_{X}(\theta)}$$

## **Equality**

If and only if 
$$S(X|\theta) = a(\theta)[W(X) - \tau(\theta)]$$

# Cramer-Rao in the multiparameter case

$$\boldsymbol{\theta} = (\theta_1, \dots \theta_k)^t$$

Define the Score function 
$$S(X|\theta) = \begin{bmatrix} \frac{\partial}{\partial \theta_1} \log f(X|\theta) \\ \vdots \\ \frac{\partial}{\partial \theta_k} \log f(X|\theta) \end{bmatrix} = \nabla \log f(X|\theta)$$

Define the Fisher information  $I(\theta) = Cov[S(X|\theta)]$ 

We have as in the univariate case that  $E[S(X|\theta)] = 0$  and

$$I(\boldsymbol{\theta}) = E\left[S(\boldsymbol{X}|\boldsymbol{\theta})S(\boldsymbol{X}|\boldsymbol{\theta})^{T}\right] = -E\left[H(\boldsymbol{X}|\boldsymbol{\theta})\right]$$
 where 
$$h_{ij} = \frac{\partial}{\partial \theta_{i}} \frac{\partial}{\partial \theta_{i}} \log f(\boldsymbol{X}|\boldsymbol{\theta}).$$

If W(X) is an unbiased estimator for  $m{ heta}$  . Then  $m{I}(m{ heta})^{^{-1}}$  is taken as an approximation to Covrack W(X)rack

# Complete statistic

### Definition 6.2.21

Let  $f(t|\theta)$  be a family of pdfs/pmfs for a statistic T(X). The family is complete if

$$E_{\theta}[g(T)] = 0 \Rightarrow P_{\theta}(g(T) = 0) = 1$$
, for all  $\theta$ .

### Completeness and the exponential class

Let  $X_1, \dots, X_n$  be iid. from an exponential family i.e.

$$f(x|\boldsymbol{\theta}) = h(x)c(\boldsymbol{\theta})e^{\sum_{i=1}^{k}w(\theta_i)t_i(x)}$$

Then  $T(X) = \left(\sum_{i=1}^{n} t_1(X_i), \sum_{i=1}^{n} t_2(X_i), \dots, \sum_{i=1}^{n} t_k(X_i), \right)$  is complete as long

as the parameter space contains an open set in  $\mathbb{R}^n$ .

Minimal sufficient if  $w_i(\theta)$ , i = 1, 2, ... n are not linearly dependent

Complete if no functional relationship exists between  $w_i(\theta)$ , i = 1, 2, ... n

Then also the distribution of

$$T(\boldsymbol{X}) = \left(\sum_{i=1}^n t_1(X_i), \sum_{i=1}^n t_2(X_i), \dots, \sum_{i=1}^n t_k(X_i), \right) \text{ is within the exponential family.}$$

## **Sufficiency and Unbiasedness**

W unbiased estimator of  $\tau(\theta)$ .

T a sufficient statistic  $E[W|T] = \tau(\theta)$  and  $Var[W|T] \le Var[W]$ ,  $\forall \theta$ 

T complete  $\Rightarrow$  Eig[Wig|Tig] is the unique best unbiased estimator for