# Presentation on CSIR UGC NET (June 2015) Q. 106

Jatin Tarachandani

CS20BTECH11021

## Some Definitions

#### **Definition**

The pmf for a binomial distribution with parameters n and p is

$$Pr(X = x; n, p) = {}^{n}C_{x}p^{x}(1-p)^{n-x}$$
(1)

#### **Definition**

The pmf for a Poisson distribution with parameter  $\lambda$  is:

$$\Pr(Y = y; \lambda) = \frac{\lambda^y}{y!} e^{-\lambda}$$
 (2)

### **Unbiased Estimators**

#### **Definition**

Suppose we have an estimator T(X, Y), acting on a set of 2 RVs X, Y; which estimates a parameter  $\theta$ , then if

$$E(T(X,Y)) = \theta \tag{3}$$

the estimator is unbiased.

## Problem statement

Let X, Y, have the joint discrete distribution such that  $X|Y=y\sim$  Binomial(y, 0.5) and  $Y\sim \text{Poisson}(\lambda)$ ,  $\lambda>0$ , where  $\lambda$  is an unknown parameter. Let T=T(X,Y) be any unbiased estimator of  $\lambda$ . Then

- $Var(T) \leq Var(Y)$  for all  $\lambda$
- ②  $Var(T) \ge Var(Y)$  for all  $\lambda$
- **③**  $Var(T) ≥ \lambda$  for all  $\lambda$
- Var(T) = Var(Y) for all  $\lambda$

## Solution

We know that since Y has a Poisson distribution with parameter  $\lambda$ ,

$$Var(Y) = \lambda \tag{4}$$

Since X, Y are discrete, we define  $p_{XY}(X, Y)$  as the joint discrete distribution of X and Y. From Bayes Theorem,

$$p_{XY}(X,Y) = \Pr(X = x | Y = y) \Pr(Y = y)$$
(5)

$$= {}^{y}C_{x}\frac{1}{2^{y}}\frac{\lambda^{y}}{y!}e^{-\lambda}$$
 (6)

### Cramer Rao lower bound

#### Definition

If T(X, Y) is an unbiased estimator of a parameter  $\lambda$ , the Cramer-Rao bound states that:

$$Var\left(T\left(X,Y\right)\right) \ge -\frac{1}{E\left(\frac{\partial^{2}\ln\left(p_{XY}\left(X,Y\right)\right)\right)}{\partial\lambda^{2}}\right)}\tag{7}$$

Since  $\lambda$  is a continuous parameter, we can apply this inequality to the logarithm of the joint discrete distribution seen in (6).

#### Lemma

$$\frac{\partial^2 \ln(p_{XY}(X,Y))}{\partial \lambda^2} = -\frac{Y}{\lambda^2}$$
 (8)

Proof.

$$p_{XY}(X,Y) = {}^{Y}C_{X}\frac{1}{2^{Y}}\frac{\lambda^{Y}}{Y!}e^{-\lambda}$$
(9)

$$\frac{\partial^{2} \ln(p_{XY}(X,Y))}{\partial \lambda^{2}} = \frac{\partial^{2} \left( \frac{\ln^{Y} C_{X} - Y \ln 2^{Y}}{+ Y \ln \lambda - \ln Y! - \lambda} \right)}{\partial \lambda^{2}}$$
(10)

$$=\frac{\partial\left(\frac{r}{\lambda}-1\right)}{\partial\lambda}\tag{11}$$

$$= -\frac{Y}{\lambda^2} \tag{12}$$

which is the required result.



From using (7) on T(X, Y),

$$Var(T(X,Y)) \ge -\frac{1}{E\left(\frac{\partial^2 \ln(p_{XY}(X,Y))}{\partial \lambda^2}\right)}$$
 (13)

From (8),

$$Var(T(X,Y)) \ge -\frac{1}{E(-\frac{Y}{\lambda^2})}$$
 (14)

$$\geq \frac{\lambda^2}{E(Y)} \tag{15}$$

$$Var(T(X,Y)) \ge \lambda$$
 (16)

because the expectation value of a Poisson R.V with parameter  $\lambda$  is  $\lambda$ .

The correct options are options (2) and (3), since by (16), we see that

$$Var(T) \ge \lambda = Var(Y)$$

(from (4)). (1) and (4) do not hold for all  $\lambda$ .