

Total points: 14

1. (6pts) Using method of moments,
 a. Find the estimators for Binomial(n, p)

$$E(x) = np \quad \text{Var}(x) = np(1-p)$$

i. $\frac{\text{Var}(x)}{E(x)} = \frac{np(1-p)}{np}$

$$p = 1 - \frac{\text{Var}(x)}{E(x)}$$

$$p = 1 - \frac{S_n^2}{\bar{X}}$$

ii. $E(x) = np$
 $n = \frac{E(x)}{p}$

$$n = \frac{\bar{X}}{1 - \frac{S_n^2}{\bar{X}}} = \frac{\bar{X}^2}{\bar{X} - S_n^2}$$

1pt for p

1pt for n

- b. Find the estimators for Normal(μ, σ^2)

$$E(x) = \mu \quad \text{Var}(x) = \sigma^2$$

i. $E(x) = \mu$

$$\bar{X} = \mu$$

$$\mu = \bar{X}$$

$$\text{Var}(x) = \sigma^2$$

$$S_n^2 = \sigma^2$$

$$\sigma^2 = S_n^2$$

1pt for μ 1pt for σ^2

c. For Exponential(θ), find two methods of moments est. for θ .

$$E(x) = \theta$$

$$\bar{x} = \theta$$

$$\boxed{\theta = \bar{x}}$$

$$\text{Var}(x) = \theta^2$$

$$\sqrt{\text{Var}(x)} = \theta$$

$$\boxed{\theta = \sqrt{s_x^2}}$$

$$\text{1pt for } \theta = \bar{x}$$

$$\text{1pt for } \theta = \sqrt{s_x^2}$$

2. (4pts) An estimator of λ when $X_i \stackrel{iid}{\sim} \text{Poisson}(\lambda)$ is $\frac{\sum x_i}{n}$

a. Is this estimator unbiased?

$\hat{\lambda} = \frac{1}{n} \sum x_i$ will be unbiased iff $E(\hat{\lambda}) = \lambda$

$$E(\hat{\lambda}) = E\left(\frac{1}{n} \sum x_i\right)$$

$$= \frac{1}{n} E\left(\sum x_i\right)$$

$$= \frac{1}{n} \sum E(x_i)$$

because x_i are independent

$$= \frac{1}{n} \sum \lambda$$

$$= \frac{n}{n} \lambda$$

$$= \lambda$$

$\therefore \hat{\lambda} = \frac{1}{n} \sum x_i$ is unbiased

1pt for proving
 $E(\hat{\lambda}) = \lambda$

1pt for concluding
unbiased.

b. Does it converge to λ ? Why?

Yes.

By the Law of Large Numbers,

$\hat{\lambda} = \frac{1}{n} \sum X_i$ converges in probability to $E(X) = \lambda$
as $n \rightarrow \infty$

lpt

lpt

3. (4pts) Find the MLE of θ when X_i come from an iid exponential distribution

$$f(x) = \frac{1}{\theta} e^{-x/\theta}$$

$$f(x_1, x_2, \dots, x_n) = \prod_{i=1}^n \frac{1}{\theta} e^{-x_i/\theta}$$

$$= \frac{1}{\theta^n} e^{-\frac{1}{\theta} \sum_{i=1}^n x_i}$$

1pt setting up joint pdf

$$l(\theta | x_1, x_2, \dots, x_n) = \ln\left(\frac{1}{\theta^n} e^{-\frac{1}{\theta} \sum_{i=1}^n x_i}\right)$$

$$= -\ln(\theta^n) + \ln\left(e^{-\frac{1}{\theta} \sum_{i=1}^n x_i}\right)$$

$$= -n \ln \theta - \frac{1}{\theta} \sum_{i=1}^n x_i$$

1pt seeking the maximum of the likelihood or log likelihood function

$$\max_{\theta} l(\theta | x_i) = \theta \text{ s.t. } \frac{d}{d\theta} l(\theta | x_i) = 0 \quad \& \quad \frac{d^2}{d\theta^2} l(\theta | x_i) \leq 0$$

$$\frac{d}{d\theta} l(\theta | x_i) = \frac{\sum x_i}{\theta^2} - \frac{n}{\theta} = 0$$

$$\frac{\sum x_i}{\theta^2} = \frac{n}{\theta}$$

$$\theta = \frac{\sum x_i}{n}$$

$$\frac{d^2}{d\theta^2} l(\theta | x_i) = \frac{n}{\theta^2} - 2 \frac{\sum x_i}{\theta^3}$$

$$\frac{d^2}{d\theta^2} l\left(\frac{1}{n} \sum x_i | x_i\right) = \frac{n}{\left(\frac{1}{n} \sum x_i\right)^2} - \frac{2 \sum x_i}{\left(\frac{1}{n} \sum x_i\right)^3}$$

$$= \frac{n^3}{\left(\sum x_i\right)^2} - \frac{2n^3 \sum x_i}{\left(\sum x_i\right)^3}$$

$$= \frac{-n^3}{\left(\sum x_i\right)^2} \leq 0 \quad \forall n > 0$$

$\forall x_i$

1pt finding that $\frac{\sum x_i}{n}$ maximizes l

1pt checking that it is a maximum

$\therefore \hat{\theta} = \frac{\sum x_i}{n} = \bar{x}$ maximizes the likelihood and is the maximum likelihood estimator