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**Grading:**

30 marks- Complete submission of Problem 2,5  
70 marks- Problem 2

1. From the graph  $G(10, \frac{x}{6})$  or from  $A$  that you constructed in the worksheet:

(a) fill in the following table from the data in worksheet:

x	# Edges

- (b) Let  $E$  denote the number of edges in a realisation of  $G(10, \frac{x}{6})$ . Find the likelihood  $L(x; E)$  that  $E$  edges occur in the random Graph  $G(10, \frac{x}{6})$ .
- (c) Find  $x^*$  that maximizes  $L(x; E)$  with respect to  $x$ . You may assume  $x \in [1, 5]$ .
- (d) Substitute your value of  $E$  from Question 1, into the expression for  $x^*$ . Is the resulting  $x^*$  close to your chosen  $x$  ?

**Solution: 1**

(a) The data from worksheet:

x	# Edges
3	21

- (b)  $G(10, x/6)$  has 10 vertices ( $n = 10$ ).  
So the possible number of edges is  ${}^{10}C_2 = 45$ .  
 $E$ = Number of edges in a realisation of  $G(10, x/6)$   
i.e.  $E$  is the event of occurrence of edges among the 45 possible edges.  
Probability of success of each edge =  $x/6$   
 $\therefore E \sim \text{Binomial}(45, x/6)$   
The p.m.f of  $E$  is given by:

$$f_x(E) = \binom{45}{E} \left(\frac{x}{6}\right)^E \left(1 - \frac{x}{6}\right)^{45-E} .$$

(c) Since we are only interested in the argument that maximizes  $f_x(E)$ , we will first take log, and then maximize.

$$\begin{aligned} \log f_x(E) &= \log \left[ \binom{45}{E} \right] + E \log \frac{x}{6} + (45 - E) \log \left(1 - \frac{x}{6}\right) \\ \Rightarrow \frac{d \log f_x(E)}{dx} &= E \frac{1}{x} \cdot \frac{1}{6} + (45 - E) \frac{1}{1 - \frac{x}{6}} \left(-\frac{1}{6}\right) \stackrel{set}{=} 0 \end{aligned}$$

$$\begin{aligned} \Rightarrow E \frac{1}{\frac{x^*}{6}} &= (45 - E) \frac{1}{1 - \frac{x^*}{6}} \\ \Rightarrow \frac{1 - \frac{x^*}{6}}{\frac{x^*}{6}} &= \frac{45}{E} - 1 \\ \Rightarrow \frac{1}{\frac{x^*}{6}} &= \frac{45}{E} \\ \Rightarrow x^* &= 6 \times \frac{E}{45} \end{aligned}$$

Also,  $\frac{d^2 \log f_x(E)}{dx^2} < 0$  ; for  $x = x^*$ .

Thus,  $x^*$  is the point of maxima for  $f_x(E)$ .

(d)  $E = 21$

$$\Rightarrow x^* = 6 \times \frac{21}{45} = 2.8 \approx 3$$

Hence, for our chosen  $x (= 3)$  is very close to 2.8.

2. Example 9.2.1.

**Solution: 2**

$X_1, X_2, \dots, X_{10}$  are i.i.d Binomial(N,p)

Number of unknown parameters = 2

Empirical realisation = 8, 7, 6, 11, 8, 5, 3, 7, 6, 9

$$\begin{aligned} \mu_1(X_1, X_2, \dots, X_{10}) &= \frac{1}{10} \sum_{i=1}^{10} X_i \\ &= \frac{1}{10} (8 + 7 + 6 + 11 + 8 + 5 + 3 + 7 + 6 + 9) \\ &= 7 \end{aligned}$$

$$\begin{aligned} \mu_2(X_1, X_2, \dots, X_{10}) &= \frac{1}{10} \sum_{i=1}^{10} X_i^2 \\ &= \frac{1}{10} (8^2 + 7^2 + 6^2 + 11^2 + 8^2 + 5^2 + 3^2 + 7^2 + 6^2 + 9^2) \\ &= 53.4 \end{aligned}$$

And,  $m_1 = E(X) = Np$

$m_2 = E(X^2) = Np(1-p) + (Np)^2$

By method of moments:

$\mu_1(X_1, X_2, \dots, X_{10}) = m_1 \Rightarrow Np = 7$  —(1)

And,  $\mu_2(X_1, X_2, \dots, X_{10}) = m_2 \Rightarrow Np(1-p) + (Np)^2 = 53.4$  —(2)

Substituting (1) in (2); we get:

$$Np(1-p) + (Np)^2 = 53.4$$

$$7(1-p) + 49 = 53.4$$

$$7 - 7p = 4.4$$

$$\therefore p = 0.371$$

Putting value of  $p$  in (1); we get:

$$N = \frac{7}{0.371} = 18.87 \approx 19$$

Thus, the method of moments estimates that the distribution from which the sample came is *Binomial*(19, 0.371).

### 3. Example 9.2.2.

**Solution: 3**

$X_1, X_2, \dots, X_n$  are i.i.d Normal( $\mu, \sigma$ )

$$\mu_1(X_1, X_2, \dots, X_n) = \frac{1}{n} \sum_{i=1}^n X_i$$

$$\mu_2(X_1, X_2, \dots, X_n) = \frac{1}{n} \sum_{i=1}^n X_i^2$$

And,  $m_1 = E(X) = \mu$

$$m_2 = E(X^2) = Var(X) + (E(X))^2 = \sigma^2 + \mu^2$$

By method of moments:

$$\mu_1(X_1, X_2, \dots, X_n) = m_1 \Rightarrow \mu = \frac{1}{n} \sum_{i=1}^n X_i \quad \text{---(1)}$$

$$\text{And, } \mu_2(X_1, X_2, \dots, X_n) = m_2 \Rightarrow \sigma^2 + \mu^2 = \frac{1}{n} \sum_{i=1}^n X_i^2 \quad \text{---(2)}$$

Substituting (1) in (2); we get:

$$\begin{aligned} \sigma^2 + \mu^2 &= \frac{1}{n} \sum_{i=1}^n X_i^2 \\ \sigma^2 &= \frac{1}{n} \sum_{i=1}^n X_i^2 - \left( \frac{1}{n} \sum_{i=1}^n X_i \right)^2 \\ \sigma^2 &= \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2 \\ \sigma^2 &= \frac{n-1}{n} S^2 \quad ; \text{ where, } S^2 = \text{Sample variance} \\ \therefore \sigma &= \sqrt{\frac{n-1}{n}} S \end{aligned}$$

Thus, the method of moment estimators for  $\mu$  and  $\sigma$  is  $\bar{X}$  and  $\sqrt{\frac{n-1}{n}} S$  respectively.

### 4. Example 9.3.2.

**Solution: 4**

$X_1, X_2, \dots, X_n$  are i.i.d Normal( $p, 1$ )

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-p)^2}{2}}$$

The likelihood function is given by:

$$\begin{aligned}
L(p; X_1, \dots, X_n) &= \prod_{i=1}^n \frac{1}{\sqrt{2\pi}} e^{-\frac{(X_i - p)^2}{2}} \\
&= \frac{1}{(\sqrt{2\pi})^n} e^{-\frac{\sum_{i=1}^n (X_i - p)^2}{2}}
\end{aligned}$$

To find MLE, treating the given realisation  $X_1, X_2, \dots, X_n$  as fixed, we need to maximise  $L$  as a function of  $p$ .

This is equivalent to finding the minimum of  $g : R \rightarrow R$  given by

$$g(p) = \sum_{i=1}^n (X_i - p)^2$$

Now,

$$\begin{aligned}
g'(p) &= -2 \sum_{i=1}^n (X_i - p) \stackrel{\text{set}}{=} 0 \\
n\hat{p} &= \sum_{i=1}^n X_i \\
\therefore \hat{p} &= \bar{X}
\end{aligned}$$

Also,  $g''(p) > 0$  for  $p = \hat{p}$

Hence, the MLE of  $p$  is given by  $\hat{p} = \bar{X}$

### 5. Example 9.3.3.

**Solution: 5**

$X_1, X_2, \dots, X_n$  are i.i.d Bernoulli( $p$ )

$$f(x|p) = \begin{cases} p^x(1-p)^{1-x} & ; \text{if } x \in 0, 1 \\ 0 & ; \text{otherwise} \end{cases}$$

The likelihood function is given by

$$\begin{aligned}
L(p; X_1, \dots, X_n) &= \prod_{i=1}^n p^{X_i} (1-p)^{1-X_i} \\
&= p^{\sum_{i=1}^n X_i} (1-p)^{n - \sum_{i=1}^n X_i}
\end{aligned}$$

To find the MLE, treating the given realisation as fixed, we need to maximize  $L$  as a function of  $p$ .

The log likelihood function is:

$$\begin{aligned}
T(p; X_1, \dots, X_n) &= \ln L(p; X_1, \dots, X_n) \\
T(p; X_1, \dots, X_n) &= \begin{cases} \ln\left(\frac{p}{1-p}\right)a + n \ln(1-p) & ; \text{if } \sum_{i=1}^n X_i = a, 0 < a < n \\ n \ln(1-p) & ; \text{if } \sum_{i=1}^n X_i = 0 \\ n \ln p & ; \text{if } \sum_{i=1}^n X_i = n \end{cases}
\end{aligned}$$

**Case 1:** If  $0 < \sum_{i=1}^n X_i < n$

$$\frac{dT(p; X_1, \dots, X_n)}{dp} = \frac{1}{p(1-p)} \sum_{i=1}^n X_i - \frac{n}{1-p} \stackrel{\text{set}}{=} 0$$

$$\frac{1}{\hat{p}(1-\hat{p})} \sum_{i=1}^n X_i = \frac{n}{1-\hat{p}}$$

$$\frac{1}{\hat{p}} \sum_{i=1}^n X_i = n$$

$$\therefore \hat{p} = \frac{\sum_{i=1}^n X_i}{n}$$

**Case 2:** If  $\sum_{i=1}^n X_i = 0$

In this case,  $T$  is a decreasing function of  $p$  and maximum occurs at  $p = 0$ .

**Case 3:** If  $\sum_{i=1}^n X_i = n$

In this case,  $T$  is an increasing function of  $p$  and maximum occurs at  $p = 1$ .

Therefore, we can conclude that  $\hat{p} = \frac{\sum_{i=1}^n X_i}{n}$ .

6. Example 9.4.2.

**Solution: 6**

$X_1, X_2, \dots, X_{16}$  are i.i.d  $X$

Sample mean ;  $\bar{X} = 10.2$

Sample standard deviation ;  $S = 3.0$

In this case, the confidence level ;  $\beta = 0.95$ .

So we must find the value of  $a$  for:

$$\begin{aligned} P(|\bar{X} - \mu| < a) &= 0.95 \\ P\left(\frac{|\bar{X} - \mu|}{S/\sqrt{n}} < \frac{a}{S/\sqrt{n}}\right) &= 0.95 \\ P\left(|T| < \frac{4a}{3}\right) &= 0.95 \\ P\left(-\frac{4a}{3} < T < \frac{4a}{3}\right) &= 0.95 \quad \text{---(1)} \end{aligned}$$

Also, we know that for t-distribution:

$$P(-2.13 < T < 2.13) = 0.95 \quad \text{---(2)}$$

On comparing (1) and (2), we get:

$$\begin{aligned} \frac{4a}{3} &= 2.13 \\ \therefore a &\approx 1.60 \end{aligned}$$

Hence, 95% confidence interval for the actual mean of the distribution  $X$  is (8.6, 11.8).