

24500 HW2

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Question 1

Since $X_i \sim \mathcal{N}(\mu, 1)$ and the observations are i.i.d., the maximum likelihood estimator (MLE) for μ is the sample mean:

$$\hat{\mu} = \bar{X} = \frac{1}{n} \sum_{i=1}^n X_i.$$

For \bar{X} , $E\bar{X} = \frac{1}{n} \sum_{i=1}^n E(X_i) = \mu$, $Var(\bar{X}) = \frac{1}{n^2} \sum_{i=1}^n Var(X_i) = \frac{1}{n}$

The distribution of \bar{X} is

$$\bar{X} \sim N\left(\mu, \frac{1}{n}\right).$$

$$\sqrt{n} \frac{\bar{X} - \mu}{1} \sim N(0, 1).$$

A 95% confidence interval for μ is:

$$\left[\bar{X} - z_{0.025} \sqrt{\frac{1}{n}}, \bar{X} + z_{0.025} \sqrt{\frac{1}{n}} \right],$$

where $z_{0.025} = 1.96$ is the critical value from the standard normal distribution for a 95% confidence level.

The length L of this interval is

$$L = 2 \times \left(z_{0.025} \sqrt{\frac{1}{n}} \right) = 2 \times 1.96 \frac{1}{\sqrt{n}} = \frac{3.92}{\sqrt{n}}.$$

We want this length to be at most 0.5, so

$$\frac{3.92}{\sqrt{n}} \leq 0.5.$$

$$3.92 \leq 0.5 \sqrt{n}$$

$$\sqrt{n} \geq \frac{3.92}{0.5}$$

$$n \geq 61.47.$$

Since n must be an integer (the sample size),

$$n \geq 62.$$

The smallest integer n that satisfies the length requirement is 62.

Question 2

Starting with

$$E[(\hat{\theta} - \theta)^2],$$

we can add and subtract $E[\hat{\theta}]$ inside the parentheses, then expand:

$$(\hat{\theta} - \theta)^2 = (\hat{\theta} - E[\hat{\theta}] + E[\hat{\theta}] - \theta)^2.$$

Taking expectation on both sides and expanding the square:

$$E[(\hat{\theta} - \theta)^2] = E[(\hat{\theta} - E[\hat{\theta}])^2] + 2E[(\hat{\theta} - E[\hat{\theta}])(E[\hat{\theta}] - \theta)] + E[(E[\hat{\theta}] - \theta)^2].$$

Here for each term:

$(E[\hat{\theta}] - \theta)$ is a constant (it does not depend on the random variable $\hat{\theta}$).

So $E[(E[\hat{\theta}] - \theta)^2] = (E[\hat{\theta}] - \theta)^2$, since $(E[\hat{\theta}] - \theta)$ is a constant.

For the term $2E[(\hat{\theta} - E[\hat{\theta}])(E[\hat{\theta}] - \theta)]$

$(E[\hat{\theta}] - \theta)$ is a constant (not random), so it can be factored out the expectation:

$$2E[(\hat{\theta} - E[\hat{\theta}])(E[\hat{\theta}] - \theta)] = 2(E[\hat{\theta}] - \theta)E[\hat{\theta} - E[\hat{\theta}]].$$

By definition,

$$E[\hat{\theta} - E[\hat{\theta}]] = E[\hat{\theta}] - E[\hat{\theta}] = 0.$$

Hence the entire product is 0:

$$2(E[\hat{\theta}] - \theta)E[\hat{\theta} - E[\hat{\theta}]] = 2(E[\hat{\theta}] - \theta) \times 0 = 0.$$

$E[(\hat{\theta} - E[\hat{\theta}])^2]$ is $\text{Var}(\hat{\theta})$ by definition.

Therefore:

$$E[(\hat{\theta} - \theta)^2] = E[(\hat{\theta} - E[\hat{\theta}])^2] + 2E[(\hat{\theta} - E[\hat{\theta}])(E[\hat{\theta}] - \theta)] + E[(E[\hat{\theta}] - \theta)^2].$$

$$E[(\hat{\theta} - \theta)^2] = \text{Var}(\hat{\theta}) + 0 + (E[\hat{\theta}] - \theta)^2.$$

$$E[(\hat{\theta} - \theta)^2] = \text{Var}(\hat{\theta}) + (E[\hat{\theta}] - \theta)^2.$$

Question 3

(a)

Definition. A stochastic process $\{N(t) : t \geq 0\}$ is called a Poisson process with rate $\lambda > 0$ if it satisfies:

1. $N(0) = 0$,
2. For any $s, t \geq 0$, the increment $N(t + s) - N(s)$ is independent of the past (independent increments),
3. For any $s, t \geq 0$,

$$N(t + s) - N(s) \sim \text{Poisson}(\lambda t).$$

From the third property above (the number of events in an interval of length t is $\text{Poisson}(\lambda t)$), let X and Y denote the number of the event observed in 10 second and 20 second intervals, then:

$$X_1, \dots, X_{180} \stackrel{\text{iid}}{\sim} \text{Poisson}(10\lambda), \quad Y_1, \dots, Y_{20} \stackrel{\text{iid}}{\sim} \text{Poisson}(20\lambda).$$

This follows because each X_i counts events in a 10-second interval, and each Y_j counts events in a 20-second interval, with an underlying Poisson rate λ per second.

The full likelihood $L(\lambda)$ is:

$$L(\lambda) = \prod_{i=1}^{180} \left[e^{-10\lambda} \frac{(10\lambda)^{x_i}}{x_i!} \right] \times \prod_{j=1}^{20} \left[e^{-20\lambda} \frac{(20\lambda)^{y_j}}{y_j!} \right].$$

Taking natural logarithms:

$$\ell(\lambda) = \ln L(\lambda) = \sum_{i=1}^{180} \left[-10\lambda + X_i \ln(10\lambda) - \ln(X_i!) \right] + \sum_{j=1}^{20} \left[-20\lambda + Y_j \ln(20\lambda) - \ln(Y_j!) \right].$$

Let

$$S_X = \sum_{i=1}^{180} X_i, \quad S_Y = \sum_{j=1}^{20} Y_j.$$

Then we can rewrite $\ell(\lambda)$ as:

$$\ell(\lambda) = -10\lambda \times 180 - 20\lambda \times 20 + S_X \ln(10\lambda) + S_Y \ln(20\lambda) + (\text{terms independent of } \lambda).$$

So

$$\ell(\lambda) = -2200\lambda + S_X \ln(10\lambda) + S_Y \ln(20\lambda) + (\text{terms independent of } \lambda).$$

$$\begin{aligned} \frac{d}{d\lambda} \ell(\lambda) &= -2200 + S_X \cdot \frac{d}{d\lambda} [\ln(10\lambda)] + S_Y \cdot \frac{d}{d\lambda} [\ln(20\lambda)]. \\ \frac{d}{d\lambda} [\ln(10\lambda)] &= \frac{1}{10\lambda} \cdot 10 = \frac{1}{\lambda}, \quad \frac{d}{d\lambda} [\ln(20\lambda)] = \frac{1}{20\lambda} \cdot 20 = \frac{1}{\lambda}. \end{aligned}$$

Thus

$$\frac{d}{d\lambda} \ell(\lambda) = -2200 + \frac{S_X}{\lambda} + \frac{S_Y}{\lambda} = -2200 + \frac{S_X + S_Y}{\lambda}.$$

Setting this derivative to zero:

$$\begin{aligned} -2200 + \frac{S_X + S_Y}{\lambda} &= 0 \\ \hat{\lambda} &= \frac{S_X + S_Y}{2200}. \end{aligned}$$

Now substitute the data:

$$S_X = \sum_{i=1}^{180} X_i = 0 \times 23 + 1 \times 77 + 2 \times 34 + 3 \times 26 + 4 \times 13 + 5 \times 7 = 310.$$

$$S_Y = \sum_{i=1}^{20} Y_i = 0 \times 2 + 1 \times 4 + 2 \times 9 + 3 \times 5 = 37.$$

$$S_X = 310, \quad S_Y = 37, \quad \hat{\lambda} = \frac{310 + 37}{2200} \approx 0.1577$$

(b)

Suppose we have an i.i.d. sample $X_1, X_2, \dots, X_n \sim \text{Poisson}(\lambda)$. The pmf of each single observation X_i is

$$P(X_i = x_i) = \frac{\lambda^{x_i} e^{-\lambda}}{x_i!}.$$

the likelihood is

$$L(\lambda) = \prod_{i=1}^n \left[e^{-\lambda} \frac{\lambda^{x_i}}{x_i!} \right] = e^{-n\lambda} \frac{\lambda^{\sum_{i=1}^n x_i}}{\prod_{i=1}^n x_i!}.$$

Taking log:

$$\ell(\lambda) = -n\lambda + \left(\sum_{i=1}^n x_i \right) \ln(\lambda) - \sum_{i=1}^n \ln(x_i!).$$

Set the derivative to 0:

$$\begin{aligned} \frac{d}{d\lambda} \ell(\lambda) &= -n + \frac{1}{\lambda} \sum_{i=1}^n x_i = 0 \\ \hat{\lambda} &= \frac{1}{n} \sum_{i=1}^n x_i = \bar{X}. \end{aligned}$$

Note that the sum of all 200 counts has a Poisson distribution:

$$\sum_{i=1}^{180} X_i + \sum_{i=1}^{20} Y_i \sim \text{Poisson}(2200\lambda) \equiv \sum_{i=1}^{2200} Z_i,$$

where each $Z_i \stackrel{\text{iid}}{\sim} \text{Poisson}(\lambda)$.

Since Z_i are i.i.d. $\text{Poisson}(\lambda)$, each has mean $E[Z_i] = \lambda$ and variance $\text{Var}(Z_i) = \lambda$. Then

$$Z = \sum_{i=1}^{2200} Z_i \quad \text{has} \quad E[Z] = 2200\lambda, \quad \text{Var}(Z) = 2200\lambda.$$

By CLT, Z can be approximated by a normal distribution:

$$\begin{aligned} Z &\approx N(2200\lambda, 2200\lambda). \\ \frac{Z - 2200\lambda}{\sqrt{2200\lambda}} &\xrightarrow{d} N(0, 1). \end{aligned}$$

the MLE for Z is

$$\hat{\lambda} = \frac{1}{2200} \sum_{i=1}^{2200} Z_i = \frac{Z}{2200}.$$

Since $Z \approx N(2200\lambda, 2200\lambda)$, dividing by 2200 gives

$$\hat{\lambda} = \frac{Z}{2200} \approx N\left(\lambda, \frac{\lambda}{2200}\right).$$

Therefore,

$$\hat{\lambda} \approx N\left(\lambda, \frac{\lambda}{2200}\right).$$

Question 4

(a)

Let Z be a standard normal random variable, i.e. $Z \sim N(0, 1)$.

$$E[Z^2] = 1, \quad E[Z^4] = 3.$$

(b)

Let Z_1, Z_2, \dots, Z_n be i.i.d. $N(0, 1)$ random variables, and define

$$Y = \sum_{i=1}^n Z_i^2.$$

For mean of Y , since each Z_i^2 has expectation

$$E[Z_i^2] = 1$$

because $Z_i \sim N(0, 1)$. Therefore,

$$E[Y] = E\left[\sum_{i=1}^n Z_i^2\right] = \sum_{i=1}^n E[Z_i^2] = n \cdot 1 = n.$$

For variance of Y , since $Z_1^2, Z_2^2, \dots, Z_n^2$ are independent,

$$\text{Var}\left(\sum_{i=1}^n Z_i^2\right) = \sum_{i=1}^n \text{Var}(Z_i^2).$$

for a standard normal variable Z_i ,

$$\text{Var}(Z_i^2) = E[Z_i^4] - (E[Z_i^2])^2.$$

We know $E[Z_i^2] = 1$ and $E[Z_i^4] = 3$,

$$\text{Var}(Z_i^2) = 3 - 1^2 = 2.$$

Hence,

$$\text{Var}(Y) = \sum_{i=1}^n \text{Var}(Z_i^2) = \sum_{i=1}^n 2 = 2n.$$

Therefore,

$$E[Y] = n \quad \text{and} \quad \text{Var}(Y) = 2n.$$