

# P8104 Homework Assignment 11

Yongyan Liu (yl6107)

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## Problem 1

Let  $X_1$  and  $X_2$  be two continuous i.i.d. random variables, and let  $m$  denote the median of their common distribution.

**Part (a)** What is the probability that the larger of  $X_1$  and  $X_2$ , i.e.,  $\max(X_1, X_2) = X_{(2)}$ , will exceed the population median?

$$P(X_{(2)} > m) = 1 - P(X_{(2)} \leq m)$$

Since  $X_{(2)} = \max(X_1, X_2)$ , we have  $X_{(2)} \leq m$  if and only if both  $X_1 \leq m$  and  $X_2 \leq m$ .

Therefore:

$$P(X_{(2)} \leq m) = P(X_1 \leq m, X_2 \leq m)$$

Since  $X_1$  and  $X_2$  are independent:

$$P(X_{(2)} \leq m) = P(X_1 \leq m) \cdot P(X_2 \leq m)$$

By definition of the median for a continuous distribution:

$$P(X_i \leq m) = \frac{1}{2}$$

Therefore:

$$P(X_{(2)} \leq m) = \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{4}$$

Thus:

$$P(X_{(2)} > m) = 1 - \frac{1}{4} = \frac{3}{4}$$

**Part (b)** Generalize the result in (a) to samples of size  $n$ , i.e., for  $n$  continuous i.i.d. random variables, compute the probability of  $\max(X_1, \dots, X_n) = X_{(n)} > m$ .

$$P(X_{(n)} > m) = 1 - P(X_{(n)} \leq m)$$

The maximum is less than or equal to  $m$  if and only if all observations are less than or equal to  $m$ :

$$P(X_{(n)} \leq m) = P(X_1 \leq m, X_2 \leq m, \dots, X_n \leq m)$$

By independence:

$$P(X_{(n)} \leq m) = \prod_{i=1}^n P(X_i \leq m) = \left(\frac{1}{2}\right)^n$$

Therefore:

$$P(X_{(n)} > m) = 1 - \left(\frac{1}{2}\right)^n = 1 - \frac{1}{2^n}$$

## Problem 2

Suppose  $X_1, \dots, X_n$  are independent random variables with  $X_i \sim N(\mu_i, \sigma_i^2)$  for all  $i \in \{1, \dots, n\}$ , and let  $\{a_1, \dots, a_n\}$  and  $\{b_1, \dots, b_n\}$  be fixed constants. Use moment-generating functions to prove that

$$Z = \sum_{i=1}^n (a_i X_i + b_i) \sim N \left( \sum_{i=1}^n (a_i \mu_i + b_i), \sum_{i=1}^n a_i^2 \sigma_i^2 \right).$$

For  $X_i \sim N(\mu_i, \sigma_i^2)$ , the MGF is:

$$M_{X_i}(t) = \exp \left( \mu_i t + \frac{\sigma_i^2 t^2}{2} \right)$$

For the linear transformation  $Y_i = a_i X_i + b_i$ :

$$M_{Y_i}(t) = E[e^{t(a_i X_i + b_i)}] = e^{b_i t} \cdot E[e^{(a_i t) X_i}] = e^{b_i t} \cdot M_{X_i}(a_i t)$$

Substituting:

$$M_{Y_i}(t) = e^{b_i t} \cdot \exp \left( \mu_i (a_i t) + \frac{\sigma_i^2 (a_i t)^2}{2} \right) = \exp \left( (a_i \mu_i + b_i) t + \frac{a_i^2 \sigma_i^2 t^2}{2} \right)$$

Since  $X_1, \dots, X_n$  are independent, so are  $Y_1, \dots, Y_n$ . For independent random variables, the MGF of the sum equals the product of the MGFs:

$$\begin{aligned} M_Z(t) &= \prod_{i=1}^n M_{Y_i}(t) = \prod_{i=1}^n \exp \left( (a_i \mu_i + b_i) t + \frac{a_i^2 \sigma_i^2 t^2}{2} \right) \\ M_Z(t) &= \exp \left( \left( \sum_{i=1}^n (a_i \mu_i + b_i) \right) t + \frac{\left( \sum_{i=1}^n a_i^2 \sigma_i^2 \right) t^2}{2} \right) \end{aligned}$$

This is the MGF of a normal distribution with:

- Mean:  $\mu_Z = \sum_{i=1}^n (a_i \mu_i + b_i)$
- Variance:  $\sigma_Z^2 = \sum_{i=1}^n a_i^2 \sigma_i^2$

Since the MGF uniquely determines the distribution, we conclude:

$$Z = \sum_{i=1}^n (a_i X_i + b_i) \sim N \left( \sum_{i=1}^n (a_i \mu_i + b_i), \sum_{i=1}^n a_i^2 \sigma_i^2 \right)$$

### Problem 3

Consider a random sample  $X_1, \dots, X_n$  of size  $n$  from a Poisson distribution with mean  $\lambda$ . Let  $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$  be the sample mean and define the statistic  $Y_n = \exp(-\bar{X})$ .

**Part (a)** Find a constant  $c$  (if it exists) such that  $Y_n \xrightarrow{P} c$ .

By the Weak Law of Large Numbers (WLLN), since  $X_1, \dots, X_n$  are i.i.d. with  $E[X_i] = \lambda$ :

$$\bar{X} \xrightarrow{P} \lambda$$

The function  $g(x) = e^{-x}$  is continuous. By the Continuous Mapping Theorem, if  $\bar{X} \xrightarrow{P} \lambda$ , then:

$$Y = g(\bar{X}) = e^{-\bar{X}} \xrightarrow{P} g(\lambda) = e^{-\lambda}$$

Therefore:

$$c = e^{-\lambda}$$

**Part (b)** Find the asymptotic normal distribution for (suitably scaled and centered)  $Y_n$ , i.e., find sequences of constants  $a_n, b_n$  such that  $a_n(Y_n - b_n) \xrightarrow{d} N(0, 1)$ .

For  $\text{Poisson}(\lambda)$ , we have  $E[X_i] = \lambda$  and  $\text{Var}(X_i) = \lambda$ .

By the Central Limit Theorem:

$$\sqrt{n}(\bar{X} - \lambda) \xrightarrow{d} N(0, \lambda)$$

Let  $g(x) = e^{-x}$ . Then  $g'(x) = -e^{-x}$ , so  $g'(\lambda) = -e^{-\lambda} \neq 0$ .

By the Delta Method, if  $\sqrt{n}(\bar{X} - \lambda) \xrightarrow{d} N(0, \lambda)$ , then:

$$\sqrt{n}(g(\bar{X}) - g(\lambda)) \xrightarrow{d} N(0, \sigma^2[g'(\lambda)]^2)$$

$$\sqrt{n}(Y_n - e^{-\lambda}) \xrightarrow{d} N(0, \lambda e^{-2\lambda})$$

To get a standard normal distribution, we divide by the standard deviation  $\sqrt{\lambda e^{-2\lambda}} = \sqrt{\lambda} e^{-\lambda}$ :

$$\frac{\sqrt{n}(Y_n - e^{-\lambda})}{\sqrt{\lambda} e^{-\lambda}} \xrightarrow{d} N(0, 1)$$

This can be rewritten as:

$$\frac{\sqrt{n}}{\sqrt{\lambda} e^{-\lambda}} (Y_n - e^{-\lambda}) \xrightarrow{d} N(0, 1)$$

Therefore:

$$a_n = \frac{\sqrt{n}}{\sqrt{\lambda} e^{-\lambda}} = \frac{e^\lambda \sqrt{n}}{\sqrt{\lambda}}, \quad b_n = e^{-\lambda}$$

## Problem 4

A manufacturer of booklets packages them in boxes of 100. It is known that on average, the booklets weigh 1 ounce, with a standard deviation of 0.05 ounce. The manufacturer is interested in calculating the following probability

$$P(100 \text{ booklets weigh more than } 100.4 \text{ ounces}),$$

a number that would help detect whether too many booklets are being put in a box. Explain how you would calculate the (approximate) value of this probability. Mention any relevant theorems or assumptions needed.

**Setup:**

Let  $X_i$  denote the weight of the  $i$ -th booklet for  $i = 1, 2, \dots, 100$ .

Given:

- $E[X_i] = \mu = 1$  ounce
- $\text{SD}(X_i) = \sigma = 0.05$  ounce
- $n = 100$  booklets

Let  $S = \sum_{i=1}^{100} X_i$  be the total weight of 100 booklets and  $\bar{X} = \frac{S}{n}$  is the sample mean.

By the CLT, for large  $n$  (and  $n = 100$  is sufficiently large):

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

We want to find

$$P(S > 100.4) = P(\bar{X} > 1.004) = P\left(\sqrt{n} \frac{\bar{X} - \mu}{\sigma} > \sqrt{n} \frac{1.004 - \mu}{\sigma}\right) = P(Z > 0.8)$$

Using the standard normal table or R:

$$P(Z > 0.8) = 1 - \Phi(0.8)$$

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1 - pnorm(0.8)
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## [1] 0.2118554
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Therefore:

$$P(100 \text{ booklets weigh more than } 100.4 \text{ ounces}) \approx 0.2119$$