

Lecture 33: Nov. 30

Last time

- MGF

Today

- Course evaluations (6/38)
- Final exam format
 - Final exam will be take home
 - Open book, open note, not open internet
 - Final exam will be released on Friday (12/09/2022) right after class
 - Final exam due 23:59 pm on Friday 12/16/2022.
 - Scan and submit your exam via email with a single pdf file
 - Send your email to both your instructor and your TA.
 - Submitted exams should be human-readable to receive non-zero scores.
- MGF cont.
- Covariance and Correlation

Moment generating function (Theorem 4.2.12) Let X and Y be independent rvs with mgfs $M_X(\cdot)$ and $M_Y(\cdot)$, respectively. Then the mgf of $Z = X + Y$ is

$$M_Z(t) = M_X(t)M_Y(t)$$

Proof:

$$\begin{aligned} M_Z(t) &= E \exp(Zt) &&= E\{\exp[(X + Y)t]\} \\ &= E[\exp(Xt) \exp(Yt)] &&= E[\exp(Xt)] \cdot E[\exp(Yt)] \\ &= M_X(t)M_Y(t) \end{aligned}$$

Corollary: If X and Y are independent and $Z = X - Y$,

$$M_Z(t) = M_X(t)M_Y(-t)$$

Example (sum of two independent Poissons) Suppose $X \sim \text{Poisson}(\lambda_X)$ and $Y \sim \text{Poisson}(\lambda_Y)$ and put $Z = X + Y$. Then, $Z \sim \text{Poisson}(\lambda_X + \lambda_Y)$. *Proof:*

$$\begin{aligned} M_Z(t) &= \exp[\lambda_X(e^t - 1)] \exp[\lambda_Y(e^t - 1)] \\ &= \exp[(\lambda_X + \lambda_Y)(e^t - 1)] \end{aligned}$$

Example (sum of two independent normals) Suppose $X \sim N(\mu_x, \sigma_x^2)$ and $Y \sim N(\mu_y, \sigma_y^2)$ and X and Y are independent and $Z = X + Y$. Then

$$Z \sim N(\mu_x + \mu_y, \sigma_x^2 + \sigma_y^2)$$

Proof:

$$\begin{aligned} M_Z(t) &= \exp\left(\mu_x t + \frac{1}{2}\sigma_x^2 t^2\right) \exp\left(\mu_y t + \frac{1}{2}\sigma_y^2 t^2\right) \\ &= \exp\left[(\mu_x + \mu_y)t + \frac{1}{2}(\sigma_x^2 + \sigma_y^2)t^2\right] \end{aligned}$$

Example (sum of two independent gammas) Suppose $X \sim \Gamma(\alpha_x, \beta)$ and independently $Y \sim \Gamma(\alpha_y, \beta)$. Let $Z = X + Y$. Then $Z \sim \Gamma((\alpha_x + \alpha_y), \beta)$.

Proof:

$$\begin{aligned} M_Z(t) &= \left(\frac{1}{1 - \beta t}\right)^{\alpha_x} \left(\frac{1}{1 - \beta t}\right)^{\alpha_y} \\ &= \left(\frac{1}{1 - \beta t}\right)^{\alpha_x + \alpha_y} \end{aligned}$$

Remember that

- If $\alpha = 1$ we have an exponential with parameter β .
- If $\alpha = n/2$ and $\beta = 2$, we have a $\chi^2(n)$ (with n d.f.). The above result states that $\chi^2(n_1) + \chi^2(n_2) = \chi^2(n_1 + n_2)$.

Covariance and Correlation Let X and Y be two random variables with respective means μ_X, μ_Y and variances $\sigma_X^2 > 0$ and $\sigma_Y^2 > 0$, all assumed to exist.

- The *covariance* of X and Y is

$$Cov(X, Y) = E[(X - \mu_X)(Y - \mu_Y)] = \sigma_{XY}$$

- The *correlation* between X and Y is

$$Cor(X, Y) = \frac{Cov(X, Y)}{\sqrt{Var(X)Var(Y)}}$$

also written as

$$\rho_{XY} = \frac{\sigma_{XY}}{\sigma_X \sigma_Y} = E\left[\left(\frac{X - \mu_X}{\sigma_X}\right)\left(\frac{Y - \mu_Y}{\sigma_Y}\right)\right]$$

Properties Let c be a constant:

1. $Cov(X, X) = Var(X),$ $Cor(X, X) = 1$
2. $Cov(X, Y) = Cov(Y, X),$ $Cor(X, Y) = Cor(Y, X)$
3. $Cov(X, c) = 0,$ $Cor(X, c) = 0$
4. $Cov(X, Y) = E(XY) - E(X)E(Y)$

5. Let $X_c = X - \mu_X, Y_c = Y - \mu_Y$. Then

$$\begin{aligned} Cov(X, Y) &= Cov(X_c, Y_c) = E(X_c Y_c) \\ Cor(X, Y) &= Cor(X_c, Y_c) \end{aligned}$$

6. Let $\tilde{X} = (X - \mu_X)/\sigma_X, \tilde{Y} = (Y - \mu_Y)/\sigma_Y$. Then,

$$Cor(X, Y) = Cor(\tilde{X}, \tilde{Y}) = Cov(\tilde{X}, \tilde{Y}) = E(\tilde{X}\tilde{Y})$$

Independent vs. Uncorrelated

- X and Y are called *uncorrelated* iff

$$Cov(X, Y) = 0 \quad \text{or equivalently} \quad \rho_{XY} = 0$$

- If X and Y are independent and $Cov(X, Y)$ exists, then $Cov(X, Y) = 0$.
- If X and Y are uncorrelated, this does **not** imply that they are independent.

Example $X \sim U[-1, 1], Y = X^2$. Then $Cov(X, Y) = 0$ but X, Y are not independent.

Correlation coefficient For any random variables X and Y ,

1. $-1 \leq \rho_{XY} \leq 1$
2. $|\rho_{XY}| = 1$ if and only if $\exists a \neq 0$ and b such that

$$\Pr(Y = aX + b) = 1.$$

if $\rho_{XY} = 1$ then $a > 0$, and if $\rho_{XY} = -1$, then $a < 0$.

proof:

Let $\tilde{X} = (X - \mu_X)/\sigma_X, \tilde{Y} = (Y - \mu_Y)/\sigma_Y$. Then $Cor(X, Y) = E(\tilde{X}\tilde{Y})$,

1.
$$\begin{aligned} 0 \leq E(\tilde{X} - \tilde{Y})^2 &= 1 + 1 - 2E(\tilde{X}\tilde{Y}) \Rightarrow E(\tilde{X}\tilde{Y}) \leq 1 \\ 0 \leq E(\tilde{X} + \tilde{Y})^2 &= 1 + 1 + 2E(\tilde{X}\tilde{Y}) \Rightarrow -1 \leq E(\tilde{X}\tilde{Y}) \end{aligned}$$

2.
$$\begin{aligned} \rho_{XY} = 1 &\iff \Pr(\tilde{Y} = \tilde{X}) = 1 \Rightarrow a > 0 \\ \rho_{XY} = -1 &\iff \Pr(\tilde{Y} = -\tilde{X}) = 1 \Rightarrow a < 0 \end{aligned}$$

Random Samples

Definition The random variables X_1, \dots, X_n are called a *random sample of size n from the population $f(x)$* if X_1, \dots, X_n are mutually independent and identically distributed (iid) random variables with the same pdf or pmf $f(x)$.

If X_1, \dots, X_n are iid, then their joint pdf or pmf is

$$f(x_1, \dots, x_n) = f(x_1)f(x_2) \dots f(x_n) = \prod_{j=1}^n f(x_j)$$

Statistics Let X_1, \dots, X_n be a random sample and let $T(x_1, \dots, x_n)$ be a function defined on \mathbb{R}^n . Then the random variable $Y = T(X_1, \dots, X_n)$ is called a *statistic*. The probability distribution of Y is called the *sampling distribution* of Y .

Note: T is only a function of (x_1, \dots, x_n) , no parameters.

Examples

$$\text{sample mean} \quad \bar{X} = \frac{1}{n} \sum_{j=1}^n X_j$$

$$\text{sample variance} \quad S^2 = \frac{1}{n-1} \sum_{j=1}^n (X_j - \bar{X})^2$$

$$\text{sample standard deviation} \quad S = \sqrt{S^2}$$

$$\text{minimum} \quad X_{(1)} = \min_{1 \leq i \leq n} X_i$$

Properties Let x_1, \dots, x_n be n numbers and define

$$\bar{x} = \frac{1}{n} \sum_{j=1}^n x_j, \quad s^2 = \frac{1}{n-1} \sum_{j=1}^n (x_j - \bar{x})^2$$

Then

$$\begin{aligned} \min_a \sum_{j=1}^n (x_j - a)^2 &= \sum_{j=1}^n (x_j - \bar{x})^2 \\ (n-1)s^2 &= \sum_{j=1}^n (x_j - \bar{x})^2 = \sum_{j=1}^n x_j^2 - n\bar{x}^2 \end{aligned}$$

Residuals Lemma: Let X_1, \dots, X_n be a random sample from a population with mean μ and variance σ^2 . Define the residuals $R_i = X_i - \bar{X}$. Then

$$\begin{aligned} E(R_i) &= 0, \quad \text{Var}(R_i) = \frac{n-1}{n} \sigma^2 \\ \text{Cov}(R_i, \bar{X}) &= 0, \quad \text{Cov}(R_i, R_j) = -\sigma^2/n \text{ if } i \neq j \end{aligned}$$

Theorem Let X_1, \dots, X_n be a random sample from a population with mgf $M_X(t)$. Then the mgf of the sample mean is

$$M_{\bar{X}}(t) = [M_X(t/n)]^n$$

Convergence

Convergence in Probability A sequence of random variables X_1, \dots, X_n *converges in probability* to a random variable X , denoted

$$X_n \xrightarrow{p} X$$

if for every $\epsilon > 0$,

$$\lim_{n \rightarrow \infty} \Pr(|X_n - X| < \epsilon) = 1$$

or equivalently

$$\lim_{n \rightarrow \infty} \Pr(|X_n - X| > \epsilon) = 0$$

In other words, X_n is more and more likely to be close to X , or less and less likely to be far from X .

Example Let $X_n = X + \epsilon_n$, where $\epsilon_n \sim N(0, 1/n)$ and X is an arbitrary random variable. Then, as $n \rightarrow \infty$,

$$X_n \xrightarrow{p} X$$

Weak law of large numbers (WLLN) Let Y_1, \dots, Y_n be iid with common mean μ and variance σ^2 . Then, as $n \rightarrow \infty$,

$$\bar{Y}_n = \frac{1}{n} \sum_{j=1}^n Y_j \xrightarrow{p} \mu$$

Proof:

The proof is quite simple, being a straightforward application of Chebychev's Inequality. We have, for every $\epsilon > 0$,

$$\Pr(|\bar{Y}_n - \mu| \geq \epsilon) = \Pr(|\bar{Y}_n - \mu|^2 \geq \epsilon^2) \leq \frac{E(\bar{X} - \mu)^2}{\epsilon^2} = \frac{\text{Var}(\bar{X})}{\epsilon^2} = \frac{\sigma^2}{n\epsilon^2} \rightarrow 0 \text{ as } n \rightarrow \infty$$

Convergence in Distribution A sequence of random variables X_1, \dots, X_n *converges in distribution* to a random variable X , denoted

$$X_N \xrightarrow{d} X$$

if

$$\lim_{n \rightarrow \infty} F_{X_n}(x) = F_X(x)$$

This is also called *convergence in law* or *weak convergence*. In other words, the distribution of X_n is closer and closer to the distribution of X .

Relation between “in distribution” and “in probability” Theorem:

1. Convergence in probability implies convergence in distribution:

$$X_n \xrightarrow{p} X \Rightarrow X_n \xrightarrow{d} X$$

2. Suppose $X_n \xrightarrow{d} X$ where X has a degenerate distribution, i.e. $\Pr\{X = a\} = 1$ for some $a \in \mathbb{R}$. Then,

$$X_n \xrightarrow{d} a \Rightarrow X_n \xrightarrow{p} a$$

Convergence in Distribution via Convergence of Mgfs Theorem: Suppose the mgf $M_n(t)$ of Y_n exists for $|t| < h$, and the mgf $M(t)$ of Y exists for $|t| < h_1 < h$. Then,

$$Y_n \xrightarrow{d} Y \iff \lim_{n \rightarrow \infty} M_n(t) = M(t), \quad |t| < h_1$$

Example Let $X_\lambda \sim \text{Poisson}(\lambda)$. Then, as $\lambda \rightarrow \infty$,

$$\begin{aligned} \frac{X_\lambda - \lambda}{\lambda} &\xrightarrow{p} 0 \\ \frac{X_\lambda - \lambda}{\sqrt{\lambda}} &\xrightarrow{d} N(0, 1) \end{aligned}$$

Central Limit Theorem Let X_1, X_2, \dots, X_n be a sequence of iid random variables whose mgfs exist in a neighborhood of 0 (that is, $M_{X_i}(t)$ exists for $|t| < h$, for some positive $h > 0$). Let $EX_i = \mu$ and $Var(X_i) = \sigma^2 > 0$. (Both μ and σ^2 are finite since the mgf exists) Define $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$. Let $G_n(x)$ denote the cdf of $\sqrt{n}(\bar{X}_n - \mu)/\sigma$. Then, for any x , $-\infty < x < \infty$,

$$\lim_{n \rightarrow \infty} G_n(x) = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}} e^{-y^2/2} dy;$$

that is, $\sqrt{n}(\bar{X}_n - \mu)/\sigma$ has a limiting standard normal distribution, in other words, $\sqrt{n}(\bar{X}_n - \mu)/\sigma \xrightarrow{d} N(0, 1)$

Proof:

Define $Y_i = (X_i - \mu)/\sigma$, and let $M_Y(t)$ denote the common mgf of Y_i s, which exists for $|t| < \sigma h$ and $M_Y(t) = M_{\frac{1}{\sigma}X_i - \mu/\sigma}(t) = e^{-\frac{\mu}{\sigma}t} M_X(\frac{t}{\sigma})$. Since

$$\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} = \frac{1}{\sqrt{n}} \sum_{i=1}^n Y_i,$$

we have,

$$\begin{aligned} M_{\sqrt{n}(\bar{X}_n - \mu)/\sigma}(t) &= M_{\sum_{i=1}^n Y_i/\sqrt{n}}(t) \\ &= M_{\sum_{i=1}^n Y_i}(t/\sqrt{n}) \\ &= [M_Y(t/\sqrt{n})]^n. \end{aligned}$$

We now expand $M_Y(t/\sqrt{n})$ in a Taylor series (power series) around 0.

$$M_Y\left(\frac{t}{\sqrt{n}}\right) = \sum_{k=0}^{\infty} M_Y^{(k)}(0) \frac{(t/\sqrt{n})^k}{k!},$$

where $M_Y^{(k)}(0) = (d^k/dt^k)M_Y(t)|_{t=0}$. Since the mgfs exist for $|t| < h$, the power series expansion is valid if $t < \sqrt{n}\sigma h$.

Using the facts that $M_Y^{(0)} = 1$, $M_Y^{(1)} = 0$, and $M_Y^{(2)} = 1$ (by construction, the mean and variance of Y are 0 and 1), we have

$$M_Y\left(\frac{t}{\sqrt{n}}\right) = 1 + \frac{(t/\sqrt{n})^2}{2!} + R_Y\left(\frac{t}{\sqrt{n}}\right),$$

where R_Y is the remainder term in the Taylor expansion such that

$$\lim_{n \rightarrow \infty} \frac{R_Y(t/\sqrt{n})}{(t/\sqrt{n})^2} = 0.$$

Therefore, for any fixed t , we can write

$$\begin{aligned} \lim_{n \rightarrow \infty} \left[M_Y\left(\frac{t}{\sqrt{n}}\right) \right]^n &= \lim_{n \rightarrow \infty} \left[1 + \frac{(t/\sqrt{n})^2}{2!} + R_Y\left(\frac{t}{\sqrt{n}}\right) \right]^n \\ &= \lim_{n \rightarrow \infty} \left[1 + \frac{1}{n} \left(\frac{t^2}{2} + nR_Y\left(\frac{t}{\sqrt{n}}\right) \right) \right]^n \\ &= e^{t^2/2} \end{aligned}$$