

# Ch11 - Part I: Sums of Independent Random Variables

# 11.1 Moment-generating functions

◆ **Definition** *For a random variable  $X$ , let*

$$M_X(t) = E(e^{tX}).$$

*$M_X(t)$  is called the  
**function** of  $X$ .*

- ◆ If  $X$  is a discrete random variable with set of possible values  $A$  and probability mass function  $p(x)$ , then

$$M_X(t) = \sum_{x \in A} e^{tx} p(x)$$

- ◆ If  $X$  is a continuous random variable with probability density function  $f(x)$ , then

$$M_X(t) =$$

# Theorem 11.1

◆ *Let  $X$  be a random variable with moment-generating function  $M_X(t)$ . Then*

$$E(X^n) =$$

*where  $M_X^{(n)}(t)$  is the  $n$ th derivative of  $M_X(t)$ .*

proof :

1. Let  $X$  be continuous with p.d.f  $f$ .

$$M'_X(t) = \frac{d}{dt} \left( \int_{-\infty}^{\infty} e^{tx} f(x) dx \right) = \int_{-\infty}^{\infty} x e^{tx} f(x) dx$$

$$M''_X(t) = \frac{d}{dt} \left( \int_{-\infty}^{\infty} x e^{tx} f(x) dx \right) = \int_{-\infty}^{\infty} x^2 e^{tx} f(x) dx$$

$\vdots$

$$M_X^{(n)}(t) =$$

where we have assumed that the derivatives of these integrals are equal to the integrals of the derivatives of their integrands.

2. Letting  $t = 0$ , we get

$$M_X^{(n)}(0) = \int_{-\infty}^{\infty} x^n f(x) dx =$$

# Example 11.1

◆ Let  $X$  be a Bernoulli random variable with parameter  $p$ , that is,

$$P(X = x) = \begin{cases} 1-p & \text{if } x = 0 \\ p & \text{if } x = 1 \\ 0 & \text{otherwise} \end{cases}$$

Determine  $M_X(t)$  and  $E(X^n)$ .

*Solution:* From the definition of a moment - generating function,

$$M_X(t) = E(e^{tX}) =$$

Since  $M_X^{(n)}(t) = pe^t$  for all  $n > 0$ , we have that  $E(X^n) =$

# Example 11.2

- ◆ Let  $X$  be a binomial random variable with parameters  $(n, p)$ .
- ◆ Find the moment-generating function of  $X$ , and use it to calculate  $E(X)$  and  $\text{Var}(X)$ .

# Example 11.2

*Solution:*

1. The p.m.f of  $X$ ,  $p(x)$ , is given by

$$p(x) = \binom{n}{x} p^x q^{n-x}, \quad x = 0, 1, 2, \dots, n, \quad q = 1 - p.$$

2. Hence,  $M_X(t) = E(e^{tx}) = \sum_{x=0}^n e^{tx} \binom{n}{x} p^x q^{n-x} = \sum_{x=0}^n \binom{n}{x} (pe^t)^x q^{n-x} = (pe^t + q)^n$  (Theorem 2.5)

3. To find the mean and the variance of  $X$ , note that

$$M'_X(t) = npe^t (pe^t + q)^{n-1}$$

$$M''_X(t) =$$

Thus

$$E(X) = M'_X(0) = np$$

$$E(X^2) = M''_X(0) = np + n(n-1)p^2$$

Therefore,  $Var(X) = E(X^2) - [E(X)]^2$

=

# Example 11.3

- ◆ Let  $X$  be an exponential random variable with parameter  $\lambda$ .
- ◆ Using moment-generating functions, calculate the mean and the variance of  $X$ .

# Example 11.3

*Solution:*

1. The p.d.f of  $X$  is given by  $f(x) = \lambda e^{-\lambda x}$ ,  $x \geq 0$

2.  $M_X(t) = E(e^{tX}) =$

3. Since the integral  $\int_0^\infty e^{(t-\lambda)x} dx$  converges if  $t < \lambda$ , restricting the domain of  $M_X(t)$  to  $(-\infty, \lambda)$ , we get  $M_X(t) = \lambda / (\lambda - t)$ .

4.  $M'_X(t) = \lambda / (\lambda - t)^2$  and  $M''_X(t) = (2\lambda) / (\lambda - t)^3$

$E(X) = M'_X(0) = 1 / \lambda$

$E(X^2) = M''_X(0) = 2 / \lambda^2$

Therefore,  $\text{Var}(X) = E(X^2) - [E(X)]^2 =$

# Theorem 11.2

- ◆ *Let  $X$  and  $Y$  be two random variables with moment-generating functions  $M_X(t)$  and  $M_Y(t)$ . If  $M_X(t) = M_Y(t)$ , then  $X$  and  $Y$  have the*
- ◆ Theorem 11.2 shows that if two random variables have the same moment-generating function, then they are

## Example 11.7

- ◆ Let the moment-generating function of a random variable  $X$  be

$$M_X(t) = \frac{1}{7}e^t + \frac{3}{7}e^{3t} + \frac{2}{7}e^{5t} + \frac{1}{7}e^{7t}$$

Since the moment-generating function of a discrete random variable with p.m.f

| $i$    | 1   | 3   | 5   | 7   | Other values |
|--------|-----|-----|-----|-----|--------------|
| $p(i)$ | 1/7 | 3/7 | 2/7 | 1/7 | 0            |

is  $M_X(t)$ . By theorem 11.2, the p.m.f of  $X$  is  $p(i)$ .

## Example 11.8

◆ Let  $X$  be a random variable with moment-generating function  $M_X(t) = e^{2t^2}$ . Find  $P(0 < X < 1)$ .

◆ Solution:

- Comparing  $M_X(t) = e^{2t^2}$  with  $\exp[\mu t + (1/2)\sigma^2 t^2]$ , the moment-generating function of  $N(\mu, \sigma^2)$ , we have that by the uniqueness of the moment-generating function.

# Example 11.8

- Let  $Z=(X-0)/2$ . Then  $Z \sim N(0,1)$ , so

$$\begin{aligned} P(0 < X < 1) &= P(0 < X/2 < 1/2) = P(0 < Z < 0.5) \\ &= \end{aligned}$$

# Supplement: From Generating Function to Distribution Function

Consider a discrete random variable  $X$  for illustration. Let

$$M_X(t) = E[e^{tX}] = E[z^X]$$

*Partial fraction expansion*

◆ Type I

$$\frac{a + bz}{(1 - cz)(1 - dz)} =$$

where  $c \neq d$ .

# Supplement: From Generating Function to Distribution Function

*Partial fraction expansion*

◆ Type I

$$\frac{a + bz}{(1 - cz)(1 - dz)} =$$

where  $c \neq d$ .

◆ Type II: in which the denominator factors are not distinct.

$$\frac{a + bz + cz^2}{(1 - dz)^2(1 - ez)} =$$

where  $d \neq e$ .

# An Example

- ◆ Assume that we are given the following generating function of random variable  $X$

$$M_X(t) = \frac{4}{(2-z)(3-z)^2}.$$

- ◆ What is the probability distribution  $\{p_n\}$  of  $X$ ?

# An Example

Ans: We need to invert  $M_X(t)$ . First, we write

$$\frac{4}{(2-z)(3-z)^2} =$$

Multiplying that by the denominator on the left side gives

$$A(3-z)^2 + B(2-z)(3-z) + C(2-z) = 4.$$

Setting  $z$  at 2, 3, and 0 in succession, we find

# An Example

The partial fraction expansion of  $M_X(t)$  is then given by

$$M_X(t) =$$

We invert the previous equation to the time domain

$$p_n = 2\left(\frac{1}{2}\right)^n - \left(\frac{4}{3}\right)\left(\frac{1}{3}\right)^n - \left(\frac{4}{9}\right)\left(\frac{1}{3}\right)^n (n+1),$$

where  $n=0, 1, 2, \dots$

# 11.2 Sum of independent random variables

## ◆ Theorem 11.3

- *Let  $X_1, X_2, \dots, X_n$  be independent random variables with moment-generating functions  $M_{X_1}(t), M_{X_2}(t), \dots, M_{X_n}(t)$ .*
- *The moment-generating function of  $X_1 + X_2 + \dots + X_n$  is given by  $M_{X_1+X_2+\dots+X_n}(t) =$*

*Proof:*

Let  $W = X_1 + X_2 + \dots + X_n$ ; by definition,

$$\begin{aligned} M_W(t) &= E(e^{tW}) = E(e^{tX_1 + tX_2 + \dots + tX_n}) \\ &= E(e^{tX_1} e^{tX_2} \dots e^{tX_n}) \\ &= E(e^{tX_1}) E(e^{tX_2}) \dots E(e^{tX_n}) \\ &= \end{aligned}$$

where the next-to-last equality follows from the independence of  $X_1, X_2, \dots, X_n$ .

# Theorem 8.6 (see p.333)

◆ *Let  $X$  and  $Y$  be independent random variables. Then for all real-valued functions  $g: \mathbf{R} \rightarrow \mathbf{R}$  and  $h: \mathbf{R} \rightarrow \mathbf{R}$ ,*

$$E[g(X)h(Y)] =$$

*where, as usual, we assume that  $E[g(X)]$  and  $E[h(Y)]$  are finite.*

# Theorem 8.6

◆ Solution: Let  $A$  be the set of possible values of  $X$ , and  $B$  be the set of possible values for  $Y$ . Let  $p(x, y)$  be the joint probability mass function of  $X$  of  $Y$ . Then

$$\begin{aligned} E[g(X)h(Y)] &= \sum_{x \in A} \sum_{y \in B} g(x)h(y)p(x, y) = \sum_{x \in A} \sum_{y \in B} g(x)h(y)p_x(x)p_y(y) = \\ &= \sum_{x \in A} [g(x)p_x(x) \sum_{y \in B} h(y)p_y(y)] = \sum_{x \in A} g(x)p_x(x)E[h(Y)] \\ &= \end{aligned}$$

# Theorem 11.4

- ◆ *Let  $X_1, X_2, \dots, X_r$  be independent binomial random variables with parameters  $(n_1, p), (n_2, p), \dots, (n_r, p)$ , respectively.*
- ◆ *Then  $X_1 + X_2 + \dots + X_r$  is a binomial random variable with parameters*

# Theorem 11.4

◆ Proof: Let, as usual,  $q=1-p$ . We know that  $M_{x_i}(t)=(pe^t+q)^{n_i}$ ,  $i=1,2,3,\dots,r$

- Let  $W=X_1+X_2+\dots+X_r$ ; then, by Theorem 11.3,

$$\begin{aligned}M_W(t) &= M_{x_1}(t)M_{x_2}(t)\dots M_{x_r}(t) \\&= (pe^t + q)^{n_1}(pe^t + q)^{n_2}\dots(pe^t + q)^{n_r} \\&= \end{aligned}$$

# Theorem 11.4

◆ Since  $(pe^t + q)^{n_1 + n_2 + \dots + n_r}$  is the moment-generating function of a binomial random variable with parameters  $(n_1 + n_2 + \dots + n_r, p)$ , the uniqueness property of moment-generating functions implies that  $W = X_1 + X_2 + \dots + X_r$  is binomial with parameters

# Theorem 11.5

◆ Let  $X_1, X_2, \dots, X_n$  be independent Poisson random variables with means  $\lambda_1, \lambda_2, \dots, \lambda_n$  respectively. Then  $X_1 + X_2 + \dots + X_n$  is a Poisson random variable with mean

# Theorem 11.5

◆ Proof: Let  $Y$  be a Poisson random variable with mean  $\lambda$ . Then

$$M_Y(t) = E(e^{tY}) = \sum_{y=0}^{\infty} e^{ty} \frac{e^{-\lambda} \lambda^y}{y!} = e^{-\lambda} \sum_{y=0}^{\infty} \frac{(e^t \lambda)^y}{y!}$$

=

Let  $W = X_1 + X_2 + \dots + X_n$ ; then, by Theorem 11.3,

$$\begin{aligned} M_W(t) &= M_{X_1}(t) M_{X_2}(t) \dots M_{X_n}(t) \\ &= \exp[\lambda_1(e^t - 1)] \exp[\lambda_2(e^t - 1)] \dots \exp[\lambda_n(e^t - 1)] \end{aligned}$$

=

# Theorem 11.5

◆ Now, since  $\exp[(\lambda_1 + \lambda_2 + \dots + \lambda_n)(e^t - 1)]$  is the moment-generating function of a Poisson random variable with mean  $\lambda_1 + \lambda_2 + \dots + \lambda_n$ , the uniqueness property of moment-generating functions implies that  $X_1 + X_2 + \dots + X_n$  is Poisson with mean

# Theorem 11.6

◆ Let  $X_1 \sim N(\mu_1, \sigma_1^2), X_2 \sim N(\mu_2, \sigma_2^2), \dots, X_n \sim N(\mu_n, \sigma_n^2)$  be independent random variables. Then  $X_1 + X_2 + \dots + X_n \sim$

◆ Proof:

In Example 11.5 we showed that if  $X$  is normal with parameters  $\mu$  and  $\sigma^2$ , then  $M_X(t) = \exp[\mu t + (1/2)\sigma^2 t^2]$ .

# Theorem 11.6

◆ Let  $W = X_1 + X_2 + \dots + X_n$ ; then

$$\begin{aligned} M_W(t) &= M_{X_1}(t) M_{X_2}(t) \dots M_{X_n}(t) \\ &= \exp\left(\mu_1 t + \frac{1}{2} \sigma_1^2 t^2\right) \exp\left(\mu_2 t + \frac{1}{2} \sigma_2^2 t^2\right) \dots \exp\left(\mu_n t + \frac{1}{2} \sigma_n^2 t^2\right) \\ &= \end{aligned}$$

◆ This implies that

$$X_1 + X_2 + \dots + X_n \sim N(\mu_1 + \mu_2 + \dots + \mu_n, \sigma_1^2 + \sigma_2^2 + \dots + \sigma_n^2)$$

# Other similar theorems

- ◆ Sums of independent geometric random variables are
- ◆ Sums of independent negative binomial random variables are
- ◆ Sums of independent exponential random variables are
- ◆ Sums of independent gamma random variables are

- ◆ Specifically, we can prove, by using moment-generating functions, that
- if  $X_1, X_2, \dots, X_n$  are  $n$  independent gamma random variables with parameters  $(r_1, \lambda), (r_2, \lambda), \dots, (r_n, \lambda)$ , respectively, then  $X_1 + X_2 + \dots + X_n$  is gamma with parameters

# Example 11.10

- ◆ Office fire insurance policies by a certain company have a \$1000 deductible.
- ◆ The company has received three claims, independent of each other, for damages caused by office fire.
- ◆ If reconstruction expenses for such claims are exponentially distributed, each with mean \$45,000, what is the probability that the total payment for these claims is less than \$120,000?

1. Let  $X$  be the total reconstruction expenses for the three claims in thousands of dollars;  
 $X$  is the sum of three independent exponential random variables, each with parameter \$45. Therefore, it is a  
with parameters 3 and  $\lambda = 1/45$ .

2.

$$f(x) = \left\{ \right.$$

3. 
$$P(X < 123) = \frac{1}{182250} \int_0^{123} x^2 e^{-x/45} dx$$
$$= \frac{1}{182250} (-45x^2 - 4050x - 182250)e^{-x/45} \Big|_0^{123} = 0.5145$$