

Ch 1 - Part I: Sums of Independent R.V.s

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Moment-generating functions

domain transform

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

discrete

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

continuous

$$M_X(t) = \int_{-\infty}^{\infty} e^{tx} f(x) dx$$

Thm 11.1

$$E[X^n] = \underline{M_X^{(n)}(0)}$$

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

Proof:

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

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

⋮

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

$$M_X^{(n)}(t) = \int_{-\infty}^{\infty} x^n f(x) dx = E[X^n]$$

Ex 11-

X : Bernoulli r.v. with p

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

$M_X(t)$ and $E[X^n]$

$$M_X(t) = E[e^{tX}] = e^{t \cdot 0} \cdot (1-p) + e^{t \cdot 1} \cdot p = 1-p + pe^t$$

$$E(X) = M_X^{(1)}(t) \Big|_{t=0} = p e^t \Big|_{t=0} = p$$

Ex 11.2

$X \sim \text{Binomial}(n, p)$

$$\Rightarrow M_X(t) = E(X), \text{Var}(X)$$

$$P(X) = \binom{n}{x} p^x (1-p)^{n-x} \leftarrow \text{binomial mass}$$

$$\begin{aligned}M_X(t) &= \sum_{x=0}^n e^{tx} \binom{n}{x} p^x (1-p)^{n-x} \\&= \sum_{x=0}^n \binom{n}{x} (\underbrace{ep}_q)^x \underbrace{(1-p)}_q^{n-x} = (pe^t + q)^n\end{aligned}$$

$$M'_x(t) = \overbrace{npe^t (pe^t + q)^{n-1}} \\ M''_x(t) = npe^t (pe^t + q)^{n-1} + n(n-1)(pe^t)^2 (pe^t + q)^{n-2}$$

$$\bar{E}(x) = M'_x(0) = np$$

$$\bar{E}(x^2) = M''_x(0) = np + n(n-1)p^2$$

$$\text{Var}(x) = \bar{E}(x^2) - (\bar{E}(x))^2 = npq$$

Thm 11.2

Let X and Y be two r.u.s

with m.g.f.s $M_X(t)$ and $M_Y(t)$.

If $M_X(t) = M_Y(t)$, then X and Y have the same distribution.

m.g.f \Leftrightarrow distribution function uniqueness

Ex 11.7

$$M_X(t) = \frac{1}{4}e^t + \frac{3}{4}e^{3t} + \frac{2}{4}e^{5t} + \frac{1}{4}e^{7t}$$

another r.u. with p.m.f.

i	1	3	5	7	Other values
$p(x=i)$	$\frac{1}{7}$	$\frac{3}{7}$	$\frac{2}{7}$	$\frac{1}{7}$	0

m.g.f. $E[e^{tX}] = \sum_{\text{all } i} e^{ti} p(x=i) = e^t \cdot \frac{1}{7} + e^{3t} \cdot \frac{3}{7} + e^{5t} \cdot \frac{2}{7} + e^{7t} \cdot \frac{1}{7}$

Theorem 11.2 shows that if two r.v.s have the same m.g.f.,
then they are identically distributed.

Ex 11.8

Let X be a r.v. with m.g.f. $M_X(t) = e^{2t^2}$.

Find $P(0 < X < 1)$.

$$\text{Sol: } M_X(t) = e^{2t^2} \Rightarrow$$

$$\text{Normal m.g.f: } \exp[\mu t + \frac{1}{2}\sigma^2 t^2]$$

$$\mu \rightarrow 0, \sigma^2 \rightarrow 4$$

$$X \sim N(\mu=0, \sigma^2=4)$$

$$Z = \frac{X-0}{\sqrt{4}} \sim \text{standard normal}$$

$$P(0 < X < 1) = P\left(0 < \frac{X}{2} < \frac{1}{2}\right) = P\left(0 < Z < \frac{1}{2}\right)$$

$$= \Phi(0.5) - \Phi(0) \approx 0.6915 - 0.5 \\ = 0.1915$$

Generating function \rightarrow Distribution (mass. density) functions

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

Partial fraction expansion

Type I :

$$\frac{a+bz}{(1-dz)(1-ez)} = \frac{A}{(1-dz)} + \frac{B}{(1-ez)}$$

Type II :

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

An example

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

$$\therefore \Pr[X \geq n] \quad \underline{\hspace{2cm}}$$

$$\Rightarrow \{ p_n \}$$

 probability distribution?

$$\frac{4}{(2-z)(3-z)^2} = \frac{A}{(2-z)} + \frac{B}{(3-z)} + \frac{C}{(3-z)^2}$$

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

$$z \leftarrow 2$$

$$A \cdot (3-2)^2 = 4$$

$$A = 4$$

$$z \leftarrow 3 \\ C \cdot (2-3) = 4$$

$$C = -4$$

$$z \leftarrow 0$$

$$4 \cdot 9 + B(2)(3) + (-4) \cdot 2 = 4$$

$$B = -4$$

$$\begin{aligned}M_X(t) &= \frac{4}{(2-t)} - \frac{4}{(3-t)} - \frac{4}{(3-t)^2} \\&= \frac{2}{(1-\frac{1}{2}t)} - \frac{3}{(1-\frac{1}{3}t)} - \frac{9}{(1-\frac{1}{3}t)^2}\end{aligned}$$

$$P_n = P_r[X \geq n] = \underline{2 \cdot \left(\frac{1}{2}\right)^n - \frac{4}{3} \left(\frac{1}{3}\right)^n - \frac{4}{9} \left(\frac{1}{3}\right)^n (n+1)}$$

$$\left(P_n = \left(\frac{1}{2}\right)^n \quad n=0, 1, 2, \dots \right)$$

$$E[\bar{z}^X] = \sum_{i=0}^{\infty} \bar{z}^i p(X=i) = \sum_{i=0}^{\infty} \bar{z}^i \left(\frac{1}{2}\right)^i = \sum_{i=0}^{\infty} \left(\frac{1}{2}\bar{z}\right)^i = \frac{1}{\left(1 - \frac{1}{2}\bar{z}\right)}$$

(1)

$$\begin{aligned} \sum_{n=0}^{\infty} \frac{4}{9} \left(\frac{1}{3}\right)^n (n+1) \bar{z}^n &= \left[\sum_{n=0}^{\infty} \frac{4}{3} \left(\frac{1}{3}\bar{z}\right)^n \right]' = \left[\frac{4}{3} \frac{1}{1 - \frac{1}{3}\bar{z}} \right]' \\ &\stackrel{(2)}{=} \frac{\frac{4}{3} \cdot \frac{1}{3}}{\left(1 - \frac{1}{3}\bar{z}\right)^2} = \frac{\frac{4}{9}}{\left(1 - \frac{1}{3}\bar{z}\right)^2} \end{aligned}$$

(2)

$$\textcircled{2} \quad \frac{4}{3} \cdot \left(\frac{1}{3}8\right)^0 + \frac{4}{3} \left(\frac{1}{3}8\right)^1 + \frac{4}{3} \left(\frac{1}{3}8\right)^2$$

$$\frac{4}{3} \cdot \frac{1}{2} \cdot \left(\frac{1}{3}8\right)^0 + \frac{4}{3} \cdot 2 \cdot \left(\frac{1}{3}8\right)^1 \cdot \frac{1}{3} + \dots$$

$$\textcircled{1} \quad \frac{4}{9} \cdot \left(\frac{1}{3}8\right)^0 \cdot 1 + \frac{4}{9} \left(\frac{1}{3}8\right)^1 \cdot 2$$

11.2 Sum of independent r.v.s

Thm 11.3

$$x_1, x_2, \dots, x_n$$

$\downarrow \quad \downarrow \quad \downarrow$

independent

$$M_{X_1}(t) \quad M_{X_2}(t) \quad M_{X_n}(t)$$

$X_1 + X_2 + \dots + X_n$

$$M_{X_1 + X_2 + \dots + X_n}(t) = M_{X_1}(t) M_{X_2}(t) \cdots M_{X_n}(t)$$

Proof: $W = X_1 + X_2 + \dots + X_n$

$$\begin{aligned} M_W(t) &= E[e^{tW}] = E[e^{t(X_1 + X_2 + \dots + X_n)}] \\ &= E[e^{tX_1} e^{tX_2} \cdots e^{tX_n}] \\ &= E[e^{tX_1}] E[e^{tX_2}] \cdots E[e^{tX_n}] \quad \leftarrow \\ &= M_{X_1}(t) M_{X_2}(t) \cdots M_{X_n}(t) \end{aligned}$$

Theorem 8.6

Let X and Y be independent r.v.s

$$E[g(x)h(y)] = E[g(x)]E[h(y)]$$

So:

$$E[g(x)h(y)] = \underbrace{\sum_{x \in A} \sum_{y \in B} g(x)h(y) p(x,y)}_{\text{independent}}$$

$$= P_X(x)P_Y(y)$$

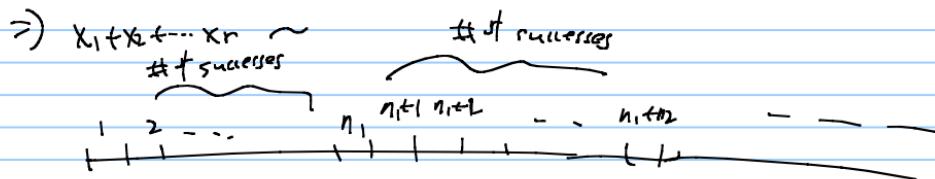
$$= \sum_{x \in A} \sum_{y \in B} g(x)h(y) P_X(x) P_Y(y)$$

$$= \underbrace{\sum_{x \in A} g(x) p_x(x)}_{\text{E}[h(Y)]}$$

$$= \text{E}[g(X)] \text{E}[h(Y)]$$

Thm 1.1.4

X_1, X_2, \dots, X_r independent binomial r.v.s with $(n_1, p), (n_2, p), \dots, (n_r, p)$



Binomial $(n_1 + n_2 + \dots + n_r, p)$

Proof:

$$M_{X_i}(t) = (pe^t + q)^{n_i}$$

$$W = X_1 + X_2 + \dots + X_r$$

$$M_W(t) = M_{X_1}(t) M_{X_2}(t) M_{X_3}(t) \dots M_{X_r}(t)$$

$$= (pe^t + q)^{n_1} (pe^t + q)^{n_2} \dots (pe^t + q)^{n_r}$$

$$= (pe^t + q)^{n_1 + n_2 + \dots + n_r}$$

By uniqueness property

$$W \sim \text{binomial}(n_1 + n_2 + \dots + n_r, p)$$

Thm 11.5 x_1, x_2, \dots, x_n independent Poisson $\lambda_1, \lambda_2, \dots, \lambda_n$

$$W = x_1 + \dots + x_n \sim \text{Poisson}(\lambda_1 + \lambda_2 + \dots + \lambda_n)$$

Ans:

$$M_Y(t) = E[e^{tY}] = \sum_{y=0}^{\infty} e^{ty} \cdot \frac{\bar{\lambda}^y}{y!} = \underbrace{e^{-\lambda} \sum_{y=0}^{\infty} \frac{(e^t \lambda)^y}{y!}}_{e^{\lambda t}} = e^{-\lambda} \cdot e^{\lambda t}$$
$$e^{\lambda t} = \exp[\lambda(e^t - 1)]$$

$$\text{Let } W = x_1 + \dots + x_n$$

$$M_W(t) = M_{x_1}(t) M_{x_2}(t) \cdots M_{x_n}(t) = \exp[\lambda_1(e^t - 1)] \exp[\lambda_2(e^t - 1)] \cdots \exp[\lambda_n(e^t - 1)]$$
$$= \exp[(\lambda_1 + \lambda_2 + \dots + \lambda_n)(e^t - 1)]$$

By uniqueness property

$$\Rightarrow W \sim \text{Poisson} \left(\underbrace{\lambda_1 + \lambda_2 + \dots + \lambda_n}_{\text{mean}} \right)$$

Theorem 11.6

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

independent r.v.s

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

Proof:

$$M_X(t) = \exp [\mu t + \frac{1}{2} \sigma^2 t^2]$$

$$W = X_1 + \dots + X_n$$

$$M_W(t) = M_{X_1}(t) M_{X_2}(t) \dots M_{X_n}(t)$$

$$= \exp\left[\mu_1 t + \frac{1}{2} \sigma_1^2 t^2\right] \exp\left[\mu_2 t + \frac{1}{2} \sigma_2^2 t^2\right] \dots \exp\left[\mu_n t + \frac{1}{2} \sigma_n^2 t^2\right]$$

$$= \exp\left[(\mu_1 + \mu_2 + \dots + \mu_n)t + \frac{1}{2}(\sigma_1^2 + \sigma_2^2 + \dots + \sigma_n^2)t^2\right]$$

Other similar theorems

- Sums of independent geometric r.v.s are Negative binomial
- Sums of negative binomial are Negative binomial
independent

- Sums of independent exponential r.v.s are gamma
- Sums of independent gamma r.v.s are gamma

If $X_1, X_2 \dots X_n$ independent gamma

$$\downarrow \quad \downarrow \quad \downarrow$$

$$(r_1, \lambda) \quad (r_2, \lambda) \quad (r_n, \lambda)$$

$$X_1 + \dots + X_n \sim \text{gamma}(r_1 + \dots + r_n, \lambda)$$

Ex 11.10

- Office fire insurance policies have a \$1000 deductible ↴
- received three claims, independent of each other
- reconstruction expenses for such claims are

exponentially distributed with mean ₦ 45,000.

\Rightarrow Pwh. that the total payment for these claims is ₦ 120,000?

Ans: Let X be the total expenses

$$X \sim \text{gamma}(\nu=3, \lambda = \frac{1}{45})$$

$$f(x) = \begin{cases} \frac{1}{45^3} e^{\frac{-x}{45}} \frac{(\frac{x}{45})^2}{2} & = \frac{1}{182250} x^2 e^{\frac{-x}{45}} & x \geq 0 \\ 0 & & \text{otherwise} \end{cases}$$

$$P(X < 123) = \frac{1}{182250} \int_0^{123} x^2 e^{\frac{-x}{45}} dx = \frac{1}{182250} \left(-45x^2 e^{\frac{-x}{45}} - 450x e^{\frac{-x}{45}} - 18225 e^{\frac{-x}{45}} \right) \Big|_0^{123}$$

= 5(45)