

MATH 201 (SUMMER 2023, SESH A2)

LECTURE 16: 06 /13/23

ANURAG SAHAY

OFF HRS: BY APPT (VIA ZOOM)

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LECTURES:

9:00 AM - 11:15 AM (ET)

M, T, W, R

{ Zoom ID:
979-4693-6650

COURSE

WEB PAGE

<https://people.math.rochester.edu/grads/asahay/summer2023/math201/index.html>

ALL PHOTOS TAKEN
FROM TEXTBOOK

ANNOUNCEMENTS

(1) OFFICE HOURS : W : 11:15 AM - 12:15 PM (OR BY APPT.)

(2) UPCOMING DEADLINES : (i) HW 7 - TODAY , (iii) HW 8 - THURS
DEADLINES : (ii) WW 8 - WED (iv) WW 9 - SAT
NEXT WEEK'S DEADLINES ARE ALSO UP! [2HW, 1WW]

(3) GRADING POLICY : EXTRA CREDIT - HW 10
CAN INCREASE UP TO 5% OF MAX.

(4) CLASS ON T, JUNE 20th TO BE FLIPPED.

(5) PLEASE KEEP VIDEOS ON, IF POSSIBLE !

§ 7.1 SUMS OF INDEPENDENT R.V.s

(CONT'D.)

RECALL :

①

X, Y DISCRETE
& INDEPENDENT

$\Rightarrow X+Y$ DISCRETE,
 $P_{X+Y} = P_X * P_Y$

$$\therefore P_{X+Y}(n) = \sum_{k+l=n} P_X(k) P_Y(l) = \sum_k P_X(k) P_Y(n-k) = \sum_l P_X(n-l) P_Y(l)$$

②

X, Y CONT. & IND.

$\Rightarrow X+Y$ CONTINUOUS, $f_{X+Y} = f_X * f_Y$

$$\therefore f_{X+Y}(z) = \int_{-\infty}^{\infty} f_X(x) f_Y(z-x) dx = \int_{-\infty}^{\infty} f_X(z-y) f_Y(y) dy$$

RECALL :

$$X \sim \text{Pois}(\lambda)$$

$$Y \sim \text{Pois}(\mu)$$

X, Y IND.

$$\Rightarrow X + Y \sim \text{Pois}(\lambda + \mu)$$

Example 7.4. (Convolution of binomials with the same success probability) Let $X \sim \text{Bin}(m_1, p)$ and $Y \sim \text{Bin}(m_2, p)$ be independent. Find the distribution of $X + Y$.

$$P(X = k) = \binom{m_1}{k} p^k (1-p)^{m_1 - k}$$

FACT :

$$\sum_{k+l} \binom{m_1}{k} \binom{m_2}{l} = \binom{m_1 + m_2}{n}$$

$$P(Y = l) = \binom{m_2}{l} p^l (1-p)^{m_2 - l}$$

$$\begin{aligned}
 P(X+Y = n) &= \sum_{k+l=n} P(X=k) P(Y=l) = \sum_{k+l=n} \binom{m_1}{k} \binom{m_2}{l} p^{k+l} (1-p)^{m_1+m_2-k-l} \\
 &= \left[\sum_{k+l=n} \binom{m_1}{k} \binom{m_2}{l} \right] p^n (1-p)^{m_1+m_2-n}
 \end{aligned}$$

$$P(X+Y=n) = \binom{m_1+m_2}{n} p^n (1-p)^{m_1+m_2-n}$$

$\Rightarrow X+Y \sim \text{Bin}(m_1+m_2, p)$

$X :$



m_1

$Y :$



m_2

$m_1 + m_2$
IND.
BERNOULLI
TRIALS.

$$\Rightarrow X+Y \sim \text{Bin}(m_1+m_2, p) \quad [w/ no calc.]$$

\therefore SUMS OF ARE $\text{Bin}(-, p)$ AND # OF TRIALS ADDED.

Example 7.5. (Convolution of geometric random variables) Let X and Y be independent geometric random variables with the same success parameter $p < 1$. Find the distribution of $X + Y$.

$$X, Y \sim \text{Geom}(p)$$

$$P(X = k) = P(Y = k) = (1-p)^{k-1} \cdot p \quad (k \in \{1, 2, 3, \dots\})$$

$$P(X+Y=n) = \sum_k P(X=k) P(Y=n-k)$$

$k \geq 1, n-k \geq 1 \Rightarrow 1 \leq k \leq n-1$

$$P(X+Y=n) = \sum_{k=1}^{n-1} \left[(1-p)^{k-1} \cdot p \right] \cdot \left[(1-p)^{n-k-1} \cdot p \right]$$

$$P(X+Y=n) = \sum_{k=1}^{n-1} \left[(1-p)^{\boxed{k-1}} \cdot p \right] \cdot \left[(1-p)^{\boxed{n-k-1}} \cdot p \right]$$

$$= \sum_{k=1}^{n-1} (1-p)^{n-2} \cdot p^2 = (n-1) (1-p)^{n-2} p^2$$

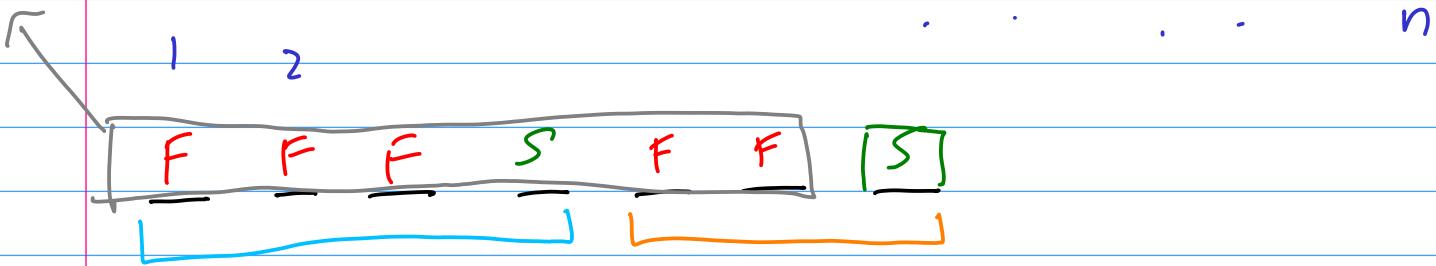
$$P_{X+Y}(n) = P(X+Y=n) = (n-1) (1-p)^{n-2} \cdot p^2$$

F F F S F F S
 X Y

$N =$ # OF CONSECUTIVE, IND.
 BERNOULLI TRIALS, UNTIL
 WE SEE 2 SUCCESSES.

$$N = X + Y, \quad X, Y \sim \text{Geom}(p)$$

NEED TO OF COUNT FIRST POS.
SUCCESS.



$$P(N=n) = (n-1) p^2 (1-p)^{n-2}$$

AGREES w/
CONVOLUTION!

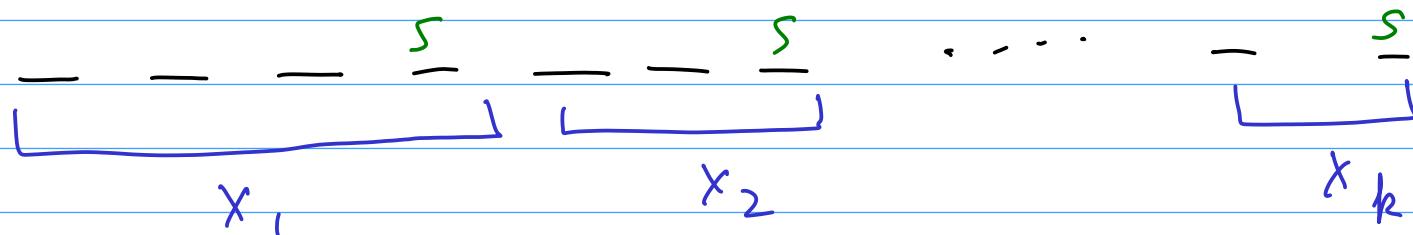
$$X = X_1 + X_2 + \dots + X_k$$

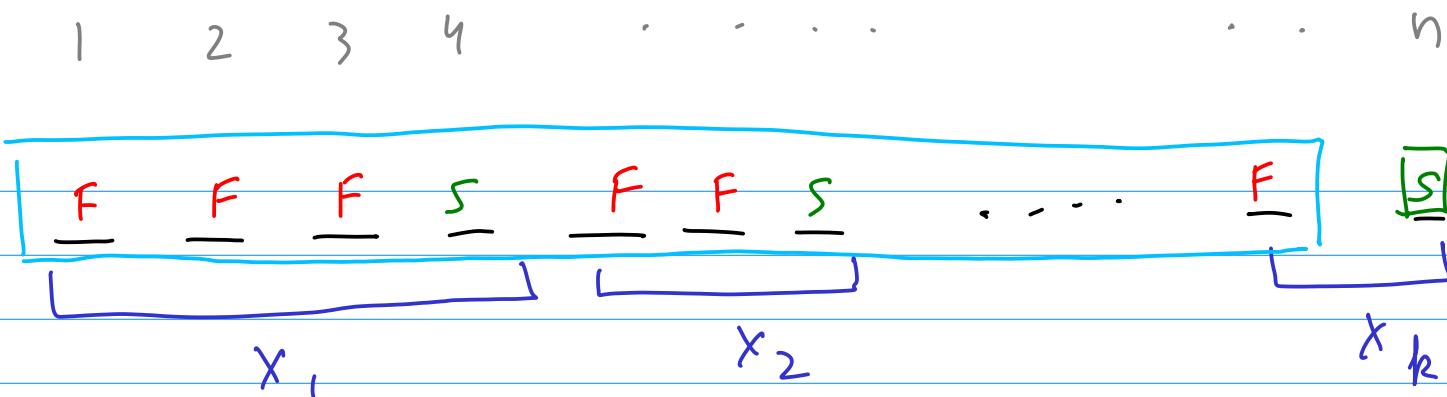
$X_j \sim \text{Geom}(p)$, i.i.d.

k CONVOLUTIONS !!!

SAME IDEA?

REINTERPRET X AS THE WAITING FLIPS
(i.e. # OF BERNoulli TRIALS) UNTIL WE SEE
 k SUCCESSES.





NEED TO
FIX POSITION
OF OTHER
k - 1 SUCCESS

$$P(X = n) = \binom{n-1}{k-1} p^k (1-p)^{n-k}$$

$$\therefore P_{X_1 + X_2 + \dots + X_k}(n) = \binom{n-1}{k-1} p^k (1-p)^{n-k}$$

$$n \in \{k, k+1, k+2, \dots\}$$

Definition 7.6. Let k be a positive integer and $0 < p < 1$. A random variable X has the **negative binomial distribution** with parameters (k, p) if the set of possible values of X is the set of integers $\{k, k+1, k+2, \dots\}$ and the probability mass function is

$$P(X = n) = \binom{n-1}{k-1} p^k (1-p)^{n-k} \quad \text{for } n \geq k.$$

Abbreviate this by $X \sim \text{Negbin}(k, p)$.

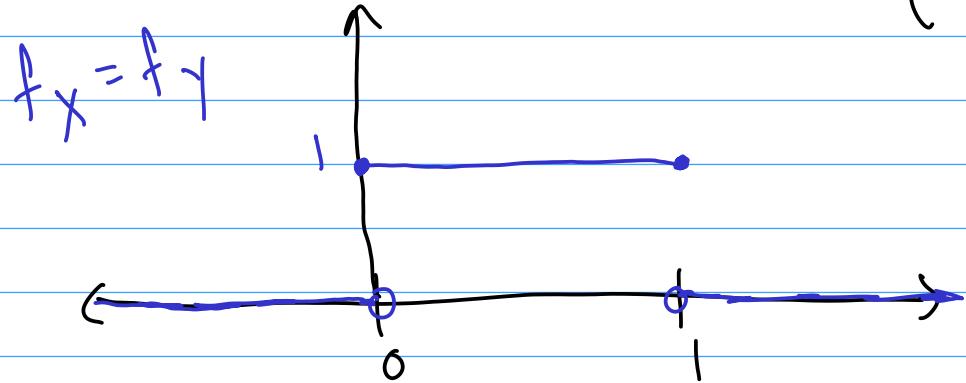
Note that the $\text{Negbin}(1, p)$ distribution is the same as the $\text{Geom}(p)$ distribution.

Negbin(k, p) \simeq [k Geom(p)]
INDEPENDENT.

Example 7.13. (Convolution of uniform random variables) Suppose that X and Y are independent and distributed as $\text{Unif}[0, 1]$. Find the distribution of $X + Y$.

$$X, Y \sim \text{Unif} [0, 1]$$

$$f_X(t) = f_Y(t) = \begin{cases} 1 & \text{IF } t \in [0, 1] \\ 0 & \text{o.w.} \end{cases}$$



$$f_{X+Y}(z) = \int_{-\infty}^{\infty} f_X(x) f_Y(z-x) dx$$

$x \in [0, 1]$

$z - x \in [0, 1]$

$$0 \leq x \leq 1$$

$$0 \leq z - x \leq 1$$

$\Rightarrow \max(0, z-1) \leq x \leq \min(1, z)$

CASES :

① $z > 2 \Rightarrow z-1 > 1 \Rightarrow x > 1$ ($\# x \leq 1$)

\Rightarrow NO x SATISFYING BOTH INEQ - $f_{x+y}(z) = 0$

② $z < 0 \Rightarrow x < 0$ ($\# x > 0$)

\Rightarrow (by) $f_{x+y}(z) = 0$

$$\max(0, z-1) \leq x \leq \min(1, z)$$

(3) $0 \leq z \leq 1 : z-1 \leq 0 \Rightarrow \max(0, z-1) = 0$

$$\& \min(1, z) = z$$

INEQ. : $0 \leq x \leq z$

$$f_{X+Y}(z) = \int_{-\infty}^{\infty} f_X(x) f_Y(z-x) dx = \int_0^z dx = z$$

($0 \leq z \leq 1$)

$$\max(0, z-1) \leq x \leq \min(1, z)$$

(3) $1 \leq z \leq 2$: $z-1 \geq 0 \Rightarrow \max(0, z-1) = z-1$

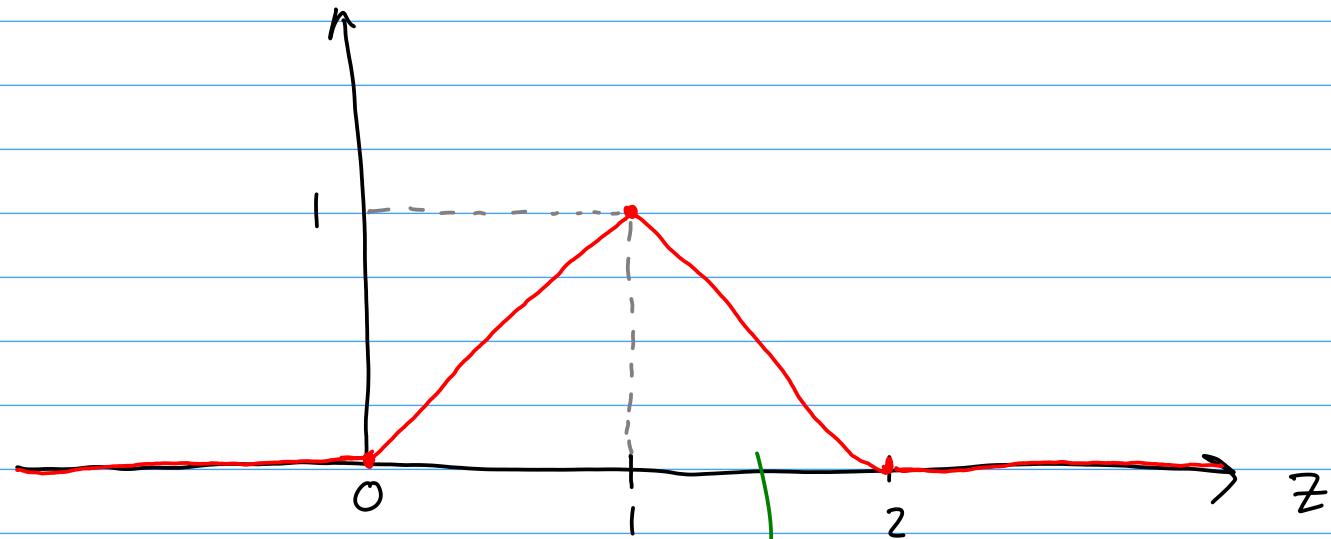
$$\min(1, z) = 1$$

INEQ. : $z-1 \leq x \leq 1$

$$f_{X+Y}(z) = \int_{-\infty}^{\infty} f_X(x) f_Y(z-x) dx = \int_{z-1}^1 dx = 2-z$$

($1 \leq z \leq 2$)

f_{x+y}



AREA = $\frac{1}{2} \cdot (2) \cdot (1) = 1$

Fact 7.9. Assume X_1, X_2, \dots, X_n are independent random variables with $X_i \sim \mathcal{N}(\mu_i, \sigma_i^2)$, $a_i \neq 0$, and $b \in \mathbb{R}$. Let $X = a_1X_1 + \dots + a_nX_n + b$. Then $\underline{X \sim \mathcal{N}(\mu, \sigma^2)}$ where

$$\mu = a_1\mu_1 + \dots + a_n\mu_n + b \quad \text{and} \quad \sigma^2 = a_1^2\sigma_1^2 + \dots + a_n^2\sigma_n^2.$$

SUMS OF INDEPENDENT
NORMALS

ARE NORMAL, WITH
MEAN & VARIANCE
PARAMS ADDED.

SIMPLEST CASE

$$X \sim \mathcal{N}(\mu_1, \sigma_1^2), \quad Y \sim \mathcal{N}(\mu_2, \sigma_2^2) \quad (\text{IND.})$$

$$X + Y \sim \mathcal{N}(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2) \Rightarrow$$

$$\mu = \mu_1 + \mu_2, \quad \sigma^2 = \sigma_1^2 + \sigma_2^2$$

$$N(\mu_1, \sigma_1^2) + N(\mu_2, \sigma_2^2) + \cdots + N(\mu_k, \sigma_k^2)$$

|| (ΣΗΔ.)

$$N(\mu_1 + \mu_2 + \cdots + \mu_k, \sigma_1^2 + \sigma_2^2 + \cdots + \sigma_k^2)$$

Example 7.10. Let $X \sim \mathcal{N}(1, 3)$ and $Y \sim \mathcal{N}(0, 4)$ be independent and let $W = \frac{1}{2}X - Y + 6$. Identify the distribution of W .

$$W = \underbrace{\frac{1}{2}X}_{\sim \mathcal{N}\left(1, \frac{3}{4}\right)} - \underbrace{Y}_{\sim \mathcal{N}(0, 4)} + \underbrace{6}_{\sim \mathcal{N}(6, 0)}$$

$$\Rightarrow W \sim \mathcal{N}\left(\frac{1}{2} + 0 + 6, \frac{3}{4} + 4\right) = \mathcal{N}\left(\frac{13}{2}, \frac{19}{4}\right)$$

Example 7.12. (Convolution of exponential random variables) Suppose that X and Y are independent $\text{Exp}(\lambda)$ random variables. Find the density of $X + Y$.

$$X \sim \text{Exp}(\lambda) , Y \sim \text{Exp}(\mu)$$

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x} & x > 0 \\ 0 & \text{o.w.} \end{cases}$$

$$f_Y(y) = \begin{cases} \mu e^{-\mu y} & y > 0 \\ 0 & \text{o.w.} \end{cases}$$

$$f_{x+y}(z) = (f_x * f_y)(z)$$

$$= \int_{-\infty}^{\infty} f_x(x) f_y(z-x) dx$$

$x \geq 0$
 $z - x \geq 0$

$\Rightarrow 0 \leq x \leq z$ (FOR INTEGRAND TO NOT VANISH)

$$f_{x+y}(z) = 0 \quad \text{IF } z < 0$$

ASSUME $z \geq 0$,

$$f_{X+Y}(z) = \int_{-\infty}^{\infty} f_X(x) f_Y(z-x) dx$$

$$= \int_0^z (\lambda e^{-\lambda x}) (\mu e^{-\mu(z-x)}) dx$$

$$= \lambda \mu e^{-\mu z} \int_0^z e^{(\mu - \lambda)x} dx$$

$$\int_0^z e^{(\mu-\lambda)x} dx$$

(I)

$$\lambda = \mu$$

$$\int_0^z e^{0x} dx = \int_0^z dx = z$$

(II)

$$\lambda \neq \mu$$

$$\int_0^z e^{(\mu-\lambda)x} dx = \frac{1}{\mu-\lambda} e^{(\mu-\lambda)x} \Big|_{x=0}^{x=z} = \frac{e^{(\mu-\lambda)z} - 1}{\mu-\lambda}$$

$$f_{X+Y}(z) = \lambda^\mu e^{-\mu z} \int_0^z e^{(\mu-\lambda)x} dx$$

\therefore If $\mu = \lambda$,

$$f_{X+Y}(z) = \lambda^2 z e^{-\lambda z} \quad (z > 0)$$

If $\mu \neq \lambda$,

$$f_{X+Y}(z) = \frac{\lambda^\mu}{\mu - \lambda} \left(e^{-\lambda z} - e^{-\mu z} \right)$$

IF $\mu = \lambda$,

$$f_{\lambda+\gamma}(z) = \begin{cases} \lambda^2 z e^{-\lambda z} & , z > 0 \\ 0 & , 0 \leq z \end{cases}$$

Gamma $(2, \lambda)$

IF $\mu \neq \lambda$

$$f_{\lambda+\gamma}(z) = \begin{cases} \frac{\lambda^\mu}{\mu - \lambda} \left(e^{-\lambda z} - e^{-\mu z} \right) & , z > 0 \\ 0 & , 0 \leq z \end{cases}$$

v. IMP.

X

Y

X + Y

(ASSUMING IND.)

① $X \sim \text{Pois}(\lambda)$

$$Y \sim \text{Pois}(\mu)$$

$$X + Y \sim \text{Pois}(\lambda + \mu)$$

② $X \sim N(\mu_1, \sigma_1^2)$

$$Y \sim N(\mu_2, \sigma_2^2)$$

$$X + Y \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$

IMP.

③ $X \sim \text{Geom}(p)$

$$Y \sim \text{Geom}(p)$$

$$X + Y \sim \text{NegBin}(2, p)$$

NOT IMP.

④

$$X \sim \text{Exp}(\lambda)$$

$$Y \sim \text{Exp}(\lambda)$$

$$X + Y \sim \text{Gamma}(2, \lambda)$$

BREAK

7 ILL 10:25

§ 5.1 MOMENT GENERATING FUNCTION

$M_X(t)$

Definition 5.1. The moment generating function of a random variable X is defined by $M(t) = E(e^{tX})$. It is a function of the real variable t .

e.g. DISCRETE $\rightarrow M(t) = \underset{\substack{J \\ t \in \mathbb{R}}}{\mathbb{E}}(e^{tX}) = \sum_k e^{tk} p_X(k)$

CONT. $\rightarrow M(t) = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx$

INTUITION: FOURIER / LAPLACE TRANSFORM

Example 5.2. Let X be a discrete random variable with probability mass function

$$P(X = -1) = \frac{1}{3}, \quad P(X = 4) = \frac{1}{6}, \quad \text{and} \quad P(X = 9) = \frac{1}{2}.$$

Find the moment generating function of X .

$$X \in \{-1, 4, 9\}$$

$$M(t) = \mathbb{E}(e^{tX}) = e^{-t} P(X = -1) + e^{4t} P(X = 4) + e^{9t} P(X = 9)$$

$$M(t) = \frac{e^{-t}}{3} + \frac{e^{4t}}{6} + \frac{e^{9t}}{2}$$

Example 5.4. (Moment generating function of the Poisson distribution) Let $X \sim \text{Poisson}(\lambda)$. The calculation is an application of formula (3.24) with the Poisson probability mass function:

$$P(X = k) = e^{-\lambda} \frac{\lambda^k}{k!} \quad (k \in \{0, 1, 2, 3, \dots\})$$

$$\begin{aligned} M(t) &= E(e^{tX}) = \sum_{k=0}^{\infty} \left(e^{tk} \right) \left[e^{-\lambda} \frac{\lambda^k}{k!} \right] \\ &= e^{-\lambda} \underbrace{\left[\sum_{k=0}^{\infty} \frac{(e^t \lambda)^k}{k!} \right]}_{\exp(e^t \lambda)} = e^{-\lambda} \cdot e^{(e^t \lambda)} \\ &= \boxed{e^{\lambda(e^t - 1)}} \end{aligned}$$

Example 5.5. (Moment generating function of the normal distribution) Let $Z \sim \mathcal{N}(0, 1)$. ~~Now the computation uses formula (3.25). To evaluate the integral we~~

$$M(t) = E(e^{tX}) = \int_{-\infty}^{\infty} (e^{tx}) \cdot \left(\frac{e^{-x^2/2}}{\sqrt{2\pi}} \right) dx$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{tx - x^2/2} dx$$

COMPLETE
THE SQUARE

$$x^2 - 2tx = \underbrace{x^2 - 2tx + t^2 - t^2}_{(x-t)^2} = (x-t)^2 - t^2$$

$$-\frac{x^2}{2} + fx = -\frac{1}{2} \left[x^2 - 2fx \right]$$

$$= -\frac{1}{2} \left[(x-f)^2 - f^2 \right]$$

$$M(f) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}[(x-f)^2 - f^2]} dx$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}(x-f)^2} \cdot e^{f^2/2} dx$$



$$M(t) = e^{t^2/2} \cdot \left[\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}(x-t)^2} dx \right]$$

= 1 \quad \left(\int_{-\infty}^{\infty} P_N(x) dx \right)

$N \sim \mathcal{N}(t, 1)$

ALTERNATIVELY,

$$u = x - t \Rightarrow \begin{cases} x = \infty, u = \infty \\ x = -\infty, u = -\infty \end{cases}, \quad dx = du$$

$$\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{u^2}{2}} du = \underline{\Phi}(\infty) = 1$$

$$\therefore M(t) = e^{t^2/2} \quad \left(\text{for } \mathcal{N}(0,1) \right)$$

Example 5.6. (Moment generating function of the exponential distribution) Let $X \sim \text{Exp}(\lambda)$. Then

$$M(t) = \mathbb{E}(e^{tX}) = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx$$

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x} & x > 0 \\ 0 & \text{o.w.} \end{cases}$$

$$M(t) = \int_0^{\infty} e^{tx} \lambda e^{-\lambda x} dx$$

$$M(t) = \int_0^\infty e^{tx} \lambda e^{-\lambda x} dx$$

CAREFUL : (\approx IMPROPER)

$$\int_0^N e^{tx} \lambda e^{-\lambda x} dx = \lambda \int_0^N e^{(t-\lambda)x} dx$$

CASE (I) : $f = \lambda$

$$M(\lambda) = \lim_{N \rightarrow \infty} \left[\lambda \int_0^N e^{(\lambda - \lambda)x} dx \right] = \lim_{N \rightarrow \infty} \lambda \int_0^N dx = \lim_{N \rightarrow \infty} (\lambda N) = \infty$$

CASE II : $t > \lambda$

$$M(t) = \lim_{N \rightarrow \infty} \left[\lambda \int_0^t e^{(t-\lambda)x} dx \right] = \lim_{N \rightarrow \infty} \left[\lambda \frac{e^{(t-\lambda)x}}{t-\lambda} \Big|_{x=0}^{x=N} \right]$$

$$= \lim_{N \rightarrow \infty} \left[\frac{\lambda}{t-\lambda} \left(e^{(t-\lambda)N} - 1 \right) \right] = \infty$$

$t - \lambda > 0$, $e^{(+ve)N} \rightarrow \infty$

CASE III : $t < \lambda$

$$M(t) = \lim_{N \rightarrow \infty} \left[\frac{\lambda}{t-\lambda} \left(e^{(t-\lambda)N} - 1 \right) \right]$$

$\curvearrowleft t - \lambda < 0$, $e^{(-ve)N} \rightarrow 0$

$$\therefore M(t) = \left[\frac{\lambda}{t-\lambda} (0 - 1) \right] = \frac{\lambda}{\lambda - t}$$

$$X \sim \text{Exp}(\lambda)$$

$$M_X(t) = \begin{cases} \frac{\lambda}{\lambda - t} & t < \lambda \\ \infty & t \geq \lambda \end{cases}$$

IMP: $M_x(t)$ IS NOT ALWAYS FINITE!

??

MOMENT GENERATING FUNCTION

RECALL : k^{th} MOMENT

$$\mathbb{E}(X^k)$$

REASON : IF $M_X(t)$ IS WELL-BEHAVED, THEN

$$M'(t) = \frac{d}{dt} [\mathbb{E}(e^{tX})] = \mathbb{E}\left[\frac{d}{dt}(e^{tX})\right] = \mathbb{E}[X e^{tX}]$$

TRUE IN
IMP. CASES.

$$\therefore M'(0) = \mathbb{E}[X \cdot e^{0 \cdot X}] = \mathbb{E}[X] = \text{MEAN} \quad / \quad 1^{\text{st}} \text{ MOMENT.}$$

MORE GENERALLY,

$$M^{(k)}(t) = \frac{d^k}{dt^k} \mathbb{E}[e^{tX}] \stackrel{?}{=} \mathbb{E}\left[\frac{d^k}{dt^k} e^{tX}\right] = \mathbb{E}[X^k e^{tX}]$$

$$\therefore M^{(k)}(0) = \mathbb{E}[X^k e^{0 \cdot X}] = \mathbb{E}[X^k] \rightarrow k\text{th moment.}$$

$M(t)$



$$M^{(k)}(0) = \mathbb{E}[X^k]$$

"MOMENT GEN. FUNCTION"

Fact 5.7. When the moment generating function $M(t)$ of a random variable X is finite in an interval around the origin, the moments of X are given by

$$E(X^n) = M^{(n)}(0).$$

NOTE : THIS ONLY WORKS IF $(\exists \epsilon > 0)$

$$M(t) < \infty \quad \text{FOR } -\epsilon < t < \epsilon$$

[IN OTHER WORDS ; $M(t) < \infty$ IN AN INTERVAL AROUND $t = 0$.]

Example 5.8. (Moments of the Bernoulli distribution)

$$P(X=1) = p, \quad P(X=0) = 1-p$$

$$M(t) = E(e^{tX}) = P(X=0) \cdot e^{t \cdot 0} + P(X=1) \cdot e^{t \cdot 1}$$

$$\therefore M(t) = (1-p) + pe^t$$

$$\therefore M^{(k)}(t) = pe^t \quad (\text{IF } k \geq 1)$$

$$\therefore E[X^k] = M^{(k)}(0) = pe^0 = p$$

6to4: $E[X^k] = P(X=0) \cdot 0^k + P(X=1) \cdot 1^k = p$

ANSWERS
MATCH.

Example 5.9. (Moments of the exponential distribution) Let $X \sim \text{Exp}(\lambda)$. From Example 5.6 its m.g.f. is

$$M(t) = \begin{cases} \frac{\lambda}{\lambda - t}, & \text{if } t < \lambda \\ \infty, & \text{if } t \geq \lambda. \end{cases}$$

$\lambda > 0$

FINITE, IT

$(-\infty, \lambda)$,

$\therefore A(\sigma)$ IN
 $(-\epsilon, \epsilon)$ FOR $t <$

$$M'(t) = \frac{d}{dt} \left[\frac{\lambda}{\lambda - t} \right] = \frac{\lambda}{(\lambda - t)^2}$$

$$M''(t) = \frac{d}{dt} \left[\frac{\lambda}{(\lambda - t)^2} \right] = \frac{2\lambda}{(\lambda - t)^3}$$

$$M^{(3)}(t) = \frac{d}{dt} \left[\frac{2\lambda}{(\lambda-t)^3} \right]$$

$$= \frac{(1 \cdot 2 \cdot 3) \lambda}{(\lambda-t)^4} = \frac{6\lambda}{(\lambda-t)^4}$$

⋮

$$M^{(k)}(t) = \frac{k! \lambda}{(\lambda-t)^{k+1}} \Rightarrow M^{(k)}(0) = \frac{k! \cdot \lambda}{\lambda^{k+1}} = \frac{k!}{\lambda^k}$$

$$X \sim \text{Exp}(\lambda)$$

$$\Rightarrow \mathbb{E}[X^k] = \frac{k!}{\lambda^k}$$

$$\boxed{k=1}$$

$$\mathbb{E}[X] = \frac{1}{\lambda}$$

$$\boxed{k=2}$$

$$\mathbb{E}[X^2] = \frac{2}{\lambda^2}$$

$$\text{Var}(X) = \frac{1}{\lambda^2}$$

$$\begin{aligned}\mathbb{E}[X^2] &= \text{Var}(X) + (\mathbb{E}[X])^2 \\ &= \frac{1}{\lambda^2} + \frac{1}{\lambda^2} = \frac{2}{\lambda^2}\end{aligned}$$

RECALL : (TAYLOR EXPANSION)

FOR "NICE" f ,

$$f(t) = \sum_{n=0}^{\infty} \frac{f^{(n)}(0)}{n!} t^n$$

\therefore IF $M_x(t)$ IS "NICE",

$$M_x(t) = \sum_{n=0}^{\infty} \frac{M^{(n)}(0)}{n!} t^n = \sum_{n=0}^{\infty} \frac{\mathbb{E}[X^n]}{n!} t^n$$


Example 5.10. (Moments of the standard normal) Let $Z \sim \mathcal{N}(0, 1)$. From Example 5.5 we have $M_Z(t) = e^{t^2/2}$. Instead of differentiating this repeatedly, we can find the derivatives directly from the Taylor expansion.

$$M(t) = e^{t^2/2} = \sum_{k=0}^{\infty} \frac{(t^2/2)^k}{k!}$$

Taylor for
 e^x

$$= \sum_{k=0}^{\infty} \frac{t^{2k}}{2^k \cdot k!} = \sum_{n=0}^{\infty} \left[\begin{array}{l} \text{IF } n \text{ ODD} \\ 2^{n/2} \cdot \binom{n}{2}! \end{array} \right] t^n = \sum_{n=0}^{\infty} \left[\begin{array}{l} \text{IF } n \text{ EVEN} \\ \boxed{E[x^n]} \end{array} \right] \frac{t^n}{n!}$$

$$\therefore \mathbb{E}[x^n] = \begin{cases} 0 & \text{IF } n \text{ IS ODD} \\ \frac{n!}{2^{n/2} \cdot (n/2)!} = \frac{(2k)!}{2^k \cdot k!} & \begin{array}{l} n = 2k \text{ IS EVEN} \\ \text{MOMENTS} \\ \text{OF STANDARD NORMAL.} \end{array} \end{cases}$$

$$\frac{\mathbb{E}[x^n]}{n!} = \frac{1}{2^{n/2} \cdot (n/2)!}$$

NOTE ① :

$n = 2k + 1$ IS ODD

ODD FUNCTION

$$E[X^{2k+1}] = \int_{-\infty}^{\infty} x^{2k+1} \phi(x) dx = 0$$

p.d.f. of $\mathcal{N}(0,1)$

NOTE ② :

$$n!! = \begin{cases} n(n-2)(n-4)\dots 2 & \text{IF } n \text{ IS EVEN} \\ n(n-2)(n-4)\dots 1 & \text{IF } n \text{ IS ODD} \end{cases}$$

$$E[x^n] = \begin{cases} 0 & n \text{ IS ODD} \\ (n-1)!! & n \text{ IS EVEN} \end{cases}$$

$E[x^n]$ =

MOMENTS

OF
STANDARD