

warmup

Show that the MGF of  $X \sim \text{Pois}(\mu)$  is

$$M_X(t) = e^{\mu(e^t - 1)}$$
 for all  $t$ .

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

$$\text{and } P(X=k) = \frac{e^{-\mu} \mu^k}{k!}$$

$$\begin{aligned} M_X(t) &= E(e^{tX}) = \sum_{k=0}^{\infty} e^{tk} P(X=k) = \sum_{k=0}^{\infty} e^{tk} \frac{e^{-\mu} \mu^k}{k!} \\ &= e^{-\mu} \sum_{k=0}^{\infty} \frac{(e^t \mu)^k}{k!} = e^{-\mu} \sum_{k=0}^{\infty} \frac{(e^{\mu})^k}{k!} \end{aligned}$$

Recall from Calculus

$$e^a = \sum_{k=0}^{\infty} \frac{a^k}{k!} \quad \text{Taylor for all } a \in \mathbb{R}$$

$$\begin{aligned} &= e^{-\mu} e^{t\mu} \\ &= \boxed{e^{\mu(e^t - 1)}} \text{ for all } t \end{aligned}$$

Note

$$E(X) = \left. \frac{d}{dt} M_X(t) \right|_{t=0} = e^{\mu(e^t - 1)} \cdot \mu e^t \Big|_{t=0} = \boxed{\mu}$$

Announcement: Q3 next Thursday  
covers Sec 4.1, 4.2, 4.4, 4.5, MGF

## Last time

### MGF

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

Then If a MGF exists in an interval

around zero,  $M^{(x)}(t)|_{t=0} = E(X^x)$

### Today

① Key properties of MGF

② Recognizing a distribution from the variable part of its density

## (1) Key Properties of MGF

(a) If an MGF exists in an interval containing zero,  $M^{(k)}(t)|_{t=0} = E(X^k)$

last time

(b) If  $X$  and  $Y$  are independent RVs,

$$M_{X+Y}(t) = M_X(t)M_Y(t).$$

Proved in MGF HW.

(c) If  $M_X(t) = M_Y(t)$  for all  $t$  in an

interval around 0 then  $F_X(z) = F_Y(z)$

(i.e.  $X$  and  $Y$  have the same distribution).

Skip proof — we can invert a MGF to get  
 $E(e^{tX})$  the CDF.

$$\text{e.g. if } M_X(t) = \frac{1}{2}e^{1t} + \frac{1}{3}e^{2t} + \frac{1}{6}e^{3t},$$

$e^{xt}$  tells us the value of  $X$  and

the associated coefficients tell us the probability

(i.e.  $X=1, 2, 3 \rightsquigarrow \text{prob } \frac{1}{2}, \frac{1}{3}, \frac{1}{6}.$ )

so MGF  $\Rightarrow$  distribution of  $X$  when  $X$  has finite # values,

Property (a) is useful to find  $E(X), \text{Var}(X)$ ,

Properties (b) and (c) allow us to prove

for example that sum of independent Poisson is Poisson.

$$\stackrel{\text{ex}}{=} \left. \begin{array}{l} X_1 \sim \text{Pois}(\lambda_1) \\ X_2 \sim \text{Pois}(\lambda_2) \end{array} \right\} \text{independent.}$$

Show that  $X_1 + X_2 \sim \text{Pois}(\lambda_1 + \lambda_2)$ .

$$M_{X_1}(t) = e^{\lambda_1(e^t - 1)} \quad \text{for all } t$$

$$M_{X_2}(t) = e^{\lambda_2(e^t - 1)} \quad \text{for all } t$$

$$M_{X_1+X_2}(t) = M_{X_1}(t)M_{X_2}(t) = \boxed{e^{(\lambda_1+\lambda_2)(e^t - 1)}} \quad \text{for all } t$$

$$\Rightarrow X_1 + X_2 \sim \text{Pois}(\lambda_1 + \lambda_2) \quad \text{for all } t.$$

$\cong$  Let  $X$  be a RV and  $a$  a constant.

Show that  $M_{aX}(t) = M_X(at) \leftarrow E(e^{Xat})$

hint  $M_{aX}(t) = E(e^{aXt})$

$$= E(e^{Xat})$$

$$= M_X(at)$$

For  $X \sim \text{Gamma}(r, \lambda)$

recall  $M_X(t) = \left(\frac{\lambda}{\lambda-t}\right)^r$  for  $t < \lambda$

ex Let  $X \sim \text{Exp}(\lambda)$  and  $a > 0$ .

Show that  $Y = aX$  is also exponential,  
and specify the new parameter.

Note  $M_X(s) = \left(\frac{\lambda}{\lambda-s}\right)^r$  for  $s < \lambda$

$$Y = aX$$

$$M_{aX}(t) = M_X(at) = \left(\frac{\lambda}{\lambda-at}\right)^r = \left(\frac{\lambda/a}{\lambda/a - t}\right)^r \text{ for } t < \frac{\lambda}{a}$$

$$\Rightarrow Y \sim \text{Exp}\left(\frac{\lambda}{a}\right)$$

for

$$\begin{matrix} r \\ " \\ " \end{matrix} \quad \lambda$$

(3 pts) Let  $X_i$  follow the Gamma ( $1/100, 2/100$ ) distribution for  $i = 1, 2, \dots, 100$ , independently of each other. We are interested in finding the distribution of the sample average,  $Y = \frac{1}{100} \sum_{i=1}^{100} X_i$ . Using properties of MGFs, identify the distribution of  $Y$ .

Recall that for  $X \sim \text{Gamma}(r, \lambda)$ ,  $M_X(t) = (\frac{\lambda}{\lambda-t})^r$ ,  $t < \lambda$ .

let  $S = \sum_{i=1}^{100} X_i$ :

$$M_S(t) = M_{X_1}(t) \cdots M_{X_{100}}(t) = \left( \left( \frac{.02}{.02-t} \right)^{.01} \right)^{100} = \left( \frac{.02}{.02-t} \right)^1$$

$$M_Y(t) = M_{\frac{1}{100}S}(t) = M_S(.01t) = \frac{.02}{.02 - .01t} = \frac{2}{2-t}$$

By the uniqueness of MGF,  $Y \sim \text{Exp}(2)$

(2)

Recognizing a distribution from the variable part of its density.

A density can be written as

$$f(t) = C h(t)$$

↑ Variable part.  
constant

$$1 = \int_{-\infty}^{\infty} f(t) dt = C \int_{-\infty}^{\infty} h(t) dt \Rightarrow C = \frac{1}{\int_{-\infty}^{\infty} h(t) dt}$$

So you can figure out the density from its variable part.

List of densities. Please circle their variable parts:

ex  $T \sim \text{Gamma}(r, \lambda)$   $f(t) = \frac{1}{\Gamma(r)} \lambda^r t^{r-1} e^{-\lambda t}, t > 0$

$T \sim \text{Normal}(\mu, \sigma^2)$   $f(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}(\frac{t-\mu}{\sigma})^2}$

$T \sim \text{Unif}(a, b)$   $f(t) = \frac{1}{b-a} \mathbf{1}_{(t \in (a, b))}$

$$T_r \sim \text{Gamma}(r, \lambda), \quad r, \lambda > 0 \quad f(t) = \begin{cases} \frac{1}{\Gamma(r)} \lambda^r t^{r-1} e^{-\lambda t} & t > 0 \\ 0 & \text{else} \end{cases}$$

$$T \sim \text{Exp}(\lambda), \quad \lambda > 0 \quad f(t) = \begin{cases} \lambda e^{-\lambda t} & t > 0 \\ 0 & \text{else} \end{cases}$$

Variable part

ex Name the distributions with the following variable part ex Gamma ( $r=4, \lambda=3$ )

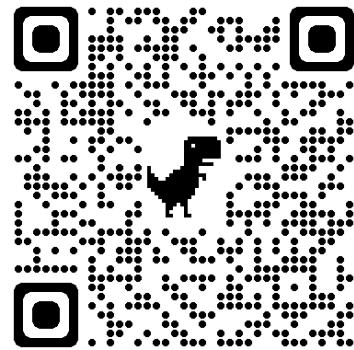
a)  $h(t) = t^3 e^{-\frac{1}{2}t}$  Gamma ( $4, \frac{1}{2}$ )

b)  $h(t) = e^{-\frac{1}{2}t^2}$  Normal ( $0, 1$ )

c)  $h(t) = e^{-3t}$  Exp (3)

d)  $h(t) = t^{\frac{1}{2}} e^{-t}$  Gamma ( $\frac{1}{2}, 1$ )

e)  $h(t) = 1_{(t \in (0,1))}$  Uniform ( $0, 1$ )



Let  $X$  be the standard normal RV. The distribution of  $Y = X^2$  is:

- a Gamma( $\frac{1}{2}, \frac{1}{2}$ )
- b Gamma( $\frac{3}{2}, \frac{1}{2}$ )
- c Normal(0,1)
- d none of the above

$$\begin{aligned} g(x) &= x^2 \\ g'(x) &= 2x \quad -x^2 \\ f(x) &= \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \end{aligned}$$

$$f(y) = \left. \frac{f(x)}{|g'(x)|} \right|_{x=\pm\sqrt{y}}$$

$$= \frac{1}{\sqrt{\pi}} \frac{e^{-y/2}}{2\sqrt{y}} + \frac{1}{\sqrt{\pi}} \frac{e^{-y/2}}{2\sqrt{y}} = \frac{1}{\sqrt{2\pi y}} e^{-y/2}$$

variable part  
of Gamma( $\frac{1}{2}, \frac{1}{2}$ )

$$f_Y(y) = \sum_{\{x | g(x)=y\}} \frac{f_X(x)}{|g'(x)|} \Big|_{x=g^{-1}(y)}$$

evaluated at  
 $x=g^{-1}(y)$