

Week 7

$$y = ax + b$$

$$; y = x_1 + x_2 + \dots + x_n$$

$$X, P(X \in B), F(x) = P(X \leq x), m(t) = E(e^{tX})$$

$$f(x) = F'(x) = -\bar{F}'(x)$$

$$F(x) = \int_{-\infty}^x f(t) dt \leftarrow \text{cta}$$

standard exponential

$$f(x) = e^{-x}, x > 0$$
$$= 0, \text{ otherwise}$$

$$m(t) = \frac{1}{1-t}, t < 1$$

$$m^{(k)}(0) = E(X^k)$$

For the exponential

$$m^{(1)}(t) = \frac{1}{(1-t)^2}, t < 1$$

$$m^{(2)}(t) = \frac{2}{(1-t)^3}, t < 1$$

$$t = 0 \rightarrow E(X) = 1 + E(X^2) = 2 + \text{Var}(X) = 1$$

Proposition If X_1, \dots, X_n are independent

then $m_{X_1 + \dots + X_n}(t) = m_{X_1}(t) \dots m_{X_n}(t)$

Proof:

$$\begin{aligned} m_{X_1 + \dots + X_n}(t) &= E\left[e^{t(X_1 + \dots + X_n)}\right] \\ &= E\left(e^{tX_1} \dots e^{tX_n}\right) \\ &= E(e^{tX_1}) \dots E(e^{tX_n}) \\ &= m_{X_1}(t) \dots m_{X_n}(t) \end{aligned}$$

eg Let X_1, \dots, X_n be iid exponential(1)

Look at

$$Y = X_1 + \dots + X_n$$

$$m_Y(t) = [m_{X_1}(t)]^n = \frac{1}{(1-t)^n}, \quad t < 1$$

$$= \int_{-\infty}^{\infty} e^{ty} f_Y(y) dy$$

Can't solve it at this point. Could guess.

Back to $Y = aX + b$

Lemma (i) $E(Y) = a E(X) + b$

(ii) $\text{Var}(Y) = a^2 \text{Var}(X)$

Suppose Y has mean μ + standard deviation $\sigma > 0$. Let

$$Z = \frac{Y - \mu}{\sigma} \quad \left(\begin{array}{l} \text{standardizing} \\ \text{a rv} \end{array} \right)$$

$$E(Z) = \frac{1}{\sigma} E(Y - \mu) = \frac{1}{\sigma} [E(Y) - \mu] = 0$$

$$\text{Var}(Z) = \frac{1}{\sigma^2} \text{Var}(Y - \mu) = \frac{\text{Var}(Y)}{\sigma^2} = 1$$

Proposition Let X_1, \dots, X_n be independent.

Then

$$\text{Var}(X_1 + \dots + X_n) = \text{Var}(X_1) + \dots + \text{Var}(X_n)$$

Proof Let $\mu_i = E(X_i)$. Then

$$\text{Var}(X_1 + \dots + X_n) = \text{Var}[X_1 + \dots + X_n - (\mu_1 + \dots + \mu_n)]$$

$$= \text{Var}[\underbrace{(X_1 - \mu_1)}_{\text{mean}=0} + \dots + \underbrace{(X_n - \mu_n)}_{\text{mean}=0}]$$

$$= E\left[\left((X_1 - \mu_1) + \dots + (X_n - \mu_n)\right)^2\right]$$

$$= E\left[(X_1 - \mu_1)^2 + \dots + (X_n - \mu_n)^2 + (X_1 - \mu_1)(X_2 - \mu_1) + (X_1 - \mu_1)(X_3 - \mu_1) + \dots\right]$$

$$= \text{Var}(X_1) + \dots + \text{Var}(X_n) + 0$$

m

Note - $Y = aX + b$

$$m_Y(t) = E(e^{tY}) = E(e^{atX + bt})$$
$$= e^{bt} E(e^{atX}) = e^{bt} m_X(at)$$

$$- m^{(k)}(0) = E(X^k)$$

$$\Rightarrow m(t) = \underbrace{m(0)}_1 + \underbrace{m^{(1)}(0)}_{E(X)} t + m^{(2)}(0) \frac{t^2}{2} + (\),$$

where $\frac{(\)}{t^2} \rightarrow 0$ as $t \rightarrow 0$. $\downarrow \frac{2}{E(X^2)}$

$(\)$ is $o(t^2)$

Let X_1, \dots, X_n be i.i.d with mean μ , variance σ^2 + mgf $m_X(t)$.

$$X_1 + \dots + X_n$$

Aside

Suppose you know the pdf of X , say $f(x)$ & $Y = aX + b$. Then we can

easily obtain the pdf of Y . Look at

$$\begin{aligned} F_Y(y) &= P(Y \leq y) \\ &= P(aX + b \leq y) = P(aX \leq y - b) \\ &= P\left(X \leq \frac{y - b}{a}\right) \end{aligned}$$

$$= F_X\left(\frac{y-b}{a}\right)$$

$$f_Y(y) = \frac{d}{dy} F_Y(y) = \frac{d}{dy} F_X\left(\frac{y-b}{a}\right)$$

$$= \frac{1}{a} f_X\left(\frac{y-b}{a}\right)$$

$$\left(\text{if } a < 0 \text{ then } f_Y(y) = \frac{1}{|a|} f_X\left(\frac{y-b}{a}\right) \right)$$



$$\text{Let } \bar{X} = \frac{X_1 + \dots + X_n}{n} \quad \left(\begin{array}{l} \approx n \text{ for} \\ \text{large } n \\ \text{Law of Large} \\ \text{Numbers} \end{array} \right)$$

$$E(\bar{X}) = \frac{1}{n} E(X_1 + \dots + X_n) = \mu$$

$$\text{Var}(\bar{X}) = \frac{1}{n^2} \text{Var}(X_1 + \dots + X_n) = \frac{n\sigma^2}{n^2} = \frac{\sigma^2}{n}$$

$$\frac{\bar{X} - \mu \leftarrow E(\bar{X})}{\underbrace{\sigma / \sqrt{n}}_{SD(\bar{X})}}$$

$$= \frac{\sqrt{n}}{\sigma} \left(\frac{1}{n} \sum_{i=1}^n X_i - \frac{1}{n} \sum_{i=1}^n \mu \right)$$

$$= \frac{1}{\sqrt{n}} \sum_{i=1}^n \left(\frac{X_i - \mu}{\sigma} \right) \leftarrow Z_i$$

Note $E(Z_i) = 0$, $\text{Var}(Z_i) = 1$. Set

$$m_Z(t) = E(e^{t' Z_i}).$$

The mgf of $\frac{1}{\sqrt{n}} (Z_1 + \dots + Z_n)$

$$= \text{mgf of } \frac{Z_1}{\sqrt{n}} + \dots + \frac{Z_n}{\sqrt{n}}$$

$$= \left(\text{mgf of } \frac{Z_1}{\sqrt{n}} \right)^n = \left[m_Z\left(\frac{t}{\sqrt{n}}\right) \right]^n$$

$$\approx \left(1 + \frac{1 \left(\frac{t}{\sqrt{m}} \right)^2}{2} \right)^m$$

$$= \left(1 + \frac{t^2}{2m} \right)^m \rightarrow e^{t^2/2}$$

We now have 2 new mgf's
 sum of n iid exponential(1)'s $\left(\frac{1}{1-t} \right)^n, t < 1$

$$e^{t^2/2}$$

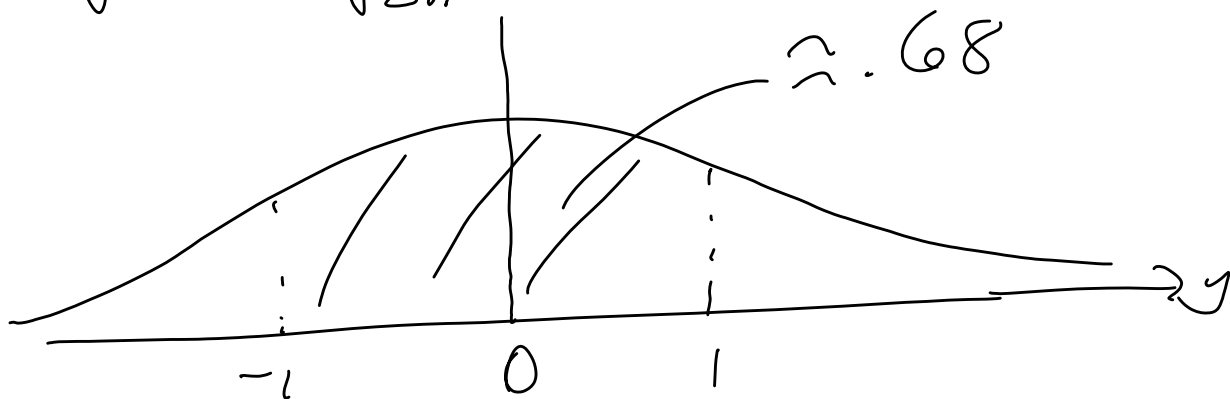
So we want

$$(1) \int_{-\infty}^{\infty} f(y) e^{ty} dy = \left(\frac{1}{1-t} \right)^n, t < 1$$

$$(2) \int_{-\infty}^{\infty} f(y) e^{ty} dy = e^{t^2/2}$$

Ex (2)

$$f(y) = \frac{1}{\sqrt{2\pi}} e^{-y^2/2}, \quad -\infty < y < \infty$$

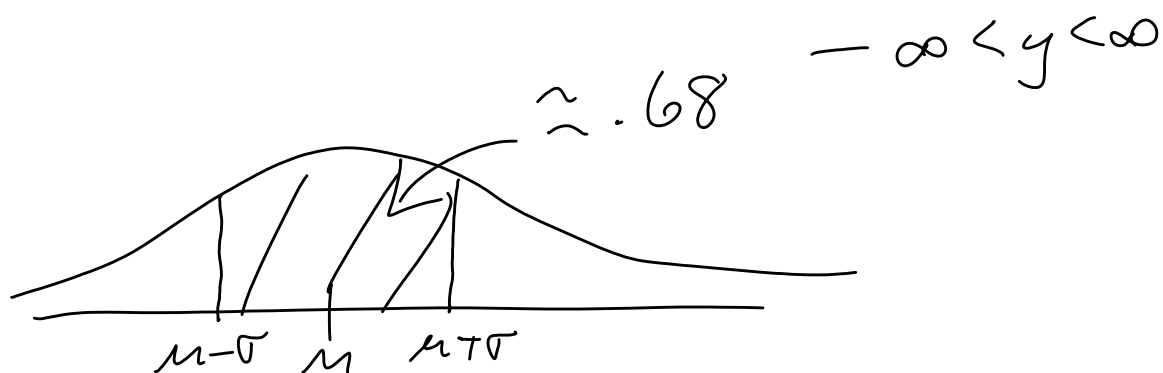


standard normal — $N(0, 1)$

Note if $Z \sim N(0, 1)$ then

$\Rightarrow \sigma Z + \mu$ is a $N(\mu, \sigma^2)$ ← def'n

$$f(y) = \frac{1}{\sqrt{2\pi} \sigma} \exp\left[-\frac{(y-\mu)^2}{2\sigma^2}\right],$$



For (1)

$$f(y) = \frac{y^{r-1} e^{-y}}{(r-1)!}, \quad y > 0$$

$$= 0, \quad \text{or}$$

gamma(r) pdf

N(0,1)

$$f(y) = \frac{1}{\sqrt{2\pi}} e^{-y^2/2}$$

a pdf? ie is the area under $e^{-y^2/2}$ $\sqrt{2\pi}$? Yes!

Aside

Let $g(x) \geq 0$ + $h(y) \geq 0$. Look at

$$g(x) h(y) \quad , \quad \begin{array}{l} -\infty < x < \infty \\ -\infty < y < \infty \end{array}$$

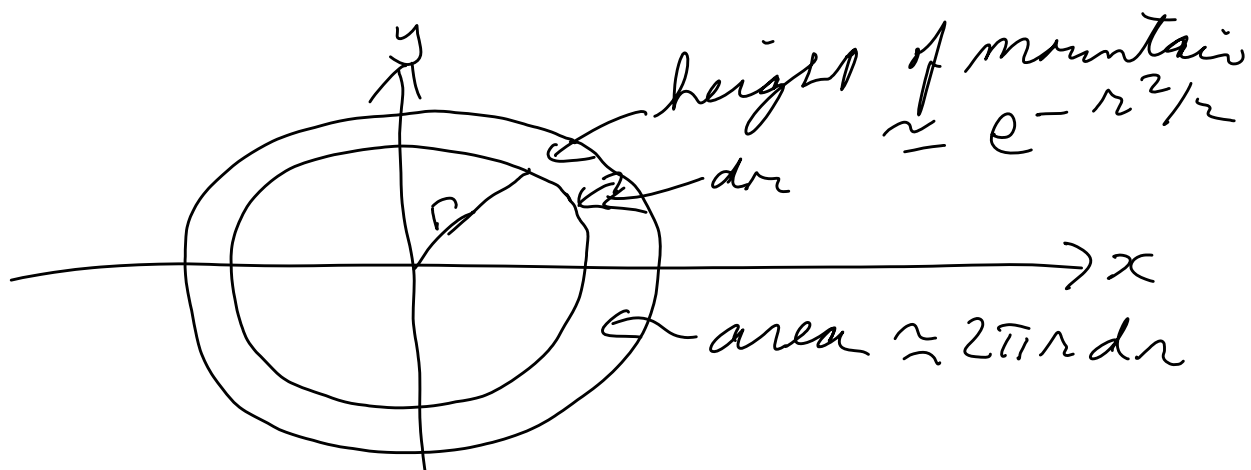
Fact volume under $g(x) h(y)$ " "
= (area under g) (area under h)

Consider $e^{-x^2/2} e^{-y^2/2}$. The volume under this is 2π .

\Rightarrow area under $e^{-x^2/2}$ is $\sqrt{2\pi}$

\Rightarrow our thing is a part

For the volume under $e^{-\frac{x^2+y^2}{2}}$



$$\text{vol} = \int_0^{\infty} e^{-r^2/2} 2\pi r dr = 2\pi$$

$$f(y) = \frac{1}{\sqrt{2\pi}} e^{-y^2/2}, \quad -\infty < y < \infty$$

is a pdf

Some immediate extensions

exponential(λ) - $\lambda > 0$

If $X \sim \text{exponential}(1)$ then $Y = \frac{X}{\lambda} \sim \text{exponential}(\lambda)$

$$\text{pdf } f(y) = \lambda e^{-\lambda y}, \quad y > 0$$

$$= 0, \quad \text{ow}$$

$$\text{mgf } m(t) = \frac{\lambda}{\lambda - t}, \quad t < \lambda \quad \left. \vphantom{\frac{\lambda}{\lambda - t}} \right\} \text{ using previous results}$$

Note $f_Y(y) = \frac{1}{\left(\frac{1}{\lambda}\right)} f_X\left(\frac{y}{\frac{1}{\lambda}}\right)$

Def $X \sim \text{exponential}(1)$ then $E(X) = 1$ + $\text{Var}(X) = 1$

$Y = \frac{X}{\lambda} \Rightarrow E(Y) = \frac{1}{\lambda}$ + $\text{Var}(Y) = \frac{1}{\lambda^2}$

λ is often called the rate. Note that the text uses $\frac{1}{\beta}$ for λ .

general normal

Def $Z \sim N(0, 1)$ then $f(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}, \quad \forall z$

+ $m_Z(t) = e^{t^2/2}$.

Def'n $Y \sim N(\mu, \sigma^2)$ if $Y = \mu + \sigma Z$, where

$Z \sim N(0, 1)$.

Note $E(Y) = \mu, \text{Var}(Y) = \sigma^2$.

$f_Y(y) = \frac{1}{\sqrt{2\pi} \sigma} \exp\left[-\frac{1}{2} \left(\frac{y-\mu}{\sigma}\right)^2\right], \quad \forall y, \quad m_Y(t) = e^{\mu t} e^{\frac{\sigma^2 t^2}{2}}$

gamma(r, λ)

Let X_1, \dots, X_n be iid exponential(1). Then

$$Y = X_1 + \dots + X_n \sim \text{gamma}(n)$$

and has pdf + mgf

$$f_Y(y) = \frac{y^{n-1} e^{-y}}{(n-1)!}, y > 0; \quad m_Y(t) = \left(\frac{1}{1-t}\right)^n, t < 1$$
$$= 0, \text{ o.w.}$$

Now divide by $\lambda > 0$ so that

$$W = \frac{Y}{\lambda} = \frac{X_1}{\lambda} + \dots + \frac{X_n}{\lambda} \sim \text{gamma}(n, \lambda)$$

$$f_W(w) = \frac{\lambda^n w^{n-1} e^{-\lambda w}}{(n-1)!}, w > 0; \quad m_W(t) = \left(\frac{\lambda}{\lambda-t}\right)^n, t < \lambda$$
$$= 0, \text{ o.w.}$$

The standard gamma, $\text{gamma}(n)$, has pdf

$$f_Y(y) = C y^{n-1} e^{-y}, y > 0$$
$$= 0, \text{ o.w.}$$

where C is such as to make the area 1.

Set $\Gamma(n) = \int_0^{\infty} y^{n-1} e^{-y} dy, n > 0$. Then

$C = \frac{1}{\Gamma(r)}$. This defines a pdf for any $r > 0$.

If $W = \frac{V}{r}$ then $W \sim \text{gamma}(r, 1)$ is
the general gamma & is defined for $r, 1 > 0$.

Some problems related to this material

1. For the $N(0, 1)$ verify
- $$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-z^2/2} e^{tz} dz = e^{t^2/2}$$

Hint Look at $\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-(z-t)^2/2} dz$

2. If $Z \sim N(0, 1)$ calculate the df + mgf

$$Y = Z^2$$

3. Use the $N(0, 1)$ mgf to obtain the $N(\mu, \sigma^2)$ mgf.

4. Verify $\Gamma(r+1) = r \Gamma(r)$, $\Gamma(1) = 1$, $\Gamma(m) = (m-1)!$ and $\Gamma(\frac{1}{2}) = \sqrt{\pi}$ Hint: For $\Gamma(\frac{1}{2})$ set $u = \sqrt{y}$ + use the properties of the normal.

5. If $Y \sim N(\mu, \sigma^2)$ then $Z = \frac{Y-\mu}{\sigma} \sim N(0, 1)$ so that $P(a < Y < b) = P\left(\frac{a-\mu}{\sigma} < Z < \frac{b-\mu}{\sigma}\right)$ + hence Y -probabilities can be reduced to Z -probabilities. Use this to calculate $P(\mu - \sigma < Y < \mu + \sigma)$ approximately (use tables, computers, etc...).

Challenge problems

6. Let X have pdf $f_X(x)$ & suppose $h: \mathbb{R} \rightarrow \mathbb{R}$ is strictly increasing and differentiable. Obtain the pdf of $Y = h(X)$ using df 's.

7. Let X be a cts rv with strictly increasing cdf F . Show (a)

$$Y = F(X) \sim \text{uniform}(0, 1)$$

(b) If $U \sim \text{uniform}(0, 1)$ then

$$X \stackrel{d}{=} F^{-1}(U),$$

where $\stackrel{d}{=}$ means both sides have the same probability dist'n.