

$$Y = g(x)$$

$$\underset{\sim}{Y} = g(x_1, x_2)$$

## STAT 712 fa 2022 Lec 10 slides

# Transformations of multiple random variables

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These slides are an instructional aid; their sole purpose is to display, during the lecture, definitions, plots, results, etc. which take too much time to write by hand on the blackboard. They are not intended to explain or expound on any material.

- 1 Bivariate transformations
- 2 Multivariate transformations, including non-1:1
- 3 Sums of independent random variables

$$y = (0, 1)$$

We often wish to find the distribution of a function of two (or more) rvs:

$$x_1 > 0, x_2 > 0$$

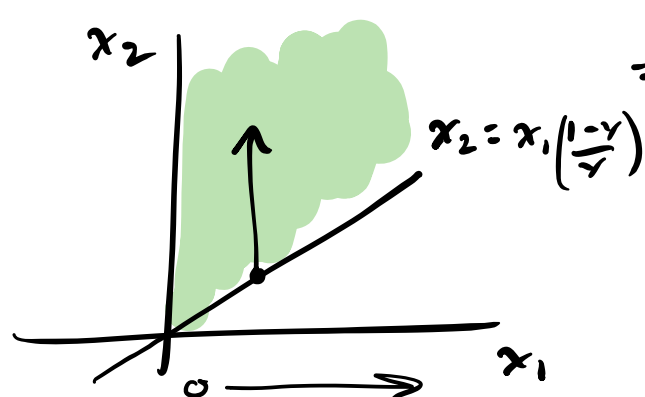
$$f_{x_1}(x_1) = \frac{1}{\lambda} e^{-x_1/\lambda} \mathbf{1}(x_1 > 0)$$

**Exercise:** Let  $X_1$  and  $X_2$  be indep. Exponential( $\lambda$ ) rvs. Let  $Y = X_1 / (X_1 + X_2)$ .

- 1 Find the cdf of  $Y$ .
- 2 Find the pdf of  $Y$ .

$$\textcircled{1} F_Y(y) = P(Y \leq y) = P\left(\frac{x_1}{x_1 + x_2} \leq y\right) = P(x_1 \leq y(x_1 + x_2))$$

$$= P(x_1 - yx_1 \leq yx_2)$$



$$= \iint_{\left\{ \frac{x_1}{x_1 + x_2} \leq y \right\}} f(x_1, x_2) dx_1 dx_2$$

$$= P\left(x_1 \left(\frac{1-y}{y}\right) \leq x_2\right)$$

$$f(x_1, x_2) = \frac{1}{\lambda^2} e^{-\frac{x_1}{\lambda}} e^{-\frac{x_2}{\lambda}} \mathbf{1}(x_1 > 0, x_2 > 0)$$

$$= \int_0^{\infty} \int_{x_1(1-\frac{y}{\lambda})}^{\infty} f(x_1, x_2) dx_2 dx_1$$

$$= \int_0^{\infty} \int_{x_1(1-\frac{y}{\lambda})}^{\infty} \frac{1}{\lambda^2} e^{-\frac{x_1}{\lambda}} e^{-\frac{x_2}{\lambda}} dx_2 dx_1$$

⋮

$$= \underline{y}$$

$$f_Y(y) = \mathbf{1}(0 < y < \lambda).$$

Setup

$$(y_1, y_2) = g(x_1, x_2)$$

$$y_1 = g_1(x_1, x_2)$$

$$y_2 = g_2(x_1, x_2)$$

Univariate transformation method:

$$X \sim f_X, \quad Y = g(X) \quad [1:1]$$

$$f_Y(y) = f_X(g^{-1}(y)) \left| \frac{d}{dy} g^{-1}(y) \right|$$

## Theorem (*Bivariate transformation method*)

Let  $(X_1, X_2)$  be a pair of cont. rvs with joint pdf  $f_{X_1, X_2}$  on  $\mathcal{X}$  and

$$Y_1 = g_1(X_1, X_2) \quad \text{and} \quad Y_2 = g_2(X_1, X_2),$$

where  $g_1$  and  $g_2$  define a 1:1 transformation of  $\mathcal{X}$  onto  $\mathcal{Y}$  (define these).

Let  $g_1^{-1}$  and  $g_2^{-1}$  be the functions satisfying

$$\begin{aligned} y_1 &= g_1(x_1, x_2) \\ y_2 &= g_2(x_1, x_2) \end{aligned} \iff \begin{aligned} x_1 &= g_1^{-1}(y_1, y_2) \\ x_2 &= g_2^{-1}(y_1, y_2) \end{aligned}$$



for all  $(x_1, x_2) \in \mathcal{X}$  and  $(y_1, y_2) \in \mathcal{Y}$ .

Then the joint pdf of  $(Y_1, Y_2)$  is given by

$$f_{Y_1, Y_2}(y_1, y_2) = f_{X_1, X_2}(\overbrace{g_1^{-1}(y_1, y_2)}^{x_1}, \overbrace{g_2^{-1}(y_1, y_2)}^{x_2}) |J(y_1, y_2)|, \text{ for } (y_1, y_2) \in \mathcal{Y},$$

where  $J(y_1, y_2)$  is the *Jacobian* (next slide), if  $J(y_1, y_2)$  is not always 0 on  $\mathcal{Y}$ .

## Jacobian

In the setup of the previous slide, the *Jacobian* of the transformation is defined as

$$J(y_1, y_2) = \begin{vmatrix} \frac{\partial}{\partial y_1} g_1^{-1}(y_1, y_2) & \frac{\partial}{\partial y_2} g_1^{-1}(y_1, y_2) \\ \frac{\partial}{\partial y_1} g_2^{-1}(y_1, y_2) & \frac{\partial}{\partial y_2} g_2^{-1}(y_1, y_2) \end{vmatrix}.$$

For real numbers  $a, b, c, d$ ,

$$\begin{vmatrix} a & b \\ c & d \end{vmatrix} = ad - bc.$$

This is called the *determinant*.

$$f(x_1, x_2) = \frac{1}{2\pi} e^{-\frac{(x_1^2 + x_2^2)}{2}}$$

$$f_{X_1}(x_1) = \frac{1}{\sqrt{2\pi}} e^{-x_1^2/2} \quad f_{X_2}(x_2) = \frac{1}{\sqrt{2\pi}} e^{-x_2^2/2}$$

Exercise: Let  $X_1, X_2$  be independent Normal(0, 1) rvs.

① Find the joint pdf of  $Y_1 = X_1/X_2$  and  $Y_2 = X_2$ .

$$Y = 1$$

② Find the marginal pdf of  $Y_1$ .

① Step 1: Identify joint support of  $(Y_1, Y_2)$

$$(Y_1, Y_2) \in \mathbb{R} \times \mathbb{R}$$

Step 2: Get inverse transform functions

$$Y_1 = \frac{x_1}{x_2} = g_1(x_1, x_2)$$

$$Y_2 = x_2 = g_2(x_1, x_2)$$

$\Leftrightarrow$

$$x_1 = Y_1 \cdot Y_2 = g_1^{-1}(Y_1, Y_2)$$

$$x_2 = Y_2 = g_2^{-1}(Y_1, Y_2)$$

$$J(y_1, y_2) = \begin{vmatrix} \frac{\partial}{\partial y_1} y_1 \cdot y_2 & \frac{\partial}{\partial y_2} y_1 \cdot y_2 \\ \frac{\partial}{\partial y_1} y_2 & \frac{\partial}{\partial y_2} y_2 \end{vmatrix}$$

$$= \begin{vmatrix} y_2 & y_1 \\ 0 & 1 \end{vmatrix}$$

$$= y_2.$$

$$f(x_1, x_2) = \frac{1}{2\pi} e^{-\frac{(x_1^2 + x_2^2)}{2}}$$

$$f(y_1, y_2) = \frac{1}{2\pi} e^{-\frac{(y_1 y_2)^2 + y_2^2}{2}} |y_2|$$

(2)

$$f_{y_1}(y_1) = \int_{-\infty}^{\infty} \frac{1}{2\pi} e^{-\frac{(y_1 y_2)^2 + y_2^2}{2}} |y_2| dy_2$$

$$= \int_{-\infty}^{\infty} |y_2| \frac{1}{2\pi} e^{-\frac{y_2^2(1+y_1^2)}{2}} dy_2$$



$$= 2 \int_0^{\infty} y_2 \frac{1}{2\pi} e^{-\frac{y_2^2(1+y_1^2)}{2}} dy_2$$

$$= 2 \int_0^{\infty} \sqrt{u} \frac{1}{2\pi} e^{-\frac{u(1+y_1^2)}{2}} \frac{1}{2\sqrt{u}} du \quad u = y_2^2, \quad y_2 = \sqrt{u} \\ dy_2 = \frac{1}{2\sqrt{u}}$$

$$= \frac{1}{2\pi} \int_0^{\infty} e^{-\frac{u(1+y_1^2)}{2}} du$$

$$= \frac{1}{2\pi} \left[ \frac{-e^{-\frac{u(1+y_1^2)}{2}}}{\frac{1+y_1^2}{2}} \right]_0^{\infty}$$

$$= \frac{1}{\pi} \frac{1}{1+y_1^2}$$

**Exercise:** Let  $X_1, X_2$  have joint pdf

$$f_{X_1, X_2}(x_1, x_2) = \frac{1}{\lambda^2} \exp\left[-\frac{x_1 + x_2}{\lambda}\right] \mathbf{1}(x_1 > 0, x_2 > 0).$$

- 1 Find the joint pdf of  $Y_1 = X_1/(X_1 + X_2)$  and  $Y_2 = X_1 + X_2$ .
- 2 Find the marginal pdf of  $Y_1$ .

$$f(x_1, x_2) = 2 \cdot x_2 \mathbb{I}(0 < x_1 < 1, 0 < x_2 < 1)$$

$$\text{Beta}(\alpha, \beta)$$

$$f_x(x) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1} \mathbb{I}(0 < x < 1)$$

$$f_{X_1}(x_1) = \mathbb{I}(0 < x_1 < 1)$$

$$f_{X_2}(x_2) = 2 x_2 \mathbb{I}(0 < x_2 < 1)$$

**Exercise:** Let  $X_1 \sim \text{Beta}(1, 1)$  and  $X_2 \sim \text{Beta}(2, 1)$  be independent rvs.

- 1 Find the joint pdf of  $Y_1 = X_1 X_2$  and  $Y_2 = X_2$ .
- 2 Find the marginal pdf of  $Y_1$ .

$$\textcircled{1} \quad (Y_1, Y_2) = \{ (x_1, x_2) : 0 < x_1 < x_2 < 1 \}$$

$$y_1 = x_1 x_2 = g_1(x_1, x_2)$$

$$y_2 = x_2 = g_2(x_1, x_2)$$

 $\Leftrightarrow$ 

$$x_1 = y_1 / y_2 = g_1^{-1}(y_1, y_2)$$

$$x_2 = y_2 = g_2^{-1}(y_1, y_2)$$

$$\begin{aligned}
 J(y_1, y_2) &= \begin{vmatrix} \frac{\partial}{\partial y_1} & \frac{y_1}{y_2} & \frac{\partial}{\partial y_1} & y_2 \\ \frac{\partial}{\partial y_2} & \frac{y_1}{y_2} & \frac{\partial}{\partial y_2} & y_2 \end{vmatrix} \\
 &= \begin{vmatrix} \frac{1}{y_2} & 0 \\ -\frac{y_1}{y_2^2} & 1 \end{vmatrix} \\
 &= \frac{1}{y_2}
 \end{aligned}$$

$$f(x_1, x_2) = (2 \cdot x_2) \mathbb{I}(0 < x_1 < 1, 0 < x_2 < 1)$$

$$\begin{aligned}
 f(y_1, y_2) &= 2 \cdot y_2 \cdot \left| \frac{1}{y_2} \right| \mathbb{I}(0 < y_1 < y_2 < 1) \\
 &= \underline{\underline{2 \cdot \mathbb{I}(0 < y_1 < y_2 < 1)}}
 \end{aligned}$$

② For  $\bar{y}_1 \in (0, 1)$

$$\begin{aligned}
 f_{\bar{y}_1}(y_1) &= \int_{y_1}^1 2 \, dy_2 = 2(1 - y_1) \\
 &= \frac{\Gamma(2+1)}{\Gamma(1)\Gamma(2)} y_1^{1-1} (1-y_1)^{2-1} \\
 &= \text{pdf of Beta}(1, 2)
 \end{aligned}$$

**Exercise:** Let  $Z_1, Z_2$  have the bivariate Normal distribution, with joint pdf

$$f_{Z_1, Z_2}(z_1, z_2) = \frac{1}{2\pi} \frac{1}{\sqrt{1 - \rho^2}} \exp \left[ -\frac{1}{2} \frac{z_1^2 - 2\rho z_1 z_2 + z_2^2}{1 - \rho^2} \right].$$

- 1 Find the joint pdf of  $U_1 = Z_1 + Z_2$  and  $U_2 = Z_1 - Z_2$ .
- 2 Find the marginal pdfs of  $U_1$  and  $U_2$ .

$$\{ (u_1, u_2) = (-1, 2) \} = \{ (z_1, z_2) = (-1, 2) \\ \text{or } (z_1, z_2) = (2, -1) \}$$

**Exercise:** Let  $Z_1, Z_2$  have the bivariate Normal distribution, with joint pdf

$$f_{Z_1, Z_2}(z_1, z_2) = \frac{1}{2\pi} \frac{1}{\sqrt{1 - \rho^2}} \exp \left[ -\frac{1}{2} \frac{z_1^2 - 2\rho z_1 z_2 + z_2^2}{1 - \rho^2} \right].$$

- 1 Find the joint pdf of  $U_1 = \min\{Z_1, Z_2\}$  and  $U_2 = \max\{Z_1, Z_2\}$ ? (Not 1:1).
- 2 Find the marginal pdf of  $U_2$  (work on this at home).

- 1 Bivariate transformations
- 2 Multivariate transformations, including non-1:1
- 3 Sums of independent random variables

Now consider how  $d \geq 1$  random variables behave together.

It is often convenient to organize our random variables into a random vector:

## Random vector

A *random vector* is a vector in which each entry is a random variable.

$$X_1, X_2, \dots, X_d \quad \underset{\sim}{\mathbf{X}} = \begin{bmatrix} X_1 \\ \vdots \\ X_d \end{bmatrix}_{dx1}$$

## Multivariate pdf/pmf

The *joint pdf* of  $\mathbf{X} = (X_1, \dots, X_d)^T$  is the function  $f : \mathbb{R}^d \rightarrow [0, \infty)$  such that

$$P(\mathbf{X} \in A) = \int_A f(\mathbf{x}) d\mathbf{x} \quad \text{for all } A \in \mathcal{B}(\mathbb{R}^d).$$

If  $X_1, \dots, X_d$  are discrete, then the *joint pmf* of  $\mathbf{X}$  is given by

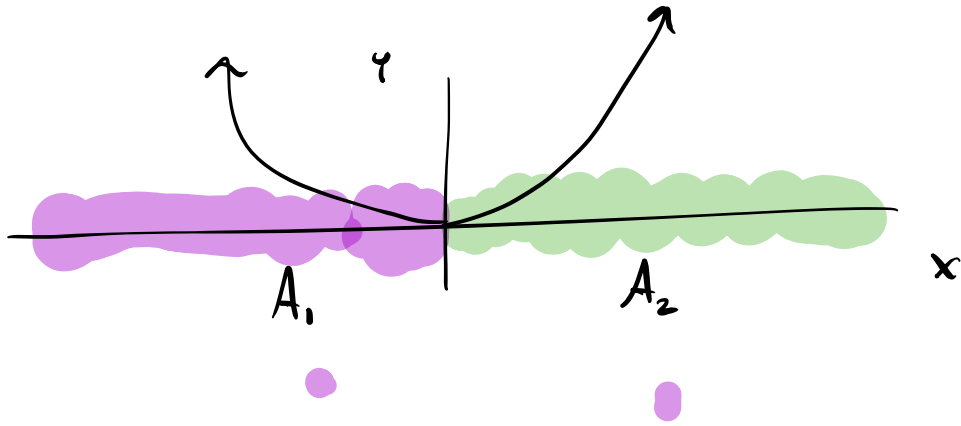
$$p(\mathbf{x}) = P(\mathbf{X} = \mathbf{x}) \quad \text{for all } \mathbf{x} \in \mathbb{R}^d.$$



$$d=1$$

$$X \sim N(0,1)$$

$$Y = X^2$$



## Multivariate transformation

Let  $\mathbf{X} \in \mathbb{R}^d$  have joint pdf  $f$  with support  $\mathcal{A}$ . Consider the rvec

$$\mathbf{Y} = (g_1(\mathbf{X}), \dots, g_d(\mathbf{X}))^T$$

for some functions  $g_1, \dots, g_d : \mathbb{R}^d \rightarrow \mathbb{R}$ .

until now  
we had  
 $d=2$   
 $m=1$

Moreover, given a partition  $(\mathcal{A}_0, \mathcal{A}_1, \dots, \mathcal{A}_m)$  of  $\mathcal{A}$ , where  $P(\mathbf{X} \in \mathcal{A}_0) = 0$ , suppose the transformation is 1:1 on each of the sets  $\mathcal{A}_1, \dots, \mathcal{A}_m$ .

For  $k = 1, \dots, m$ , let the inverse transformation on  $\mathcal{A}_k$  be given by

$$\mathbf{x} = (g_{1k}^{-1}(\mathbf{y}), \dots, g_{dk}^{-1}(\mathbf{y}))$$

for some functions  $g_{1k}^{-1}, \dots, g_{dk}^{-1}$  and let  $\mathbf{J}_k(\mathbf{y})$  be the corresponding Jacobian.

Then the joint pdf of  $\mathbf{Y}$  is given by

$$f_{\mathbf{Y}}(\mathbf{y}) = \sum_{k=1}^m f((g_{1k}^{-1}(\mathbf{y}), \dots, g_{dk}^{-1}(\mathbf{y}))^T) |\mathbf{J}_k(\mathbf{y})|.$$

$$d=2 \quad f(z_1, z_2) = \frac{1}{\sqrt{2\pi}} e^{-z_1^2/2} \frac{1}{\sqrt{2\pi}} e^{-z_2^2/2} = \frac{1}{2\pi} e^{-\frac{z_1^2+z_2^2}{2}}$$

Exercise: Let  $Z_1, Z_2 \stackrel{\text{ind}}{\sim} \text{Normal}(0, 1)$  and consider the rvs

$$Y_1 = Z_1^2 + Z_2^2$$

$$Y_2 = Z_1 / \sqrt{Z_1^2 + Z_2^2}$$

$$(Y_1, Y_2) \in \left\{ (y_1, y_2) : y_1 \in (-1, 1), y_2 > 0 \right\}$$

- 1 Find the joint pdf of  $(Y_1, Y_2)$ .
- 2 Check whether  $Y_1$  and  $Y_2$  are independent.
- 3 Find the marginal pdf of  $Y_2$ .

$$z_1 = y_2 \cdot \sqrt{y_1}$$

$$\begin{aligned} z_2^2 &= y_1 - z_1^2 = y_1 - (y_2 \sqrt{y_1})^2 \\ &= y_1 - y_1 y_2^2 \\ &= y_1 (1 - y_2^2) \end{aligned}$$

$$z_2 = \pm \sqrt{y_1 (1 - y_2^2)}$$

$$\begin{aligned} y_1 &= z_1^2 + z_2^2 = g_1(z_1, z_2) \\ y_2 &= z_1 / \sqrt{z_1^2 + z_2^2} = g_2(z_1, z_2) \end{aligned} \quad \Leftrightarrow$$

$A_1$	$A_2$
$z_1 = y_2 \sqrt{y_1}$ $z_2 = \sqrt{y_1(1-y_2^2)}$	$z_1 = y_2 \sqrt{y_1}$ $z_2 = -\sqrt{y_1(1-y_2^2)}$
	$J_2(y_1, y_2)$

$$J_1(y_1, y_2) = \begin{vmatrix} \frac{\partial}{\partial y_1} & y_2 \sqrt{y_1} & \frac{\partial}{\partial y_1} & \sqrt{y_1(1-y_2^2)} \\ \frac{\partial}{\partial y_2} & y_2 \sqrt{y_1} & \frac{\partial}{\partial y_2} & \sqrt{y_1(1-y_2^2)} \end{vmatrix}$$

$$= \begin{vmatrix} \frac{y_2}{2\sqrt{y_1}} & \frac{1-y_2^2}{2\sqrt{y_1(1-y_2^2)}} \\ \sqrt{y_1} & \frac{-2y_1 y_2}{2\sqrt{y_1(1-y_2^2)}} \end{vmatrix}$$

$$= \frac{-y_2^2}{2\sqrt{1-y_2^2}} - \frac{1-y_2^2}{2\sqrt{1-y_2^2}}$$

$$= -\frac{1}{2\sqrt{1-y_2^2}}$$

$$f(z_1, z_2) = \frac{1}{2\pi} e^{-\frac{z_1^2 + z_2^2}{2}}$$

$n=1$

$$f(y_1, y_2) = \frac{1}{2\pi} e^{-\frac{(y_2 \sqrt{y_1})^2 + (\sqrt{y_1(1-y_2^2)})^2}{2}} \left| J_1(y_1, y_2) \right|$$

$n=2$

$$\frac{1}{2\pi} e^{-\frac{(y_2 \sqrt{y_1})^2 + (-\sqrt{y_1(1-y_2^2)})^2}{2}} \left| J_2(y_1, y_2) \right|$$

$$= \frac{1}{2\pi} e^{-\frac{y_1}{2}} \frac{1}{2\sqrt{1-y_2^2}} + \frac{1}{2\pi} e^{-\frac{y_1}{2}} \frac{1}{2\sqrt{1-y_2^2}}$$

$$= \frac{1}{2} e^{-\frac{y_1}{2}} \frac{1}{\pi \sqrt{1-y_2^2}}$$

pdf of Expon(2)

$$\text{So } f(y_1, y_2) = \underbrace{\frac{1}{2} e^{-\frac{y_1}{2}} \mathbb{1}(y_1 > 0)}_{g(y_1)} \underbrace{\frac{1}{\pi \sqrt{1-y_2^2}} \mathbb{1}(y_2 \in (-1, 1))}_{h(y_2)}$$

$$d=3$$

**Exercise:** Let  $X_1, X_2, X_3 \stackrel{\text{ind}}{\sim} \text{Exponential}(1)$  and consider

$$Y_1 = \frac{X_1}{X_1 + X_2}$$

$$Y_2 = \frac{X_1 + X_2}{X_1 + X_2 + X_3}$$

$$Y_3 = X_1 + X_2 + X_3.$$

- 1 Find the joint pdf of  $(Y_1, Y_2, Y_3)$ .
- 2 Check whether  $Y_1, Y_2,$  and  $Y_3$  are mutually independent.
- 3 Find the marginal distributions  $Y_1, Y_2,$  and  $Y_3$ .

- 1 Bivariate transformations
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We extend our definition of independence to a collection of more than two rvs.

## Mutual independence for a collection of rvs

Let the rvs  $X_1, \dots, X_d$  have joint pdf/pmf  $f(x_1, \dots, x_d)$  and marginal pdfs/pmfs such that  $X_i \sim f_{X_i}$ ,  $i = 1, \dots, d$ . If

$$f(x_1, \dots, x_d) = \prod_{j=1}^d f_{X_j}(x_j) \quad \text{for all } (x_1, \dots, x_d) \in \mathbb{R}^d,$$

*d=2 until now*

we say that  $X_1, \dots, X_d$  are *mutually independent* rvs.

## Theorem (Quick check for mutual independence)

The rvs  $X_1, \dots, X_d$  with joint pdf/pmf  $f$  are mutually independent if and only if there exist functions  $g_1, \dots, g_d$  such that

$$f(x_1, \dots, x_d) = \prod_{j=1}^d g_j(x_j) \quad \text{for all } (x_1, \dots, x_d) \in \mathbb{R}^d.$$



$$X \perp\!\!\!\perp Y \Rightarrow \mathbb{E} f(X) h(Y) = \mathbb{E} f(X) \mathbb{E} h(Y).$$

## Expectation of a product of functions

If  $X_1, \dots, X_d$  are mutually independent, then

$$\mathbb{E}(g_1(X_1) \cdots g_d(X_d)) = \prod_{i=1}^d \mathbb{E} g_i(X_i)$$

for any functions  $g_1, \dots, g_d: \mathbb{R} \rightarrow \mathbb{R}$ .

$$X \perp\!\!\!\perp Y \Rightarrow M_{X+Y}(t) = M_X(t) M_Y(t)$$

## Theorem (mgf method for sums of independent rvs)

Let  $X_1, \dots, X_n$  be ind. rvs with mgfs  $M_{X_1}, \dots, M_{X_n}$ , resp. Let  $Y = X_1 + \dots + X_n$ .

The mgf of  $Y$  is given by

$$M_Y(t) = \prod_{i=1}^n M_{X_i}(t).$$

*independent,  
identically distributed*

Moreover, if  $X_1, \dots, X_n$  are ind. and all have mgf  $M_X$  (are iid), then

$$M_Y(t) = [M_X(t)]^n.$$

$$M_Y(t) = \mathbb{E} e^{tY} = \mathbb{E} e^{t(X_1 + \dots + X_n)}$$

Exercise: Prove the above.

$$\begin{aligned} &= \mathbb{E} \left[ e^{tX_1} \cdot e^{tX_2} \cdot \dots \cdot e^{tX_n} \right] \\ &= \mathbb{E} e^{tX_1} \cdot \mathbb{E} e^{tX_2} \cdot \dots \cdot \mathbb{E} e^{tX_n} \\ &= M_{X_1}(t) \cdot M_{X_2}(t) \cdot \dots \cdot M_{X_n}(t) = \prod_{i=1}^n M_{X_i}(t) \end{aligned}$$

$$M_{X_i}(t) = (1-2t)^{-\nu_i/2}$$

Gamma( $\alpha, \beta$ ) has mgf  $(1-\beta t)^{-\alpha}$

$$\chi^2_\nu = \text{Gamma}\left(\frac{\nu}{2}, 2\right)$$

Exercise: Let  $X_1, \dots, X_n$  be ind. chi-squared rvs with dfs  $\nu_1, \dots, \nu_n$ , resp. Find the distribution of  $Y = X_1 + \dots + X_n$ .

$$M_Y(t) = \prod_{i=1}^n M_{X_i}(t) = \prod_{i=1}^n (1-2t)^{-\nu_i/2}$$

$$\begin{aligned} &= (1-2t)^{-\nu_1/2} \cdot (1-2t)^{-\nu_2/2} \cdot \dots \cdot (1-2t)^{-\nu_n/2} \\ &= (1-2t)^{-\frac{\sum_{i=1}^n \nu_i}{2}} \\ &= \text{mgf of } \chi^2_{\sum_{i=1}^n \nu_i} \end{aligned}$$

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

$$Z^2 \sim \chi^2_1$$

$$Z_1, \dots, Z_n \stackrel{\text{ind.}}{\sim} N(0,1)$$

$$\sum_{i=1}^n Z_i^2 \sim \chi^2_n$$

$$X_i \sim N(\mu_i, \sigma_i^2)$$

**Exercise:** Let  $X_1, \dots, X_n$  be ind. Normal rvs with means  $\mu_1, \dots, \mu_n$  and variances  $\sigma_1^2, \dots, \sigma_n^2$ , resp.

- 1 Find the distribution of  $Y = X_1 + \dots + X_n$ .
- 2 Find the distribution of  $V = a_1 X_1 + \dots + a_n X_n$ , for  $a_1, \dots, a_n \in \mathbb{R}$ .
- 3 Find the distribution of  $\bar{X}_n = (X_1 + \dots + X_n)/n$ ,

and suppose  $\mu_1 = \dots = \mu_n = \mu$   
 $\sigma_1^2 = \dots = \sigma_n^2 = \sigma^2$

$$M_V(t) = M_{a_1 X_1 + \dots + a_n X_n}(t) = M_{a_1 X_1}(t) \cdot M_{a_2 X_2}(t) \cdot \dots \cdot M_{a_n X_n}(t)$$

$$= \prod_{i=1}^n M_{a_i X_i}(t)$$

$$= \prod_{i=1}^n M_{X_i}(a_i t)$$

$$M_{aX+b}(t) = e^{tb} M_X(at)$$

$$M_{X_i}(t) = e^{\mu_i t + \sigma_i^2 t^2 / 2}$$

$$= \prod_{i=1}^n e^{\mu_i (s_i t) + \sigma_i^2 (s_i t)^2 / 2}$$

$$= e^{\left( \sum_{i=1}^n \mu_i s_i \right) t + \left( \sum_{i=1}^n s_i^2 \sigma_i^2 \right) t^2 / 2}$$

is of Normal  $\left( \underbrace{\sum_{i=1}^n \mu_i s_i}, \sum_{i=1}^n s_i^2 \sigma_i^2 \right)$

③  $\bar{X}_n \sim \text{Normal} \left( \underbrace{\sum_{i=1}^n \mu_i \cdot \frac{1}{n}}, \sum_{i=1}^n \left( \frac{1}{n} \right)^2 \sigma_i^2 \right)$

$$= \text{Normal} \left( \mu, \frac{\sigma^2}{n} \right)$$