

# Lecture 17

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Plan:

1) Map on Farming

2) Normal distribution.

Special Gamma.

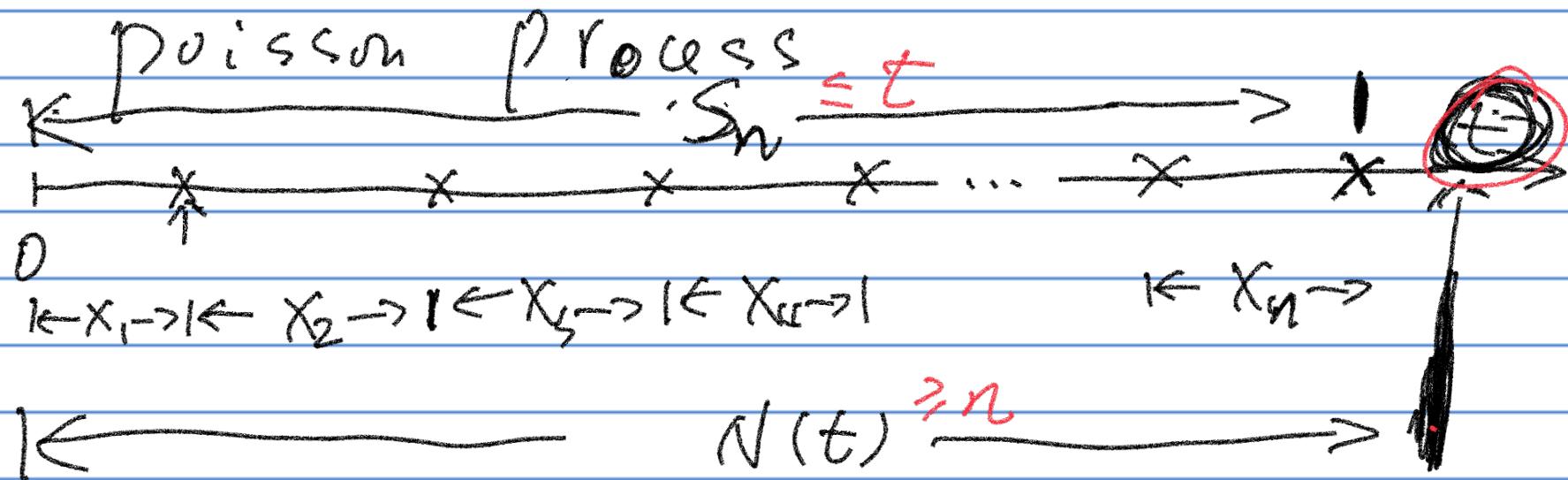
1)  $\alpha = 1, \beta = 1$

$$f(x) = \frac{e^{-x} x^{\alpha-1}}{\Gamma(\alpha)} = e^{-x} \text{ for } x > 0$$

$$\text{Gamma}(\alpha=1, \beta=1) = \exp(1)$$

$$\text{Gamma}(\alpha=1, \beta) = \exp\left(\frac{1}{\beta}\right)$$

2) Erlang distribution  $\alpha = n$ .



$\{ N(t) = \# \text{ of events b/w } [0, t] \}$

$$S_n = X_1 + X_2 + \dots + X_n$$

$N(t)$  takes values  $0, 1, 2, \dots$

$S_n$  is continuous,  $S_n \geq 0$

This process is called Poisson process

with rate  $\lambda$  if

$$N(t) \sim \text{Poisson}(\lambda t) \quad \checkmark$$

and something more,

$$E(N(t)) = \lambda t$$

$$E(N(1)) = \lambda$$

Thm:

$$N(t) \sim \text{Poisson}(\lambda t)$$

$$\Downarrow \Rightarrow S_n = X_1 + \dots + X_n \sim \text{Gamma}(n, \beta = \frac{\lambda}{\lambda})$$

$X_1, \dots, X_n$  are IID.  $\exp(\lambda)$

Pf:

$$F_{S_n}(t) = P(S_n \leq t) = P(N(t) \geq n)$$

$$P(S_n \leq t) = P(N(t) \geq n)$$

$$= \sum_{k=n}^{+\infty} \frac{e^{-\lambda t} (\lambda t)^k}{k!}$$

$$F'_{S_n}(t) = \left[ \frac{d}{dt} \sum_{k=n}^{+\infty} \frac{(e^{-\lambda t})(\lambda t)^k}{k!} \right]$$

$$= \sum_{k=n}^{+\infty} e^{-\lambda t} (\cancel{-\lambda}) (\lambda t)^k + \cancel{e^{-\lambda t}} (\lambda t)^{k+1} \cdot \cancel{\frac{1}{k+1}}$$

$$= \sum_{k=n}^{+\infty} \frac{e^{-\lambda t} (\lambda t)^k}{(k+n)!}$$

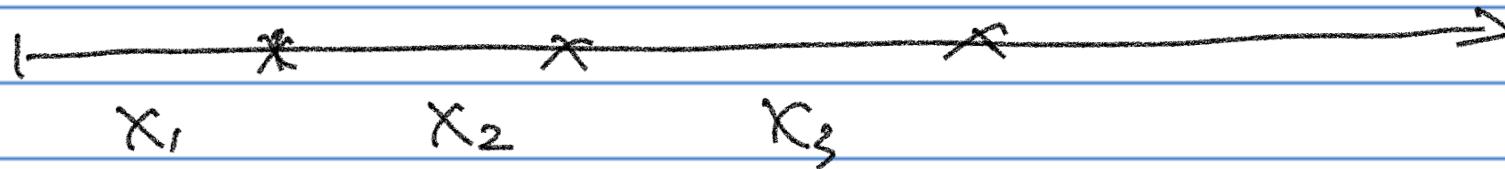
$$\begin{aligned}
 &= \lambda \cdot \left[ - \sum_{k=0}^{+\infty} \frac{e^{-\lambda t} (\lambda t)^k}{k!} + \sum_{k=n}^{+\infty} \frac{e^{-\lambda t} (\lambda t)^{k-1}}{(k-1)!} \right] \\
 &= \lambda \left[ - \sum_{k=0}^{n-1} \frac{e^{-\lambda t} (\lambda t)^k}{k!} + \sum_{k=n-1}^{+\infty} \frac{e^{-\lambda t} (\lambda t)^k}{k!} \right] \\
 &= \lambda \frac{e^{-\lambda t} (\lambda t)^{n-1}}{(n-1)!}
 \end{aligned}$$

This is the P.D.F. of Gamma( $n, \beta = \frac{1}{\lambda}$ )

$$S_n \sim \text{Gamma}(n, \beta = \frac{1}{\lambda})$$

Erlang distribution

$$S_1 = X_1 \sim \text{Gamma}(1, \frac{1}{\lambda}) = \exp(\lambda)$$



$$X_1, X_2, \dots, X_n \stackrel{\text{IID}}{\sim} \exp(\lambda)$$

Stoch(1,  $\frac{1}{\lambda}$ )

$$S_n = X_1 + \dots + X_n$$

sum of  $n$  IID  $\exp(\lambda)$  r.v.

Thm: additivity of Gamma

If  $X_i \sim \text{Gamma}(\underline{d_i}, \beta)$ ,

$X_1, \dots, X_n$  are independent.

then

$$\underline{X_1 + \dots + X_n} \sim \text{Gamma}\left(\sum_{i=1}^n d_i, \beta\right)$$

$$\text{pf: } M_{X_i}(t) = \left(1 - \frac{t}{\beta}\right)^{-d_i}$$

$$\begin{aligned} M_{X_1 + \dots + X_n}(t) &= \prod_{i=1}^n M_{X_i}(t) = \prod_{i=1}^n \left(1 - \frac{t}{\beta}\right)^{d_i} \\ &= \left(1 - \frac{t}{\beta}\right)^{\sum_{i=1}^n d_i} \end{aligned}$$

This is the M.G.F. of  $\text{Gamma}\left(\sum_{i=1}^n d_i, \beta\right)$

Additivity of Binomial.

If  $X_i \sim \text{Bin}(n_i, p)$ , indep.

then  $S_n = X_1 + \dots + X_n \sim \text{Bin}\left(\sum_{i=1}^K n_i, p\right)$ .

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

$$\begin{aligned} M_{S_n}(t) &= \prod_{i=1}^K M_{X_i}(t) \\ &= (q + pe^t)^{\sum_{i=1}^K n_i} \end{aligned}$$

Addition of Poisson( $\lambda$ ).

If  $X_i \sim \text{Poisson}(\lambda_i)$ , independently

for  $i=1, \dots, n$

then  $S_n = X_1 + \dots + X_n \sim \text{Poisson}\left(\sum_{i=1}^n \lambda_i\right)$

pf:  $M_{X_i}(t) = e^{\lambda_i(e^t - 1)}$

$$M_{S_n}(t) = e^{\sum_{i=1}^n \lambda_i(e^t - 1)}$$

Beta distribution.

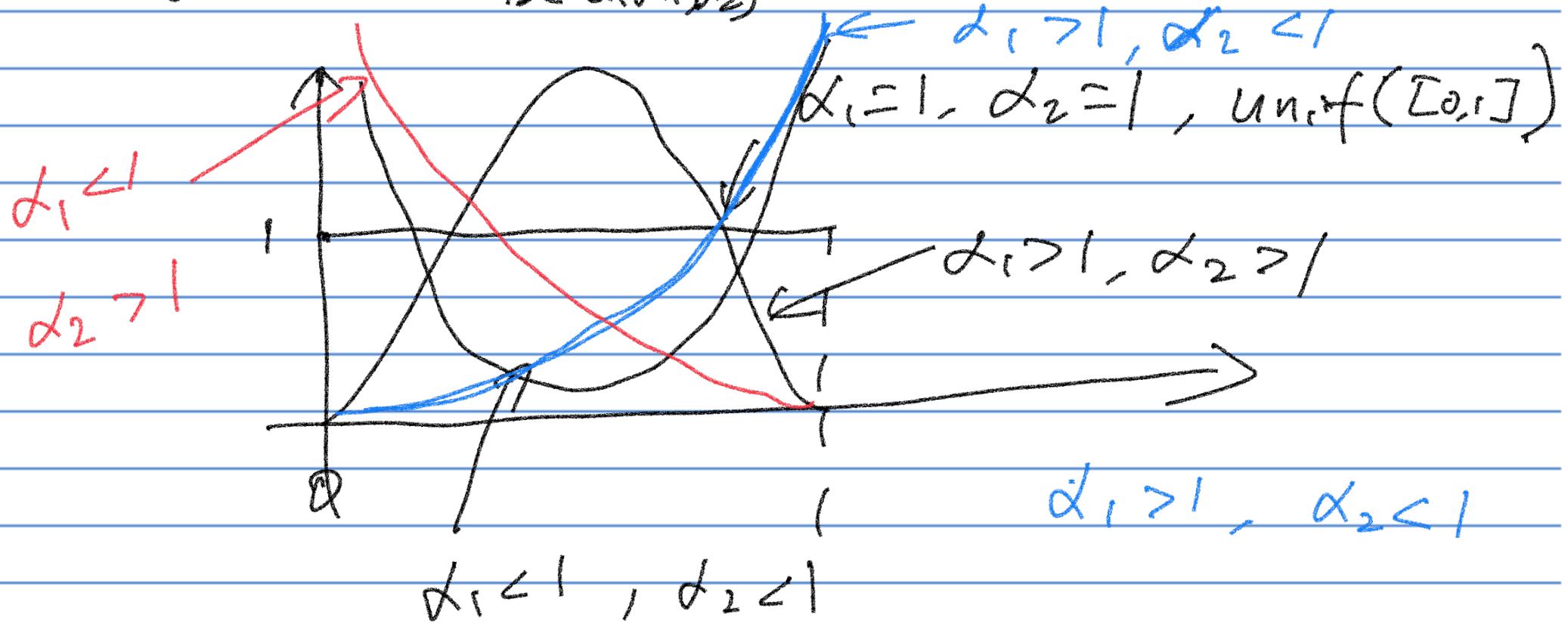
$$X \sim \text{Gamma}(\alpha_1, 1)$$

$$Y \sim \text{Gamma}(\alpha_2, 1)$$

$$W = \frac{X}{X+Y} \sim \text{Beta}(\alpha_1, \alpha_2)$$

$$W \in [0, 1]$$

$$f(\omega) = \frac{1}{\text{Beta}(\alpha_1, \alpha_2)} \cdot \omega^{\alpha_1-1} (1-\omega)^{\alpha_2-1}, \text{ for } \omega \in [0,1]$$



$$E(X) = \frac{\alpha_1}{\alpha_1 + \alpha_2}$$

$$V(X) = \frac{\alpha_1 \cdot \alpha_2}{(\alpha_1 + \alpha_2 + 1)(\alpha_1 + \alpha_2)^2}$$

A remark:  $X \sim \text{Gamma}(\alpha_1, \beta)$ ,  $\frac{X}{\beta} \sim \text{Gamma}(\alpha_1)$   
 $Y \sim \text{Gamma}(\alpha_2, \beta)$ ,  $\frac{Y}{\beta} \sim \text{Gamma}(\alpha_2)$

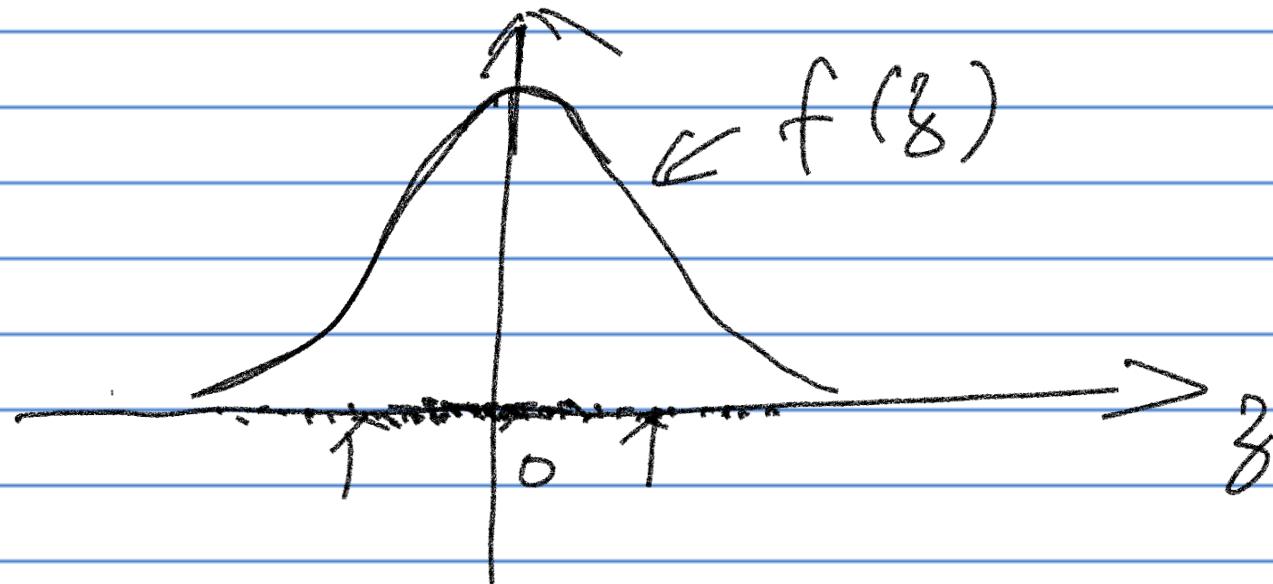
$$W = \frac{X}{X+Y} = \frac{\frac{X}{\beta}}{\frac{X}{\beta} + \frac{Y}{\beta}} \sim \text{Beta}(\alpha_1, \alpha_2)$$

# Normal distribution

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

P.D.F.

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



$$E(z) = 0$$

$$V(z) = E(z^2)$$

$$= \int_{-\infty}^{+\infty} z^2 \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz$$

$$= 2 \cdot \frac{1}{\sqrt{2\pi}} \int_0^{+\infty} z^2 e^{-\frac{z^2}{2}} dz \quad z = \sqrt{x}$$

$$= 2 \cdot \frac{1}{\sqrt{2\pi}} \int_0^{+\infty} x e^{-\frac{x}{2}} d\sqrt{x}$$

C

$$= 1$$

M.G.F.

$$M_Z(t) = E(e^{tZ})$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} e^{tz} e^{-\frac{z^2}{2}} dz$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} e^{-\frac{1}{2}[z^2 - 2tz + t^2 - t^2]} dz$$

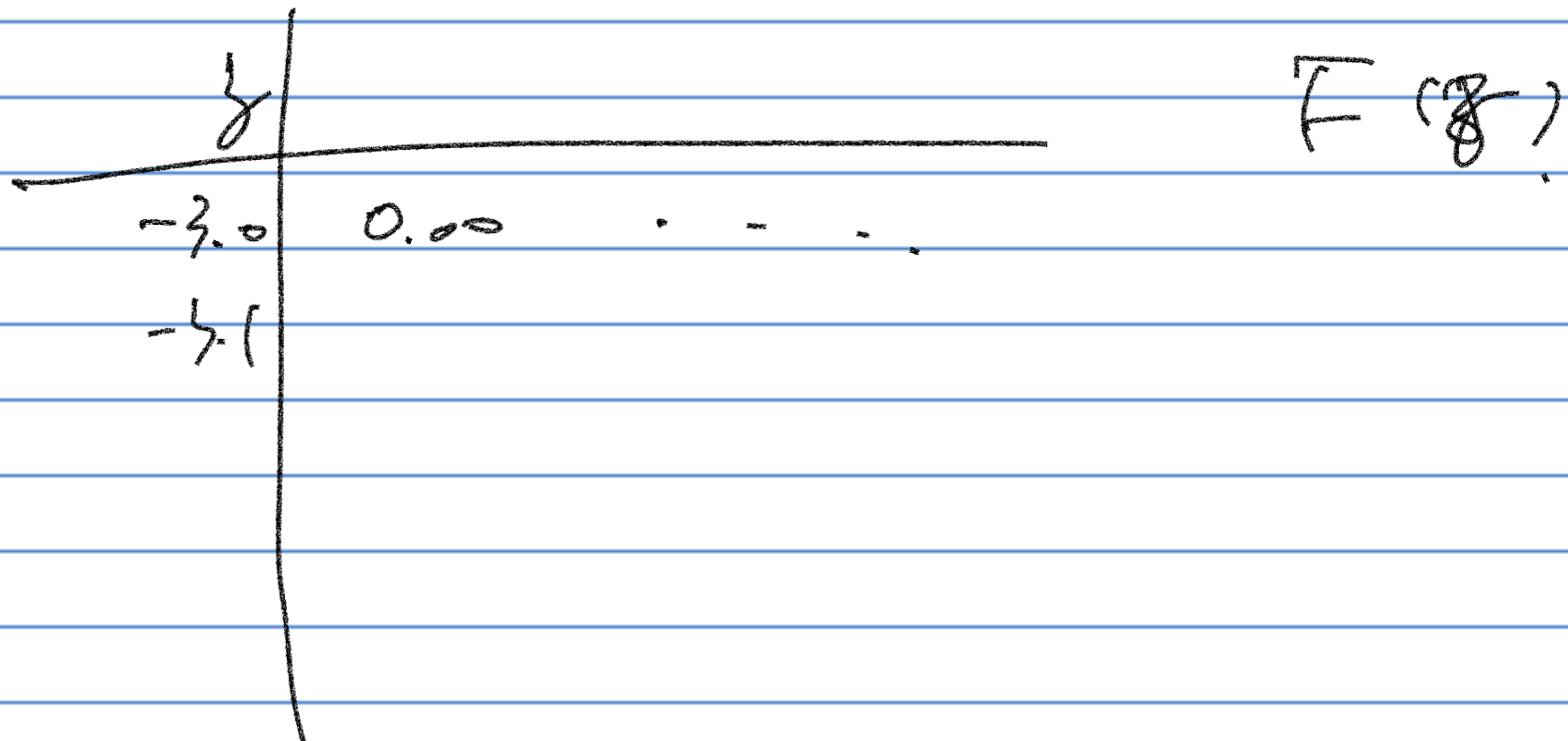
$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} e^{-\frac{1}{2}[z-t]^2 + \frac{1}{2}t^2} dz$$

$$= e^{\frac{1}{2}t^2} \cdot \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} e^{-\frac{1}{2}(z-t)^2} dz, z=t-x$$

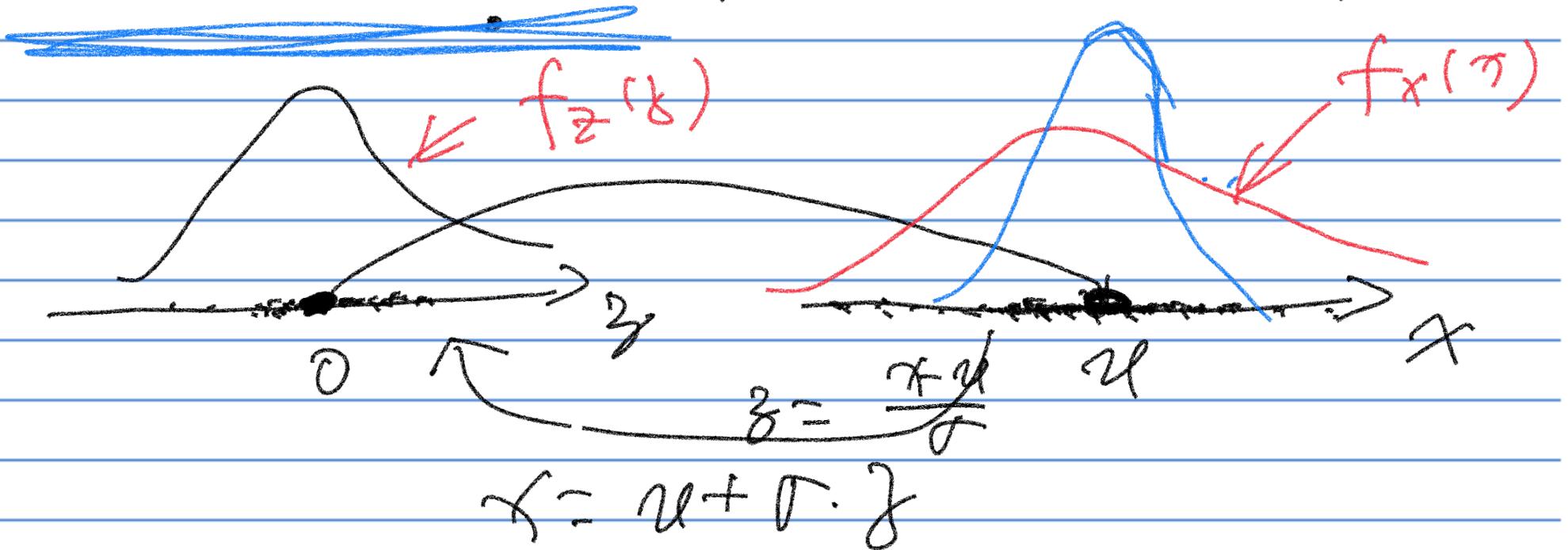
$$= e^{\frac{1}{2}t^2} \underbrace{\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} e^{-\frac{1}{2}x^2} dx}_{1}$$

$$= e^{\frac{1}{2}t^2}$$

$$F_2(z) = \int_{-\infty}^z f(\gamma) d\gamma, \text{ no closed form}$$



$$X = \mu + \sigma Z, Z \sim U(0,1)$$



$$X = \mu + \sigma Z$$

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

P.D.F. of  $X$

$$f_x(x) = f_z\left(\frac{x-u}{\sigma}\right) \cdot \left| \frac{d}{dx} \right| +$$
$$= f_z\left(\frac{x-u}{\sigma}\right) \circledcirc \frac{1}{\sigma}$$
$$= \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-u)^2}{2\sigma^2}} \cdot \frac{1}{\sigma}$$

$$E(X) = E(u + \sigma z)$$

$$= u + \tau \cdot E(z)$$

$$= u$$

$$V(X) = V(u + \sigma z)$$

$$= \tau^2 \cdot V(z) = \sigma^2$$

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

$$= E(e^{t(u+\sigma z)})$$

$$= e^{tu} \cdot E(e^{\sigma u z})$$

$$= e^{tu} \cdot e^{\frac{1}{2}(\sigma u)^2}$$

$$= e^{ut + \frac{1}{2}\sigma^2 t} \quad \square$$

Additivity of  $N(\mu, \sigma^2)$

Thm:

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

$X_1, \dots, X_n$  are indep.

$$X_1 + \dots + X_n \sim N\left(\sum_{i=1}^n \mu_i, \sum_{i=1}^n \sigma_i^2\right)$$

Df:

$$M_{X_i}(t) = e^{\underline{u_i t + \frac{1}{2} \sigma_i^2 t^2}}$$

$$\begin{aligned} M_{X_1 + \dots + X_n}(t) &= \prod_{i=1}^n M_{X_i}(t) \\ &= e^{\sum_{i=1}^n (u_i t + \frac{1}{2} \sigma_i^2 t^2)} \\ &= e^{\sum_{i=1}^n u_i t + \frac{1}{2} \sum_{i=1}^n \sigma_i^2 t^2} \end{aligned}$$

This is the MGF of  $N\left(\sum_{i=1}^n u_i, \sum_{i=1}^n \sigma_i^2\right)$

Σεμψ

$$X_1 \sim N(\mu_1, \sigma_1^2)$$

$$X_2 \sim N(\mu_2, \sigma_2^2)$$

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

$$X_1 - X_2 \sim N(\mu_1 - \mu_2, \sigma_1^2 + \sigma_2^2)$$

Thm:

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

then  $\sum_{i=1}^n a_i X_i \sim N\left(\sum_{i=1}^n a_i \mu_i, \sum_{i=1}^n a_i^2 \sigma_i^2\right)$

Pf.:

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

applying previous formula

Example:

$$X_1, \dots, X_n \stackrel{\text{IID}}{\sim} N(\mu, \sigma^2)$$

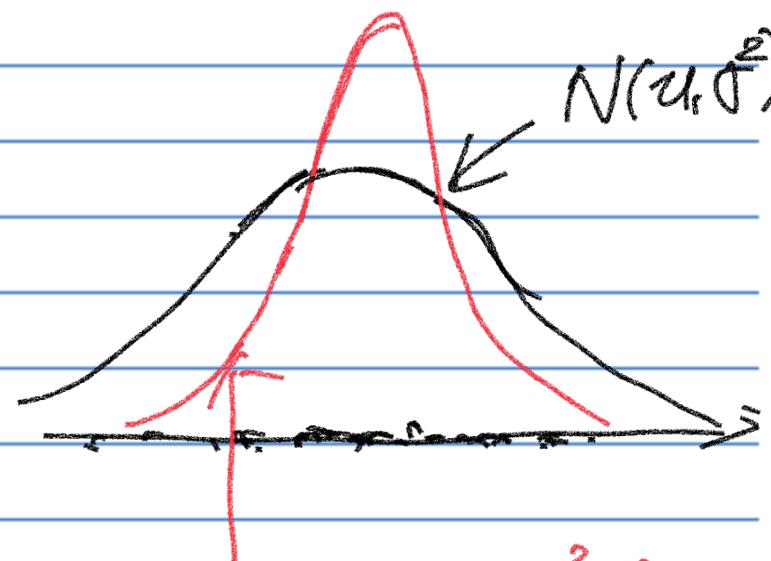
$$\bar{X} = \frac{X_1 + \dots + X_n}{n} = \sum_{i=1}^n a_i X_i$$

where  $a_i = \frac{1}{n}$

$$\sum_{i=1}^n a_i \mu_i = \sum \left( \frac{1}{n} \cdot \mu \right) = \mu$$

$$\sum_{i=1}^n a_i^2 \sigma_i^2 = \sum \frac{1}{n^2} \cdot \sigma^2 = \frac{\sigma^2}{n}$$

$$\text{so } \bar{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$



$$N\left(\mu, \frac{\sigma^2}{n}\right)$$