# Stat 134 lec 30

**warmup 10:00-10:10**

If $R_1 \sim$ Ray (Rayleigh) (density $f_R(r) = re^{-\frac{1}{2}r^2}$)

find the density of $W = \frac{1}{\sqrt{3}} R_1$

$$f_W(w) = \frac{1}{\frac{1}{\sqrt{3}}} \cdot re^{-\frac{1}{2}r^2} \Big|_{r=\sqrt{3}w}$$

$$= \sqrt{3} \cdot \sqrt{3}\, we^{-\frac{3}{2}w^2} = \boxed{3we^{-\frac{3}{2}w^2}}$$

so $W = \frac{1}{\sqrt{3}}$ Ray is also the minimum of $R_1, R_2, R_3$

i.e. $\min(R_1, R_2, R_3) \sim \frac{1}{\sqrt{3}}$ Ray

## Last time

**Sec 5.3 independent normal variables**

a) $T \sim Exp(\frac{1}{2}) \Rightarrow R = \sqrt{T}$ has density $f(r) = re^{-\frac{1}{2}r^2}$, $r>0$

← called Rayleigh RV

b) Using Rayleigh distribution we showed if $X, Y \overset{iid}{\sim} N(0,1)$

① $\sqrt{X^2+Y^2} = R$

② $\phi(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}z^2}$

③ $E(Z) = 0$

④ $SD(Z) = 1$

c) for $R_1, R_2, R_3 \overset{iid}{\sim} Ray \Rightarrow \min(R_1, R_2, R_3) \sim \frac{1}{\sqrt{3}} Ray$

**ex**

Let $R_1, R_2, R_3, R_4 \overset{iid}{\sim} Ray$

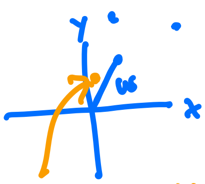
let $W = \min(R_1, R_2, R_3) \sim \frac{1}{\sqrt{3}} Ray$

Find $P(R_4 < W)$

Hint: Find $P(R_4^2 < W^2)$

$R_4^2 \sim Exp(\frac{1}{2})$, $\quad W^2 \sim \frac{1}{3} Ray^2 \sim Exp(\frac{3}{2})$, $\quad Ray^2 = Exp(\frac{1}{2})$

Recall
$c\,Exp(\lambda) = Exp(\frac{\lambda}{c})$




Chance you get dart closest to bullseye is 1/4.

we have competing exponentials

$P(R_4 < W) = P(R_4^2 < W^2) = \frac{1/2}{\frac{1}{2} + 3/2} = \boxed{1/4}$

## Today

① Sec 5.3 Sum of independent normals

② Chi square distribution

Sec 5.4

③ Convolution formula for the density of X+Y

## ① Sec 5.3 Sum of independent normals

**Definition of the Normal $(\mu, \sigma^2)$ distribution:**

We know the density of the std normal $\phi(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}$. Make a change of scale $X = \mu + \sigma Z$. By the change of variable rule you can show

$$f_X(x) = \frac{1}{\sigma}\phi\left(\frac{x-\mu}{\sigma}\right) = \frac{1}{\sqrt{2\pi}\,\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

**MGF Review** (lecture 24)

Recall the MGF of a RV $X$ is $M(t) = E(e^{Xt})$.

**MGF of std normal**

$X \sim N(0,1)$, $M(t) = e^{\frac{t^2}{2}}$ for all $t$

**Properties of MGF**

$X, Y$ are independent if $M_{X+Y}(t) = M_X(t) M_Y(t)$

for $t$ in an interval containing zero

$M_X(t) = M_Y(t)$ iff $X \overset{d}{=} Y$

same distribution

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

ex Use the properties of MGF to find the MGF of $X \sim N(\mu, \sigma^2)$

Hint: let $Z \sim N(0,1)$, $\mu \in \mathbb{R}$, $\sigma > 0$ and $X = \mu + \sigma Z$

$M_X(t) = M_{\mu+\sigma Z}(t) = e^{\mu t} M_Z(\sigma t) = e^{\mu t} e^{\frac{1}{2}(\sigma t)^2}$

$= \boxed{e^{\mu t} e^{\frac{\sigma^2 t^2}{2}} \text{ for all } t \in \mathbb{R}}$

if $X \sim N(0, 2)$ ← $\sigma^2$

$M_X(t) = e^{t^2}$

ex Use MGF to prove that the sum of two independent std normals is $N(0,2)$.

hint

$$X \sim N(\mu, \sigma^2) \Rightarrow M_X(t) = e^{\mu t} e^{\frac{\sigma^2 t^2}{2}}$$

$$M_{Z_1+Z_2}(t) = M_{Z_1}(t) M_{Z_2}(t)$$

$$= e^{t^2/2} \cdot e^{t^2/2} = e^{t^2} \text{ for all } t$$

$\uparrow$ MGF of $N(0,2)$ for all $t$.

$$\Rightarrow Z_1 + Z_2 \sim N(0,2)$$

Thm Let $X_1 \sim N(\mu_1, \sigma_1^2)$, $X_2 \sim N(\mu_2, \sigma_2^2)$ } indep.

then $aX_1 + bX_2 \sim N(a\mu_1 + b\mu_2, a^2\sigma_1^2 + b^2\sigma_2^2)$

Pf/ $M_{X_1}(t) = e^{\mu_1 t} e^{\sigma_1^2 \frac{t^2}{2}}$

$M_{aX_1}(t) = M_{X_1}(at) = e^{\mu_1 a t} e^{\sigma_1^2 a^2 \frac{t^2}{2}}$

Then $M_{aX_1 + bX_2}(t) = M_{aX_1}(t) M_{bX_2}(t)$

$= e^{\mu_1 a t} e^{\sigma_1^2 a^2 \frac{t^2}{2}} \cdot e^{\mu_2 b t} e^{\sigma_2^2 b^2 \frac{t^2}{2}}$

$= e^{(\mu_1 a + \mu_2 b)t} e^{(\sigma_1^2 a^2 + \sigma^2 b^2)\frac{t^2}{2}}$

by uniqueness of MGF

$aX_1 + bX_2 \sim N(\mu_1 a + \mu_2 b, \sigma_1^2 a^2 + \sigma^2 b^2)$

$\square$

2. Let $X \sim N(68, 3^2)$ and $Y \sim N(66, 2^2)$ be independent. $P(X > Y)$ equals

**a** $1 - \Phi(\frac{0-2}{\sqrt{3^2+2^2}})$

**b** $1 - \Phi(\frac{0-2}{3^2+2^2})$

**c** $1 - \Phi(\frac{68-66}{\sqrt{3^2+2^2}})$

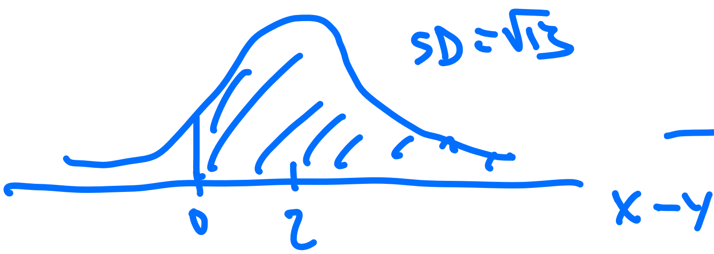
**d** none of the above

$P(x > y) = P(x - y > 0)$

$x - y \sim N(68-66, 3^2+2^2) = N(2, 13)$

$SD = \sqrt{13}$

$Z = \frac{(x-y)-2}{\sqrt{13}}$





$\frac{0-2}{\sqrt{13}}$

area is

$1 - \Phi\left(\frac{0-2}{\sqrt{13}}\right)$

② Sec 5.3 Chi-square distribution

**Fact** see end of lecture notes

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

$$Z^2 \sim Gamma\left(\tfrac{1}{2}, \tfrac{1}{2}\right)$$

Recall that if $T \sim Gamma(r, \lambda)$,

$$M_T(t) = \left(\frac{\lambda}{\lambda - t}\right)^r, \quad t < \lambda$$

Hence $M_{Z^2}(t) = \left(\dfrac{\frac{1}{2}}{\frac{1}{2} - t}\right)^{1/2}, \quad t < 1/2$

Let $Z_1, \dots, Z_n \overset{iid}{\sim} N(0,1)$

$$M_{Z_1^2 + \dots + Z_n^2}(t) = \left(\frac{\frac{1}{2}}{\frac{1}{2} - t}\right)^{1/2 \cdot n}, \quad t < \frac{1}{2}$$

By uniqueness of MGF

$$Z_1^2 + \dots + Z_n^2 \sim Gamma\left(\tfrac{n}{2}, \tfrac{1}{2}\right)$$

called chi square distribution with n degrees of freedom,

$\chi^2_n$, with n degrees of freedom

ex Let $X, Y \overset{iid}{\sim} N(0,1)$

Let $R = \sqrt{X^2 + Y^2}$ be Raleigh distribution.

Then $R^2 = X^2 + Y^2 \sim \chi^2_2 = Exp(1/2) = Gamma(1, 1/2)$

(3) Sec 5.4 The Density Convolution Formula

ex Let $X$ and $Y$ be discrete RVs
taking values $\{0,1,2,3,4,5,6\}$.
Let $S = X+Y$.
Find the probability mass function of $S$.

$$P(S=3) = P(X=0, Y=3-0) + P(X=1, Y=3-1) + P(X=2, Y=3-2) + P(X=3, Y=3-3)$$

$$P(S=s) = \sum_{x=0}^{s} P(X=x, Y=s-x)$$

convolution formula.

## Appendix

If $Z \sim N(0,1)$, then $Z^2 \sim \text{Gamma}(\frac{1}{2}, \frac{1}{2})$

Proof/

$\lambda > 0$, pos integer $r$,

gamma $(r, \lambda)$ density

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

let $Z$ = std normal

$X = Z^2$ change of variable rule.

Find $f_X(x) = \frac{1}{\sqrt{2\pi}} x^{-1/2} e^{-\frac{1}{2}x}, \quad x > 0$

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

$\sqrt{\pi}$ $\Gamma(\frac{1}{2})$

$\Rightarrow X \sim \text{gamma}(\frac{1}{2}, \frac{1}{2})$

$\square$