

STUDENT'S t -distribution.

Let $Z \sim N(0,1)$, $U \sim \chi^2(\underline{m})$ be independent r.v.s

Then

$$T = \frac{Z}{\sqrt{U/m}} \sim \underbrace{t(\underline{m})}_{t\text{-student distr. with } m \text{ d.o.f.}}$$

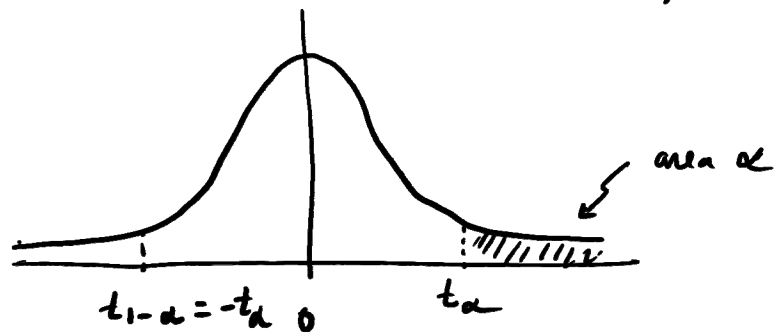
VERY IMPORTANT / KEY EXAMPLE

X_1, X_2, \dots, X_n random sample from a $N(\mu, \sigma^2)$ distribution, then:

$$\left. \begin{aligned} (1) \quad \bar{X}_n &\sim N\left(\mu, \frac{\sigma^2}{n}\right) \Rightarrow Z = \frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} \sim N(0,1) \\ (2) \quad U = \frac{(n-1)S^2}{\sigma^2} &\sim \chi^2(\underline{n-1}) \end{aligned} \right\} \begin{array}{l} Z \text{ and } \frac{(n-1)S^2}{\sigma^2} \\ \text{are independent r.v.} \end{array}$$

$$(3) \quad T = \frac{Z}{\sqrt{U/(n-1)}} = \frac{\frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}}}{\sqrt{\frac{(n-1)S^2}{\sigma^2}/(n-1)}} \Rightarrow T = \frac{\bar{X}_n - \mu}{S/\sqrt{n}} \sim t(n-1)$$

graph of t -distributions looks bell shaped



$$P(T \geq t_\alpha) = \alpha$$

$$t_{1-\alpha} = -t_\alpha$$

$$\text{as } n \rightarrow \infty \quad t(n) \xrightarrow{D} N(0, 1)$$

M.G.F TECHNIQUE:

Def of m.g.f (from 3501)

X is a r.v with pmf / pdf $f(x)$.

m.g.f of X is $M_X(t) = E[e^{tX}] =$

$$\begin{cases} \int_{-\infty}^{\infty} e^{tx} \cdot f(x) dx, & X \text{ continuous} \\ \sum_x e^{tx} f(x), & X \text{ discrete} \end{cases}$$

from most of relevant families
of r.v.s we can pick $M_X(t)$ from the formula sheet.

↓ VERY IMPORTANT: X_1, X_2, \dots, X_n ^{iid} random sample from a distribution with m.g.f $M_X(t)$

To find the m.g.f of $Y = \sum_{i=1}^n X_i$;

$$\begin{aligned} M_Y(t) &= E[e^{tY}] = E[e^{t(X_1 + X_2 + \dots + X_n)}] = E[e^{tX_1} \cdot e^{tX_2} \cdot \dots \cdot e^{tX_n}] \\ &\stackrel{\text{def of } M_Y}{=} \stackrel{\text{def of } Y}{=} \stackrel{\text{prop. of exp}}{=} \stackrel{\text{independence}}{=} \stackrel{\text{independence of } X_1, \dots, X_n}{=} E[e^{tX_1}] \cdot \dots \cdot E[e^{tX_n}] \\ &= M_X(t) \cdot \dots \cdot M_X(t) \\ &= (M_X(t))^n \end{aligned}$$

Sec. 5.4 Ex. 4

Let $X_1 \sim \text{Poisson}(\mu_1)$, $X_2 \sim \text{Poisson}(\mu_2)$, ..., $X_n \sim \text{Poisson}(\mu_n)$, with $\mu_i > 0$ for $i=1, 2, \dots, n$,
be independent r.v.s.

To show that $Y = \sum_{i=1}^n X_i \sim \text{Poisson}(\mu_1 + \mu_2 + \dots + \mu_n)$ we can use
the mg.f technique:

$$M_Y(t) = E[e^{tY}] = E\left[e^{t \sum_{i=1}^n X_i}\right] = E\left[\underbrace{e^{tX_1} \cdot e^{tX_2} \cdots e^{tX_n}}_{\prod_{i=1}^n e^{tX_i}}\right]$$

$$\begin{aligned} \text{independence} \leadsto & \underbrace{E[e^{tX_1}] \cdot E[e^{tX_2}] \cdots E[e^{tX_n}]}_{\prod_{i=1}^n E[e^{tX_i}]} = M_{X_1}(t) \cdot M_{X_2}(t) \cdots M_{X_n}(t) \\ & = e^{\mu_1(e^t-1)} \cdot e^{\mu_2(e^t-1)} \cdots e^{\mu_n(e^t-1)} \\ & = \exp\left(\mu_1(e^t-1) + \mu_2(e^t-1) + \cdots + \mu_n(e^t-1)\right) = e^{(\mu_1 + \mu_2 + \cdots + \mu_n)(e^t-1)} \end{aligned}$$

CONCLUSION

$$\text{Since } M_Y(t) = \exp \left((\mu_1 + \mu_2 + \dots + \mu_n)(e^t - 1) \right)$$

is of the form $\underbrace{e^{\lambda(e^t - 1)}}_{\text{m.g.f of Poisson}}$ with $\lambda = \mu_1 + \mu_2 + \dots + \mu_n$

then $Y \sim \text{Poisson}(\mu_1 + \mu_2 + \dots + \mu_n)$

6.3.3 $Y_1 < Y_2 < \dots < Y_5$ order statistics of from exp. dist. with
 mean $\theta = 3$ associated with x_1, x_2, \dots, x_5 }

b) pdf $f(x) = \frac{1}{3} e^{-x/3}, x > 0$

$P(Y_4 < 5) = ??$

cdf $\underline{\underline{F(x) = 1 - e^{-x/3}, x > 0}}$

Define another r.v., call it (N_1) representing the number of observations
 out of $\underline{x_1, x_2, \dots, x_5}$ $n=5$ observations that have value less than 5.

$N \sim \text{Binomial}(n, p)$ where $\begin{cases} n=5 \\ p = P(x_i < 5) = F(5) = 1 - e^{-5/3} \end{cases}$

$\underline{\underline{P(Y_4 < 5) = P(N=4 \text{ or } N=5) = \sum_{k=4}^5 \binom{5}{k} (1 - e^{-5/3})^k \cdot (e^{-5/3})^{5-k}}}$
 = evaluate

$$c) P(1 < Y_1) = P(1 < \min\{X_1, X_2, \dots, X_5\})$$

$$= P(1 < X_1, 1 < X_2, \dots, 1 < X_5)$$

independence ↙

$$= P(1 < X_1) \cdot P(1 < X_2) \dots P(1 < X_5)$$

↑ ↗
all have the same dist.

$$= \left(P(1 < X_1) \right)^5 = \left(P(X_1 > 1) \right)^5$$

$$= \left(1 - \underbrace{P(X_1 \leq 1)}_{F_{X_1}(1)} \right)^5 = \left(1 - (1 - e^{-1/3}) \right)^5$$

$$= e^{-5/3}$$

pdf: $f(x) = \frac{1}{3} e^{-x/3}, \quad \underline{x > 0}$

cdf = ?? Take $x > 0$;

$$F(x) = P(\underline{X \leq x}) = \int_{-\infty}^x f(u) du = \int_0^x \frac{1}{3} e^{-u/3} du$$

def of cdf

X is continuous r.v.

$$= \left[-e^{-u/3} \right]_{u=0}^{u=x}$$

$$= -e^{-x/3} - (-e^0)$$

$$= 1 - e^{-x/3}$$

Sec. 5.5 Ex 16

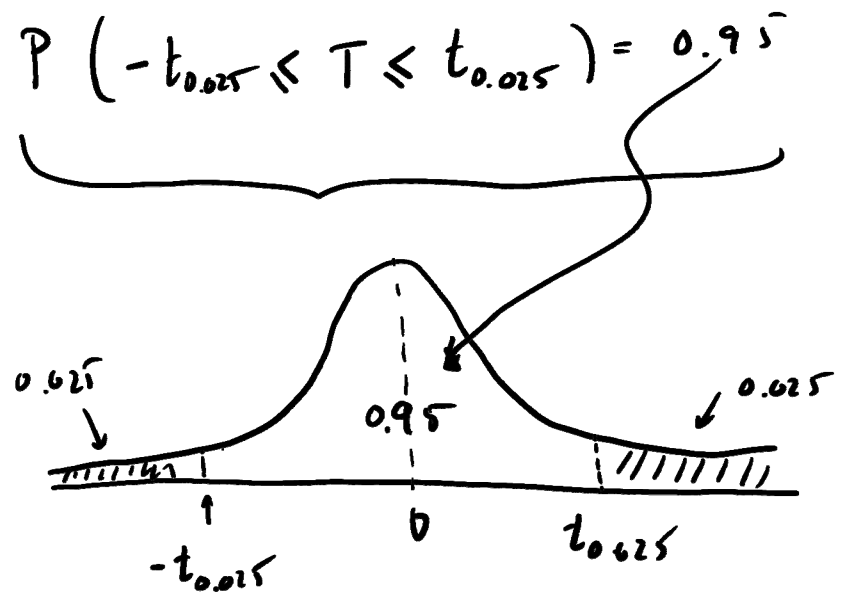
Let $n=9$ and $T = \frac{\frac{\bar{X} - \mu}{S/\sqrt{n}}}{\sqrt{\frac{(n-1)S^2}{S^2/(n-1)}}} = \frac{\bar{X} - \mu}{S/\sqrt{n}} \sim t(n-1)$

a) let us find $t_{0.025}$ so that
check the table for

$t_{0.025}$ when $\nu = n-1 = 8$

to get $t_{0.025} = 2.306$

CONCLUSION: $P(-2.306 \leq T \leq 2.306) = 0.95$



$$b) \quad -t_{0.025} \leq T \leq t_{0.025} \quad (t_{0.025} = 2.306)$$

$$-t_{0.025} \leq \frac{\bar{X} - \mu}{S/\sqrt{n}} \leq t_{0.025} \quad (n=9)$$

Multiply by
 $\frac{S}{\sqrt{n}}$

$$-t_{0.025} \cdot \frac{S}{\sqrt{n}} \leq \bar{X} - \mu \leq t_{0.025} \cdot \frac{S}{\sqrt{n}}$$

subtract
 \bar{X}

$$-\bar{X} - t_{0.025} \frac{S}{\sqrt{n}} \leq -\mu \leq -\bar{X} + t_{0.025} \frac{S}{\sqrt{n}}$$

multiply
by -1

$$\bar{X} - t_{0.025} \frac{S}{\sqrt{n}} \leq \mu \leq \bar{X} + t_{0.025} \frac{S}{\sqrt{n}}$$

3.3-12. If the moment-generating function of X is given by $M(t) = e^{\underline{500t} + \underline{1250t^2}}$, where $-\infty < t < \infty$, find $P[6,765 \leq \underbrace{(X - 500)^2}_{\mu} \leq 12,560]$.

Note that $M(t)$ is of the form $e^{\mu t + \frac{1}{2} \sigma^2 t^2}$ ← m.g.f of $N(\mu, \sigma^2)$ with

$$\mu = 500 \text{ and } \frac{1}{2} \sigma^2 = 1250, \text{ that is } \sigma^2 = 2500$$

$$\text{This means that } X \sim N(500, 2500) \Rightarrow Z = \frac{X - \mu}{\sigma} \sim N(0, 1)$$

$$\Rightarrow U = Z^2 = \left(\frac{X - \mu}{\sigma} \right)^2 = \frac{(X - 500)^2}{2500} \sim \chi^2(1)$$

$$\text{Then, we find that } P(6,765 \leq (X - 500)^2 \leq 12,560)$$

$$= P\left(\frac{6,765}{2500} \leq \underbrace{\frac{(X - 500)^2}{2500}}_{U \sim \chi^2(1)} \leq \frac{12,560}{2500} \right)$$

$$= P(2.706 \leq U \leq 5.024) = F(5.024) - F(2.706)$$

if we let F be
the cdf of $\chi^2(1)$

table

$$= 0.975 - 0.9 = 0.075$$

$$X \sim N(\mu, \sigma^2) \Rightarrow Z = \frac{X - \mu}{\sigma} \sim N(0, 1)$$

$$\Rightarrow U = Z^2 = \left(\frac{X - \mu}{\sigma} \right)^2 \sim \underline{\underline{\chi^2(1)}}$$

OVERVIEW OF F distr.

If $U \sim \chi^2(\pi_1)$ and $V \sim \chi^2(\pi_2)$ independent

Then $W = \frac{U/\pi_1}{V/\pi_2} \sim F(\pi_1, \pi_2)$ } take this as
the def of F
distribution

PROPERTY : If $W = \frac{U/\pi_1}{V/\pi_2} \sim F(\pi_1, \pi_2) \Rightarrow \frac{1}{W} = \frac{V/\pi_2}{U/\pi_1} \sim F(\pi_2, \pi_1)$

IMPORTANT APPLICATION / EXAMPLE

Let X_1, \dots, X_m random sample from $N(\mu_x, \sigma_x^2)$ AND Y_1, \dots, Y_m random sample from $N(\mu_y, \sigma_y^2)$
independent then

$$\begin{aligned} (1) U &= (m-1)S_x^2/\sigma_x^2 \sim \chi^2(m-1) \\ (2) V &= (m-1)S_y^2/\sigma_y^2 \sim \chi^2(m-1) \end{aligned} \Rightarrow W = \frac{\frac{(m-1)S_x^2}{\sigma_x^2} / (m-1)}{\frac{(m-1)S_y^2}{\sigma_y^2} / (m-1)} = \frac{S_x^2}{S_y^2} \cdot \frac{\sigma_y^2}{\sigma_x^2} \sim F(m-1, m-1)$$

To find $F_{1-\alpha}(n_1, n_2)$

we do

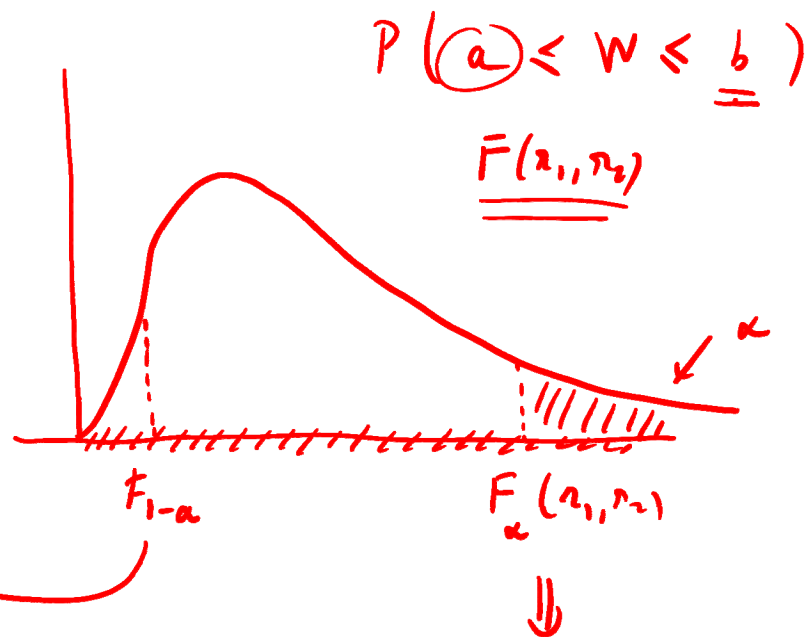
$$F_{1-\alpha}(n_1, n_2) = \frac{1}{F_{\alpha}(n_2, n_1)}$$

because

$$P(W \leq F_{1-\alpha}(n_1, n_2)) = \alpha$$

$$P\left(\frac{1}{W} > \frac{1}{F_{1-\alpha}(n_1, n_2)}\right) = \alpha$$

$$\frac{1}{F_{1-\alpha}(n_1, n_2)} = F_{\alpha}(n_2, n_1)$$



$$P(W > F_{\alpha}(n_1, n_2)) = \alpha$$