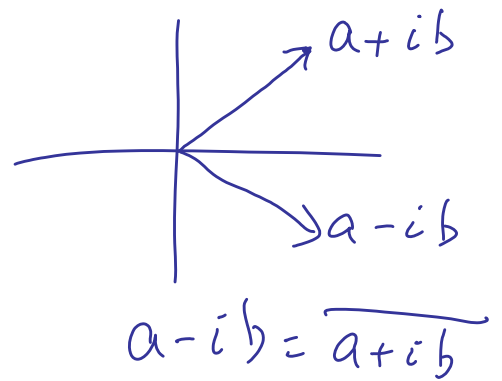


$$e^{i\theta} = \cos\theta + i \overset{\sqrt{-1}}{\downarrow} \sin\theta$$

$$\overline{e^{i\theta}} = e^{-i\theta}$$



$$|e^{i\theta_2} - e^{i\theta_1}| \leq |\theta_2 - \theta_1|$$

$$(a+ib)\overline{(a+ib)} = a^2 + b^2 = |a+ib|^2$$

cf $c(t) = E(e^{itX}) = E(\cos tX) + i E(\sin tX)$

Note $c(0) = 1$

$$c_{X+Y}(z) = c_X(z) c_Y(z) \quad \text{if } X \text{ \& } Y \text{ ind}$$

eg $X \sim \text{Cauchy}$

$$f(x) = \frac{1}{\pi(1+x^2)}$$

$$E(\sin tX) = \int_{-\infty}^{\infty} \frac{\sin tx}{\pi(1+x^2)} dx = 0$$

$$E(\cos tX) = \int_{-\infty}^{\infty} \frac{\cos tx}{\pi(1+x^2)} dx \stackrel{\text{tricky}}{=} e^{-|t|}$$

$$c(t) = e^{-|t|}$$

Let $Y = -X$. Then $c_Y(t) = E(e^{itY}) = E(e^{it(-1)X}) = c_X(-t) = e^{-|t|}$

Look at $Y = a + bX$

$$\Rightarrow C_Y(t) = e^{iat} C_X(bt)$$

Theorem $C(t)$, $-\infty < t < \infty$ determines the dist'n.

Theorem $m(t) = E(e^{tX})$ determines the dist'n if A is finite in a neighborhood of $t = 0$.

Remark In the cts case the Inversion

Theorem gives no formula for $f(x)$ in terms of $C(t)$. N/A so much for mgf's.

$$\left. \begin{array}{l} X \sim \text{Cauchy} \\ Y = X \end{array} \right\} W = X + Y$$

$$C_W(t) = C_{2X}(t) = C_X(2t) = e^{-2|t|}$$

$$C_X(t) C_Y(t) = e^{-2|t|} \text{ in this case}$$

so that in this case $C_{X+Y}(t) = C_X(t) C_Y(t)$

but X & Y are not independent.

vec $\tilde{Y} = \begin{pmatrix} Y_1 \\ \vdots \\ Y_m \end{pmatrix}$ $\tilde{t}'\tilde{Y} = t_1 Y_1 + \dots + t_m Y_m$

$$C_{\tilde{Y}}(\tilde{t}) = E\left[e^{i(\tilde{t} \cdot \tilde{Y})}\right]$$

$$= E\left[e^{i t_1 Y_1} \dots e^{i t_m Y_m}\right]$$

Theorem If $C_{\tilde{Y}}(\tilde{t}) = C_{Y_1}(t_1) \dots C_{Y_m}(t_m)$, $\forall \tilde{t}$
 then Y_1, \dots, Y_m are independent

Note Also true for mgf's $M_{\tilde{Y}}(\tilde{t}) = E(e^{\tilde{t} \cdot \tilde{Y}})$

" " " d.f.'s

$$F_{\tilde{Y}}(y) = P(\tilde{Y} \leq y) = \underbrace{P(Y_1 \leq y_1)}_{F_{Y_1}(y_1)} \dots \underbrace{P(Y_m \leq y_m)}_{F_{Y_m}(y_m)}$$

" " for pdf's

If \tilde{Y} is cto then \exists a pdf $f(y)$ s.t.

$$E[g(\tilde{Y})] = \int g(y) f(y) dy$$

real

Note Knowing $E[g(\tilde{Y})]$, $\forall g$, determines the dist'n.

So if we have 2 pdf's $f_1(y) + f_2(y)$
st

$$\int g(y) f_1(y) dy = \int g(y) f_2(y) dy, \quad \forall g$$

$$\Rightarrow f_1 = f_2$$

$$\forall f(y) = f_1(y_1) \dots f_m(y_m)$$

$$\Rightarrow E[g_1(Y_1) \dots g_m(Y_m)] = \int g_1(y_1) \dots g_m(y_m) f_1(y_1) \dots f_m(y_m) dy$$

$$= \int g_1(y_1) f_1(y_1) dy_1 \dots \int g_m(y_m) f_m(y_m) dy_m$$

$$= E(g_1(Y_1)) \dots E(g_m(Y_m)), \quad \forall g_1, \dots, g_m$$

$\Rightarrow Y_1, \dots, Y_m$ are ind

(also true in the discrete case)

$$F(y) = P(Y_1 \leq y_1, \dots, Y_m \leq y_m)$$

In the cts case this will be an integral &

$$\frac{\partial^m}{\partial y_1 \dots \partial y_m} F(y) = f(y) \quad (*)$$

& if $F(y) = F_1(y_1) \dots F_m(y_m)$ & (*) holds
then $f(y) = f_1(y_1) \dots f_m(y_m) \Rightarrow$ independence

$$\left. \begin{aligned}
 E(e^{t^T Y} | X) &= E(e^{t^T Y}) \\
 E(e^{it^T Y} | X) &= E(e^{it^T Y}) \\
 F(y | X) &= F(y) \\
 \text{etc} \\
 \vdots
 \end{aligned} \right\} \Rightarrow \text{ind of } X \text{ \& } Y$$

Can use this to show that X_1, \dots, X_n iid $N(\mu, \sigma^2)$

$$\Rightarrow \bar{X} \text{ \& } S^2 = \frac{1}{n} \sum (X_i - \bar{X})^2$$

are ind (see web for the calculation)

Change of variables

$$\underbrace{X}_{\tilde{m} \times 1} \text{ \& } \underbrace{Y}_{\tilde{m} \times 1} = \underbrace{h}_{1-1}(\underbrace{X}_{\tilde{m}}) \quad \text{then}$$

$$f_Y(y) = \int_{\tilde{X}} f_X(h^{-1}(y)) \left| \det \left(\frac{d\tilde{x}}{dy'} \right) \right|$$

where $\frac{d\tilde{x}}{dy'} = \begin{pmatrix} \frac{dx_1}{dy_1} & \frac{dx_1}{dy_2} & \dots & \frac{dx_1}{dy_m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{dx_m}{dy_1} & \frac{dx_m}{dy_2} & \dots & \frac{dx_m}{dy_m} \end{pmatrix} \leftarrow \begin{matrix} \text{Jacobian} \\ \text{matrix} \end{matrix}$

$m \times m$

$$E[g(\underline{X})] = \int g(\underline{y}) \underbrace{f_{\underline{Y}}(\underline{y})}_{\text{pdf of } \underline{Y}} d\underline{y}$$

||

$$E[g \circ h(\underline{X})] = \int g(h(\underline{x})) \underbrace{f_{\underline{X}}(\underline{x})}_{\text{pdf of } \underline{X}} d\underline{x}$$

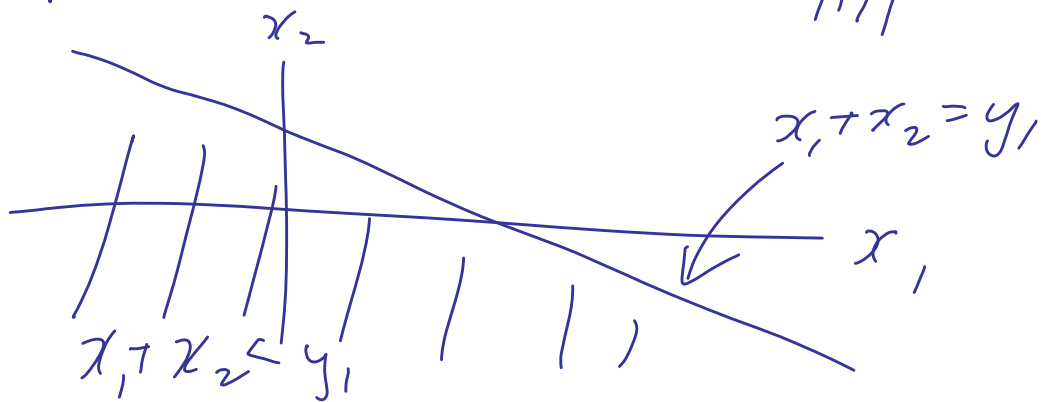
|| ∇g

$$\stackrel{\underline{u} = h(\underline{x})}{=} \int g(\underline{u}) \underbrace{f_{\underline{X}}(h^{-1}(\underline{u})) \left| \det \left(\frac{\partial \underline{x}}{\partial \underline{u}} \right) \right|}_{\text{pdf of } \underline{X} \text{ transformed}} d\underline{u}$$

& so we use our formula.

eg X_1 & X_2 ind & $Y_1 = X_1 + X_2$

\downarrow $f_1(x_1)$ \downarrow $f_2(x_2)$ $\underbrace{f_1(x_1) f_2(x_2)}_{\text{joint pdf}}$
 $P(Y_1 \leq y_1) = \int \int f(x_1, x_2) dx_1 dx_2$



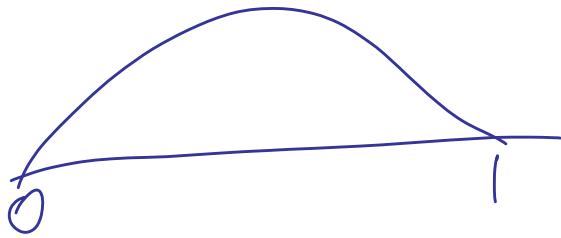
get $F(y_1)$ & then $f(y_1) = F'(y_1)$.

Or

$$\left. \begin{aligned} Y_1 &= X_1 + X_2 \\ Y_2 &= X_1 \end{aligned} \right\} \begin{aligned} X &\rightarrow Y \\ &\text{- apply change of variables} \\ &\text{- } f(y_1, y_2) \rightarrow f(y_1) = \int_{-\infty}^{\infty} f(y_1, y_2) dy_2 \end{aligned}$$

Problem $\left. \begin{array}{l} X \sim \text{gamma}(n_1, \lambda) \\ \text{and } Y \sim \text{'' } (n_2, \lambda) \end{array} \right\} W = \frac{X}{X+Y}$

Then W is a beta rv.



$Z \sim N(0, 1)$; $E(e^{tZ}) = e^{t^2/2}$

\Rightarrow pdf is $f(z) \propto e^{-z^2/2}$

$Y \sim N(\mu, \sigma^2)$; $E(e^{tY}) = e^{\mu t} e^{\sigma^2 t^2/2}$

$Y \stackrel{d}{=} \mu + \sigma Z$

Now the dist'n of Y is determined by the dist'n of all $\underline{c}' \underline{Y}$.

Lemma if \underline{X} has mean $\underline{\mu} = E(\underline{X})$ & $\Sigma = \text{Var}(\underline{X}) = \{ \text{cov}(X_i, X_j) \}$ then

(1) $E(A\underline{X} + \underline{b}) = A E(\underline{X}) + \underline{b}$

(2) $\text{Var}(A\underline{X} + \underline{b}) = A \text{Var}(\underline{X}) A'$

proof \downarrow

Def'n \underline{Y} is $N(\underline{\mu}, \underline{\Sigma})$ if
 $\underline{c}' \underline{Y}$ is $N(\underline{c}' \underline{\mu}, \underline{c}' \underline{\Sigma} \underline{c})$, $\forall \underline{c}$

Theorem $\underline{Y} \sim N(\underline{\mu}, \underline{\Sigma})$
 $\Rightarrow A \underline{Y} + \underline{b} \sim N(A \underline{\mu} + \underline{b}, A \underline{\Sigma} A')$

Proof: Easy \leftarrow do it

mgf of a $N(\underline{\mu}, \underline{\Sigma})$

$$\underline{Y} \sim N(\underline{\mu}, \underline{\Sigma})$$

$$m(\underline{t}) = E(e^{\underline{t}' \underline{Y}})$$

Now $\underline{t}' \underline{Y} \sim N(\underline{t}' \underline{\mu}, \underline{t}' \underline{\Sigma} \underline{t})$

$$\Rightarrow E(e^{\underline{t}' \underline{Y}}) = e^{\underline{t}' \underline{\mu}} e^{\underline{t}' \underline{\Sigma} \underline{t} / 2}$$

Now $\underline{\Sigma} = T T'$ ($\underline{\Sigma}^{\frac{1}{2}}$ $\underline{\Sigma}^{\frac{1}{2}}$) \swarrow diag elements ≥ 0

$$\underline{\Sigma} = Q D Q' = \underbrace{Q D^{\frac{1}{2}} Q' Q D^{\frac{1}{2}} Q'}_{\underline{\Sigma}^{\frac{1}{2}}}$$

Take Z_1, \dots, Z_m to be $N(0, 1)$ & i.i.d then
 if $\underline{z} = \begin{pmatrix} z_1 \\ \vdots \\ z_m \end{pmatrix}$ we have $\underline{\mu} + T \underline{z} \sim N(\underline{\mu}, \Sigma)$

The pdf of \underline{z} is $\left(\frac{1}{\sqrt{2\pi}}\right)^m e^{-|\underline{z}|^2/2}$ & if Σ

has an inverse then so does T & then
 the pdf of

$$\underline{w} = \underline{\mu} + T \underline{z}$$

$$\& \text{ so } \underline{z} = T^{-1}(\underline{w} - \underline{\mu}) \Rightarrow \frac{\partial \underline{z}}{\partial \underline{w}'} = T^{-1}$$

$$\Rightarrow \det\left(\frac{\partial \underline{z}}{\partial \underline{w}'}\right) = \frac{1}{\det(T)} = \frac{1}{\sqrt{|\Sigma|}}$$

Now use the change of variable formula
 to get

$$f(\underline{y}) \propto e^{-\frac{1}{2}(\underline{y} - \underline{\mu})' \Sigma^{-1} (\underline{y} - \underline{\mu})}$$

Now let $\underline{v} \sim N(\underline{\mu}, \Sigma)$. Then

$$m_{\underline{v}}(\underline{t}) = e^{-\frac{1}{2} \underline{\mu}' \underline{t}} e^{-\frac{1}{2} \underline{t}' \Sigma \underline{t}}$$

so that Σ diagonal \Rightarrow the components
 are independent

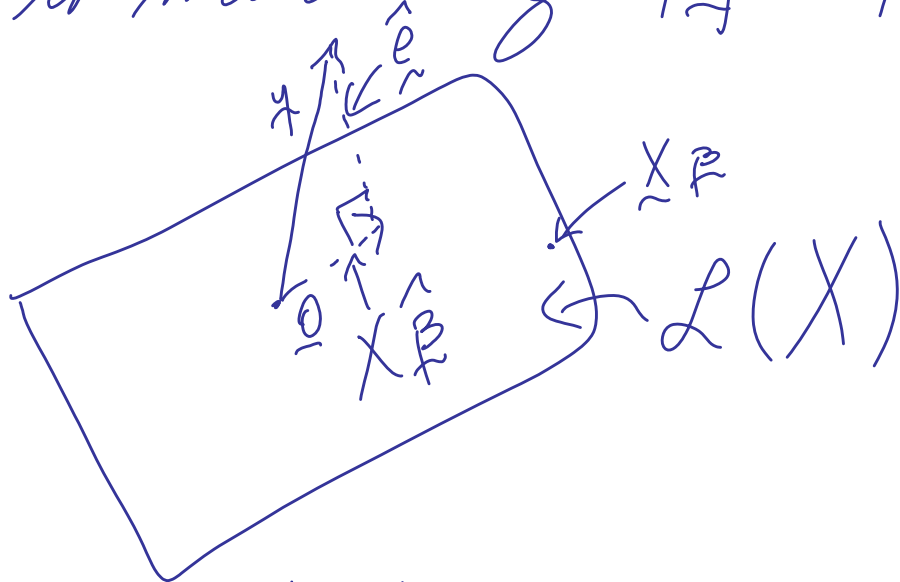
eg $y = X\beta + e$ $e \sim N(0, \sigma^2 I)$

\uparrow \uparrow
 $m \times n$ $n \times 1$
 \uparrow known

y_1, \dots, y_m iid $N(\mu, \sigma^2)$. Then

$$y = X \begin{matrix} \mu \\ \beta \\ (n=1) \end{matrix} + e$$

Choose $\hat{\beta}$ to minimize $\|y - X\hat{\beta}\|^2$



$$X\hat{\beta} = X(X'X)^{-1}X'y$$

projection matrix ← call it P

Notice $P = P'$, $P = P^2$. It is idempotent. Also, since

$c'Pc \geq 0$ (clearly?) we have $P = QDQ'$ where $QQ' = Q'Q = I$ + D is diagonal with ≥ 0 diagonal elements

$$\text{Now } P^2 = Q D Q' Q D Q' \\ = Q D^2 Q' = P = Q D Q'$$

so that $Q D^2 Q' = Q D Q' \Rightarrow D^2 = D$ & hence the diagonal terms of D are 0's & 1's. The # of 1's will be the rank of P which in this case is also the rank of X & of $X'X$.

Set $\hat{y} = X \hat{\beta} = P y$. Then $\hat{e} = y - \hat{y} = (I - P) y$. $I - P$ is the projection matrix for $L(X)^\perp$ - the subspace \perp to $L(X)$. If X has rank r then $I - P$ will have rank $n - r$. Now

$$\begin{pmatrix} \hat{y} \\ \hat{e} \end{pmatrix} = \begin{pmatrix} P \\ I - P \end{pmatrix} y$$

so that this is a vector normal. We can calculate its variance to be

$$\text{Var} \begin{pmatrix} \hat{y} \\ \hat{e} \end{pmatrix} = \sigma^2 \begin{pmatrix} P^2 & 0 \\ 0 & (I - P)^2 \end{pmatrix} = \sigma^2 \begin{pmatrix} P & 0 \\ 0 & I - P \end{pmatrix}$$

& hence \hat{y} & \hat{e} are independent. In the special case of a sample from a $N(\mu, \sigma^2)$ we have

$$\hat{y} = \bar{y} \mathbf{1} \quad \& \quad \hat{e} = y - \bar{y} \mathbf{1}$$

being independent so that \bar{y} and $|y - \bar{y} \mathbf{1}|^2 = \sum_{k=1}^n (y_k - \bar{y})^2$ are independent.

Notice $|\hat{e}|^2 = |(I - P) y|^2 = |Q D Q' y|^2$, where

D has $m-r$ diagonal 1's + r diagonal 0's. Since

$$(I-P)y = (I-P)X\beta + (I-P)e = 0 + (I-P)e = (I-P)e$$

we have

$$\begin{aligned} |e|_r^2 &= |QDQ'e|_r^2 = e_r' QDQ'QDQ'e \\ &= e_r' D e_r \quad (D^2=D) \\ &\stackrel{d}{=} \sigma^2 (Z_1^2 + \dots + Z_{m-r}^2), \end{aligned}$$

where Z_1, \dots, Z_{m-r} are iid $N(0,1)$. Hence

$$\frac{|e|_r^2}{\sigma^2} \stackrel{d}{=} Z_1^2 + \dots + Z_{m-r}^2$$

+ this is a $\chi^2(m-r)$ rv. In the special problem of a sample of size n from a $N(\mu, \sigma^2)$ we have $\bar{y} \sim N(\mu, \sigma^2/n)$ + this is independent of $\sum_{k=1}^n (y_k - \bar{y})^2 / \sigma^2$ which is $\chi^2(n-1)$. If we set $s^2 = \sum_{k=1}^n (y_k - \bar{y})^2 / (n-1)$ we then have

$$\frac{\bar{y} - \mu}{s/\sqrt{n}} \sim t(n-1)$$

Remark 1 An alternative approach to showing the independence of \bar{y} + s^2 when sampling from a normal uses conditional mgf's + a change of variables. It is given below.

② A derivation of the pdf of a chi-squared rv using the def + its derivative may be found at the end of this document.

eg Let X_1, \dots, X_m be iid $N(\mu, \sigma^2)$.

Then

$$\bar{X} = \frac{X_1 + \dots + X_m}{m} \quad \text{+} \quad S^2 = \sum_{i=1}^m (X_i - \bar{X})^2$$

are independent.

Sol'n We will calculate $E(e^{tS^2} | \bar{X})$
+ show it does not depend on \bar{X} .

We know $\bar{X} \sim N(\mu, \sigma^2/m)$. Now
look at the j 'th pdf of \bar{X}, X_2, \dots, X_m .

We have

$$\bar{x} = \frac{x_1 + \dots + x_m}{m}$$

$$x_2 = x_2$$

\vdots

$$x_m = x_m$$

$$\Rightarrow x_1 = m\bar{x} - (x_2 + \dots + x_m)$$

$$x_2 = x_2$$

\vdots

$$x_m = x_m$$

$$\Rightarrow \frac{\partial \mathcal{L}}{\partial (\bar{x}, x_2, \dots, x_m)} = \begin{pmatrix} m & -1 & -1 & \dots & -1 \\ 0 & 1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & 0 & 1 \end{pmatrix}$$

$$\Rightarrow \det(\quad) = m$$

The pdf of $\underline{x} = \begin{pmatrix} x_1 \\ \vdots \\ x_m \end{pmatrix}$ is

$$f(\underline{x}) = \left(\frac{1}{\sqrt{2\pi} \sigma} \right)^m \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^m (x_i - \mu)^2 \right)$$

$$\text{NB} \quad \sum_{i=1}^m (x_i - \mu)^2 = \underbrace{\sum_{i=1}^m (x_i - \bar{x})^2}_{s^2} + m(\bar{x} - \mu)^2$$

$$\Rightarrow (x_1 - \mu)^2 = s^2 + m(\bar{x} - \mu)^2 - \sum_{i=2}^m (x_i - \mu)^2$$

$$\begin{aligned} \therefore f(\bar{x}, x_2, \dots, x_m) &= f(\underline{x} \text{ in terms of } \begin{pmatrix} \bar{x} \\ x_2 \\ \vdots \\ x_m \end{pmatrix}) \cdot m \\ &= m f(n\bar{x} - x_2 - \dots - x_m, x_2, \dots, x_m) \end{aligned}$$

$$= n \prod (n\bar{x} - x_2 - \dots - x_n) f(x_2) \dots f(x_n)$$

$$= n \left(\frac{1}{\sqrt{2\pi} \sigma} \right)^m \exp \left(-\frac{1}{2\sigma^2} (\Delta^2 + n(\bar{x} - \mu)^2) \right) \quad (*)$$

$$\Rightarrow f(x_2, \dots, x_n | \bar{x})$$

$$= \frac{f(\bar{x}, x_2, \dots, x_n)}{f(\bar{x})}$$

$$= \frac{(*)}{\frac{1}{\sqrt{2\pi}} \frac{1}{\sigma/\sqrt{n}} \exp \left(-\frac{n}{2\sigma^2} (\bar{x} - \mu)^2 \right)}$$

$$= \frac{n \left(\frac{1}{\sqrt{2\pi} \sigma} \right)^m \exp \left(-\frac{\Delta^2}{2\sigma^2} \right)}{\frac{1}{\sqrt{2\pi}} \frac{1}{\sigma/\sqrt{n}} \exp \left(-\frac{n}{2\sigma^2} (\bar{x} - \mu)^2 \right)}$$

$$= \frac{\sqrt{n}}{(\sqrt{2\pi} \sigma)^{m-1}} \exp \left(-\frac{\Delta^2}{2\sigma^2} \right)$$

$$\Rightarrow \int \dots \int e^{-\frac{s^2}{2\sigma^2}} dx_2 \dots dx_m = \frac{(\sqrt{2\pi} \sigma)^{m-1}}{\sqrt{m}}$$

Now

$$E(e^{t s^2 / \sigma^2} | \bar{x})$$

$$= \int \dots \int e^{t s^2 / \sigma^2} c e^{-\frac{s^2}{2\sigma^2}} dx_2 \dots dx_m$$

$$= c \int \dots \int \exp\left(-\frac{s^2}{2\sigma^2} (1-2t)\right) dx_2 \dots dx_m$$

$$= c \int \dots \int \exp\left(-\frac{s^2}{2\sigma_t^2}\right) dx_2 \dots dx_m,$$

where $\sigma_t^2 = \frac{\sigma^2}{1-2t}$ & so we get

$$\frac{c (\sqrt{2\pi} \sigma_t)^{m-1}}{\sqrt{m}} = \frac{\sqrt{m}}{(\sqrt{2\pi} \sigma)^{m-1}} \frac{(\sqrt{2\pi} \sigma_t)^{m-1}}{\sqrt{m}}$$

$$= \left(\frac{\sigma^2}{\sigma^2} \right)^{n-1} = \left(\frac{1}{\sqrt{1-2t}} \right)^{n-1}$$

so that $\frac{S^2}{\sigma^2} \perp \bar{X}$ are

ind \perp hence so are
 $S^2 \perp \bar{X}$.

Remark The above also
yields

$$E\left(e^{t \frac{S^2}{\sigma^2}}\right) = \left(\frac{1}{\sqrt{1-2t}} \right)^{n-1}, \quad t < \frac{1}{2}$$

which is the mgf of a
 $\chi^2(n-1)$.

2 vec \underline{Y}

mgf of \underline{Y} is

$$m(\underline{t}) = E(e^{\underline{t}' \underline{Y}})$$

Fact - $m(\underline{t})$ determines the dist'n if it exists in an open neighborhood of $\underline{0}$

$$- m(\underline{t}) = f'_1(t_1) \cdots f'_n(t_n)$$

\Leftrightarrow components of \underline{Y} are independent

Let Σ be a variance matrix.

Let Z_1, \dots, Z_n be iid $N(0, 1)$

$$\underline{Z} = \begin{pmatrix} Z_1 \\ \vdots \\ Z_n \end{pmatrix}$$

$$\Sigma = \overset{\perp}{Q} D Q' = \Sigma^{\frac{1}{2}} \Sigma^{\frac{1}{2}} = T T'$$

$$\underline{Y} \sim N(\underline{\mu}, \Sigma) \quad \text{if}$$

$$\underline{Y} \stackrel{d}{=} \underline{\mu} + \Sigma^{\frac{1}{2}} \underline{Z}$$

If Σ^{-1} exists then we can easily use a change of variables to get

$$f(\underline{y}) = \left(\frac{1}{\sqrt{2\pi}}\right)^n \frac{1}{\sqrt{\det(\Sigma)}} e^{-\frac{1}{2}(\underline{y}-\underline{\mu})' \Sigma^{-1}(\underline{y}-\underline{\mu})}, \quad \forall \underline{y}$$

The mgf of \underline{Y} is

$$\begin{aligned} E(e^{\underline{t}' \underline{Y}}) &= E(e^{\underline{t}' \underline{\mu} + \underline{t}' \Sigma^{\frac{1}{2}} \underline{Z}}) \\ &= e^{\underline{t}' \underline{\mu}} e^{\underline{t}' \Sigma \underline{t} / 2} \end{aligned}$$

Prop $\underline{Y} \sim N(\underline{\mu}, \Sigma)$

$$\Rightarrow A \underline{Y} + \underline{b} \sim N(A \underline{\mu} + \underline{b}, A \Sigma A')$$

If Easy - use mgf's

So the mgf of a $N(\underline{\mu}, \Sigma)$ is

$$m(\underline{t}) = e^{\underline{t}'\underline{\mu}} e^{-\frac{1}{2}\underline{t}'\Sigma\underline{t}}$$

which "factors out" if $\text{cov}(Y_i, Y_j) = 0$ for $i \neq j$. So for normal vec's independence & uncorrelated are the same.

chi-squared χ^2

$$\underline{Z} \sim N(\underline{0}, I); \quad f(\underline{z}) = \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-|\underline{z}|^2/2}$$

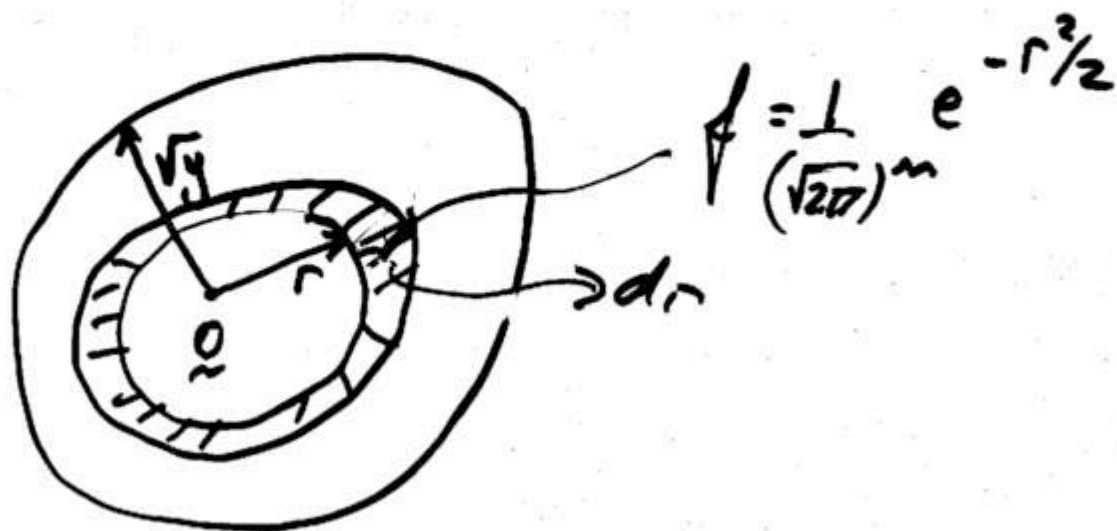
If $Y \stackrel{d}{=} |\underline{Z}|^2$ then we say Y is chi-squared with n degrees of freedom. We want to derive its pdf.

Sol'n Let Z_1, \dots, Z_m be iid $N(0, 1)$; $\underline{Z} = \begin{pmatrix} Z_1 \\ \vdots \\ Z_m \end{pmatrix}$; $Y = |\underline{Z}|^2$

We know that the volume of a ball (sphere) of radius $r = cr^m$
 \Rightarrow surface area $= mcr^{m-1}$.

Let $y > 0$ then

$$\begin{aligned} F(y) &= P(Y \leq y) \\ &= P(|\underline{Z}| \leq \sqrt{y}) \end{aligned}$$



$$f\left(\frac{x}{\sigma}\right) = \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-|x|^2/2}$$

$$F(y) = \int_0^{\sqrt{y}} \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-r^2/2} n c r^{n-1} dr$$

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

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

Now $\int_0^{\infty} f(y) dy = 1$

$$\Rightarrow \int_0^{\infty} \frac{c n}{2} \left(\frac{1}{\sqrt{2\pi}}\right)^n y^{\frac{n}{2}-1} e^{-y/2} dy = 1$$

$$\begin{aligned} u = y/2 \\ \Rightarrow \int_0^{\infty} c n \left(\frac{1}{\sqrt{2\pi}}\right)^n (2u)^{\frac{n}{2}-1} e^{-u} du = 1 \end{aligned}$$

$$\Rightarrow \frac{c m 2^{\frac{m}{2}-1}}{(\sqrt{2\pi})^m} \underbrace{\int_0^{\infty} u^{\frac{m}{2}-1} e^{-u} du}_{\Gamma(\frac{m}{2})} = 1$$

$$\begin{aligned} \Rightarrow c &= \frac{(2\pi)^{m/2}}{2^{\frac{m}{2}-1} m \Gamma(\frac{m}{2})} \\ &= \frac{\pi^{m/2}}{\frac{m}{2} \Gamma(\frac{m}{2})} = \frac{\pi^{m/2}}{\Gamma(\frac{m}{2} + 1)} \end{aligned}$$

= volume of a ^{ball}/sphere of radius 1 in n -dim

Also,

$$Y \sim \text{gamma}\left(\frac{m}{2}, \frac{1}{2}\right)$$

~~~~~

Another Take on the Normal

$$\begin{aligned} X \sim N(\mu, \sigma^2) &\Leftrightarrow m(t) = e^{\mu t + \sigma^2 t^2 / 2} \\ &\Leftrightarrow c(t) = e^{i \mu t - \sigma^2 t^2 / 2} \end{aligned}$$

$$\underline{Y} \sim N(\underline{\mu}, \underline{\Sigma})$$

$$\Leftrightarrow \underline{c}' \underline{Y} \sim N(\underline{c}' \underline{\mu}, \underline{c}' \underline{\Sigma} \underline{c})$$

$$\Leftrightarrow m(\underline{t}) = E(e^{\underline{t}' \underline{Y}}) = e^{\underline{\mu}' \underline{t} + \underline{t}' \underline{\Sigma} \underline{t} / 2}$$

$$\Leftrightarrow c(\underline{t}) = e^{i \underline{\mu}' \underline{t} - \underline{t}' \underline{\Sigma} \underline{t} / 2}$$

Theorem

$$\perp \underline{Y} \sim N(\underline{\mu}, \underline{\Sigma}) \Rightarrow A \underline{Y} + \underline{b} \sim N(A \underline{\mu} + \underline{b}, A \underline{\Sigma} A')$$

$$\cong \text{Let } \underline{Y} = \begin{pmatrix} \underline{Y}_1 \\ \underline{Y}_2 \end{pmatrix} \sim N(\underline{\mu}, \underline{\Sigma})$$

$$\underline{Y}_1 \perp \underline{Y}_2 \text{ ind} \Leftrightarrow \Sigma_{12} = 0$$

$$\text{where } \underline{\Sigma} = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}$$

Theorem Suppose $\underline{Y} \sim N(\underline{\mu}, \underline{\Sigma})$ where $\underline{\Sigma}^{-1}$ exists. Then \underline{Y} has pdf

$$(*) \quad f(\underline{y}) = \frac{1}{\sqrt{(2\pi)^n \det(\underline{\Sigma})}} \exp\left[-\frac{1}{2}(\underline{y}-\underline{\mu})' \underline{\Sigma}^{-1}(\underline{y}-\underline{\mu})\right]$$

Proof $\underline{\Sigma}^{-1}$ exists $\Rightarrow \underline{\Sigma} = \underline{T}\underline{T}'$ with \underline{T} triangular + > 0 diagonal terms (so that $\det(\underline{T}) > 0 (= \sqrt{\det(\underline{\Sigma})})$). Now if

$\underline{Z} = \begin{pmatrix} Z_1 \\ \vdots \\ Z_n \end{pmatrix}$ iid $N(0, 1)$ then

$$\underline{\mu} + \underline{T}\underline{Z} \sim N(\underline{\mu}, \underline{\Sigma})$$

Now use the change of variables formula to show $\underline{\mu} + \underline{T}\underline{Z}$ has pdf (*)

QED