

Let's do a general proof. Let \vec{Y} be a random vector with dim n . Let $\vec{\mu} = E(\vec{Y})$

let $A \in \mathbb{R}^{m \times n}$ Recall $\Sigma := \text{Var}(\vec{Y}) = E[\vec{Y}\vec{Y}^T] - E[\vec{Y}]E[\vec{Y}]^T$

$E(A\vec{Y}) = A\vec{\mu}$, $E[\vec{Y}^T A^T] = \vec{\mu}^T A^T$ ← from previous class

$$\text{Var}[A\vec{Y}] = E[A\vec{Y}(A\vec{Y})^T] - E(A\vec{Y})E(A\vec{Y})^T$$

$$= E[A\vec{Y}\vec{Y}^T A^T] - (A\vec{\mu})(A\vec{\mu})^T$$

$$= A E[\vec{Y}\vec{Y}^T] A^T - A\vec{\mu}\vec{\mu}^T A^T$$

$$= A (E[\vec{Y}\vec{Y}^T] A^T - \vec{\mu}\vec{\mu}^T A^T)$$

$$= A (E[\vec{Y}\vec{Y}^T] - \vec{\mu}\vec{\mu}^T) A^T$$

$$= A \Sigma A^T$$

Let $\vec{Z} \sim N_n(\vec{0}, I_n)$, $\vec{X} = \vec{\mu} + A\vec{Z}$

$$\Rightarrow \text{Var}(\vec{X}) = \text{Var}(\vec{\mu} + A\vec{Z}) = \text{Var}(A\vec{Z}) = A I A^T = A A^T = \Sigma$$

Σ is symmetric $\Rightarrow (A A^T)^T = A^T A^T A^T = A A^T$

AKA the

let $\vec{X} \sim N_n(\vec{\mu}, \Sigma)$

$D := (\vec{X} - \vec{\mu})^T \Sigma^{-1} (\vec{X} - \vec{\mu}) \sim ?$ "Mahalanobis Distance"

Remember $\Sigma^{-1} = (A^{-1})^T A^{-1}$ i.e. $\exists A$ such that this is true!

$$\Rightarrow D = (\vec{X} - \vec{\mu})^T (A^{-1})^T A^{-1} (\vec{X} - \vec{\mu}) = ((\vec{X} - \vec{\mu}) A^{-1})^T (A^{-1} (\vec{X} - \vec{\mu})) = \vec{Z}^T \vec{Z} \sim \chi_n^2$$

Recall $\vec{Z} = L(\vec{X}) = (\vec{X} - \vec{\mu}) A^{-1}$ ↑

Beyond Given Σ , how to find A ?

diag of $\Sigma = P^T O P$ diagonal

$= P^T O^{\frac{1}{2}} O^{\frac{1}{2}} P$

let $A = P^T O^{\frac{1}{2}}$

$$\vec{Z} \sim N_n(\vec{0}, I_n) \Leftrightarrow Z_1, \dots, Z_n \stackrel{iid}{\sim} N(0,1)$$

$$\phi_{\vec{Z}}(\vec{z}) = E[e^{i\vec{t}^T \vec{Z}}] = \phi_{Z_1}(t_1) \dots \phi_{Z_n}(t_n) = \prod_{i=1}^n e^{-\frac{t_i^2}{2}} = e^{-\frac{1}{2} \sum t_i^2} = e^{-\frac{1}{2} \vec{t}^T \vec{t}}$$

For $A \in \mathbb{R}^{m \times n}$ matrix, $\vec{\mu} \in \mathbb{R}^n$

$$\vec{X} = A\vec{Z} + \vec{\mu} \sim N_n(\vec{\mu}, \Sigma) \text{ where } \Sigma = AA^T$$

$$\begin{aligned} \phi_{\vec{X}}(\vec{x}) &\stackrel{(p2)}{=} e^{i\vec{t}^T \vec{\mu}} \phi_{\vec{Z}}(A^T \vec{t}) = e^{i\vec{t}^T \vec{\mu}} e^{-\frac{1}{2} (A^T \vec{t})^T (A^T \vec{t})} = e^{i\vec{t}^T \vec{\mu} - \frac{1}{2} \vec{t}^T A A^T \vec{t}} \\ &= e^{i\vec{t}^T \vec{\mu} - \frac{1}{2} \vec{t}^T \Sigma \vec{t}} \end{aligned}$$

For any $A \in \mathbb{R}^{m \times n}$, $\vec{\mu} \in \mathbb{R}^n$. Is it possible to derive...

$$\vec{X} = A\vec{Z} + \vec{\mu}$$

$$\text{Seemingly... } \phi_{\vec{X}}(\vec{x}) = e^{i\vec{t}^T \vec{\mu} - \frac{1}{2} \vec{t}^T \Sigma \vec{t}} \Rightarrow \vec{X} \sim N_m(\vec{\mu}, \Sigma)$$

Can this go wrong??

$$= \frac{1}{\sqrt{(2\pi)^m \det(\Sigma)}} e^{-\frac{1}{2} (\vec{x} - \vec{\mu})^T \Sigma^{-1} (\vec{x} - \vec{\mu})}$$

Yes!! $\det(\Sigma)$ must be > 0 ! Otherwise density doesn't exist

You must be able to invert Σ must be

$\Rightarrow \Sigma = AA^T$ and full rank $\Leftrightarrow \Sigma$ is "positive definite"

$\Downarrow \Sigma$ is symmetric

In 342 we prove

$$\text{rank}(\Sigma) = \text{rank}(A) \Rightarrow \Sigma \in \mathbb{R}^{m \times m} \Rightarrow m \leq n$$

Since rank of any matrix \leq # columns...

How: $\vec{X} \sim N_n(\vec{\mu}, \Sigma)$ given

$$\vec{Y} = B\vec{X} + \vec{c} \text{ where } B \in \mathbb{R}^{m \times n}, \vec{c} \in \mathbb{R}^m \quad \vec{Y} \sim ? \text{ Conditions on } B, \vec{c}?$$

$$\vec{X} \sim N_n(\vec{\mu}, \Sigma), \quad X_i \sim ? \quad \text{Use (P9) ...}$$

$$\begin{aligned} \phi_{\vec{X}}\left(\begin{pmatrix} 0 \\ \vdots \\ 0 \\ t \\ 0 \\ \vdots \\ 0 \end{pmatrix}\right) &= e^{i[0 \dots 0 \ t \ 0 \dots 0]\vec{\mu}} - \frac{1}{2}[0 \dots 0 \ t \ 0 \dots 0] \Sigma \begin{pmatrix} 0 \\ \vdots \\ 0 \\ t \\ 0 \\ \vdots \\ 0 \end{pmatrix} \\ &= e^{it\mu_i} - \frac{1}{2}[0 \dots 0 \ t \ 0 \dots 0] \vec{\Sigma}_{\cdot i} \quad \checkmark \text{ the } i\text{th col of } \Sigma \\ &= e^{it\mu_i} - \frac{1}{2}\Sigma_{ii} \quad \checkmark \end{aligned}$$

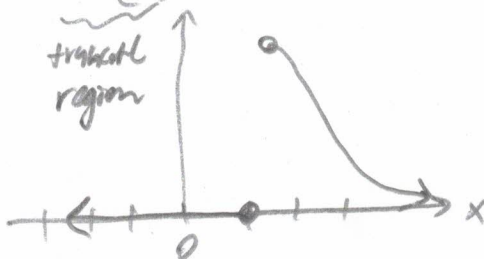
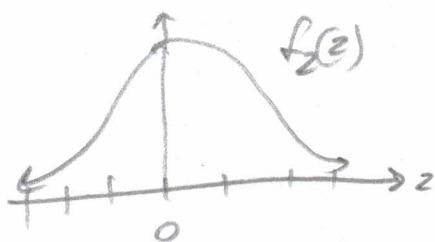
$$\textcircled{P1} \Rightarrow X_i \sim N(\mu_i, \Sigma_{ii})$$

$$\text{Hence: } \vec{X} \sim N_n(\vec{\mu}, \Sigma), \quad \begin{bmatrix} X_i \\ X_j \end{bmatrix} \sim ? \quad \text{Use (P9) then (P1) ...}$$

It will be MVN

Truncated distribution

Let $Z \sim N(0,1)$, $X = Z \mathbb{1}_{Z \in (1,\infty)} \sim f_X(x) = ?$ Draw a picture:



Same shape as $f_Z(z)$ in the truncated region
so all we need to do is scale this truncated
density so it integrates to 1.

$$\Rightarrow f_X(x) = \frac{f_Z(x) \mathbb{1}_{x \in (1,\infty)}}{\int_{(1,\infty)} f_Z(u) du} \approx \frac{1}{0.16} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \mathbb{1}_{x \in (1,\infty)}$$

In general, given density $Y \sim f_Y(y)$, $X = Y \mathbb{1}_{y \in R} \sim \frac{f_Y(x) \mathbb{1}_{x \in R}}{\int_R f_Y(y) dy}$

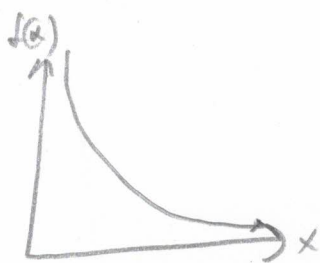
As promised, a discussion of the Weibull. What we've proved already

$$X \sim \text{Weibull}(k, \lambda) = k\lambda^k x^{k-1} e^{-(\lambda x)^k} \mathbb{1}_{x \in (0, \infty)}, F(x) = 1 - e^{-(\lambda x)^k} \Rightarrow S(x) = P(X > x) = e^{-(\lambda x)^k}$$

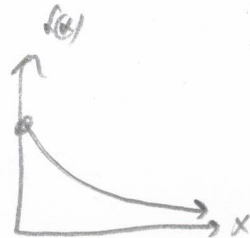
$\lambda > 0, k > 0$

if $k=1$ $\text{Weibull}(1, \lambda) = \lambda e^{-\lambda x} \mathbb{1}_{x \in (0, \infty)} = \text{Exp}(\lambda)$

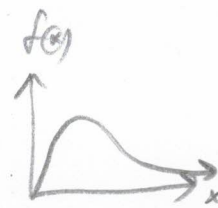
\Rightarrow Weibull is a generalization of the exponential rv. Three types of Weibulls:



$k \in (0, 1)$



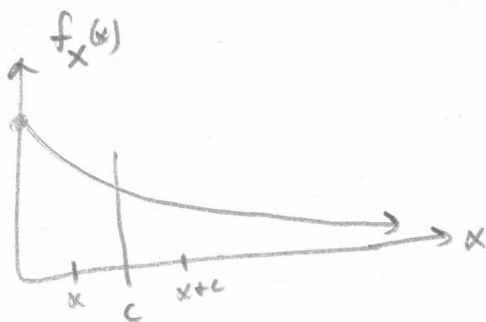
$k=1$ (exponential)



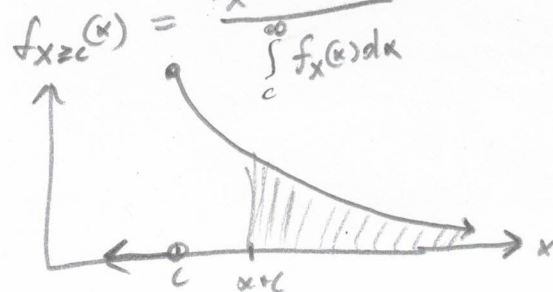
$k > 1$

Consider the conditional probability

$$P(X \geq x+c \mid X \geq c) \text{ where } c > 0$$



\Rightarrow



A truncated dist

$$P(X \geq x+c \mid X \geq c) = \frac{P(X \geq x+c \cap X \geq c)}{P(X \geq c)} = \frac{P(X \geq x+c)}{P(X \geq c)} = \frac{e^{-(\lambda(x+c))^k}}{e^{-(\lambda c)^k}}$$

$$= e^{-(\lambda(x+c))^k + (\lambda c)^k} = e^{\lambda^k (c^k - (x+c)^k)}$$

K is called the "weibull modulus"

$$\text{If } k=1, P(X \geq x+c | X > c) = e^{\lambda'(c' - (x+c)')} = e^{-\lambda x} = P(X > x) = e^{-\lambda x} \quad \forall x, c > 0$$

This is known as the "memoryless" property of the exponential.

No matter how long you wait, the rv "resets" itself.

$$\text{If } k > 1, P(X \geq x+c | X > c) = e^{\lambda^k(c^k - (x+c)^k)} < P(X > x) = e^{-(\lambda x)^k} \quad \forall x, c > 0$$

Examples?
human lifetimes

Proof let $r := \frac{e^{\lambda^k(c^k - (x+c)^k)}}{e^{-\lambda^k x^k}}$ WTS: $r < 1 \Leftrightarrow \ln(r) < 0$

$$r = e^{\lambda^k(c^k + x^k - (x+c)^k)} \Rightarrow \ln(r) = \lambda^k(c^k + x^k - (x+c)^k)$$

$$\text{WTS } c^k + x^k - (x+c)^k < 0 \Rightarrow \left(\frac{c}{x}\right)^k + 1 - \left(1 + \frac{c}{x}\right)^k < 0 \Rightarrow d^{k+1} - (1+d)^k < 0$$

$$d^{k+1} < (1+d)^k \quad \text{let } k = 1 + \beta \Rightarrow \beta > 0 \text{ since } k > 1$$

$$\Rightarrow d d^{\beta} + 1 < (1+d)(1+d)^{\beta} = (1+d)^{\beta} + d(1+d)^{\beta}$$

$$\text{true since } 1 < (1+d)^{\beta} \Rightarrow 0 < \beta \ln(1+d)$$

$$d d^{\beta} < d(1+d)^{\beta} \Rightarrow \beta \ln(d) < \beta \ln(1+d) \quad \text{since } \ln \text{ is a strictly increasing function}$$

$$\text{If } k \in (0,1) \quad P(X \geq x+c | X > c) = e^{\lambda^k(c^k - (x+c)^k)} > P(X > x) = e^{-(\lambda x)^k} \quad \forall x, c > 0$$

$$\text{WTS } r > 1 \Leftrightarrow \ln(r) > 0 \Rightarrow d^{k+1} > (1+d)^k$$

$$\text{let } k = 1 + \beta \Rightarrow \beta < 0$$

$$\Rightarrow d d^{\beta} + 1 > (1+d)^{\beta} + d(1+d)^{\beta}$$

$$\text{true since } 1 > (1+d)^{\beta} \Rightarrow 0 > \beta \ln(1+d)$$

$$d d^{\beta} > d(1+d)^{\beta} \Rightarrow \beta \ln(d) > \beta \ln(1+d) \Rightarrow \ln(d) < \ln(1+d)$$

Examples?
infant mortality,
age-hadning
alloys