

# GENERAL FACTS ABOUT CONTINUOUS R.V.'S

$f: \mathbb{R} \rightarrow \mathbb{R}$  is the probability density function

Recall that:

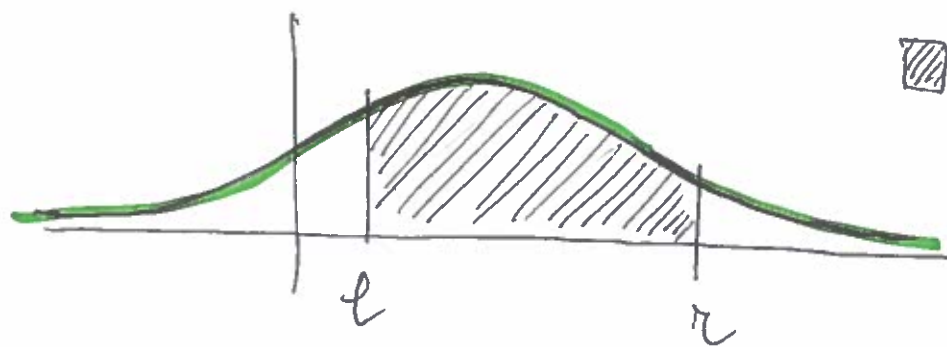
a)  $f(x) \geq 0 \quad \forall x \in \mathbb{R}$

b)  $f$  is integrable on any interval.

c)  $\int_{-\infty}^{+\infty} f(x) dx = 1$

## ① CONNECTION BETWEEN $f$ and the PROBABILITY

$$P[X \in (l, r)] = \int_l^r f(x) dx \quad l < r.$$



$$\boxed{\text{shaded area}} = P[X \in (l, r)]$$

## ② EXPECTATION

$$E[X] \stackrel{\text{Def}}{=} \int_{-\infty}^{+\infty} x f(x) dx.$$

(Whenever the integral makes sense)

If  $f(x) = 0$  outside  $[a, b]$ , then

$$E[X] = \int_a^b x f(x) dx$$

### 3) EXPECTATION OF A TRANSFORMED R.V.'S

Let  $h: \mathbb{R} \rightarrow \mathbb{R}$  be a given function.

Then  $\boxed{\mathbb{E}[h(x)] = \int_{-\infty}^{+\infty} h(x) f(x) dx}$

whenever the integral makes sense.

In particular, we have

$h(x) = x^2 \Rightarrow$  SECOND MOMENT

$$\boxed{\mathbb{E}[X^2] = \int_{-\infty}^{+\infty} x^2 f(x) dx}$$

$h(x) = x^n \Rightarrow$  n-th MOMENT

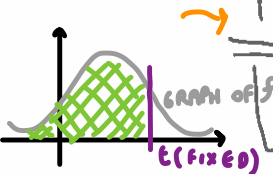
$$\boxed{\mathbb{E}[X^n] = \int_{-\infty}^{+\infty} x^n f(x) dx}$$

### 4) DISTRIBUTION FUNCTION

CONSIDER  $X \in \mathbb{E}$

$$\boxed{F(t) = P[X \leq t] = P[X \in (-\infty, t]] =$$

FOR CONTINUOUS CASE



$$= \int_{-\infty}^t f(x) dx, \quad t \in \mathbb{R}.$$

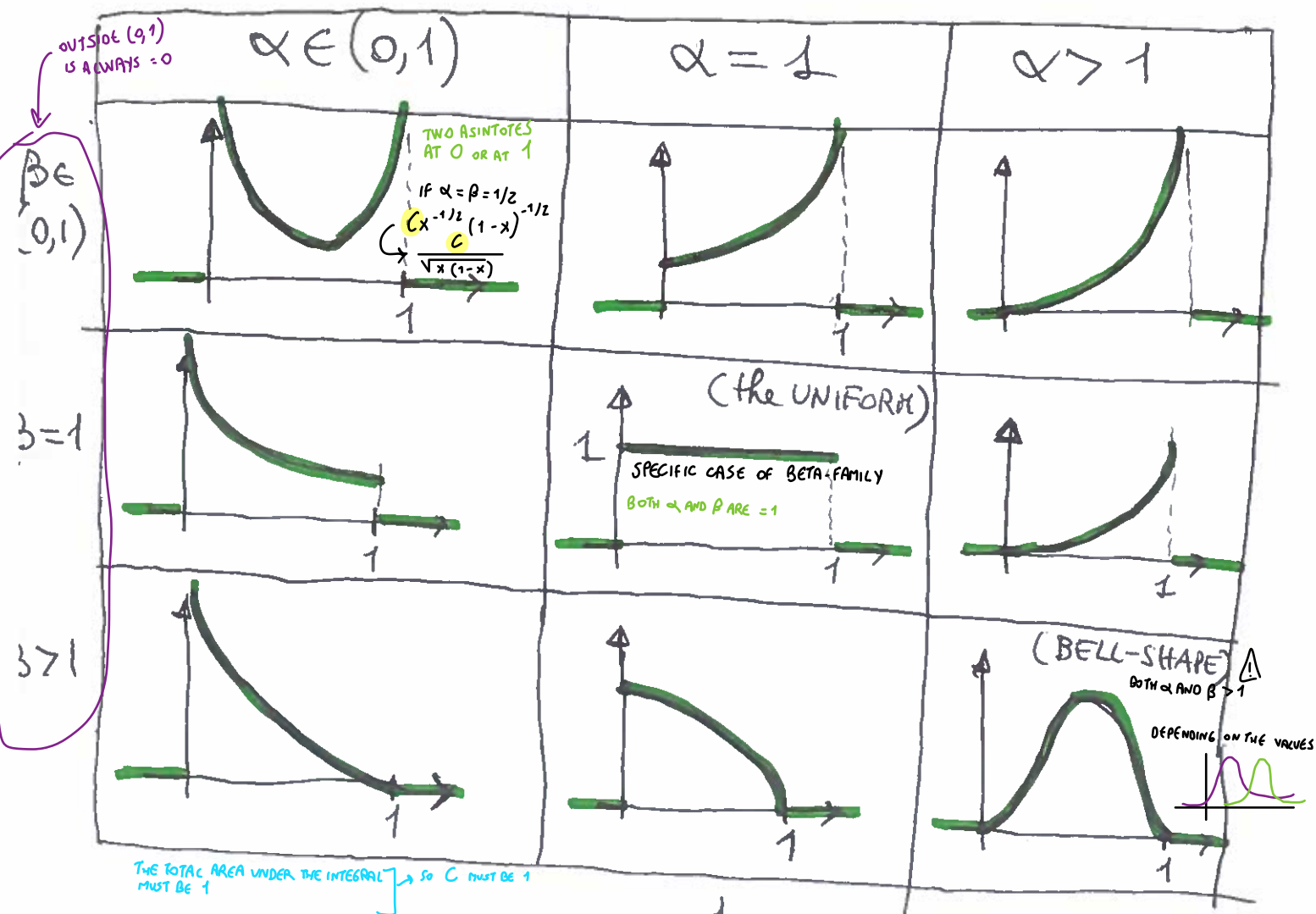
Viceversa,  $\boxed{f(x) = F'(x)}, \quad \forall x \in \mathbb{R}$

# CONTINUOUS RANDOM VARIABLE : THE BETA

Let  $\alpha, \beta$  be fixed  $> 0$ .  
 Put  $f(x) = \begin{cases} C(\alpha, \beta) x^{\alpha-1} (1-x)^{\beta-1}, & \text{if } x \in (0, 1) \\ 0 & \text{otherwise} \end{cases}$

$C(\alpha, \beta)$  is just a constant ( $> 0$ ). We will see later its characterization. α, β FIXED PARAMETER

The graph of  $f$  is as follows:



Proposition 1.  $\forall \alpha, \beta > 0, \int_0^1 x^{\alpha-1} (1-x)^{\beta-1} dx < +\infty$ .

Thus,  $C(\alpha, \beta) = \frac{1}{\int_0^1 x^{\alpha-1} (1-x)^{\beta-1} dx}$

THE INTEGRAL IS ALWAYS FINITE

IF YOU HAVE 1 OR 2 ASYMPTOTES IS NOT CLEAR

CONSIDER  $\epsilon \Rightarrow \int_{\epsilon}^{1-\epsilon} x^{\alpha-1} (1-x)^{\beta-1} dx = 2 \cdot \int_{\epsilon}^{1-\epsilon} x^{\alpha-1} dx$

NOW LET  $\epsilon \rightarrow 0$

THE INTEGRAL IS ALWAYS FINITE

With this choice of  $C(\alpha, \beta)$ ,  $f$  is a probability density function that generalizes the uniform case.

A further characterization of  $C(\alpha, \beta)$  can be given in terms of a special function, called **GAMMA FUNCTION**.

$$\Gamma(z) := \int_0^{+\infty} e^{-t} \cdot t^{z-1} dt, \quad z > 0$$

Thus  $\Gamma: \mathbb{R}_+ \rightarrow \mathbb{R}_+$ . The following facts about the gamma function are worth noticing:

1)  $\Gamma(1) = \int_0^{+\infty} e^{-t} dt = 1$

2)  $\Gamma(z+1) = z \cdot \Gamma(z)$  [by integration by parts]

3)  $\Gamma(2) = 1 \cdot \Gamma(1) = 1 = 1!$

$$\Gamma(3) = 2 \cdot \Gamma(2) = 2 = 2!$$

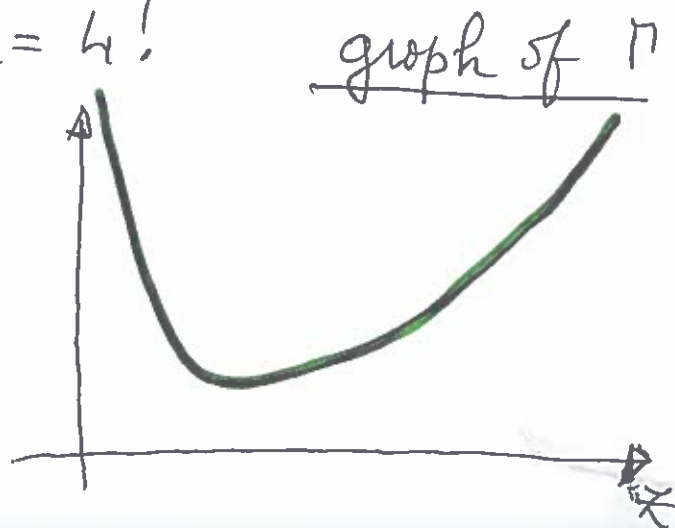
$$\Gamma(4) = 3 \cdot \Gamma(3) = 3 \cdot 2 = 3!$$

$$\Gamma(5) = 4 \cdot \Gamma(4) = 4 \cdot 3 \cdot 2 = 4!$$

$$\boxed{\Gamma(n+1) = n!}$$

4)  $\Gamma(1/2) = \sqrt{\pi}$

5)  $\lim_{z \rightarrow 0^+} \Gamma(z) = +\infty$



The interest for the gamma function comes from this very nice:

## EULER'S THEOREM

(After L. Euler (1707-1783))

$$\int_0^1 x^{\alpha-1} (1-x)^{\beta-1} dx = \frac{\Gamma(\alpha) \Gamma(\beta)}{\Gamma(\alpha+\beta)}$$

Example: Solve  $\int_0^1 x^6 (1-x)^4 dx$ . [very lengthy by hands]  
 $(\alpha=7, \beta=5)$

By Euler's theorem =  $\frac{\Gamma(7) \Gamma(5)}{\Gamma(12)} = \frac{6! 4!}{11!}$  FROM BEFORE

$$= \frac{\cancel{6!} \cancel{4 \cdot 3 \cdot 2}}{11 \cdot 10 \cdot \cancel{9 \cdot 8 \cdot 7 \cdot 6!}} = \frac{1}{11 \cdot 10 \cdot 21}$$

$$= \frac{1}{2 \cdot 3 \cdot 10}$$

IS THE INVERSE BECAUSE SHOULD BE  
 $\frac{1}{\text{AREA}} \Rightarrow \frac{1}{\frac{\Gamma(\alpha) \Gamma(\beta)}{\Gamma(\alpha+\beta)}} \Rightarrow \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha) \Gamma(\beta)}$

Thus, the beta density becomes

$$f(x) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha) \Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1} dx & \text{if } x \in (0,1) \\ 0 & \text{otherwise} \end{cases}$$

It is a probability density function because  
 $f(x) \geq 0 \forall x \in \mathbb{R}$ , and  $\int_{-\infty}^{+\infty} f(x) dx = \int_0^1 f(x) dx = 1$ .

## MEAN VALUE

$$E[X] = \int_{-\infty}^{+\infty} x f(x) dx \quad [\text{general formula}]$$

$$= \int_0^1 x \cdot \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1} dx$$

SUBSTITUTE

$$= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \int_0^1 x^{(\alpha+1)-1} (1-x)^{\beta-1} dx$$

IS A CONSTANT

(Euler's th.)

$$\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \frac{\Gamma(\alpha+1)\Gamma(\beta)}{\Gamma(\alpha+\beta+1)}$$

(Prop 2) of  $\Gamma$

$$\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)} \frac{\alpha \Gamma(\alpha)}{(\alpha+\beta)\Gamma(\alpha+\beta)} = \boxed{\frac{\alpha}{\alpha+\beta}}$$

UNIFORM:  $\alpha$  AND  $\beta = 1$   
 $\hookrightarrow 1/2$  (EXACTLY THE MIDDLE POINT)

## SECOND MOMENT

$$E[X^2] = \int_{-\infty}^{+\infty} x^2 f(x) dx \quad [\text{general formula}]$$

$$= \int_0^1 x^2 \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1} dx$$
$$= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \int_0^1 x^{(\alpha+2)-1} (1-x)^{\beta-1} dx$$
$$= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \frac{\Gamma(\alpha+2)\Gamma(\beta)}{\Gamma(\alpha+\beta+2)}$$

$$= \frac{\cancel{\Gamma(\alpha+\beta)}}{\cancel{\Gamma(\alpha)}} \cdot \frac{\alpha(\alpha+1)\cancel{\Gamma(\alpha)}}{(\alpha+\beta)(\alpha+\beta+1)\cancel{\Gamma(\alpha+\beta)}} = \boxed{\frac{\alpha(\alpha+1)}{(\alpha+\beta)(\alpha+\beta+1)}}$$

## VARIANCE

$$\text{Var}(X) = \mathbb{E}[X^2] - (\mathbb{E}[X])^2$$

$$= \frac{\alpha(\alpha+1)}{(\alpha+\beta)(\alpha+\beta+1)} - \frac{\alpha^2}{(\alpha+\beta)^2}$$

$$= \frac{\alpha}{\alpha+\beta} \left[ \frac{\alpha+1}{\alpha+\beta+1} - \frac{\alpha}{\alpha+\beta} \right]$$

$$= \frac{\alpha \left[ \cancel{\alpha^2} + \cancel{\alpha\beta} + \cancel{\alpha+\beta} - \cancel{\alpha^2} - \cancel{\alpha\beta} - \cancel{\alpha} \right]}{(\alpha+\beta)^2(\alpha+\beta+1)}$$

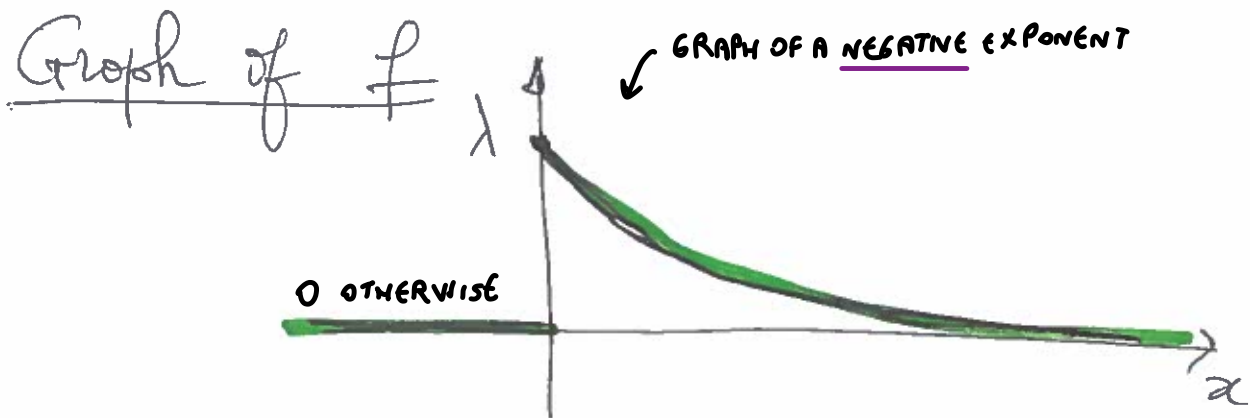
$$= \boxed{\frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}}$$

# CONTINUOUS RANDOM VARIABLES: THE EXPONENTIAL

ONLY 1 PARAMETER:  $\lambda$

Let  $\lambda > 0$  be fixed.

$$\text{Put } f(x) = \begin{cases} \lambda e^{-\lambda x} & \text{if } x > 0 \\ 0 & \text{otherwise.} \end{cases}$$



$f$  is a probability density function, because

$$1) f(x) \geq 0 \quad \forall x \in \mathbb{R}$$

$$2) \int_{-\infty}^{+\infty} f(x) dx = \int_0^{+\infty} \lambda e^{-\lambda x} dx = \left[ -e^{-\lambda x} \right]_{x=0}^{x \rightarrow +\infty}$$

0 IF  $f(x)$  IS NEGATIVE

$x \rightarrow +\infty$

$x \rightarrow 0$

TOTAL AREA

$$= 0 - (-1) = +1$$

[observe that  $-e^{-\lambda x}$  is a primitive of  $\lambda e^{-\lambda x}$ ,  $\forall x > 0$ , meaning that

$$\frac{d}{dx}(-e^{-\lambda x}) = \lambda e^{-\lambda x}.$$



## MEAN VALUE

$$\begin{aligned} \mathbb{E}[X] &= \int_{-\infty}^{+\infty} x f(x) dx \quad \text{[General formula]} \\ &= \int_0^{+\infty} x \lambda e^{-\lambda x} dx \quad \text{[CHANGE OF VARIABLE } \lambda x = y \text{]} \\ &= \frac{1}{\lambda} \int_0^{+\infty} y e^{-y} dy \quad \text{[FIND } z \text{]} \\ &= \frac{1}{\lambda} \Gamma(2) = \left( \frac{1}{\lambda} \right) \end{aligned}$$

OR:  $y = \lambda x$   
 $x = \frac{y}{\lambda}$   
 $dx = \frac{1}{\lambda} dy$

$\Gamma(z) = \int_0^{+\infty} e^{-t} t^{z-1} dt$   
 $\Gamma(2) = \int_0^{+\infty} e^{-t} t^{2-1} dt$   
 $z=2$

## SECOND MOMENT

$$\begin{aligned} \mathbb{E}[X^2] &= \int_{-\infty}^{+\infty} x^2 f(x) dx \quad \text{[General]} \\ &= \int_0^{+\infty} x^2 \lambda e^{-\lambda x} dx \quad \text{[} \lambda x = y \text{]} \\ &= \frac{1}{\lambda^2} \int_0^{+\infty} y^2 e^{-y} dy \\ &= \frac{1}{\lambda^2} \Gamma(3) = \left( \frac{2}{\lambda^2} \right) \end{aligned}$$

## VARIANCE :

$$\begin{aligned} \text{Var}(X) &= \mathbb{E}[X^2] - (\mathbb{E}[X])^2 \\ &= \frac{2}{\lambda^2} - \left( \frac{1}{\lambda} \right)^2 = \frac{2-1}{\lambda^2} \\ &= \left( \frac{1}{\lambda^2} \right) \end{aligned}$$

# CONTINUOUS RANDOM VARIABLES : THE GAMMA

Let  $\lambda, \tau > 0$  be fixed.

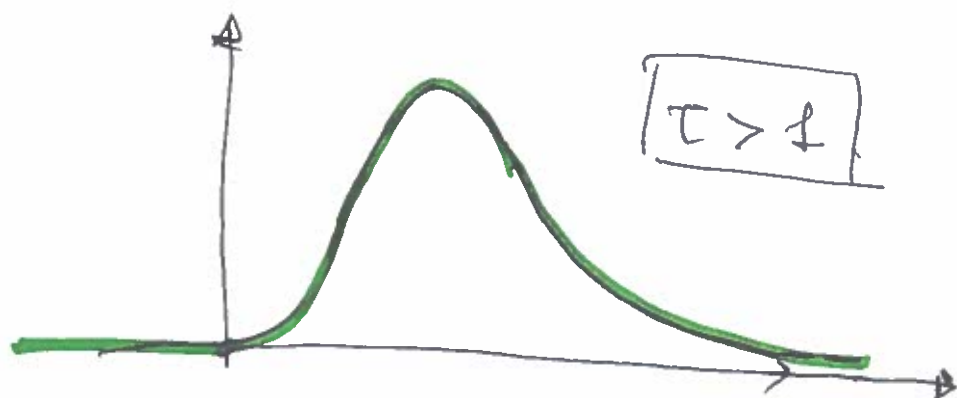
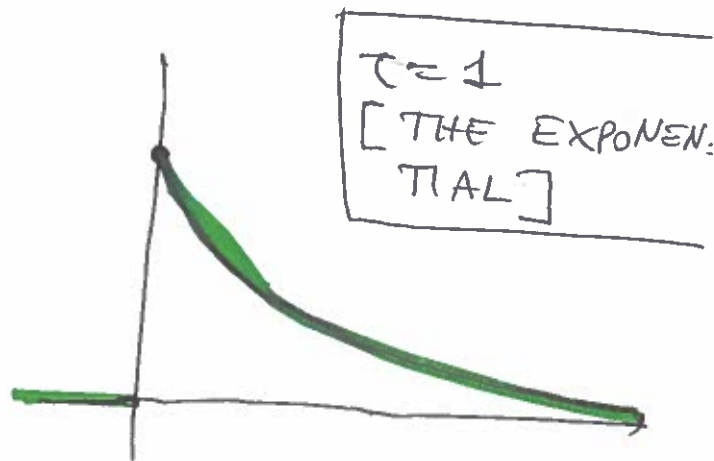
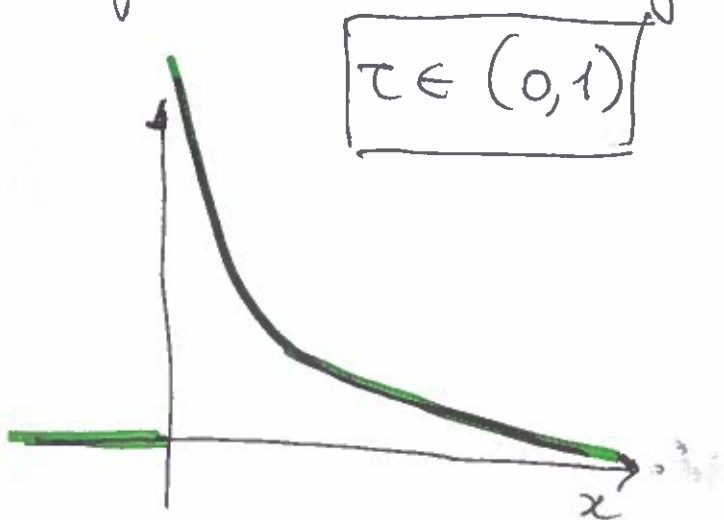
2 PARAMETERS:  $\lambda, \tau$

$$\text{Put } f(x) = \begin{cases} \frac{\lambda^\tau}{\Gamma(\tau)} x^{\tau-1} e^{-\lambda x}, & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

$\uparrow$  CONSTANT       $\uparrow$  POWER       $\uparrow$  EXPONENTIAL

- $\lambda$  is the SCALE PARAMETER
- $\tau$  is the SHAPE PARAMETER.

Indeed, the graph of  $f$  changes its form according to the value of  $\tau$ .



# SPECIAL CASE [ VERY, VERY IMPORTANT IN STATISTICS ]

When  $\lambda = \frac{1}{2}$ ,  $\tau = \frac{n}{2}$  ( $n \in \mathbb{R}$ )  
the density

$$f(x) = \begin{cases} \frac{1}{2^{n/2} \Gamma(n/2)} x^{n/2-1} e^{-x/2}, & x > 0 \\ 0 & \text{otherwise} \end{cases}$$

is named **CHI-SQUARED DENSITY**  
**WITH  $n$  DEGREES OF FREEDOM**,

For generic  $\lambda, \tau > 0$ ,  $f$  is a probability density function! In fact,

1)  $f(x) \geq 0 \quad \forall x \in \mathbb{R}$

2)  $\int_{-\infty}^{+\infty} f(x) dx = \int_0^{+\infty} \frac{\lambda^\tau}{\Gamma(\tau)} x^{\tau-1} e^{-\lambda x} dx =$   
 $= \frac{1}{\Gamma(\tau)} \int_0^{+\infty} y^{\tau-1} e^{-y} dy = \frac{\Gamma(\tau)}{\Gamma(\tau)} = 1.$

*Annotations: "CHECK THAT  $\int_0^{+\infty} \frac{\lambda^\tau}{\Gamma(\tau)} x^{\tau-1} e^{-\lambda x} dx = 1$ " above the first line; "CONSTANT" above the fraction; "SUBSTITUTE  $[\lambda x = y]$ " to the right; "ARROW" pointing from the integral definition of  $\Gamma(\tau)$  to the final integral; "1" circled in orange at the end.*

	ILL	NOT-ILL
SMOKER	30	10
NOT SMOKER	20	40

NUMBER OF DEGREES = (NUMBER OF ROWS - 1) (NUMBER OF COLUMNS - 1)



## THE MEAN

$$\mathbb{E}[X] = \int_{-\infty}^{+\infty} x f(x) dx \quad [\text{General}]$$

$$= \int_0^{+\infty} x \cdot \frac{\lambda^\tau}{\Gamma(\tau)} x^{\tau-1} e^{-\lambda x} dx \quad [\lambda x = y]$$

$$= \frac{1}{\Gamma(\tau)} \frac{1}{\lambda} \int_0^{+\infty} \frac{y^{(\tau+1)-1}}{y} e^{-y} dy = \frac{\Gamma(\tau+1)}{\lambda \Gamma(\tau)}$$

$$= \frac{\tau \Gamma(\tau)}{\lambda \Gamma(\tau)} = \left( \frac{\tau}{\lambda} \right)$$

## THE SECOND MOMENT

$$\mathbb{E}[X^2] = \int_{-\infty}^{+\infty} x^2 f(x) dx \quad [\text{General}]$$

$$= \int_0^{+\infty} x^2 \frac{\lambda^\tau}{\Gamma(\tau)} x^{\tau-1} e^{-\lambda x} dx \quad [\lambda x = y]$$

$$= \frac{1}{\Gamma(\tau)} \frac{1}{\lambda^2} \int_0^{+\infty} \frac{y^{(\tau+2)-1}}{y^2} e^{-y} dy = \frac{\Gamma(\tau+2)}{\lambda^2 \Gamma(\tau)}$$

$$= \frac{\tau(\tau+1) \cancel{\Gamma(\tau)}}{\lambda^2 \cancel{\Gamma(\tau)}} = \left( \frac{\tau(\tau+1)}{\lambda^2} \right)$$

VARIANCE :

$$\text{Var}(X) = \mathbb{E}[X^2] - (\mathbb{E}[X])^2$$
$$= \frac{\tau(\tau+1)}{\lambda^2} - \frac{\tau^2}{\lambda^2} = \left( \frac{\tau}{\lambda^2} \right)$$

# CONTINUOUS RANDOM VARIABLES: THE GAUSSIAN

Let  $m \in \mathbb{R}$ ,  $\sigma^2 > 0$  be fixed.

Put

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

$x \in \mathbb{R}$

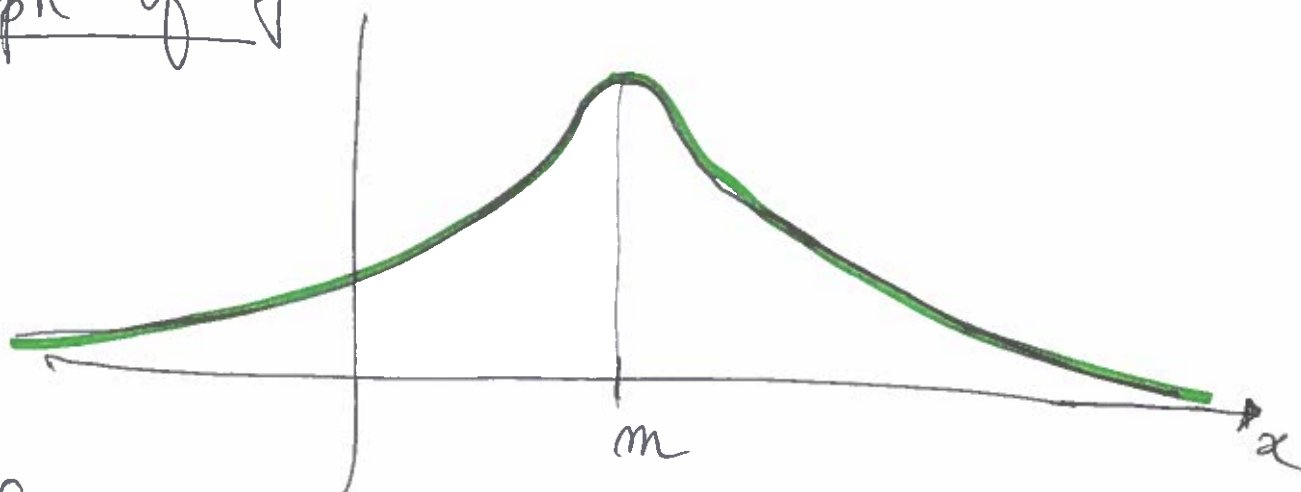
CONSTANT

$m$  is called MEAN

$\sigma^2$  is called VARIANCE

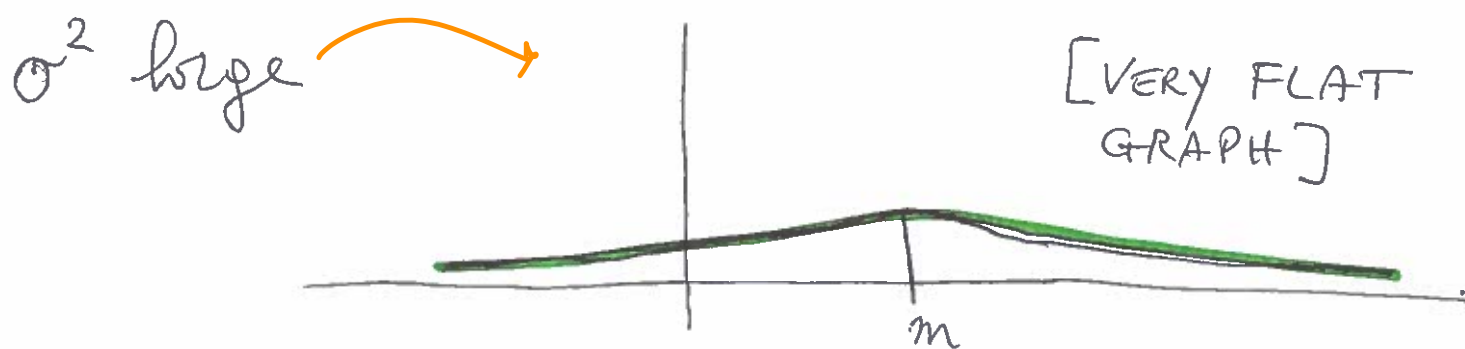
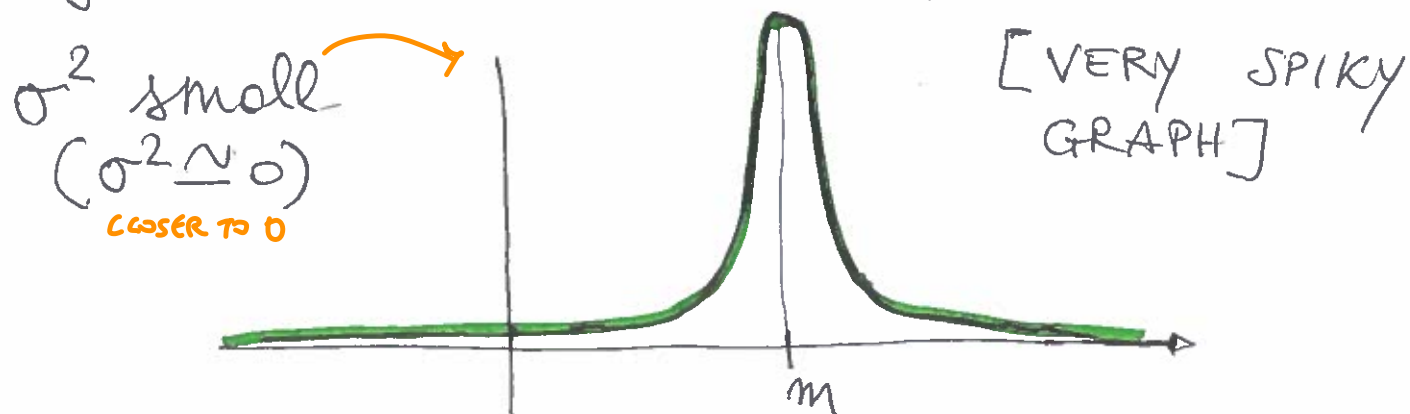
As we shall see, it is actually true that  $E[X] = m$ ,  $\text{Var}(X) = \sigma^2$ .

Graph of  $f$



- )  $f$  is maximum at  $x=m$
- )  $f(x) > 0 \quad \forall x \in \mathbb{R}$
- )  $\lim_{x \rightarrow \pm\infty} f(x) = 0$

Thus, the parameter  $\mu$  is the abscissa of the (unique) maximum point of  $f$ .  
 The geometric meaning of  $\sigma^2$  is to regulate the openness of the bell-shape.



We see now that  $f$  is a density because  $\int_{-\infty}^{+\infty} f(x) dx = 1$ . Indeed,

$$\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\} dx = \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{y^2}{2\sigma^2}\right\} dy = \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{z^2}{2}\right\} dz$$

CHANGE OF VARIABLE  
 $[x - \mu = y]$   
 $\left[\frac{y}{\sigma} = z\right]$   
 Where  $\sigma := \sqrt{\sigma^2}$

$$\begin{aligned}
 &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} e^{-z^2/2} dz = \frac{2}{\sqrt{2\pi}} \int_0^{+\infty} e^{-z^2/2} dz \\
 &= \frac{2}{\sqrt{2\pi}} \int_0^{+\infty} e^{-w} \frac{\sqrt{2} dw}{2\sqrt{w}} = \frac{1}{\sqrt{\pi}} \int_0^{+\infty} e^{-w} \frac{dw}{\sqrt{w}} = \\
 &= \frac{1}{\sqrt{\pi}} \int_0^{+\infty} e^{-w} \cdot w^{\frac{1}{2}-1} dw = \frac{1}{\sqrt{\pi}} \cdot \Gamma(1/2) = \frac{\sqrt{\pi}}{\sqrt{\pi}} = 1
 \end{aligned}$$

### THE MEAN

$$\begin{aligned}
 \mathbb{E}[X] &= \int_{-\infty}^{+\infty} x f(x) dx = \int_{-\infty}^{+\infty} x \cdot \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\} dx \\
 x-\mu &= y \\
 &= \int_{-\infty}^{+\infty} (y+\mu) \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{y^2}{2\sigma^2}\right\} dy \\
 \text{[linearity]} &= \underbrace{\int_{-\infty}^{+\infty} y \cdot \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{y^2}{2\sigma^2}\right\} dy}_{=0} + \mu \\
 &= (\mu)
 \end{aligned}$$

### THE VARIANCE. $\text{Var}(X) = \mathbb{E}[(X-\mu)^2] =$

$$\begin{aligned}
 &\int_{-\infty}^{+\infty} (x-\mu)^2 \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\} dx \quad [x-\mu=y] \\
 &= \int_{-\infty}^{+\infty} y^2 \frac{1}{\sqrt{2\pi\sigma^2}} e^{-y^2/2\sigma^2} dy = \sigma^2 \int_{-\infty}^{+\infty} z^2 \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz \\
 &\quad \left[\frac{y}{\sigma} = z\right]
 \end{aligned}$$

$$= \frac{2\sigma^2}{\sqrt{2\pi}} \int_0^{+\infty} z^2 e^{-z^2/2} dz = \frac{2\sigma^2}{\sqrt{2\pi}} \int_0^{+\infty} (2w) e^{-w} \frac{\sqrt{2}}{2\sqrt{w}} dw$$

$z^2/2 = w$

$$= \frac{2\sigma^2}{\sqrt{\pi}} \int_0^{+\infty} w^{3/2-1} e^{-w} dw = \frac{2\sigma^2}{\sqrt{\pi}} \Gamma(3/2) =$$

$$= \frac{2\sigma^2}{\sqrt{\pi}} \cdot \frac{1}{2} \Gamma(1/2) = \sigma^2.$$

THE STANDARD NORMAL (GAUSSIAN)  
(OR GAUSSIAN DISTRIBUTION w/  
 $m=0; \sigma^2=1$ )

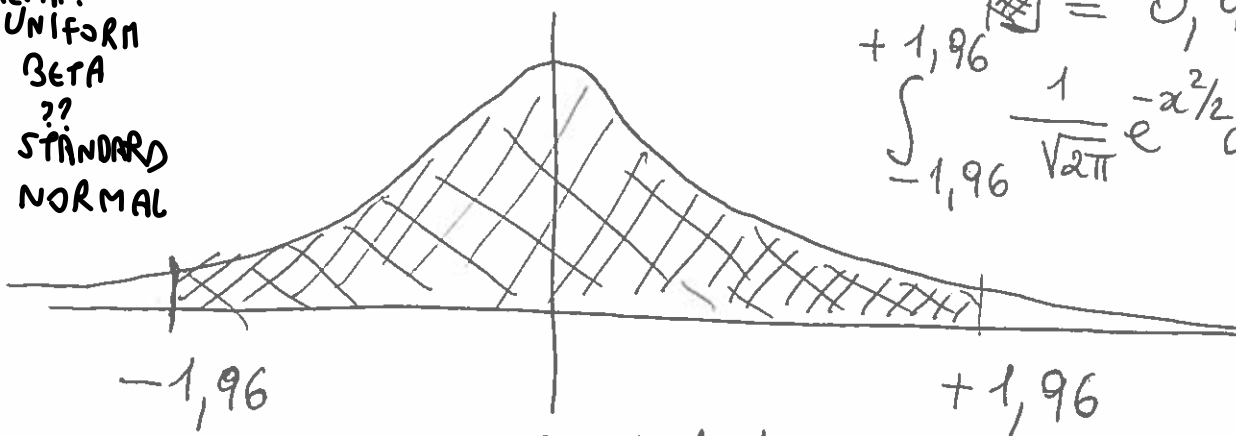
It is obtained by putting  $m=0$  and  $\sigma^2=1$ . That is,

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}, \quad x \in \mathbb{R}$$

$Z \sim N(m, \sigma^2)$  SHORTER  
TO DENOTE THAT Z HAS  
GAUSSIAN DENSITY WITH  
MEAN  $m$  AND VARIANCE  $\sigma^2$

In particular

RECAP:  
UNIFORM  
BETA  
??  
STANDARD  
NORMAL



$$\begin{aligned} & \boxed{\text{shaded area}} = 0,95 \\ & \int_{-1,96}^{+1,96} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx = 0,95 \\ & \text{95\%} \end{aligned}$$

Usually, the r.v. is denoted by  $Z$ ,  $\rightarrow$  FOR STANDARD NORMAL  
USE  $Z$  FOR RANDOM VARIABLE



# TRANSFORMATION OF R.V.'S. [Chopt. 5]

Let  $X: \Omega \rightarrow \mathbb{R}$  be a r.v. of continuous type, with density  $f_X$ .  
(SINCE WE ARE CONTINUOUS)

Let  $h: \mathbb{R} \rightarrow \mathbb{R}$  be a function such that

a)  $h$  is one-to-one

(injective and surjective)

b)  $h$  is differentiable

c)  $h^{-1}$  is differentiable

THE GRAPH INTERSECT ANY HORIZONTAL LINE IN EXACTLY ONE POINT

EVERY ORIENTAL LINE HAVE AT LEAST ONE INTERSECTION

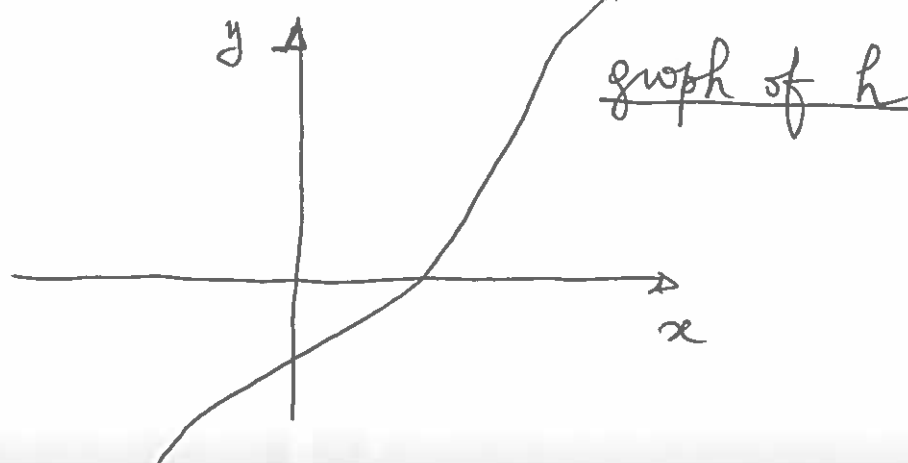
REVERSE

$$y = h(x) \rightarrow x = h^{-1}(y)$$

We put  $Y = h(X)$ . We find that  $Y$  is again a continuous random variable.

Problem. Find the density of  $Y$ .

Solution. If  $h$  fulfills a)-b)-c),  $h$  must be strictly monotonic. With loss of generality, we can suppose  $h$  strictly increasing.



Let us consider the distribution function of  $Y$ , that is

CONNECT THE NOTION of DENSITY w/ THE NOTION of PROBABILITY

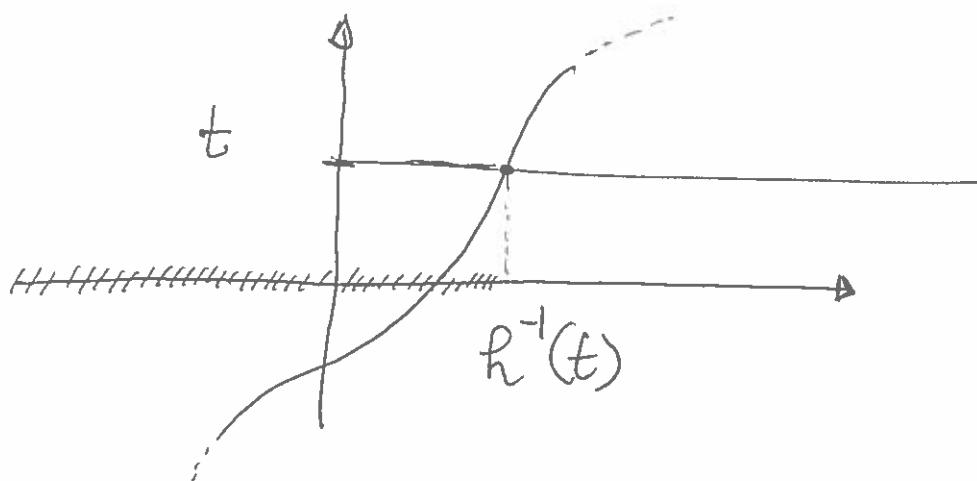
$$F_Y(t) \stackrel{\text{Def}}{=} P[Y \leq t] = P[h(X) \leq t]$$

$\forall t \in \mathbb{R}$ . Observe that the inequality

$$h(x) \leq t$$

is equivalent to

$$x \leq h^{-1}(t)$$



$$\begin{aligned} \text{Thus, } F_Y(t) &= P[h(X) \leq t] = P[X \leq h^{-1}(t)] \\ &= F_X(h^{-1}(t)) = \int_{-\infty}^{h^{-1}(t)} f_X(x) dx \end{aligned}$$

Now, we change the variable in the integral

putting  $y = h(x) \Rightarrow x = h^{-1}(y)$

- ) CHANGE OF THE DOMAIN:  $(-\infty, h^{-1}(t)] \rightarrow [-y, t]$
- ) CHANGE OF THE INTEGRAND:  $f_X(x) \rightarrow f_X(h^{-1}(y))$
- ) CHANGE OF THE DIFFERENTIAL:  $dx \rightarrow \frac{d}{dy} h^{-1}(y) dy$

Whence,  $\int_{-\infty}^{h^{-1}(t)} f_X(x) dx = \int_{-\infty}^t f_X(h^{-1}(y)) \left[ \frac{d}{dy} h^{-1}(y) \right] dy$

Since  $F_Y(t) = \int_{-\infty}^t f_Y(y) dy$ , we deduce

$$f_Y(y) = f_X(h^{-1}(y)) \cdot \left[ \frac{d}{dy} h^{-1}(y) \right] \quad y \in \mathbb{R}$$

Remark: The same formula works if

$h: (a,b) \rightarrow (c,d)$  such that

a)  $h$  is one-to-one

b)  $h$  is differentiable

c)  $h^{-1}$  is differentiable

and  $f_X(x) = 0 \quad \forall x \in [a,b]$ .

In this case,

$$f_Y(y) = f_X(h^{-1}(y)) \cdot \left[ \frac{d}{dy} h^{-1}(y) \right] \quad y \in (c,d)$$

# EXAMPLE/EXERCISE: THE LOG-NORMAL R.V.

Let  $Z$  be a r.v. with density equal to the standard gaussian (standard normal) that is

$$f_Z(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}, \quad x \in \mathbb{R}$$

We take  $h(x) = e^x$ , so  $h: \mathbb{R} \rightarrow (0, +\infty)$  is one-to-one and both  $h$  and  $h^{-1}$  are differentiable.  $h^{-1}(y) = \log y$ ,  $h^{-1}: (0, +\infty) \rightarrow \mathbb{R}$

We put  $Y = h(Z)$ . Thus,

$$f_Y(y) = f_X(h^{-1}(y)) \cdot \left[ \frac{d}{dy} h^{-1}(y) \right], \quad y \in (0, +\infty)$$

$$= f_X(\log y) \cdot \frac{1}{y}$$

$$= \left[ \frac{1}{\sqrt{2\pi} \cdot y} \exp\left\{-\frac{(\log y)^2}{2}\right\} \right] \quad y \in (0, +\infty)$$

EXERCISE. Let  $Z \sim \mathcal{N}(0,1)$ . [standard Normal].  
Then,  $W = Z^2 \sim \text{Gamma}(\frac{1}{2}, \frac{1}{2}) = \chi^2(1)$

SOLUTION. We need to find the density of W.  
Let us first consider the distribution function  $F_W$  of  $W$ , that is:  
( $t > 0$ )

$$\begin{aligned} F_W(t) &= P[W \leq t] = P[Z^2 \leq t] = \\ &= P[Z \in [-\sqrt{t}, \sqrt{t}]] \\ &= \int_{-\sqrt{t}}^{\sqrt{t}} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx = 2 \int_0^{\sqrt{t}} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx \end{aligned}$$

$$\begin{aligned} \left[ \begin{array}{c} x^2 = y \\ \downarrow \\ x = \sqrt{y} \end{array} \right] &= \frac{2}{\sqrt{2\pi}} \int_0^t e^{-y/2} \frac{dy}{2\sqrt{y}} = \frac{1}{\sqrt{2\pi}} \int_0^t y^{\frac{1}{2}-1} e^{-y/2} dy \end{aligned}$$

Since  $F_W(t) = \int_0^t f_W(y) dy$ , we have

$$f_W(y) = \frac{1}{\sqrt{2\pi}} y^{\frac{1}{2}-1} e^{-y/2} = \boxed{\frac{(\frac{1}{2})^{\frac{1}{2}}}{\Gamma(\frac{1}{2})} y^{\frac{1}{2}-1} e^{-y/2}}$$

which is the Gamma density with  
 $\lambda = \frac{1}{2}$  and  $\tau = \frac{1}{2}$ .