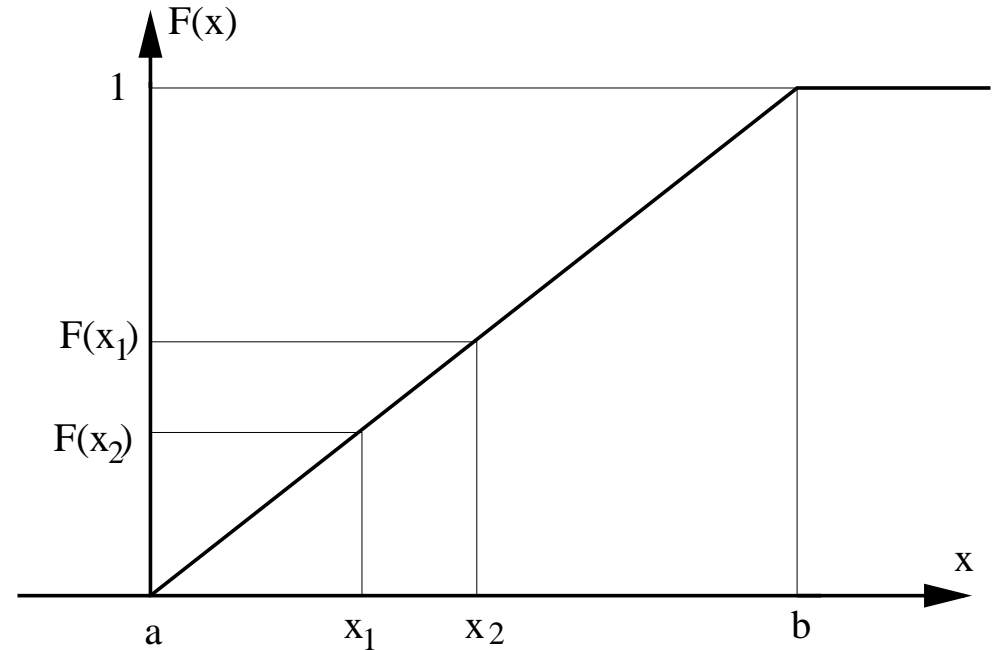
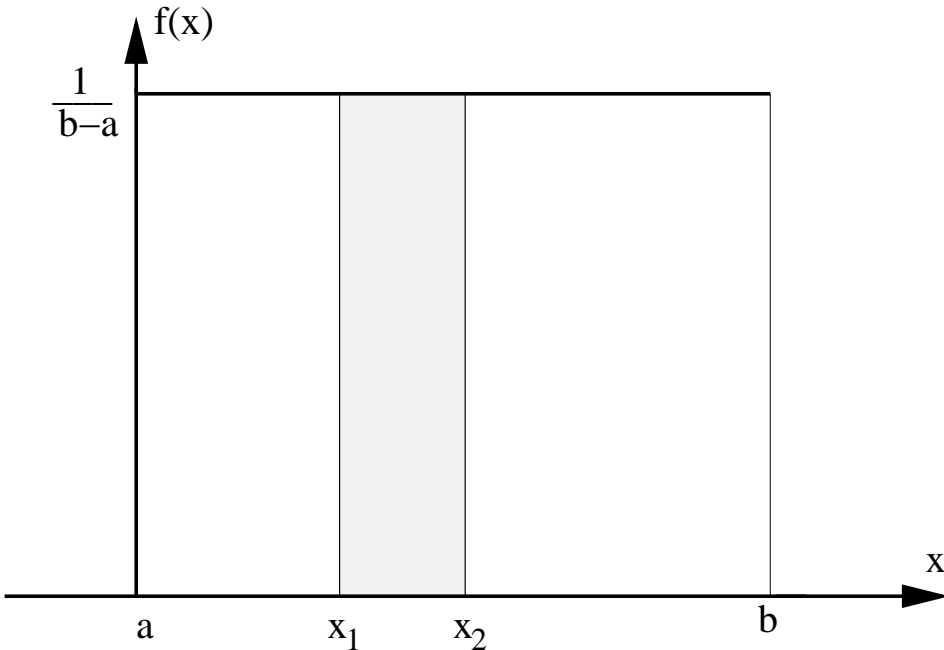


# SPECIAL CONTINUOUS RANDOM VARIABLES

## The Uniform Random Variable

$$f(x) = \begin{cases} \frac{1}{b-a}, & a < x \leq b \\ 0, & \text{otherwise} \end{cases}, \quad F(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ 1, & x > b \end{cases}$$



(Already introduced earlier for the special case  $a = 0, b = 1$  .)

**EXERCISE :**

Show that the *uniform density function*

$$f(x) = \begin{cases} \frac{1}{b-a} , & a < x \leq b \\ 0 , & \text{otherwise} \end{cases}$$

has *mean*

$$\mu = \frac{a + b}{2} ,$$

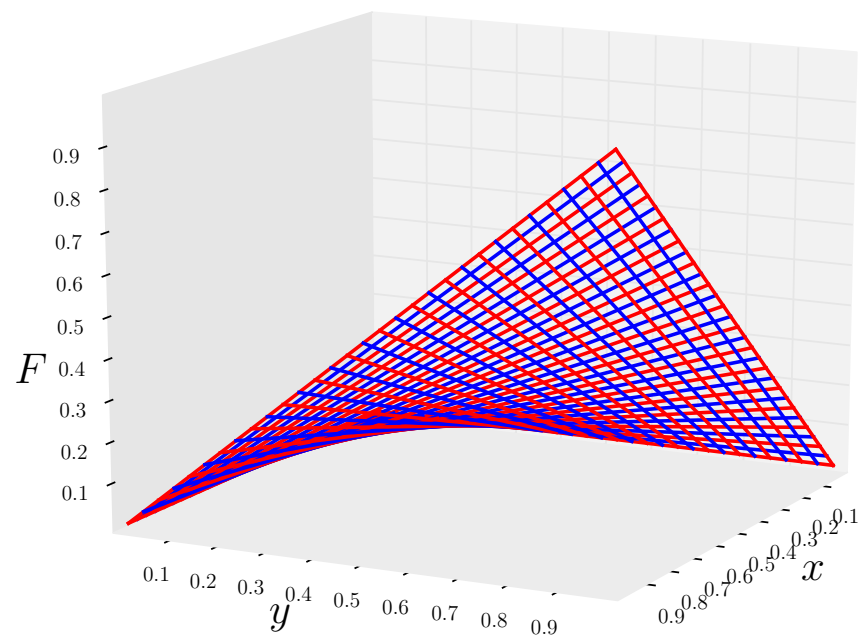
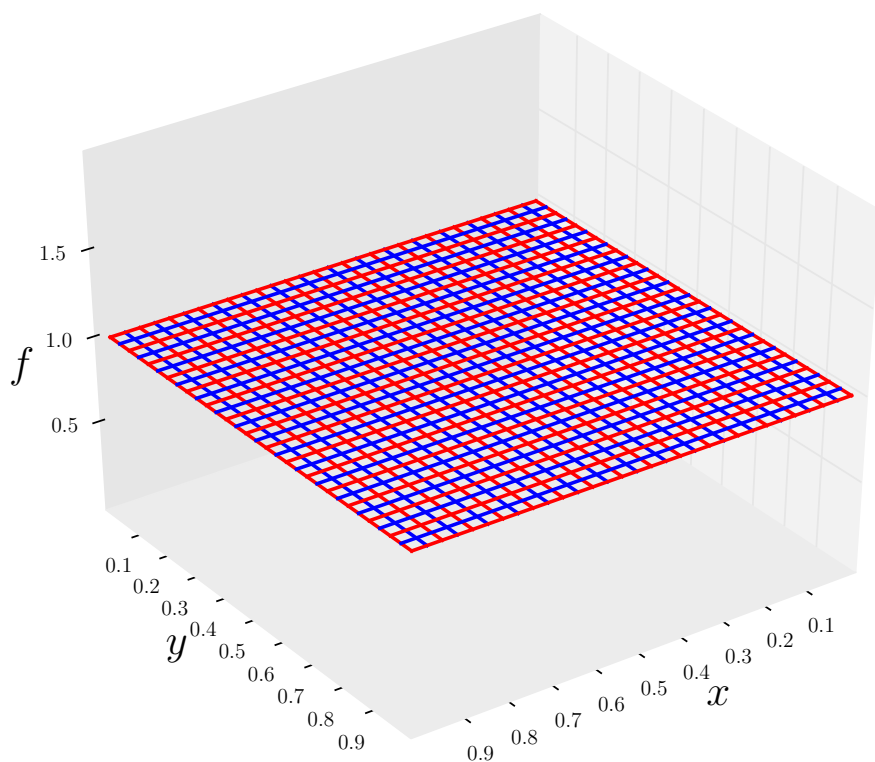
and *standard deviation*

$$\sigma = \frac{b - a}{2\sqrt{3}} .$$

A *joint uniform* random variable :

$$f(x, y) = \frac{1}{(b-a)(d-c)} \quad , \quad F(x, y) = \frac{(x-a)(y-c)}{(b-a)(d-c)} \quad ,$$

for  $x \in (a, b]$ ,  $y \in (c, d]$ .



Here  $x \in [0, 1]$ ,  $y \in [0, 1]$  .

**EXERCISE :**

Consider the *joint uniform density function*

$$f(x, y) = \begin{cases} c & \text{for } x^2 + y^2 \leq 4, \\ 0 & \text{otherwise.} \end{cases}$$

- What is the value of  $c$  ?
- What is  $P(X < 0)$  ?
- What is  $P(X < 0, Y < 0)$  ?
- What is  $f(x | y = 1)$  ?

**HINT :** No complicated calculations are needed !

## The Exponential Random Variable

$$f(x) = \begin{cases} \lambda e^{-\lambda x}, & x > 0 \\ 0, & x \leq 0 \end{cases}, \quad F(x) = \begin{cases} 1 - e^{-\lambda x}, & x > 0 \\ 0, & x \leq 0 \end{cases}$$

with

$$E[X] = \mu = \int_0^{\infty} x \lambda e^{-\lambda x} dx = \frac{1}{\lambda} \quad (\text{Check!}),$$

$$E[X^2] = \int_0^{\infty} x^2 \lambda e^{-\lambda x} dx = \frac{2}{\lambda^2} \quad (\text{Check!}),$$

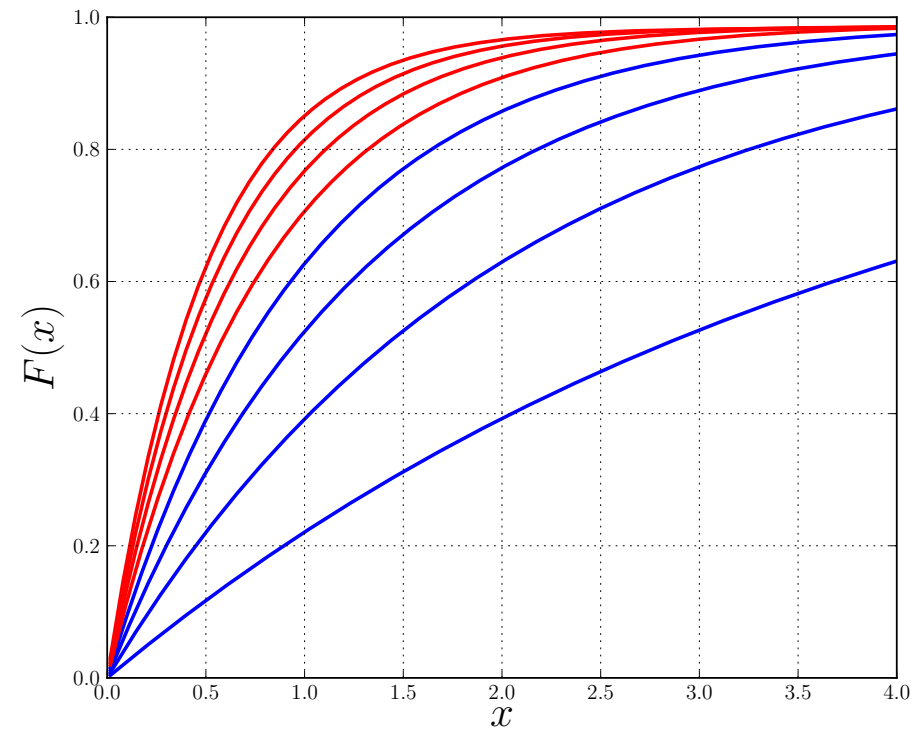
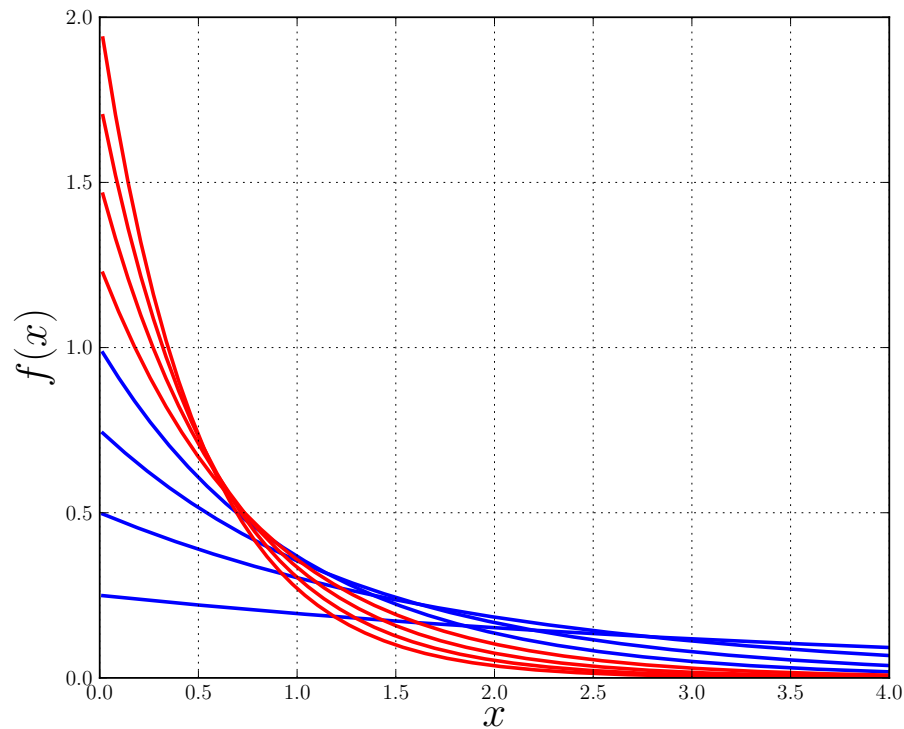
$$\text{Var}(X) = E[X^2] - \mu^2 = \frac{1}{\lambda^2},$$

$$\sigma(X) = \sqrt{\text{Var}(X)} = \frac{1}{\lambda}.$$

**NOTE** : The two integrals can be done by “*integration by parts*”.

**EXERCISE** : (Done earlier for  $\lambda = 1$ ) :

Also use the *Method of Moments* to compute  $E[X]$  and  $E[X^2]$ .



The Exponential *density* and *distribution* functions

$$f(x) = \lambda e^{-\lambda x} \quad , \quad F(x) = 1 - e^{-\lambda x} \quad ,$$

for  $\lambda = 0.25, 0.50, 0.75, 1.00$  (*blue*),  $1.25, 1.50, 1.75, 2.00$  (*red*).

**PROPERTY** : From

$$F(x) \equiv P(X \leq x) = 1 - e^{-\lambda x}, \quad (\text{for } x > 0),$$

we have

$$P(X > x) = 1 - (1 - e^{-\lambda x}) = e^{-\lambda x}.$$

Also, for  $\Delta x > 0$ ,

$$\begin{aligned} P(X > x + \Delta x \mid X > x) &= \frac{P(X > x + \Delta x, X > x)}{P(X > x)} \\ &= \frac{P(X > x + \Delta x)}{P(X > x)} = \frac{e^{-\lambda(x+\Delta x)}}{e^{-\lambda x}} = e^{-\lambda \Delta x}. \end{aligned}$$

**CONCLUSION** :  $P(X > x + \Delta x \mid X > x)$

*only depends* on  $\Delta x$  (and  $\lambda$ ), and *not* on  $x$ !

We say that the exponential random variable is "*memoryless*".

**EXAMPLE :**

Let the density function  $f(t)$  model *failure* of a device,

$$f(t) = e^{-t}, \quad (\text{taking } \lambda = 1),$$

*i.e.*, the *probability of failure* in the time-interval  $(0, t]$  is

$$F(t) = \int_0^t f(t) dt = \int_0^t e^{-t} dt = 1 - e^{-t},$$

with

$$F(0) = 0, \quad (\text{the device works at time } 0).$$

and

$$F(\infty) = 1, \quad (\text{the device must fail at some time}).$$



**EXAMPLE :** ( continued  $\dots$  )  $F(t) = 1 - e^{-t}$  .

Let  $E_t$  be the *event* that the device still *works* at time  $t$  :

$$P(E_t) = 1 - F(t) = e^{-t} .$$

The probability it still works at time  $t + 1$  is

$$P(E_{t+1}) = 1 - F(t + 1) = e^{-(t+1)} .$$

The probability it still works at time  $t + 1$ , given it works at time  $t$  is

$$P(E_{t+1}|E_t) = \frac{P(E_{t+1}E_t)}{P(E_t)} = \frac{P(E_{t+1})}{P(E_t)} = \frac{e^{-(t+1)}}{e^{-t}} = \frac{1}{e} ,$$

which is *independent of*  $t$  !

**QUESTION :** Is such an exponential distribution realistic if the “device” is your **heart**, and time  $t$  is measured in decades ?

## The Standard Normal Random Variable

The *standard normal* random variable has *density function*

$$f(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2}, \quad -\infty < x < \infty,$$

with *mean*

$$\mu = \int_{-\infty}^{\infty} x f(x) dx = 0, \quad (\text{Check!})$$

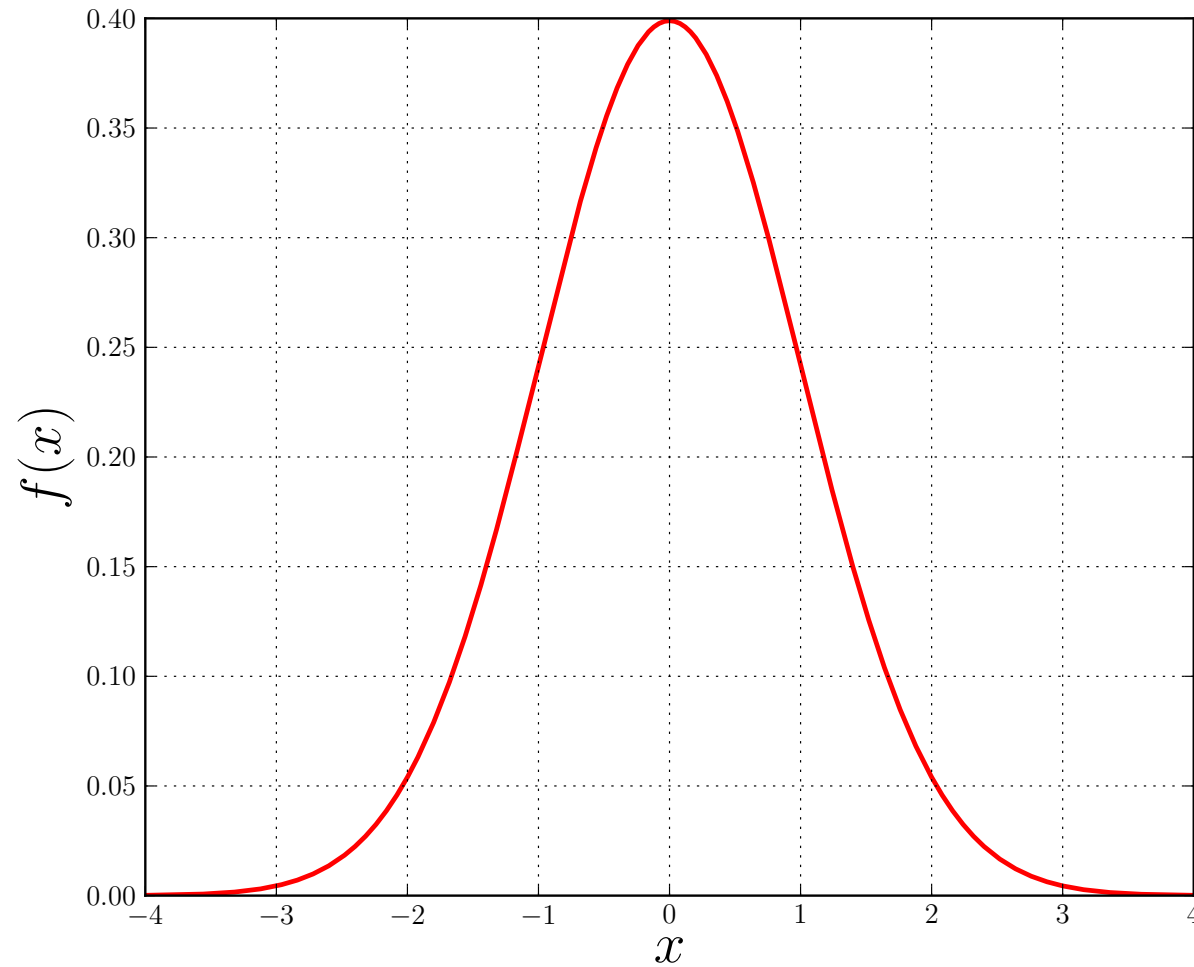
Since

$$E[X^2] = \int_{-\infty}^{\infty} x^2 f(x) dx = 1, \quad (\text{more difficult } \dots)$$

we have

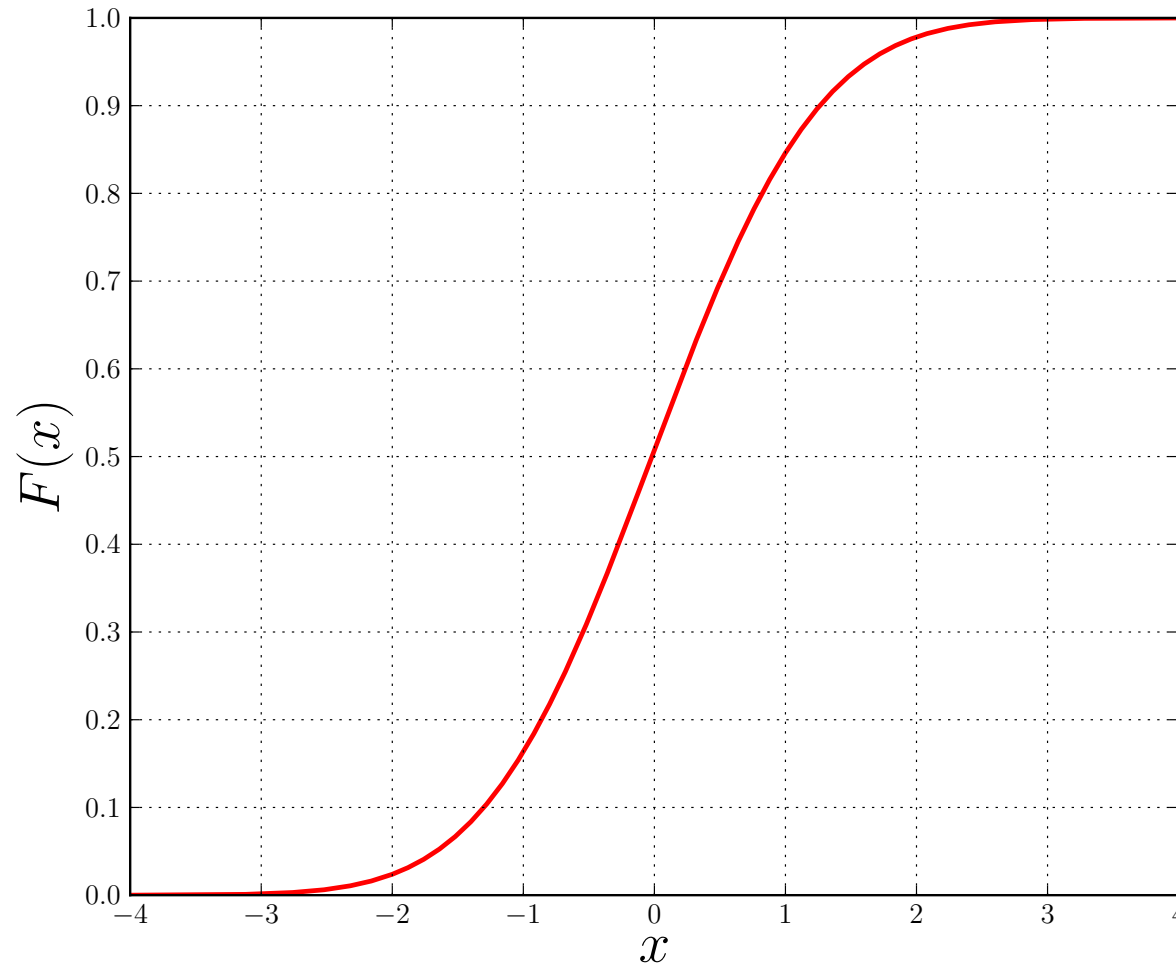
$$\text{Var}(X) = E[X^2] - \mu^2 = 1, \quad \text{and} \quad \sigma(X) = 1.$$

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



The *standard normal density function*  $f(x)$  .

$$\Phi(\mathbf{x}) = F(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{1}{2}x^2} dx$$



The *standard normal distribution function*  $F(x)$   
( often denoted by  $\Phi(\mathbf{x})$  ) .

## The Standard Normal Distribution $\Phi(z)$

$z$	$\Phi(z)$	$z$	$\Phi(z)$
0.0	.5000	-1.2	.1151
-0.1	.4602	-1.4	.0808
-0.2	.4207	-1.6	.0548
-0.3	.3821	-1.8	.0359
-0.4	.3446	<b>-2.0</b>	<b>.0228</b>
-0.5	.3085	-2.2	.0139
-0.6	.2743	-2.4	.0082
-0.7	.2420	-2.6	.0047
-0.8	.2119	-2.8	.0026
-0.9	.1841	-3.0	.0013
-1.0	.1587	-3.2	.0007

( For example,  $P(Z \leq -2.0) = \Phi(-2.0) = 2.28\%$  )

**QUESTION** : How to get the values of  $\Phi(z)$  for *positive*  $z$  ?

## EXERCISE :

Suppose the random variable  $X$  has the *standard normal* distribution.

What are the values of

- $P( X \leq -0.5 )$
- $P( X \leq 0.5 )$
- $P( | X | \geq 0.5 )$
- $P( | X | \leq 0.5 )$
- $P( -1 \leq X \leq 1 )$
- $P( -1 \leq X \leq 0.5 )$

## The General Normal Random Variable

The *general normal density function* is

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

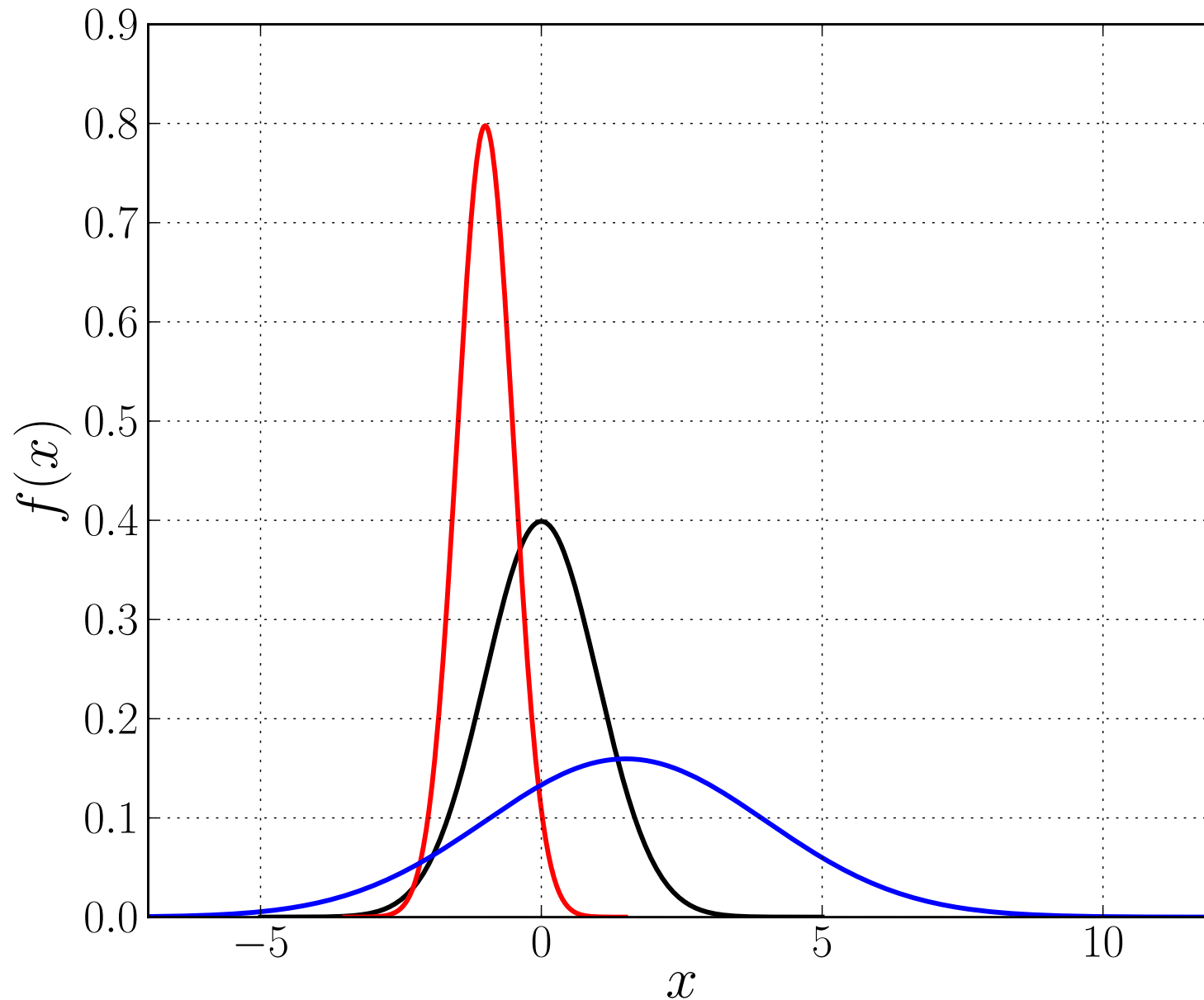
where, not surprisingly,

$$E[X] = \mu \quad (\text{Why ?})$$

One can also show that

$$\text{Var}(X) \equiv E[(X - \mu)^2] = \sigma^2 ,$$

so that  $\sigma$  is in fact the *standard deviation* .



The standard normal (*black*) and the normal density functions with  $\mu = -1$ ,  $\sigma = 0.5$  (*red*) and  $\mu = 1.5$ ,  $\sigma = 2.5$  (*blue*).



To compute the *mean* of the *general normal density function*

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

consider

$$\begin{aligned} E[X - \mu] &= \int_{-\infty}^{\infty} (x - \mu) f(x) dx \\ &= \frac{1}{\sqrt{2\pi} \sigma} \int_{-\infty}^{\infty} (x - \mu) e^{-\frac{1}{2}(x-\mu)^2/\sigma^2} dx \\ &= \frac{-\sigma^2}{\sqrt{2\pi} \sigma} e^{-\frac{1}{2}(x-\mu)^2/\sigma^2} \Big|_{-\infty}^{\infty} = 0. \end{aligned}$$

Thus the *mean* is indeed

$$E[X] = \mu .$$

**NOTE** : If  $X$  is *general normal* we have the *very useful formula* :

$$P\left(\frac{X - \mu}{\sigma} \leq c\right) = \Phi(c) ,$$

*i.e.*, we can use the *Table* of the *standard normal distribution* !

**PROOF** : For any constant  $c$  we have

$$P\left(\frac{X - \mu}{\sigma} \leq c\right) = P(X \leq \mu + c\sigma) = \frac{1}{\sqrt{2\pi} \sigma} \int_{-\infty}^{\mu + c\sigma} e^{-\frac{1}{2}(x-\mu)^2/\sigma^2} dx .$$

Let  $y \equiv (x - \mu)/\sigma$  , so that  $x = \mu + y\sigma$  .

Then the new variable  $y$  ranges from  $-\infty$  to  $c$  , and

$$(x - \mu)^2/\sigma^2 = y^2 \quad , \quad dx = \sigma dy ,$$

so that

$$P\left(\frac{X - \mu}{\sigma} \leq c\right) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^c e^{-\frac{1}{2}y^2} dy = \Phi(c) .$$

( the *standard normal distribution* )

**EXERCISE** : Suppose  $X$  is normally distributed with

*mean*  $\mu = 1.5$  and *standard deviation*  $\sigma = 2.5$  .

Use the *standard normal Table* to determine :

- $P( X \leq -0.5 )$
- $P( X \geq 0.5 )$
- $P( | X - \mu | \geq 0.5 )$
- $P( | X - \mu | \leq 0.5 )$

## The Chi-Square Random Variable

Suppose  $X_1, X_2, \dots, X_n,$   
are *independent standard normal* random variables.

Then  $\chi_n^2 \equiv X_1^2 + X_2^2 + \dots + X_n^2,$

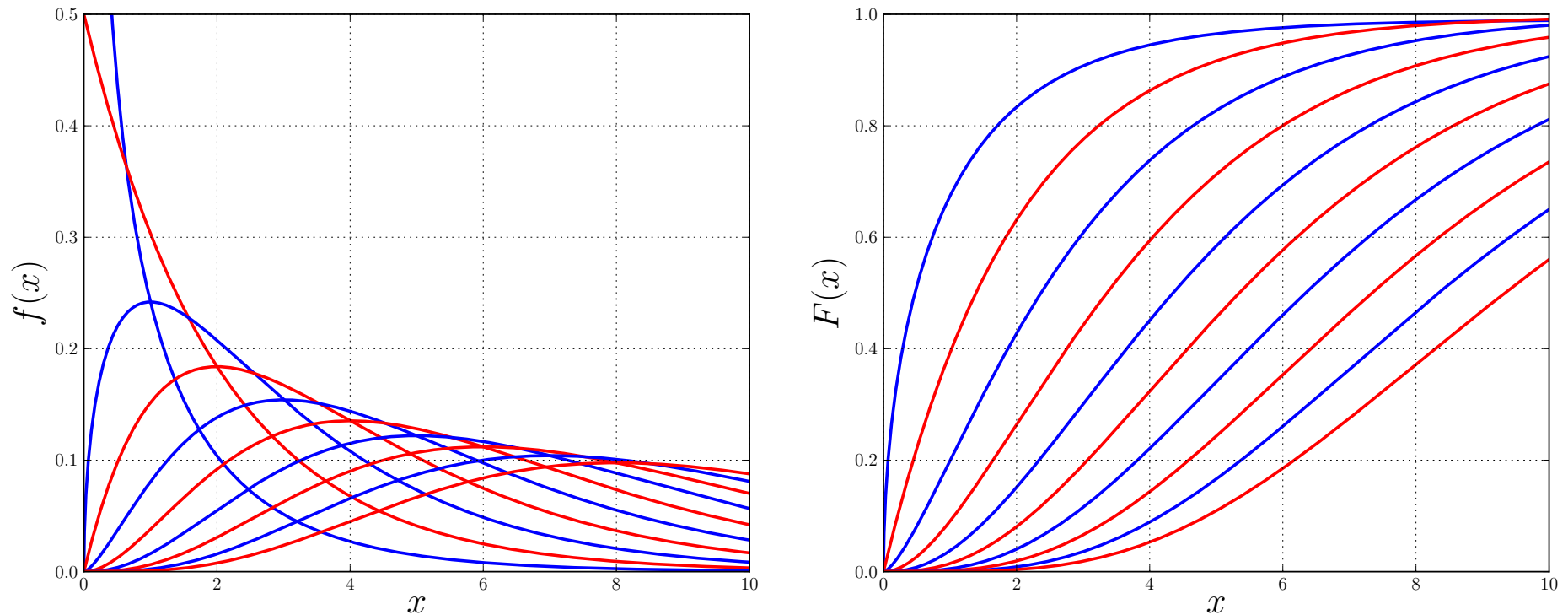
is called the *chi-square random variable* with  $n$  *degrees of freedom*.

We will show that

$$E[\chi_n^2] = n, \quad \text{Var}(\chi_n^2) = 2n, \quad \sigma(\chi_n^2) = \sqrt{2n}.$$

**NOTE :**

The  $^2$  in  $\chi_n^2$  is part of its *name*, while  $^2$  in  $X_1^2, \text{ etc.}$  is “*power 2*” !



The Chi-Square *density* and *distribution* functions for  $n = 1, 2, \dots, 10$ .

( In the Figure for  $F$ , the value of  $n$  increases from left to right. )

If  $n = 1$  then

$$\chi_1^2 \equiv X_1^2, \quad \text{where } X \equiv X_1 \text{ is standard normal.}$$

We can compute the *moment generating function* of  $\chi_1^2$  :

$$\begin{aligned} E[e^{t\chi_1^2}] &= E[e^{tX^2}] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{tx^2} e^{-\frac{1}{2}x^2} dx \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}x^2(1-2t)} dx \end{aligned}$$

Let

$$1 - 2t = \frac{1}{\hat{\sigma}^2}, \quad \text{or equivalently, } \hat{\sigma} \equiv \frac{1}{\sqrt{1-2t}}.$$

Then

$$E[e^{t\chi_1^2}] = \hat{\sigma} \cdot \frac{1}{\sqrt{2\pi} \hat{\sigma}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}x^2/\hat{\sigma}^2} dx = \hat{\sigma} = \frac{1}{\sqrt{1-2t}}.$$

(integral of a normal density function)

Thus we have found that :

The *moment generating function* of  $\chi_1^2$  is

$$\psi(t) \equiv E[e^{t\chi_1^2}] = \frac{1}{\sqrt{1-2t}},$$

with which we can compute

$$E[\chi_1^2] = \psi'(0) = 1, \quad (\text{Check!})$$

$$E[(\chi_1^2)^2] = \psi''(0) = 3, \quad (\text{Check!})$$

$$\text{Var}(\chi_1^2) = E[(\chi_1^2)^2] - E[\chi_1^2]^2 = 2.$$

We found that

$$E[\chi_1^2] = 1 \quad , \quad Var(\chi_1^2) = 2 .$$

In the *general case* where

$$\chi_n^2 \equiv X_1^2 + X_2^2 + \cdots + X_n^2 ,$$

we have

$$E[\chi_n^2] = E[X_1^2] + E[X_2^2] + \cdots + E[X_n^2] = n ,$$

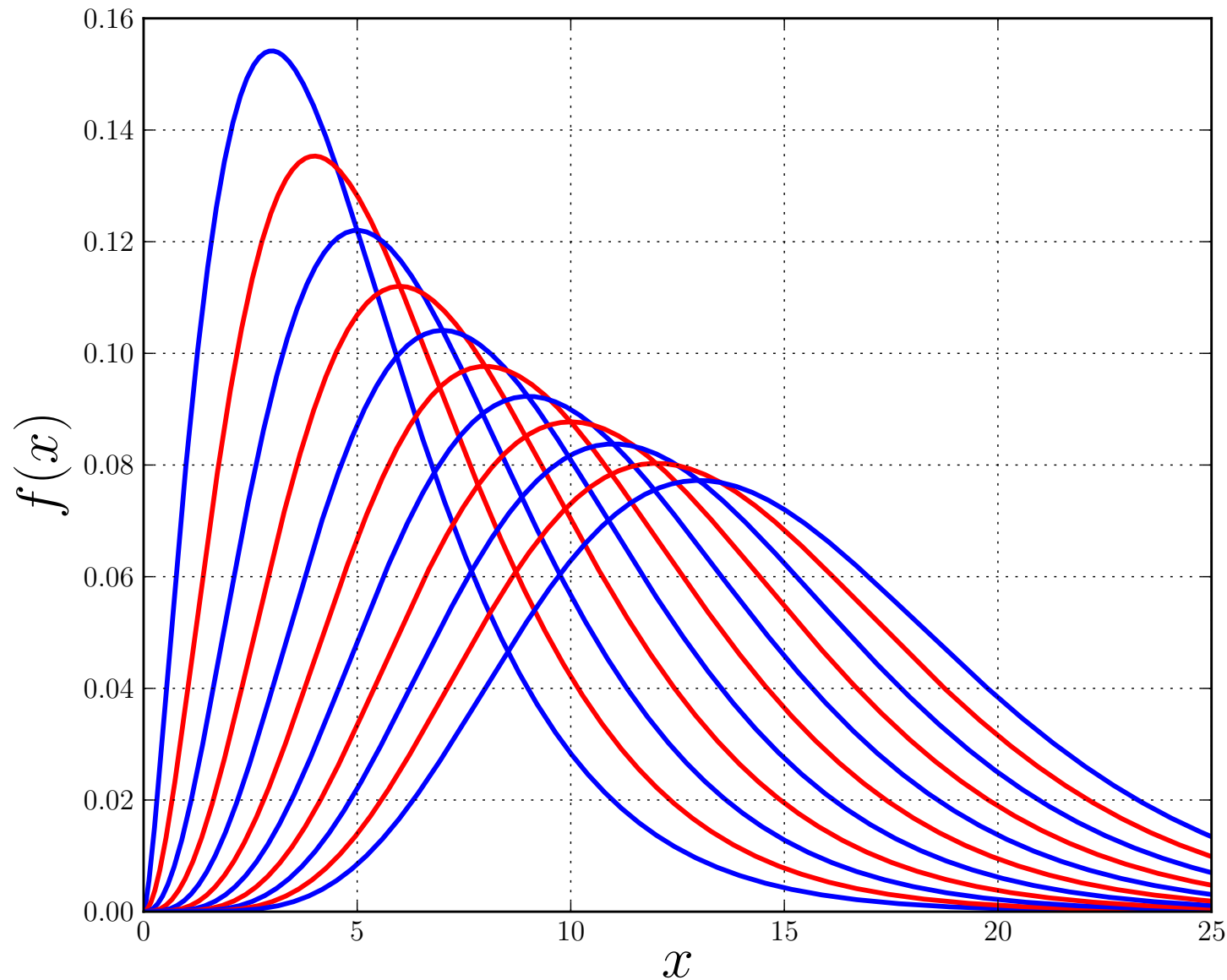
and since the  $X_i$  are assumed *independent* ,

$$Var[\chi_n^2] = Var[X_1^2] + Var[X_2^2] + \cdots + Var[X_n^2] = 2n ,$$

and

$$\sigma(\chi_n^2) = \sqrt{2n} .$$





The Chi-Square *density* functions for  $n = 5, 6, \dots, 15$  .  
( For *large*  $n$  they look like *normal* density functions ! )

## THE CENTRAL LIMIT THEOREM

The density function of the **Chi-Square** random variable

$$\chi_n^2 \equiv \tilde{X}_1 + \tilde{X}_2 + \cdots + \tilde{X}_n ,$$

where

$$\tilde{X}_i = X_i^2 , \quad \text{and} \quad X_i \text{ is standard normal, } i = 1, 2, \dots, n ,$$

starts looking like a *normal density function* when  $n$  gets large.

- This remarkable fact holds much more generally !
- It is known as the *Central Limit Theorem* (CLT).