

# 9 The Gaußian Distribution

COMS10011

`coms10011.github.io`

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# Continuous random variables

Continuous probability distributions work are defined in terms of a density function  $p(x)$ :

- $p(x)$  is like the probability per length

So to work out a probability for an interval

$$\text{Prob}(x_1 < x < x_2) = \int_{x_1}^{x_2} p(x) dx$$

# Introducing the Gaußian distribution I

- You can tell the Gaußian distribution is important because it has different names: the *Gaußian distribution*, the *normal distribution* or *the bell curve*.
- It is a continuous distribution which is used to model a whole range of natural phenomenon.
- Much of statistics assumes almost everything has a Gaußian distribution
- There is a theorem we'll look at later, the *Central Limit Theorem*, that tells us why it is so common.

# Introducing the Gaußian distribution II

## The Gaussian distribution

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

where we'll show later that  $\mu$  is the mean and  $\sigma^2$  is the variance, as you'd expect from the choice of symbols.

# Introducing the Gaußian distribution III

## The Gaussian distribution

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

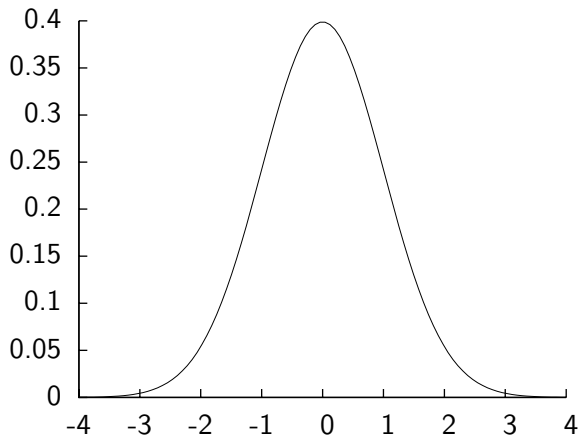
What about the  $1/\sqrt{2\pi\sigma^2}$ ? That is there to normalize the curve:

$$\int_{-\infty}^{\infty} e^{-x^2/2} dx = \sqrt{2\pi\sigma^2}$$

- We can do this particular definite integral going from minus infinity to infinity, but the corresponding indefinite integral can't be done.
- There is a nice trick for doing the definite integral which we won't look at here for reasons of time.

# Introducing the Gaußian distribution IV

The Gaussian distribution for  $\mu = 0$  and  $\sigma = 1$



# The moment generating function I

Amazingly it is easier to work out the moment generating function than to work out the mean and variance directly. Recall

$$m(t) = \langle e^{tX} \rangle$$

and this allows you to work out the moments because

$$\frac{d^n m}{dt^n}(0) = \mu_n$$

where

$$\mu_n = \langle X^n \rangle$$

# The moment generating function II

So for the Gaußian

$$m(t) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} e^{xt} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

Now using

$$e^a e^b = e^{a+b}$$

this gives

$$m(t) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} e^{-\frac{(x-\mu)^2}{2\sigma^2} + xt} dx$$



# The moment generating function III

Now we have

$$m(t) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} e^{-\frac{(x-\mu)^2}{2\sigma^2} + xt} dx$$

and write

$$\frac{(x-\mu)^2}{2\sigma^2} - xt = \frac{1}{2\sigma^2}(x^2 - 2\mu x + \mu^2 - 2\sigma^2 xt)$$

then add and take away what is needed to make a square

$$\begin{aligned} x^2 - 2\mu x + \mu^2 &= 2\sigma^2 xt \\ &= x^2 - 2(\mu + \sigma^2 t)x + (\mu + \sigma^2 t)^2 - 2\mu\sigma^2 t - \sigma^4 t^2 \\ &= (x - \mu - \sigma^2 t)^2 - 2\mu\sigma^2 t - \sigma^4 t^2 \end{aligned}$$

# The moment generating function IV

Hence

$$m(t) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} e^{-\frac{(x-\mu-\sigma^2 t)^2}{2\sigma^2} + \mu t + \frac{1}{2}\sigma^2 t^2} dx$$

move the stuff with no  $x$ s outside the integral

$$m(t) = \left( \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} e^{-\frac{(x-\mu-\sigma^2 t)^2}{2\sigma^2}} dx \right) e^{\mu t + \frac{1}{2}\sigma^2 t^2}$$

and the stuff in the big brackets is just one, it is the integral of the Gaussian with mean  $\mu + \sigma^2 t$ , so

$$m(t) = e^{\mu t + \frac{1}{2}\sigma^2 t^2}$$

# The mean and variance at last I

Remember that

$$\frac{d^n m}{dt^n}(0) = \mu_n$$

Now, remember the chain rule

$$\frac{d}{dt}e^{f(t)} = \frac{df}{dt}e^{f(t)}$$

Using it we we get

$$\frac{d}{dt}e^{\mu t + \frac{1}{2}\sigma^2 t^2} = (\mu + \sigma^2 t)e^{\mu t + \frac{1}{2}\sigma^2 t^2}$$

If we set  $t = 0$  this tells us that  $\langle X \rangle = \mu$ .

# The mean and variance at last II

Going back to

$$\frac{d}{dt}e^{\mu t + \frac{1}{2}\sigma^2 t^2} = (\mu + \sigma^2 t)e^{\mu t + \frac{1}{2}\sigma^2 t^2}$$

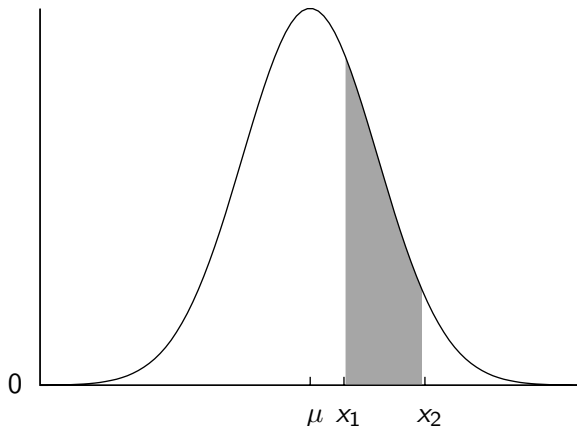
we differentiate again to get

$$\frac{d^2}{dt^2}e^{\mu t + \frac{1}{2}\sigma^2 t^2} = \frac{d}{dt}(\mu + \sigma^2 t)e^{\mu t + \frac{1}{2}\sigma^2 t^2} = [(\mu + \sigma^2 t)^2 + \sigma^2]e^{\mu t + \frac{1}{2}\sigma^2 t^2}$$

and if we set  $t = 0$  we get  $\langle X^2 \rangle = \sigma^2 + \mu^2$  and hence  $\langle X^2 \rangle - \langle X \rangle^2 = \sigma^2$ .

# Working out Gaussian probabilities I

$$\text{Prob}(x_1 < x < x_2) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{x_1}^{x_2} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$



# Can't do the integral

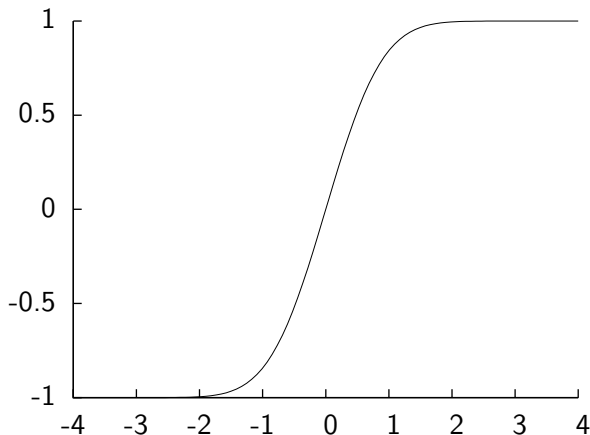
$$\text{Prob}(x_1 < x < x_2) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{x_1}^{x_2} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

The problem is we can't do this integral:

- We can't write this integral in terms of functions we know.
- To get around this we define a new function specifically so we can relate the integral to that.
- This is known as a *special function*, a new function defined for some special purpose.
- The values of the special function can be calculated numerically.

# The error function

$$\operatorname{erf}(x) = \frac{1}{\sqrt{\pi}} \int_{-\infty}^x e^{-y^2} dy = \frac{2}{\sqrt{\pi}} \int_0^x e^{-y^2} dy$$



## Working out Gaußian probabilities II

So

$$\text{Prob}(x_1 < x < x_2) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{x_1}^{x_2} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

Now do a change of variables

$$z = \frac{x - \mu}{\sqrt{2}\sigma}$$

so

$$dz = \frac{dx}{\sqrt{2}\sigma}$$

and when  $x = x_1$  we have

$$z = z_1 = \frac{x_1 - \mu}{\sqrt{2}\sigma}$$

and for  $x = x_2$  similar.



# Working out Gaussian probabilities III

Putting this into the integral we have

$$\text{Prob}(x_1 < y < x_2) = \frac{1}{\sqrt{\pi}} \int_{z_1}^{z_2} e^{-\frac{z^2}{2}} dz$$

then using

$$\int_a^b f(x) dx = - \int_b^a f(x) dx$$

and

$$\int_a^b f(x) dx = \int_a^0 f(x) dx + \int_0^b f(x) dx$$

we have

$$\text{Prob}(x_1 < y < x_2) = -\frac{1}{\sqrt{\pi}} \int_0^{z_1} e^{-z^2} dz + \frac{1}{\sqrt{\pi}} \int_0^{z_2} e^{-z^2} dz$$

# Working out Gaußian probabilities IV

Hence

$$\text{Prob}(x_1 < x < x_2) = \frac{1}{2}[\text{erf}(z_2) - \text{erf}(z_1)]$$

## An example

- The loudness of songs at a concert are normally distributed with mean 75 dB and standard deviation  $\sigma = 10\text{dB}$ .
- What is the probability that the next song has loudness between 80 and 90 dB?

$$\text{Prob}(80 < x < 90) = \frac{1}{2}[\text{erf}(z_2) - \text{erf}(z_1)]$$

where

$$\sqrt{2}z_1 = \frac{80 - 75}{10} = 0.5$$

and

$$\sqrt{2}z_2 = \frac{90 - 75}{10} = 1.5$$

Working out numbers on a calculator or computer gives

$$\text{Prob}(80 < x < 90) = 0.2417$$