

15 Apr 2026

Gaussians!

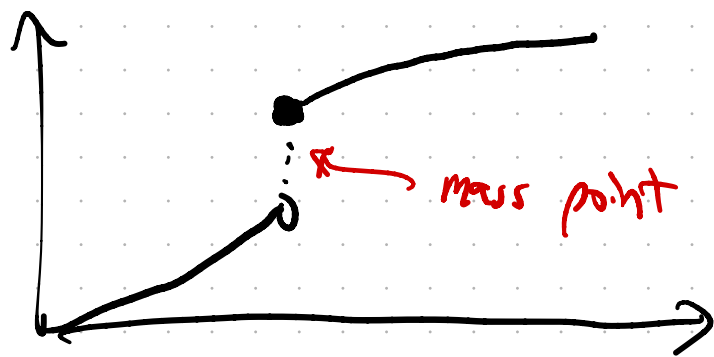
Continuous distributions on \mathbb{R} can be encoded by their CDF

$$F(t) = \Pr(X \leq t)$$

random variable
threshold.

F is always

- ① non-decreasing
- ② right-continuous, $F(t) = \lim_{t' \downarrow t} F(t')$.



$$\Pr(X = t) > 0.$$

When F is differentiable its derivative $f(t)$ is called the probability density of X .

$$f(t) \geq 0, \quad \text{not necessarily } \leq 1.$$

$$\int_{-\infty}^{\infty} f(t) dt = 1.$$

The distributions we talk about will either have mass points or a density function.

Another way to think about probability densities:

The probability of $|X - t| \leq \frac{\epsilon}{2}$

"X is in an interval of length ϵ centered at t "

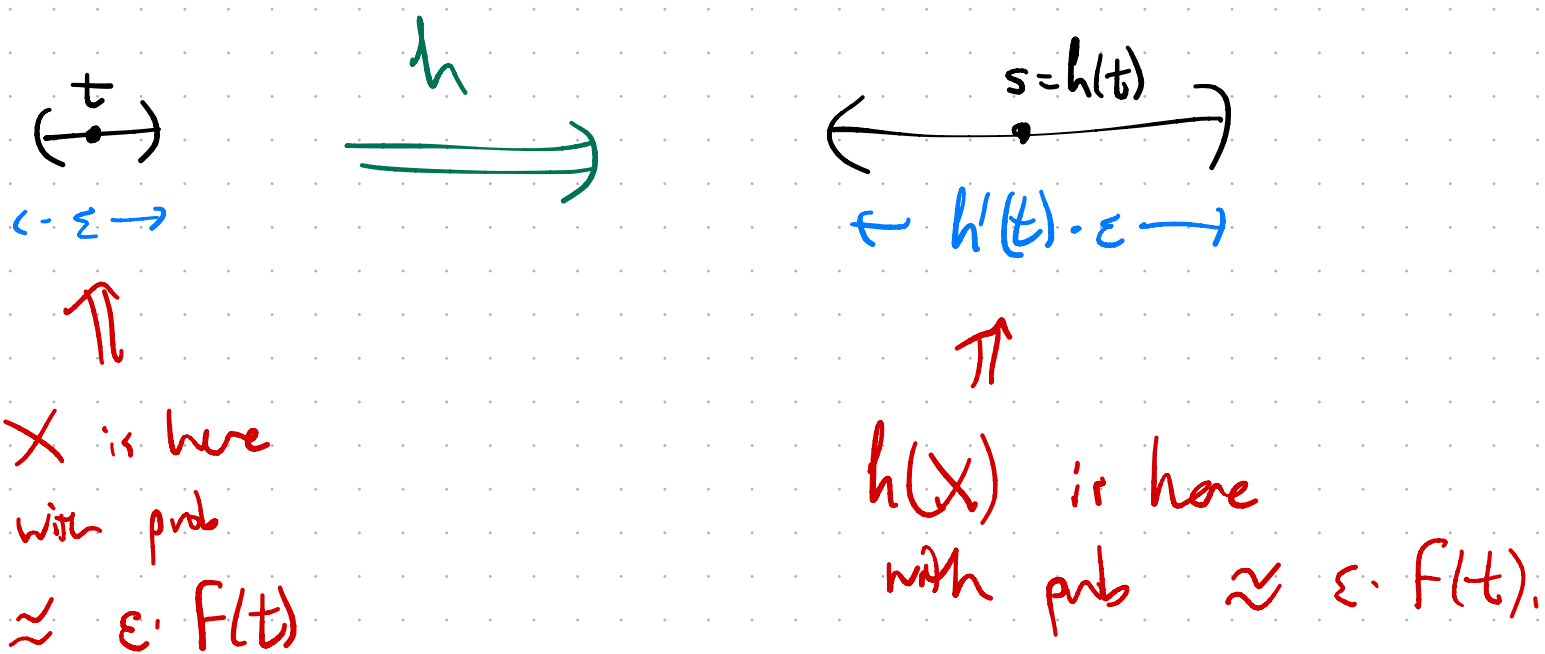
behaves like $\epsilon \cdot f(t) + o(\epsilon)$ as $\epsilon \rightarrow 0$.

Probabilities of small intervals near t

are $\epsilon \cdot (\text{interval length}) + \text{lower-order terms}$
 • density $f(t)$

E.g. Suppose h is differentiable func $\mathbb{R} \rightarrow \mathbb{R}$
 and X has prob. density f .

What is the density of $h(X)$
 at $s = h(t)$?



$$\text{density of } h(X) \text{ at } s = \frac{\text{Pr}(\text{interval})}{\epsilon \cdot \text{length}(\text{int})} = \frac{\epsilon \cdot f(t)}{\epsilon \cdot h'(t)} = \frac{f(t)}{h'(t)}$$

The higher-dimensional analogue: for vector-valued random variable $\vec{X} \in \mathbb{R}^n$,

$$\Pr(\vec{X} \in B_\varepsilon) = \varepsilon \cdot f(\vec{t}) + (\text{lower order terms})$$

\nearrow
n-dimensional
box of volume ε
centered at $\vec{t} \in \mathbb{R}^n$

The Gaussian distribution $N(0, 1)$ is the distribution on \mathbb{R} with density

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

\uparrow important exponential function

the necessary normalizing factor that makes $\int_{-\infty}^{\infty} f(t) dt = 1$.

The CDF $F(t) = \int_{-\infty}^t f(t) dt$ cannot be written in closed form.

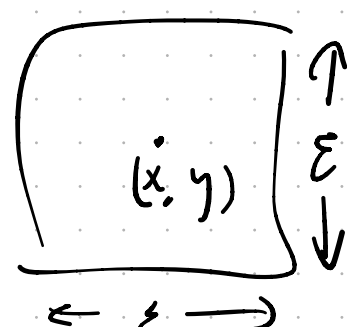
If X and Y are independent and both are $N(0,1)$ distributed,

their joint density is

$$f(x, y) = \left(\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} \right) \cdot \left(\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}y^2} \right) \\ = \frac{1}{2\pi} e^{-\frac{1}{2}(x^2 + y^2)}$$

The joint distrib of (X, Y) is

- (a) rotationally invariant
- (b) independent.



$$\epsilon^2 \cdot f(x, y) = (\epsilon f(x)) \cdot (\epsilon f(y)) \\ f(x, y) = f(x) \cdot f(y)$$

↗ This is what's so special about Gaussians.

Sampling from continuous distributions.

Lemma. If X is a rand var with continuous CDF $F(x)$, then the rand var $Y = F(x)$ is unif distrib. in $[0, 1]$.

Proof. To show: $\Pr(Y \leq t) = t \quad \forall t \in (0,1)$

$$\Pr(Y \leq t) = \Pr(F(X) \leq t)$$

$$= \Pr(X \leq F^{-1}(t))$$

$$= F(F^{-1}(t)) = t, \quad \text{QED.}$$

↖ maximum s
s.t. $F(s) = t$

Cor. If $Y \in [0,1]$ uniformly rand,

$X = F^{-1}(Y)$ has CDF F .

Ex. Exponential rate 1 rand var has

CDF
density

$$F(x) = 1 - e^{-x}$$

$$f(x) = e^{-x} \quad (x \geq 0)$$

Sampling from expt distrib.

① Draw $Y \sim \text{unif}[0,1]$

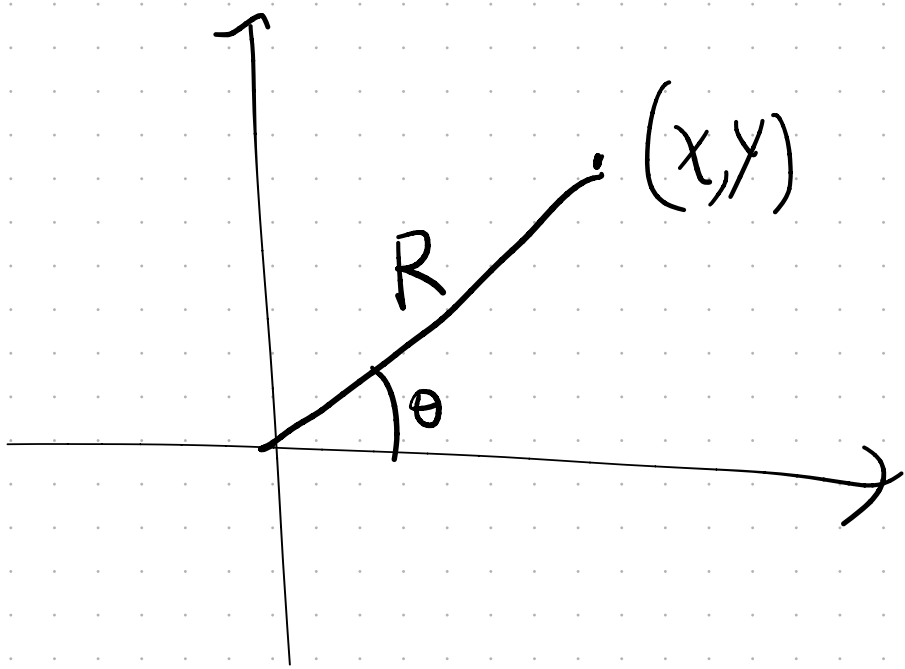
② $X = F^{-1}(Y) = -\ln(1-Y)$.

Sampling from Gaussian.

If X, Y are independent $N(0, 1)$,

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

In polar coords: let $R = \sqrt{X^2 + Y^2}$
 $\Theta = \tan^{-1}(Y/X)$



Density in polar: $f_{\text{polar}}(r, \theta) = \frac{1}{2\pi} e^{-\frac{1}{2}r^2} \cdot r$

