

Probability and Statistics

4 – Continuous Random Variables

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1.) Let X be a random variable with cdf $F_X(x)$. For $a, b \in \mathbb{R}, a \neq 0$ consider the random variable

$$Y = aX + b$$

and show that its cdf is given by:

$$F_Y(x) = \begin{cases} F_X\left(\frac{x-b}{a}\right) & \text{if } \underline{a > 0} \\ \underline{1 - F_X\left(\frac{x-b}{a}\right) + \Pr(X = \frac{x-b}{a})} & \text{if } \underline{a < 0} \end{cases} \quad \checkmark$$

Y r.v.

$Y: \Omega \rightarrow \mathbb{R}$

$(\Omega, \mathcal{A}, \mathbb{P})$

Proof: $F_Y(x) = \mathbb{P}_r(Y \leq x) = \mathbb{P}_r(Y^{-1}((-\infty, x])) = \mathbb{P}_r(\{\omega \in \Omega \mid Y(\omega) \leq x\})$

$$= \mathbb{P}_r(aX + b \leq x) = \mathbb{P}_r(a \cdot X \leq x - b)$$

$$= \begin{cases} \mathbb{P}_r(X \leq \frac{x-b}{a}) = \underline{F_X\left(\frac{x-b}{a}\right)} & a > 0 \\ \mathbb{P}_r(X \geq \frac{x-b}{a}) = \underbrace{1 - \mathbb{P}_r(X \leq \frac{x-b}{a})}_{1 - F_X\left(\frac{x-b}{a}\right)} + \mathbb{P}_r(X = \frac{x-b}{a}) & \underline{a < 0} \end{cases}$$

- 2.) Let X and Y be as in exercise 1. Furthermore assume that X is continuous with pdf $f_X(x)$.
Show that Y is continuous with pdf:

$$f_Y(x) = \frac{1}{|a|} \cdot f_X\left(\frac{x-b}{a}\right)$$

$$\begin{aligned} F_Y(x) &= \int_{-\infty}^x f_Y(t) dt = \int_{-\infty}^x \frac{1}{|a|} \cdot f_X\left(\frac{t-b}{a}\right) dt & u = \frac{t-b}{a} \\ &= \frac{1}{|a|} \cdot \int_{-\infty}^{\frac{x-b}{a}} f_X(u) \cdot \underbrace{\frac{du}{dt}}_{= \frac{1}{a}} du & \frac{du}{dt} = \frac{1}{a} \\ & & a > 0 \\ & & a < 0 \end{aligned}$$

$$\begin{aligned} &= \begin{cases} \frac{1}{|a|} F_X\left(\frac{x-b}{a}\right) & a > 0 \\ \frac{1}{|a|} \cdot \left(-\int_{\frac{x-b}{a}}^{\infty} f_X(u) du\right) = (-1) \cdot \left(-\left(1 - F_X\left(\frac{x-b}{a}\right)\right)\right) & a < 0 \end{cases} \end{aligned}$$

- 3.) Let X be a continuous random variable with cdf $F_X(x)$ and pdf $f_X(x)$. For $a \in \mathbb{R}^+$ and $b \in \mathbb{R}$ consider the random variable

$$Y = \frac{X-b}{a} = \frac{1}{a} \cdot X - \frac{b}{a}$$

and show that its cdf and pdf are given by:

$$F_Y(x) = F_X(ax+b)$$

$$f_Y(x) = a \cdot f_X(ax+b) = a \cdot f_X\left(a\left(x + \frac{b}{a}\right)\right)$$

In particular, if X has finite expectation $\mu = E(X)$ and variance $\sigma^2 = \text{Var}(X)$ then the normalized version of X given by $\frac{X-\mu}{\sigma}$ possesses the pdf:

$$f_X(x) = \sigma \cdot f_X(\sigma x + \mu)$$

Normal Distributions

Theorem (4.48)

$$\begin{aligned} \text{(i)} \quad & \int_{-\infty}^{\infty} e^{-x^2} dx = \sqrt{\pi} \\ \text{(ii)} \quad & \frac{1}{\sqrt{2\pi} \cdot \sigma} \int_{-\infty}^{\infty} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx = 1 \quad \text{for all } \mu, \sigma \in \mathbb{R} \text{ with } \sigma > 0 \end{aligned}$$

Definition (4.49)

A random variable has a *normal distribution* $\mathcal{N}(\mu, \sigma)$ for some parameters $\mu, \sigma \in \mathbb{R}$ and $\sigma > 0$ if it has a pdf defined by:

$$f_X(x) = \frac{1}{\sqrt{2\pi} \cdot \sigma} \cdot e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

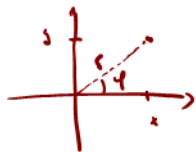
Proof of Theorem (4.48)

(i) A substitution with polar coordinates,

$$0 < r, \quad \varphi \in (-\pi, \pi]$$

$$\underline{(x, y) = (r \cos \varphi, r \sin \varphi)}, \quad \begin{vmatrix} \frac{\partial x}{\partial r} & \frac{\partial x}{\partial \varphi} \\ \frac{\partial y}{\partial r} & \frac{\partial y}{\partial \varphi} \end{vmatrix} = \begin{vmatrix} \cos(\varphi) & -r \sin(\varphi) \\ \sin \varphi & r \cos \varphi \end{vmatrix} = r$$

gives: $\left(\int_{-\infty}^{\infty} e^{-x^2} dx \right)^2 = \int_{-\infty}^{\infty} e^{-x^2} dx \cdot \int_{-\infty}^{\infty} e^{-y^2} dy$



$$\begin{aligned} &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-(x^2+y^2)} dx dy = \int_0^{\infty} \int_{-\pi}^{\pi} e^{-r^2} r d\varphi dr \\ &= \int_0^{\infty} 2\pi r e^{-r^2} dr = -\pi \int_0^{\infty} -2r \cdot e^{-r^2} dr = -\pi \cdot e^{-r^2} \Big|_0^{\infty} = 0 + \pi \end{aligned}$$

Proof of Theorem (4.48)

$$u = \frac{x - \mu}{\sqrt{2\pi} \cdot \sigma}, \quad \frac{du}{dx} = \frac{1}{\sqrt{2\pi} \cdot \sigma}$$

$$(ii) \quad \frac{1}{\sqrt{2\pi} \cdot \sigma} \int_{-\infty}^{\infty} e^{-\frac{1}{2} \left(\frac{x - \mu}{\sigma} \right)^2} dx = \frac{1}{\sqrt{2\pi} \cdot \sigma} \int_{-\infty}^{\infty} \sqrt{2\pi} \cdot \sigma e^{-u^2} du = \frac{1}{\sqrt{\pi}} \int_{-\infty}^{\infty} e^{-u^2} du = 1$$

Standard Normal Distribution

Definition (4.50)

$$\mu = 0, \sigma = 1$$

The normal distribution $\mathcal{N}(0, 1)$ is called the *standard normal distribution*. Its pdf and cdf are denoted by

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

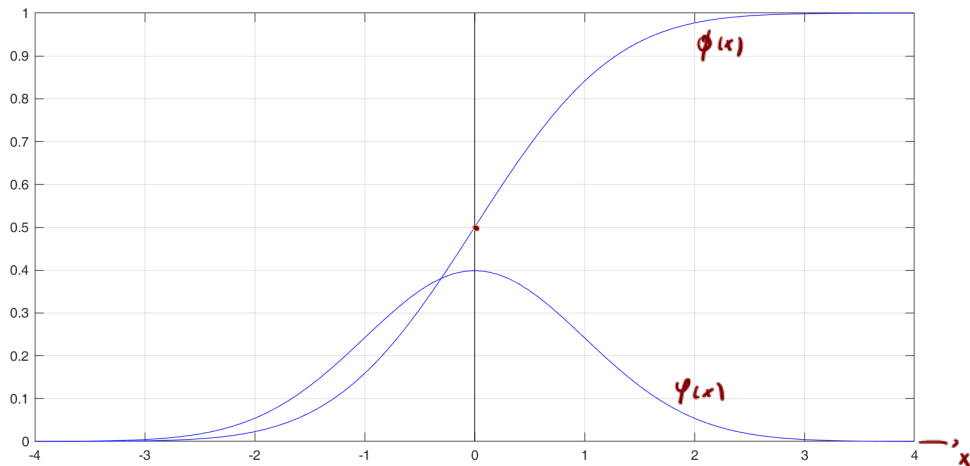
and

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \cdot \int_{-\infty}^x e^{-\frac{1}{2}u^2} du$$

→ no closed form
to calculate values

respectively.

Standard Normal Distribution



Normal Distributions

Lemma (4.51)

If $X \sim \mathcal{N}(\mu, \sigma)$, then:

- (i) $E(X) = \mu$
- (ii) $\text{Var}(X) = \sigma^2$
- (iii) $\phi_X(t) = e^{\mu t + \frac{1}{2}\sigma^2 t^2}$ (for all $t \in \mathbb{R}$)
- (iv) $aX + b \sim \mathcal{N}(a\mu + b, |a| \cdot \sigma)$ if $a \neq 0$
- (v) $F_X(x) = \Phi\left(\frac{x - \mu}{\sigma}\right)$
- (vi) $\Phi(-x) = 1 - \Phi(x)$ for all $x \in \mathbb{R}$
- (vii) $\Phi^{-1}(p) = -\Phi^{-1}(1 - p)$ for all $p \in (0, 1)$

Proof of (4.51)(i): $E(X) = \mu$

$$\begin{aligned} E(X) &= \frac{1}{\sqrt{2\pi} \cdot \sigma} \int_{-\infty}^{\infty} x e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx \\ &= \frac{1}{\sqrt{2\pi} \cdot \sigma} \int_{-\infty}^{\infty} (x - \mu + \mu) e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx \\ &= \frac{\sigma}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \frac{x - \mu}{\sigma^2} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx + \frac{1}{\sqrt{2\pi} \cdot \sigma} \int_{-\infty}^{\infty} \mu e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx \\ &= -\frac{\sigma}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \Bigg|_{-\infty}^{\infty} + \mu = \mu \end{aligned}$$

Proof of (4.51)(ii): $\text{Var}(X) = \sigma^2$

$$E((X-\mu)^2)$$

$$\text{Var}(X) = \frac{1}{\sqrt{2\pi} \cdot \sigma} \int_{-\infty}^{\infty} (x - \mu)^2 e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} dx$$

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

$$= -\frac{\sigma}{\sqrt{2\pi}} \left((x - \mu) \cdot e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} \Big|_{-\infty}^{\infty} - \int_{-\infty}^{\infty} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} dx \right)$$

$$= -\frac{\sigma}{\sqrt{2\pi}} (0 - \sqrt{2\pi} \cdot \sigma) = \sigma^2$$

Integration by
parts

Proof of (4.51)(iii): $\phi_X(t) = e^{\mu t + \frac{1}{2}\sigma^2 t^2}$ (for all $t \in \mathbb{R}$)

$$\begin{aligned}
 \phi_X(t) &= \frac{1}{\sqrt{2\pi} \cdot \sigma} \int_{-\infty}^{\infty} e^{tx} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx \\
 &= \frac{1}{\sqrt{2\pi} \cdot \sigma} \int_{-\infty}^{\infty} e^{-\frac{1}{2} \frac{x^2 - 2\mu x + \mu^2 - 2\sigma^2 tx}{\sigma^2}} dx \\
 &= \frac{1}{\sqrt{2\pi} \cdot \sigma} \int_{-\infty}^{\infty} e^{-\frac{1}{2} \frac{\overbrace{x^2 - 2(\mu + \sigma^2 t)x + (\mu + \sigma^2 t)^2}^{\text{green}} - \overbrace{2\mu\sigma^2 t - \sigma^4 t^2}^{\text{orange}}}{\sigma^2}} dx \\
 &= \frac{1}{\sqrt{2\pi} \cdot \sigma} \int_{-\infty}^{\infty} e^{\overbrace{\mu t + \frac{1}{2}\sigma^2 t^2}^{\text{orange}}} e^{-\frac{1}{2} \left(\frac{\overbrace{x - (\mu + \sigma^2 t)}^{\text{green}}}{\sigma} \right)^2} dx \\
 &= e^{\mu t + \frac{1}{2}\sigma^2 t^2} \quad \text{part of } \mathcal{N}(\mu + \sigma^2 t, \sigma)
 \end{aligned}$$