Probability and Random Process (SWE3026)

Continuous and Mixed Random Variables

JinYeong Bak
jy.bak@skku.edu
College of Computing, SKKU

H. Pishro-Nik, "Introduction to probability, statistics, and random processes", available at https://www.probabilitycourse.com, Kappa Research LLC, 2014.

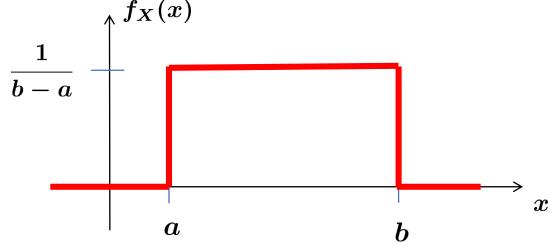
• Uniform Distribution: $X \sim Uniform(a,b)$

$$f_X(x) = egin{cases} rac{1}{b-a} & a < x < b \ 0 & x < a ext{ or } x > b \end{cases}$$

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

$$Var(X) = EX^{2} - (EX)^{2}$$

$$= \frac{(b-a)^{2}}{12}.$$



Example. Let $X \sim Uniform(-1,3)$,

$$E[X] = rac{3 + (-1)}{2} = 1,$$

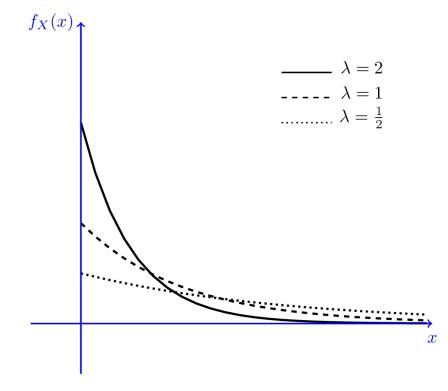
$$\operatorname{Var}(X) = \frac{(3 - (-1))^2}{12} = \frac{16}{12} = \frac{4}{3}.$$

• Exponential Distribution: $X \sim Exponential(\lambda)$

$$f_X(x) = \left\{egin{array}{l} \lambda e^{-\lambda x} & x > 0 \ 0 & ext{else} \end{array}
ight. \ = \lambda e^{-\lambda x} \; u(x)$$

Where u(x) denote the unit step function.

$$u(x) = egin{cases} 1 & x \geq 0 \ 0 & ext{otherwise} \end{cases}$$



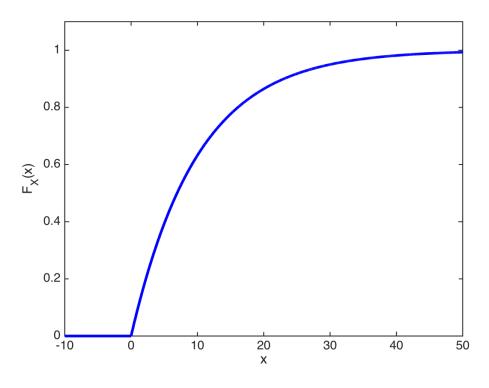
We find the CDF using the equation

$$F_X(x) = \int_0^x f_X(t)dt = \int_0^x \lambda e^{-\lambda t}dt = 1 - e^{-\lambda x}.$$

So

$$F_X(x) = \left(1 - e^{-\lambda x}\right) u(x).$$

Example. CDF of $Exponential(rac{1}{10})$



Expected value

$$egin{aligned} EX &= \int_0^\infty x \lambda e^{-\lambda x} dx \ &= rac{1}{\lambda} \int_0^\infty y e^{-y} dy & ext{choosing } y = \lambda x \ &= rac{1}{\lambda} igg[-e^{-y} - y e^{-y} igg]_0^\infty \ &= rac{1}{\lambda}. \end{aligned}$$

$$extbf{Var}(m{X}): \quad E[X^2] = \int_0^\infty x^2 \lambda e^{-\lambda x} dx = rac{2}{\lambda^2}.$$

Thus, we obtain

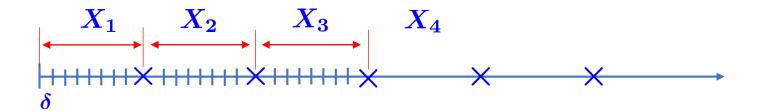
$$Var(X) = EX^2 - (EX)^2 = \frac{2}{\lambda^2} - \frac{1}{\lambda^2} = \frac{1}{\lambda^2}.$$

If $X \sim Exponential(\lambda)$, then

$$EX = rac{1}{\lambda}, \quad \mathrm{Var}(X) = rac{1}{\lambda^2}.$$

If X is exponential with parameter $\lambda>0$, then X is a memoryless random variable, that is

$$P(X > x + a \mid X > a) = P(X > x), \text{ for } a, x \ge 0.$$



Proof:

$$P(X > x + a | X > a) = \frac{P(X > x + a, X > a)}{P(X > a)} = \frac{P(X > x + a)}{P(X > a)}$$
 $= \frac{1 - F_X(x + a)}{1 - F_X(a)} = \frac{e^{-\lambda(x + a)}}{e^{-\lambda a}} = e^{-\lambda x}$
 $= P(X > x).$

Exponential random variables are often used to model times between arrivals at service centers (these are called interarrival times) – the memoryless property says that no matter how long you have waited for an arrival (X>a), the probability that you will have to wait for more than x more time instants is always P(X>x) (that is, it doesn't depend on a).

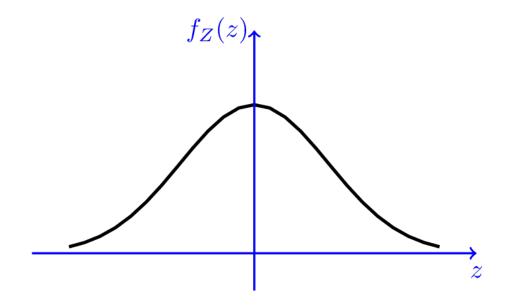
Normal (Gaussian) Distribution:

The normal distribution is by far the most important probability distribution. One of the main reasons for that is the Central Limit Theorem (CLT).

As we'll see later: The Central Limit Theorem says that random variables that are formed as sums of many independent random variables have distributions that are approximately Gaussian (e.g., the random voltage caused by electronic noise that results from the summed contributions of a very large number of randomly-located charge carriers).

• Standard normal random variable: $Z \sim N(0,1)$

$$f_Z(z) = rac{1}{\sqrt{2\pi}} e^{-rac{z^2}{2}}, \qquad ext{for all } z \in \mathbb{R}.$$



Expected value of the standard normal:

$$E[Z] = rac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} u e^{-rac{u^2}{2}} du = 0,$$
 $g(u)$

Since g(u) is an odd function.

Variance of the standard normal:

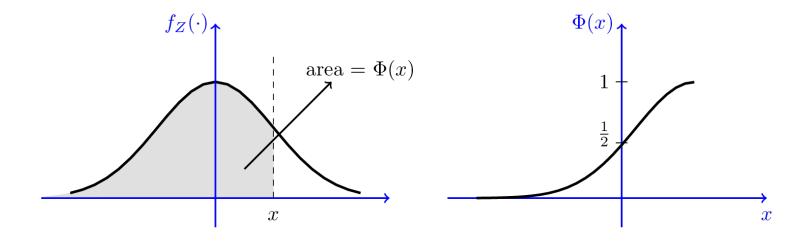
$$\mathrm{Var}(Z) = E[Z^2] - (EZ)^2 = E[Z^2] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} u^2 e^{-\frac{u^2}{2}} du = 1.$$

Integration by parts.

$$Z \sim N(0,1) \; \Rightarrow \left\{ egin{array}{l} E[Z] = 0 \ \mathrm{Var}(Z) = 1 \end{array}
ight.$$

CDF of the standard normal: The CDF of the standard normal distribution is denoted by the Φ function.

$$\Phi(x) = P(Z \le x) = rac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-rac{u^2}{2}} du.$$



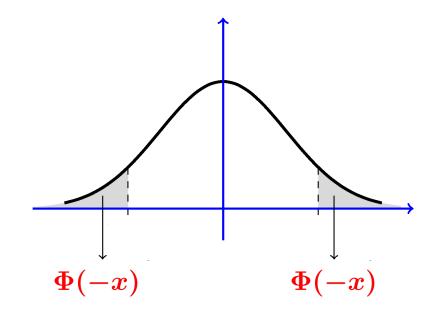
Here are some properties of the Φ function:

1)
$$\lim_{x\to\infty}\Phi(x)=1,\ \lim_{x\to-\infty}\Phi(x)=0;$$

2)
$$\Phi(0) = \frac{1}{2};$$

3)
$$\Phi(-x) = 1 - \Phi(x)$$
, for all $x \in \mathbb{R}$;

4)
$$\Phi(-x) + \Phi(x) = 1$$
.



The standard normal CDF $\Phi(z)$ can't be evaluated in closed form (except at a few specific values of z), but numerical approximations are widely available

General Normal random variables:

$$X=\sigma Z+\mu, \qquad ext{where } \sigma>0, \; \mu\in\mathbb{R}.$$
 $Z\sim N(0,1)$ $\Rightarrow \; X\sim N(\mu,\sigma^2).$ $EX=E[\sigma Z+\mu]=\sigma EZ+\mu=\mu, \; ext{(linearity of expectation)}$

General Normal random variables:

$$\operatorname{Var}(X) = \operatorname{Var}(\sigma Z + \mu) = \sigma^2 \operatorname{Var}(Z) = \sigma^2.$$

$$X \sim N(\mu, \sigma^2) \; \Rightarrow \; \left\{ egin{array}{l} E[X] = \mu \ \mathrm{Var}(X) = \sigma^2 \end{array}
ight.$$

CDF and PDF of Normal random variables ($X \sim N(\mu, \sigma^2)$):

$$F_X(x) = P(X \le x) = P(\sigma Z + \mu \le x) \ = P\left(Z \le \frac{x - \mu}{\sigma}\right) = \Phi\left(\frac{x - \mu}{\sigma}\right).$$

$$f_X(x) = rac{d}{dx} F_X(x) = rac{d}{dx} \Phi\left(rac{x-\mu}{\sigma}
ight) = rac{1}{\sigma\sqrt{2\pi}} \exp\left\{-rac{(x-\mu)^2}{2\sigma^2}
ight\}.$$

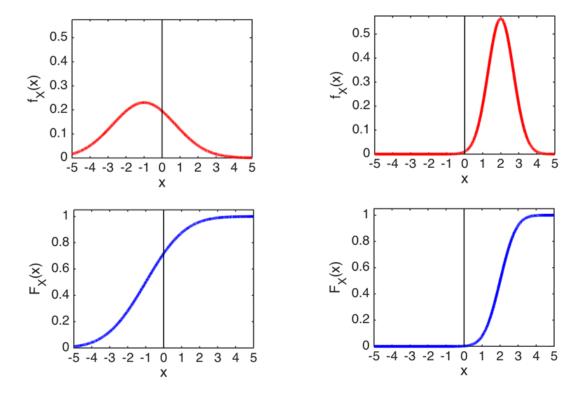
If
$$X \sim N(\mu, \sigma^2)$$
 , $E[X] = \mu; \; \mathrm{Var}(X) = \sigma^2,$

$$f_X(x) = rac{1}{\sigma\sqrt{2\pi}} \exp\left\{-rac{(x-\mu)^2}{2\sigma^2}
ight\},$$

$$F_X(x) = P(X \le x) = \Phi\left(rac{x-\mu}{\sigma}
ight),$$

$$P(a < X \le b) = F_X(b) - F_X(a) = \Phi\left(rac{b-\mu}{\sigma}
ight) - \Phi\left(rac{a-\mu}{\sigma}
ight).$$

Example. PDF (top) and CDF (bottom) of N(-1,3) random variable (left) and N(2,0.5) random variable (right):



Example. Suppose that $X \sim N(\mu, \sigma^2)$. Then:

$$egin{align} P(|X-\mu| \leq \sigma) &= P(\mu-\sigma \leq X \leq \mu+\sigma) \ &= \Phi\left(rac{\mu+\sigma-\mu}{\sigma}
ight) - \Phi\left(rac{\mu-\sigma-\mu}{\sigma}
ight) \ &= \Phi(1) - \Phi(-1) = 2\Phi(1) - 1 = 0.6827 \ \end{gathered}$$

$$P(|X - \mu| \le 3\sigma) = P(\mu - 3\sigma \le X \le \mu + 3\sigma)$$

$$= \Phi\left(\frac{\mu + 3\sigma - \mu}{\sigma}\right) - \Phi\left(\frac{\mu - 3\sigma - \mu}{\sigma}\right)$$

$$= \Phi(3) - \Phi(-3) = 2\Phi(3) - 1 = 0.9973$$

 So, the probability that a Gaussian random variable takes a value within 1 standard deviation from its mean is 0.6827.

 The probability that a Gaussian random variable takes a value within 3 standard deviations from its mean is 0.9973.

Theorem. If $X \sim N(\mu_X, \sigma_X^2)$, and Y = aX + b , where $a,b \in \mathbb{R}$, then $Y \sim N(\mu_Y, \sigma_Y^2)$, where

$$\mu_Y = a\mu_X + b, \quad \sigma_Y^2 = a^2\sigma_X^2.$$

$$E[Y] = E[aX + b] = aEX + b = a\mu + b,$$

$$Var(Y) = Var(aX + b) = a^2Var(X) = a^2\sigma^2$$
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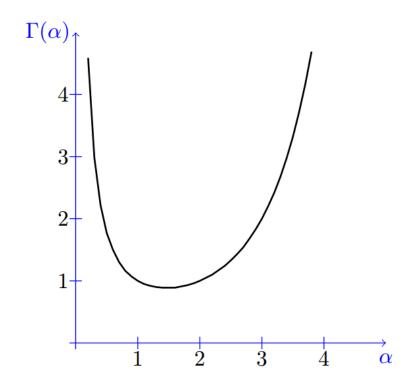
Gamma Distribution

Gamma function: $X \sim Gamma(\alpha, \lambda)$

$$\Gamma(lpha) = \int_0^\infty x^{lpha-1} e^{-x} \mathrm{d}x, \quad ext{for } lpha > 0.$$

$$\Gamma(\alpha+1)=\alpha\Gamma(\alpha), \text{ for } \alpha>0.$$

$$\Gamma(n)=(n-1)!, \text{ for } n\in\mathbb{N};$$



Gamma Distribution

Gamma Distribution:

$$f_X(x) = rac{\lambda^{lpha} x^{lpha-1} e^{-\lambda x}}{\Gamma(lpha)} \hspace{0.5cm} x > 0$$

If
$$\alpha = 1$$
:

- $f_X(x) = \lambda e^{-\lambda x}$ x > 0
- $Gamma(1, \lambda) = Exponential(\lambda)$

Gamma Distribution

If X_1, X_2, \cdots, X_n are independent, then

$$X_1, X_2, \cdots, X_n \sim Exponential(\lambda)$$

$$X_1 + X_2 + \cdots + X_n \sim Gamma(n, \lambda)$$