

(1) The mean of independent normal distributions

(a) Show that the moment generating function (mgf) of  $X \sim \mathcal{N}(\mu, \sigma^2)$  is of the form

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

(b) Let  $X \sim \mathcal{N}(\mu, \sigma^2)$  and let  $Y = aX + b$  with fixed real constants  $a$  and  $b$ . Show that  $Y \sim \mathcal{N}(a\mu + b, a^2\sigma^2)$ .

(c) Let  $X_1, \dots, X_n$  be independent identically distributed random variables with  $X_1 \sim \mathcal{N}(\mu, \sigma^2)$ . Show that the mean  $\bar{X} = \frac{1}{n}(X_1 + \dots + X_n)$  is also normally distributed and  $\bar{X} \sim \mathcal{N}(\mu, \frac{\sigma^2}{n})$ .

$$a) M_X(t) = \mathbb{E}(e^{tX}) = \int_{-\infty}^{\infty} e^{tx} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} \exp\left(\frac{2\sigma^2 tx - x^2 + 2x\mu - \mu^2}{2\sigma^2}\right) dx$$

$$\left| \begin{array}{l} u = \frac{x}{\sqrt{2}\sigma} - \left(\frac{\sigma t}{\sqrt{2}} + \frac{\mu}{\sqrt{2}\sigma}\right) \\ \frac{du}{dx} = \frac{1}{\sqrt{2}\sigma} \\ dx = \sqrt{2}\sigma du \end{array} \right| = \frac{1}{\sqrt{\pi}} \int_{-\infty}^{\infty} \exp\left(-u^2 + \frac{\sigma^2 t^2}{2} + t\mu\right) du = e^{\mu t + \frac{\sigma^2 t^2}{2}}$$

$$\left(\frac{x}{\sqrt{2}\sigma} - \left(\frac{\sigma t}{\sqrt{2}} + \frac{\mu}{\sqrt{2}\sigma}\right)\right)^2 = \frac{x^2}{2\sigma^2} - 2\frac{x}{\sqrt{2}\sigma} \left(\frac{\sigma t}{\sqrt{2}} + \frac{\mu}{\sqrt{2}\sigma}\right) + \frac{\sigma^2 t^2}{2} + t\mu + \frac{\mu^2}{2\sigma^2}$$

b) Case 1:  $a=0$ , then  $Y=b$ , hence  $P(Y \leq c) = \begin{cases} 0, & \text{if } c < b \\ 1, & \text{else} \end{cases}$ , could maybe be viewed as the limit " $\mathcal{N}(b, 0)$ "

Case 2:  $y = ax + b \Leftrightarrow x = \frac{y-b}{a}$  and  $\left(\frac{y-b}{a} - \mu\right)^2 = \frac{(y - (\mu a + b))^2}{a^2}$

$$f_Y(y) = f_X\left(\frac{y-b}{a}\right) \frac{1}{a} = \frac{1}{\sqrt{2\pi}\sigma a} \exp\left(-\frac{(y - (\mu a + b))^2}{2\sigma^2 a^2}\right), \text{ hence } Y \sim \mathcal{N}(\mu a + b, a^2\sigma^2)$$

$$c) Y_n := \sum_{i=1}^n X_i$$

Claim:  $\forall n \in \mathbb{N}: Y_n \sim \mathcal{N}(n\mu, n\sigma^2)$

$$n=1: Y_1 = X_1 \sim \mathcal{N}(\mu, \sigma^2)$$

$n \rightarrow n+1$ : Assume that  $Y_n \sim \mathcal{N}(n\mu, n\sigma^2)$  for  $n \in \mathbb{N}$ , then

$$Y_{n+1} = Y_n + X_{n+1} \sim \mathcal{N}((n+1)\mu, (n+1)\sigma^2), \text{ because}$$

$$f_{Y_n + X_{n+1}}(z) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(z-t-\mu)^2}{2\sigma^2}\right) \frac{1}{\sqrt{2\pi n}\sigma} \exp\left(-\frac{(t-n\mu)^2}{2n\sigma^2}\right) dt$$

$$= \frac{1}{2\pi\sigma^2\sqrt{n}} \int_{-\infty}^{\infty} \exp\left(-\left(\frac{z^2}{2\sigma^2} - \frac{zt}{\sigma^2} + \frac{t^2}{2\sigma^2} - \frac{z\mu}{\sigma^2} + \frac{t\mu}{\sigma^2} + \frac{\mu^2}{2\sigma^2} + \frac{t^2}{2n\sigma^2} - \frac{n\mu t}{\sigma^2} + \frac{n\mu^2}{2\sigma^2}\right)\right) dt$$

$$= \frac{\sqrt{2}\sigma(n+1)}{2\pi\sigma^2\sqrt{n}} \int_{-\infty}^{\infty} \exp\left(-u^2 + \frac{z^2(n+1)^2 - 1}{2\sigma^2} + \frac{z\mu}{\sigma^2} + \frac{\mu^2}{2\sigma^2} + \frac{n\mu^2}{2\sigma^2}\right) du$$

$$= \frac{n+1}{\sqrt{2}\pi\sigma} \exp\left(-\frac{(z - (n+1)\mu)^2}{2(n+1)\sigma^2}\right) \int_{-\infty}^{\infty} e^{-u^2} du = \frac{n+1}{\sqrt{2}\pi\sigma} \exp\left(-\frac{(z - (n+1)\mu)^2}{2(n+1)\sigma^2}\right)$$

$$\left(\frac{t}{\sqrt{2}\sigma(n+1)} - \frac{z(n+1)}{2\sigma}\right)^2 = \frac{t^2}{2\sigma^2(n+1)^2} - \frac{zt}{\sigma^2} + \frac{z^2(n+1)^2}{2\sigma^2} \Rightarrow \frac{1}{n} Y_n \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right)$$

## (2) Sum of two independent distributions

- (a) Let  $X \sim \mathcal{P}(\lambda_1)$  and  $Y \sim \mathcal{P}(\lambda_2)$  be two independent Poisson random variables.  
Show that

$$X + Y \sim \mathcal{P}(\lambda_1 + \lambda_2).$$

- (b) Let  $U$  and  $V$  be two independent random variables with exponential distribution  $\exp(\lambda)$ .  
Show that

$$U + V \sim \text{Gamma}(2, \lambda) \quad \text{and} \\ \min\{U, V\} \sim \exp(2\lambda).$$

*Hint:* It is useful to use moment generating functions. Recall, the pdf of a random variable  $X \sim \text{Gamma}(\alpha, \beta)$  is

$$f(x) = \begin{cases} \frac{x^{\alpha-1} e^{-\frac{x}{\beta}}}{\Gamma(\alpha) \beta^\alpha} & x > 0 \\ 0, & x \leq 0 \end{cases},$$

and its mgf is of the form  $\left(\frac{1}{1-\beta t}\right)^\alpha$  for  $t < \frac{1}{\beta}$ . Particularly, the pdf of a random variable  $X \sim \exp(\lambda) = \text{Gamma}(1, \frac{1}{\lambda})$  is of the form

$$f(x) = \begin{cases} \lambda e^{-\lambda x}, & x \geq 0 \\ 0, & x \leq 0 \end{cases}.$$

$$\begin{aligned} a) \quad M_X(t) &= \mathbb{E}(e^{tx}) = e^{-\lambda_1} \sum_{k=0}^{\infty} e^{tk} \frac{\lambda_1^k}{k!} = e^{-\lambda_1} \sum_{k=0}^{\infty} \frac{(\lambda_1 e^t)^k}{k!} = e^{-\lambda_1} e^{\lambda_1 e^t} = e^{\lambda_1(e^t - 1)} \\ M_Y(t) &= e^{\lambda_2(e^t - 1)} \\ M_X(t) M_Y(t) &= e^{(\lambda_1 + \lambda_2)(e^t - 1)} = M_{X+Y}(t) \end{aligned}$$

Hence,  $X+Y \sim \mathcal{P}(\lambda_1 + \lambda_2)$

$$b) \quad M_U(t) = M_V(t) = \frac{1}{1-\lambda t} \quad , \quad M_{U+V}(t) = M_U(t) M_V(t) = \frac{1}{(1-\lambda t)^2}$$

Hence,  $U+V \sim \text{Gamma}(2, \lambda)$  , since  $\exp(\lambda) = \text{Gamma}(1, \lambda)$  !!!

with pdf  $f(x) = \frac{\lambda^2}{\Gamma(2)} x^{2-1} e^{-\lambda x}, 0 < x < \infty$

$$\begin{aligned} \mathbb{P}(\min(U, V) < z) &= 1 - \mathbb{P}(U \geq z \wedge V \geq z) = 1 - \mathbb{P}(U \geq z) \mathbb{P}(V \geq z) = 1 - (1 - \mathbb{P}(U < z))^2 \\ &= 1 - (1 - (1 - e^{-\lambda z}))^2 = 1 - e^{-2\lambda z}, \quad \text{where } F_U(x) = 1 - e^{-\lambda x}, 0 < x < \infty \end{aligned}$$

is the cdf of an exponential distribution.

### (3) Real roots

Let  $A$ ,  $B$  and  $C$  be independent random variables, uniformly distributed on  $(0, 1)$ .

(a) What is the probability that the quadratic equation  $Ax^2 + Bx + C = 0$  has real roots?

(b) Consider the following code in R.

What does it do and how is it related to your solution in part (a)?

```
n=10000
a=runif(n)
b=runif(n)
c=runif(n)
sum(b^2 > 4*a*c)/n
```

*Hint:* In HW2/ex. 3(b) we showed that if  $X$  has uniform  $(0, 1)$  distribution then  $-\log X$  has exponential distribution  $\exp(1)$ . In an analogue way, one can prove that  $-s \log X \sim \exp(\frac{1}{s})$  for any  $s > 0$ . Also, in HW4/ex. 2(b) we proved that the sum of two independent exponential distributions is a gamma distribution. Namely, if  $X \sim \exp(1)$  and  $Y \sim \exp(1)$  are independent then  $X + Y \sim \text{Gamma}(2, 1)$ .

a)  $Ax^2 + Bx + C = 0 \Leftrightarrow x = \frac{-B \pm \sqrt{B^2 - 4AC}}{2A}$ , hence the quadratic equation has real roots if and only if  $B^2 - 4AC \geq 0$ .

$$\begin{aligned} P(B^2 - 4AC \geq 0) &= P(B^2 \geq 4AC) = P(\log(B^2) \geq \log(4AC)) = P(\log(B^2) \geq \log(4) + \log(AC)) \\ &= P(\log(B^2) - \log(AC) \geq \log(4)) = P(-\log(AC) \geq -\log(B^2) + \log(4)) \end{aligned}$$

$$-\log(A) \sim \exp(1), \quad -\log(C) \sim \exp(1), \quad -\log(AC) = (-\log(A)) + (-\log(C)) \sim \text{Gamma}(2, 1)$$

$$g: (0, 1) \rightarrow (0, \infty): x \mapsto -\log(x^2) \text{ has got the inverse } h: (0, \infty) \rightarrow (0, 1): y \mapsto e^{-\frac{y}{2}}$$

$$f_B(x) = \mathbb{1}_{(0,1)}(x) \Rightarrow f_{-\log(B^2)}(x) = \mathbb{1}_{(0,1)}(e^{-\frac{x}{2}}) e^{-\frac{x}{2}} = \mathbb{1}_{(0,1)}(x) \frac{1}{2} e^{-\frac{x}{2}}, \text{ hence } -\log(B^2) \sim \exp\left(\frac{1}{2}\right)$$

Clearly,  $-\log(B^2)$  and  $-\log(AC)$  are independent and we conclude

$$\begin{aligned} P(-\log(AC) \geq -\log(B^2) + \log(4)) &= \int_{\log(4)}^{\infty} \int_0^{y - \log(4)} f_{-\log(AC)}(y) f_{-\log(B^2)}(x) dx dy \\ &= \int_{\log(4)}^{\infty} y e^{-y} \int_0^{y - \log(4)} \frac{1}{2} e^{-\frac{x}{2}} dx dy \\ &= \int_{\log(4)}^{\infty} y e^{-y} \left(1 - \exp\left(-\frac{\log(4) - y}{2}\right)\right) dy \\ &= \int_{\log(4)}^{\infty} y e^{-y} dy - \int_{\log(4)}^{\infty} 2y e^{-\frac{3y}{2}} dy \\ &= \frac{1}{4} (1 + \log(4)) - \frac{1}{9} (1 + \log(8)) \approx 0,2544 \end{aligned}$$

b) The code gives an approximation of the probability that was calculated in (a).

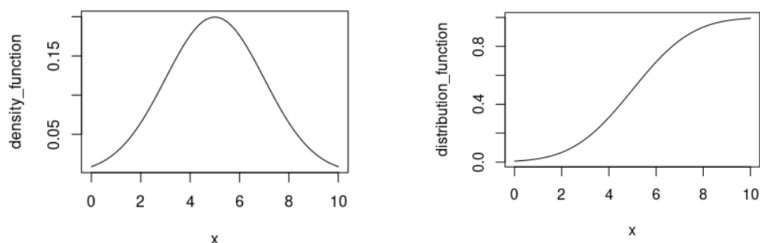
(4) **Sum and average**

Let  $X$  be a random variable with  $\mathcal{N}(5, 2^2)$ . Let  $X_1, X_2, \dots, X_{50}$  be independent identically distributed copies of  $X$ . Let  $S$  be their sum and  $\bar{X}$  their average, i.e.

$$S = X_1 + \dots + X_{50} \quad \text{and} \quad \bar{X} = \frac{1}{50}(X_1 + \dots + X_{50}).$$

- (a) Plot the density and the distribution function for  $X$  using R.
- (b) What are the expectation and the standard deviation of  $S$  and of  $\bar{X}$ ?
- (c) Generate a sample of 50 numbers from  $\mathcal{N}(5, 2^2)$ . Plot the histogram for this sample.  
Do the same for a sample of 500 numbers from  $\mathcal{N}(5, 2^2)$ .

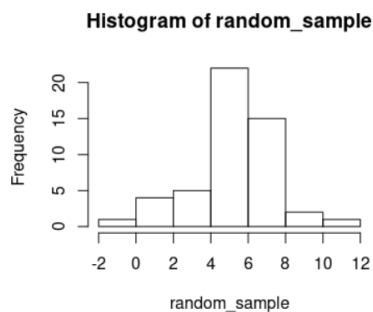
d)



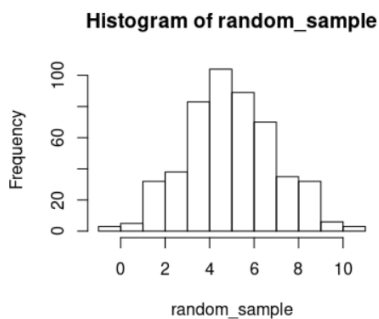
b) By problem 1 we have  $\bar{X} \sim \mathcal{N}(\mu, \frac{\sigma^2}{n})$  and  $S = n\bar{X} \sim \mathcal{N}(n\mu, n\sigma^2)$

Hence  $E(\bar{X}) = \mu$ ,  $\sqrt{\text{Var}(\bar{X})} = \frac{\sigma}{\sqrt{n}}$ ,  $E(S) = n\mu$ ,  $\sqrt{\text{Var}(S)} = \sqrt{n} \sigma$

2)  $n=50$



$n=500$



(5) **Central Limit Theorem**

Let  $\bar{X}_1$  and  $\bar{X}_2$  be the means of two independent samples of size  $n$  from the same population with variance  $\sigma^2$ . Use the Central limit theorem to find a value for  $n$  so that

$$P(|\bar{X}_1 - \bar{X}_2| < \frac{\sigma}{50}) \approx 0.99.$$

Justify your calculations.

we rename  $\bar{Y}_n := \bar{X}_1$  and  $\bar{Z}_n := \bar{X}_2$

$$\mathbb{E}(\bar{Y}_n - \bar{Z}_n) = \mathbb{E}\left(\frac{1}{n} \sum_{i=1}^n Y_i - \frac{1}{n} \sum_{i=1}^n Z_i\right) = \frac{1}{n} \sum_{i=1}^n (\mathbb{E}(Y_i) - \mathbb{E}(Z_i)) = 0$$

$$V(\bar{Y}_n - \bar{Z}_n) = V(\bar{Y}_n) + V(-\bar{Z}_n) = \frac{1}{n^2} \sum_{i=1}^n (V(Y_i) + V(Z_i)) = \frac{2\sigma^2}{n}$$

Chebyshev's inequality (13.14 in K usolitsch) says that

$$P(|\bar{Y}_n - \bar{Z}_n| \geq \frac{\sigma}{50}) \leq \frac{V(\bar{Y}_n - \bar{Z}_n)}{(\frac{\sigma}{50})^2} = \frac{(\frac{2\sigma^2}{n})}{(\frac{\sigma}{50})^2} = \frac{100^2}{n^2}, \text{ hence}$$

$$P(|\bar{Y}_n - \bar{Z}_n| < \frac{\sigma}{50}) \geq 1 - \frac{100^2}{n^2} \stackrel{!}{=} \frac{99}{100} \Leftrightarrow \frac{1}{100} = \frac{100^2}{n^2} \Leftrightarrow n^2 = 100^3 \Leftrightarrow n = \underline{\underline{100^{\frac{3}{2}} = 1000}}$$