

## Random variable generation

In the resolution of the following problems **do not** use any of the **R** random variable generation built-in functions, nor any **R** function referring to the densities of random variables.

Fix your **R** random seed to 123 in all simulations.

1. The **Box-Muller** method is a method for generating samples from two independent random variables  $X, Y \sim N(0, 1)$  from the  $U(0, 1)$  distribution. The algorithm proceeds as follows:

```
1. generate two observations  $u_1$  and  $u_2$  from  $U(0, 1)$ 
2. set  $\theta = 2\pi u_1$  and  $R = \sqrt{-2 \log(u_2)}$ 
3. set  $x = R \cos(\theta)$  and  $y = R \sin(\theta)$ 
4. repeat the previous steps until you reach the desired sample size
```

Often, when using this algorithm one is just interested in one of the variables  $X$  or  $Y$ . Also, if one is interested in generating a sample from  $Z \sim N(\mu, \sigma^2)$ , then the algorithm only requires the additional step  $Z = \mu + \sigma X$ .

- (a) Implement the Box-Muller method in **R**. Call your simulation routine `sim.norm()` and let it receive as input generic sample size  $m$  and parameters  $\mu$  and  $\sigma$  from the Normal distribution. Provide both algorithm and **R** code.

Consider the following results:

Let  $Z_1, \dots, Z_\nu$  be  $\nu$  independent random variables such that  $Z_i \sim N(0, 1)$ . Then

$$\sum_{i=1}^{\nu} Z_i^2 \sim \chi_\nu^2.$$

Let  $Z \sim N(0, 1)$  and  $V \sim \chi_\nu^2$  such that  $Z$  and  $V$  are independent random variables. Then,

$$\frac{Z}{\sqrt{\frac{V}{\nu}}} \sim t_\nu.$$

- (b) Implement a routine `sim.t()` in **R** for generating a sample of the t-student distribution  $t_\nu$ . Let `sim.t()` receive as input the sample size  $m$  and the number of degrees of freedom  $\nu$  of the t-student distribution. Use the results above and routine `sim.norm()` developed in (a). Provide both algorithm and **R** code.

- (c) Use routine `sim.t()` to generate a sample of size  $m = 10000$  of  $X \sim t_3$ .
  - (d) Plot the histogram referring to (c) with true p.d.f. superimposed.
2. Let  $X \sim \text{Gumbel}(\mu, \sigma)$ ,  $\mu \in \mathbb{R}$ ,  $\sigma > 0$ , which has cumulative distribution function (c.d.f.)

$$F(x) = e^{-e^{-\frac{x-\mu}{\sigma}}}, \quad x \in \mathbb{R}.$$

- (a) Describe and implement the **inverse-transform** method in R for generating a sample from  $F$ . Call your routine `sim.gum()` and let it receive as input a generic sample size  $m$  and the Gumbel  $\mu$  and  $\sigma$  parameters. Provide both algorithm and **R** code.
- (b) Use routine `sim.gum()` to generate a sample of size  $m = 10000$  of  $X \sim \text{Gumbel}(0, 1)$ .
- (c) Plot the histogram referring to (c) with true p.d.f. superimposed.

## Monte Carlo integration

In the resolution of the problems in this section you may already use the R random variable generation built-in functions as well as any R function referring to the densities of random variables.

Fix your R random seed to 456 in all simulations.

3. Let  $\mathcal{I} = \int_0^1 \frac{e^{-x}}{1+x^2} dx$ .

- (a) Use the R function `integrate()` to compute the value of  $\mathcal{I}$ .
- (b) Describe and implement in R the Monte Carlo method of size  $m = 10000$  for estimating  $\mathcal{I}$ . Report an estimate of the variance of the Monte Carlo estimator  $\hat{\mathcal{I}}_{MC}$  of  $\mathcal{I}$ .
- (c) Describe and implement in R the Monte Carlo method of size  $m = 10000$  based on **antithetic variables** for estimating  $\mathcal{I}$ . Report an estimate of the variance of the Monte Carlo estimator  $\hat{\mathcal{I}}_A$  of  $\mathcal{I}$ .

Report an estimate of the variance of the Monte Carlo estimator  $\hat{\mathcal{I}}_A$  of  $\mathcal{I}$ .

- (d) What's the percentage of variance reduction that is achieved when using  $\hat{\mathcal{I}}_A$  instead of  $\hat{\mathcal{I}}_{MC}$ ?

## Hypothesis testing

In the resolution of the problems in this section you may already use the R random variable generation built-in functions as well as any R function referring to the densities of random variables.

Fix your R random seed to 789 in all simulations.

4. Let  $X_1, \dots, X_n$  be a random sample from the population  $X \sim N(-2, 1)$ .
- (a) Validate via a Monte Carlo simulation study that  $T = \frac{\bar{X} + 2}{S/\sqrt{n}} \sim t_{n-1}$ . Consider in your study the number of simulations  $m = 1000$  and a sample size of  $n = 15$ . For validation purposes provide:

- the histogram of the simulated  $T_1, \dots, T_{1000}$  with the theoretical density superimposed;
- the plot of the empirical cumulative distribution (ecdf) of  $T_1, \dots, T_{1000}$  with the theoretical cumulative probability function (pdf) superimposed (use the R built-in `ecdf()` function to create the sample ecdf);
- perform a Kolmogorov-Smirnov two-sided test to test your hypothesis (use the R built-in `ks.test()` function);
- Compute the theoretical quantiles 0.90, 0.95, 0.975 with the empirical quantiles (use the R built-in `qchisq()` and `quantile()` functions, respectively).

(b) Assume one wants to test the hypothesis

$$H_0 : \mu \geq -2 \qquad H_1 : \mu < -2$$

at the significance level  $\alpha = 0.05$ . Compute the empirical p-values for this test using the previous Monte Carlo simulation. Compute the empirical significance level  $\hat{\alpha}$  and perform the binomial test to assess if  $\hat{\alpha}$  departs significantly from  $\alpha$ .

(c) For the hypothesis test above and the  $m$  simulations, construct a power plot for the alternative values  $\mu = -50, -49, \dots, -4, -3$ . In face of these results, how far from  $H_0$  does one need to be so that the power of the test gets higher than 75%?