

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.

- Let X be a discrete random variable with probability mass function (p.m.f.) f proportional to $g(x) = 1 - x + x^2$, $x = 0, 1, 2, 3, 4$.
 - Identify the p.m.f. f
 - Derive the cumulative distribution function (c.d.f.) F of X .
 - Describe and implement the **inverse-transform** method in **R** for generating a sample from f . Call your routine `sim.itm()` and let it receive as input a generic sample size m . Provide both algorithm and **R** code. Finally, use `sim.itm()` to generate a sample of size $m = 10000$ of f .
 - The same as in (c) but now using the **acceptance-rejection** method. Call your new simulation routine `sim.arm()`. Compute the rejection rate.
 - Plot the discrete histograms from (c) and (d) with the true p.m.f. superimposed.
 - Display the hit-and-miss plot referring to `sim.arm(10)`.
- Some random variables can be generated from the exponential distribution (**exponential-based method**), which we know how to obtain from the $U(0, 1)$ distribution. Such is the case of the random variable $X \sim \text{Beta}(a, b)$:

$$\text{If } Y_i \underset{iid}{\sim} \text{Exp}(1) \text{ then } X = \frac{\sum_{i=1}^a Y_i}{\sum_{i=1}^{a+b} Y_i} \sim \text{Beta}(a, b), \quad a, b = 1, 2, \dots$$

- Implement the **exponential-based method** in **R** for generating a sample from $X \sim \text{Beta}(a, b)$, which has probability density function (p.d.f.)

$$f(x) = \frac{x^{a-1}(1-x)^{b-1}}{B(a, b)}, \quad \alpha, \beta > 0, \quad x \in [0, 1]$$

where $B(a, b)$ is the *beta* function. Call your routine `sim.beta()` and let it receive as input a generic sample size m and the Beta distribution parameters a and b (note that here $a, b \in \mathbb{N}$). Provide both algorithm and **R** code.

- (b) Use routine `sim.beta()` to generate a sample of size $m = 10000$ from $X \sim \text{Beta}(3, 2)$.
- (c) Plot the histogram referring to (b) 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 $\mathcal{I} = \int_0^1 \frac{\sqrt{-\log(x)}}{2} dx$.

- (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} .
- (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 $X \sim N(0, 2)$.
 - (a) Validate via a Monte Carlo simulation study that $\chi = \frac{(n-1)S^2}{2} \sim \chi_{n-1}^2$. Consider in your study the number of simulations $m = 1000$ and a sample size of $n = 20$. For validation purposes provide:
 - the histogram of the simulated $\chi_1, \dots, \chi_{1000}$ with the theoretical density superimposed;
 - the plot of the empirical cumulative distribution (ecdf) of $\chi_1, \dots, \chi_{1000}$ 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

$$H_0 : \sigma^2 = 2 \qquad H_1 : \sigma^2 \neq 2$$

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 α .

- (c) For the hypothesis test above and the m simulations, construct a power plot for the alternative values $\sigma^2 = 3, 4, \dots, 50$. 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 80%?