

# Computational Statistics, M1 MAS DS, Aix-Marseille University

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# 1 Random variable simulation

[?, ?, ?]

## 1.1 Transformation methods

**Lemma 1.** *Let  $F : \mathbb{R} \rightarrow [0, 1]$  be a non-decreasing function. If a random variable  $X$  has  $F$  as its cumulative distribution function (CDF), then the random variable  $U = F(X) \sim U(0, 1)$ .*

*Proof.* □

**Example 1** (Normal variable generation). *The cumulative distribution function (CDF) of a Gaussian random variable with mean  $\mu$  and standard deviation  $\sigma$  is given by:*

$$F(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^x e^{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2} dt. \quad (1)$$

*The function  $F$  is a diffeomorphism. Assuming  $\mu = 0$  and  $\sigma = 1$ , an approximation  $F_a^{-1}$  of the inverse function  $F^{-1}$  can be computed to arbitrary precision ([?], Example 2.6). To generate a random sample of size  $n$  from the standard Gaussian distribution, we first generate  $n$  random samples from the uniform distribution,  $\{u_1, u_2, \dots, u_n\}$ . Then, we map this sample to the Gaussian distribution using the inverse approximation :*

$$\{F_a^{-1}(u_1), F_a^{-1}(u_2), \dots, F_a^{-1}(u_n)\}.$$

**Exercise 1.**

1. Generate a sample  $\mathcal{S} = \{u_1, u_2, \dots, u_n\}$  of size  $n = 500$  from the uniform distribution.
2. Implement the function

$$F_a^{-1}(u) = t - \frac{a_0 + a_1 t}{1 + b_1 t + b_2 t^2}, \quad u \in (0, 1),$$

where  $t^2 = \log(u^{-2})$  and  $a_0 = 2.30753, a_1 = 0.27061, b_1 = 0.99229, b_2 = 0.04481$

3. Plot the histogram of the set  $F_a^{-1}(\mathcal{S})$  and comment the results.
4. ♣ Repeat the process for a larger value of  $n$  (e.g.,  $n = 50000$ ). Compare the generated sample with a standard Gaussian random variable generator and comment the results.

## 1.2 Accept-reject method

## 2 Importance sampling

```
set.seed(12)

# Define the target distribution (Gamma distribution)
target_dist <- function(x, shape = 2, rate = 1) {
  ifelse(x > 0, x^(shape - 1) * exp(-rate * x), 0)
}

# Define the proposal distribution (Normal distribution)
proposal_dist <- function(x) {
  dnorm(x, mean = 2, sd = 2) # Normal(2, 2) PDF
}

# Generate samples from the proposal distribution
n_samples <- 2000

# proposal sample
ps <- rnorm(n_samples, mean = 2, sd = 2)

# Compute the weights for each sample
weights <- target_dist(ps) / proposal_dist(ps)

# Estimate the mean of the target distribution using IS
importance_sampling_mean <- sum(weights * ps) / sum(weights)
print(importance_sampling_mean)

## [1] 2.011539
```

## 3 Bootstrap

**Exercise 2.** Let  $S = \{x_1, x_2, \dots, x_n\}$  be a random sample from the uniform distribution on the interval  $(0, \theta)$ . Assume we want to estimate the unknown parameter  $\theta$ , so we use the estimator  $X_{(n)} = \max x_i$ .

1. If  $X_1, X_2, \dots, X_n$  are iid with uniform distribution on  $(0, \theta)$ , what is the distribution of the random variable  $X_{(n)} = \max X_i$ ?  
(Hint: Determine the cumulative distribution function of  $X_{(n)}$ )
2. Is the estimator  $X_{(n)}$  biased?
3. How would you use the bootstrap to estimate the bias in  $X_{(n)}$  for  $\theta$ ?

## 4 Monte Carlo methods

## 5 Gibbs algorithms for bayesian statistics

### 5.1 Metropolis Hastings algorithm

### 5.2 MCMC

bibliography