

# Computer simulations and Monte Carlo Methods (chapter 5)

Assume that we can simulate  $U \sim \text{Uniform}(0, 1)$ . Recall that:

Every programming language has a *random number generator* that simulates a  $U$ . In R, this function is `runif()`. Subsequent calls to this function will give draws that are “independent” for all practical purposes.

# Simulating from discrete distributions

**Simulating**  $X \sim \text{Bernoulli}(p)$ :

Recall: If  $X \sim \text{Bernoulli}(p)$ ,  $P(X = 1) = p$ ,  $P(X = 0) = 1 - p$ .

1. Generate  $U$ .
2. If  $U \leq p$ ; set  $X = 1$ , else set  $X = 0$ .

Verification:

## Simulating $X \sim f(x)$ , arbitrary discrete distribution:

Suppose  $X$  takes values  $x_0, x_1, \dots$ , with probabilities  $p_0, p_1, \dots$ , where  $p_i = P(X = x_i)$  and  $\sum_i p_i = 1$ .

1. Divide the interval  $[0, 1]$  into subintervals as shown below.
2. Generate  $U$ .
3. If  $U$  falls in subinterval  $i$ , take  $X = x_i$ .

Verification:

# Simulating from continuous distributions

**Result:** If  $X$  is a continuous rv with cdf  $F(x)$ , then  $U = F(X)$  follows Uniform(0, 1) distribution.

Inverse transform method: To simulate a  $X$ ,

1. Generate  $U$ .
2. Set  $U = F(X)$
3. Solve for  $X$  (i.e., invert the cdf).

Often the equation cannot be solved explicitly or efficiently.  
Alternatives are available.

## Simulating from Exponential( $\lambda$ ) distribution:

Recall: If  $X \sim \text{Exponential}(\lambda)$ ,  $F(x) = 1 - \exp(-\lambda x)$ .

# Solving problems by Monte Carlo methods

Estimating  $\mu = E(X)$  and  $\sigma^2 = \text{var}(X) = E(X - \mu)^2$ :

Simulate a large number ( $N$ ) of independent draws from the distribution of  $X$ , say,  $X_1, X_2, \dots, X_N$

*MC estimator of  $\mu$ :*

*MC estimator of  $E[g(X)]$  where  $g$  is a given function:*

*MC estimator of  $\sigma^2$ :*

## Estimating an integral $I = \int_a^b g(x)dx$ :

## Estimating $p = P(X \in A)$ for a given region $A$ :

Simulate a large number ( $N$ ) of independent draws from the distribution of  $X$ , say,  $X_1, X_2, \dots, X_N$

Define  $Y_1, \dots, Y_N$  as:

*MC estimator of  $p$ :*

*Properties of  $\hat{p}$ :*



## Accuracy of a Monte Carlo study:

Error in estimation:

Specify a small *margin of error*  $\epsilon$  and a small probability  $\alpha$ .

Want  $N$  such that

$$P(|\hat{p} - p| > \epsilon) \leq \alpha \quad (1)$$

or equivalently

- Error exceeds  $\epsilon$  with probability  $\alpha$  or less
- Error is  $\epsilon$  or less with probability more than  $1 - \alpha$ .

To derive a formula for  $N$ , suppose  $Z \sim N(0, 1)$  and  $z_{\alpha/2}$  is such that  $P(Z > z_{\alpha/2}) = \alpha/2$ .

From the symmetry,

$$P(|Z| > z_{\alpha/2}) = \tag{2}$$

Now, let's derive an expression for  $P(|\hat{p} - p| > \epsilon)$ :

Comparing (2) and (3), and noticing that  $P(|Z| > x)$  is decreasing in  $x$ , we can conclude that (1) approximately holds if

*A practical problem:*

Alternative 1:

Alternative 2:

**Note:** This formula is valid only if  $N$  is large.

**Ex:** Suppose the desired accuracy is  $(\epsilon, \alpha) = (0.03, 0.05)$ .  $N = ?$