

Monte Carlo sampling: → procedure of **generating** service and interarrival times from the given probability distributions.

Steps of Monte Carlo sampling:

1. Establish probability distributions for important input variables.
 - A. Service times
 - B. Interarrival times
2. Build a cumulative probability distribution for each variable in 1 (if it does not exist).
3. Generate an interval to translate random numbers to random variable outcomes.
 - A. Continuous variables: use inverse transformation method.
4. Generate random numbers.
5. Generate random variable outcomes.
6. Simulate a series of trials.

$m = 2^{31} - 1$ = prime number
— ensures a cycle length
= magnitude of the modulus
 m = non-prime number
— ensure a cycle length
< magnitude of the modulus

Random number generators

► Important characteristics:

1. Computationally fast.
2. Requires little computer memory.
3. Sufficiently spread out.
4. Identically replicable.
5. Has a long cycle (before repeating).

Example: Linear Congruential Random Number Generator

$$R_i = \frac{x_i}{m} \quad \text{where} \quad x_i = (a x_{i-1} + c) \% m$$

and : ► x_0 : seed number (given/specified)
► a : constant multiplier ($a = 7^5$)
► c : increment (given/specified)
► m : modulus ($m = 2^{31} - 1$)

Inverse transformation method:

1. Find the cumulative density function:
$$F(x) = \int_{-\infty}^x f(t) dt,$$
2. Create a random number R
3. Set $F(x)=R$ and solve for x with:
$$x = F^{-1}(R)$$
4. $x_i = F^{-1}(R_i)$ = random variable generator.

① Examples: uniform distribution

$$\text{pdf: } f(t) = \frac{1}{b-a}, \quad a \leq t \leq b$$

$$\text{cdf: } F(t) = \int_a^t \frac{1}{b-a} \cdot dt = \begin{cases} 0 & t < a \\ \frac{t-a}{b-a} & a \leq t \leq b \\ 1 & t > b \end{cases}$$

$$\text{inverse transform: } \frac{t_i - a}{b-a} = R_i \\ \Rightarrow t_i = R_i(b-a) + a$$

② Examples: exponential distribution

$$\text{pdf: } f(t) = \lambda e^{-\lambda t}, \quad t \geq 0, \lambda > 0$$

$$\text{cdf: } F(t) = \int_0^t \lambda e^{-\lambda t} \cdot dt = \begin{cases} 0 & t < 0 \\ 1 - e^{-\lambda t} & t \geq 0, \lambda > 0 \end{cases}$$

$$\text{inverse transform: } 1 - e^{-\lambda t} = R_i \\ t_i = -\frac{1}{\lambda} \cdot \ln(1 - R_i)$$

③ Examples: normal distribution

$$\text{inverse transform (in R):} \\ z = \text{qnorm}(R, \mu, \sigma)$$

Acceptance Rejection Method:

1. Select a constant M such that: $M = \max\{f(t) \mid t \in [a, b]\}$
2. While $i < n$:
 - A. Generate two random numbers r_1 and r_2 .
 - B. Compute $t^* = a + (b - a) \cdot r_1$
 - C. Evaluate $f(t^*)$
 - a. If $r_2 < f(t^*)/M \rightarrow t_i = t^*$ and $i = i + 1$
 - D. Return to step 2

When do we use ARM?

- ▶ $f(t)$ defined over a finite interval $\therefore [a, b]$
- ▶ distributions where CDF don't exist in closed form

Direct Method:

1. Generate two random numbers r_1 and r_2 .
2. Transform r_1 and r_2 into two normal random variates, (each with mean 0 and variance 1), using the direct transformations:

$$\begin{aligned} Z_1 &= (-2 \ln r_1)^{1/2} \sin 2\pi r_2 \\ Z_2 &= (-2 \ln r_1)^{1/2} \cos 2\pi r_2 \end{aligned} \quad \sim N(0, 1) \quad \left. \vphantom{\begin{aligned} Z_1 &= (-2 \ln r_1)^{1/2} \sin 2\pi r_2 \\ Z_2 &= (-2 \ln r_1)^{1/2} \cos 2\pi r_2 \end{aligned}} \right\} \text{choose one}$$

3. Transform these standardized normal variates into normal variates from the distribution with mean μ and variance σ^2 , using the equations:

$$\begin{aligned} X_1 &= \mu + \sigma Z_1 \\ X_2 &= \mu + \sigma Z_2 \end{aligned} \quad \sim N(\mu, \sigma^2)$$

When do we use DM?

- ▶ distributions where CDF don't exist in closed form
- ▶ $F(t)$ not defined over a finite interval $[a, b]$

→ normal distribution