Random Number Generation

732A90 Computational Statistics

Krzysztof Bartoszek (krzysztof.bartoszek@liu.se)

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Department of Computer and Information Science
Linköping University

Pseudorandom numbers

• A computer is a deterministic machine

• Congruential generators

• Functions of time

• Be careful with respect to application

First step: Generating Unif[0,1]

Linear congruential generator

Define a sequence of integers according to

$$x_{k+1} = (a \cdot x_k + c) \mod m, \quad k \ge 0$$

 x_0 is **seed**, e.g. based on time

mod m: remainder after division by m

- $x_k \in \{0, \ldots, m-1\}$ and integer
- $x_k/m \sim \text{Unif}[0,1]$
- $a, c \in [0, m)$ need to be carefully selected

First step: Generating Unif[0, 1]

Generated numbers will get into a loop with a certain **period**

$$x_{k+1} = (a \cdot x_k + c) \mod m, \quad k \ge 0$$

$$x_0 = a = c = 7, m = 10$$

- $2 x_1 = (7 \cdot 6 + 7) \mod 10 = 49 \mod 10 = 9$
- $3 x_1 = (7 \cdot 9 + 7) \mod 10 = 70 \mod 10 = 0$
- **6** $x_1 = (7 \cdot 7 + 7) \mod 10 = 56 \mod 10 = 6$
- **6** . . .

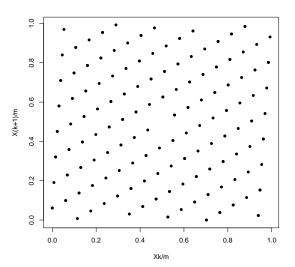
First step: Generating Unif[0,1]

```
fthreebits <- function (k,s,L,N) {
     X0 < -4*s + 1; a < -8*k + 5; m < -2^L; X < -X0
     for (i in 1:N) {
           \mathbf{print}(\mathbf{c}(X, \mathbf{rev}(\mathbf{intToBits}(X)[1:5])))
           X < -(a*X)\% m \#c = 0
          > source("CongGen.R");fthreebits(k=2,s=3,L=8.N=10)
          [1] 73 0 1 0 0 1
```

Last three bits change between 001 and 101 Discard less significant bits

First step: Generating Unif[0,1]

See also D. E. Knuth (1998). The Art of Computer Programming, Volume 2, Addison–Wesley. Ch. 3.3.4



 $732 \texttt{A} 90_\texttt{ComputationalStatistics} \\ \texttt{H} \texttt{T} 2022_\texttt{Lecture} \\ 03 \texttt{codeSlide} \\ 06. \\ \texttt{R} \\ \texttt{T} \\ \texttt{T}$

First step: Generating Unif[0, 1]

- Period is $\leq m$ by definition
- a, c, m (large) have to be chosen carefully

 - $a = 1 \mod p$ for every prime divisor p of m
 - $a = 1 \mod 4$ if 4 divides m
 - ① Then full period m reached (what about a = c = 1?)

- Seed defines the random sequence same seed, same sequence
 - Be careful when re-opening an R workspace
- Other methods (not in this course)

Second step: Generating Unif[a, b]

• $U \sim \text{Unif}[0,1]$ can be transformed into $X \sim \text{Unif}[a,b]$ as

$$X = a + U \cdot (b - a)$$

• U can also be transformed into **discrete** uniform distribution on integers $\in \{1, \ldots, n\}$ as $([\cdot], \text{ integer part})$

$$X = [nU] + 1$$

Questions

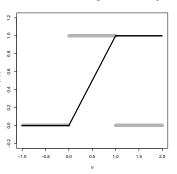
- **1** Why +1?
- ② How can U be transformed into Y, where Y is discrete uniform on integers (50, 55, 60)?

Second step: Generating nonuniform random numbers

- $U \sim \text{Unif}(0,1)$
- Let F_U be the cumulative distribution function (CDF) of U

$$F_U(u) = P(U \le u) = \begin{cases} 0 & u \le 0 \\ u & 0 < u \le 1 \\ 1 & 1 < u \end{cases}$$

ullet The probability distribution function (PDF) of U



$$f_U(u) = \begin{cases} 1 & 0 < u < 1 \\ 0 & u \notin (0, 1) \end{cases}$$

Inverse CDF method

Let X be a random variable with CDF $X \sim F_X$ (F_X strictly increasing)

Consider
$$Y = F_X^{-1}(U)$$
, where $U \sim \text{Unif}(0, 1)$
 $F_Y(y) = P(Y \le y) = P(F_X^{-1}(U) \le y)$
 $= P(F_X(F_X^{-1}(U)) \le F_X(y))$
 $= P(U \le F_X(y)) = F_U(F_X(y)) = F_X(y)$

Y has same probability distribution as X

Inverse CDF method

If we can generate $U \sim \text{Unif}(0,1)$, then

we can generate $X \sim F_X$ as

$$X = F_X^{-1}(U)$$

Provided we can calculate F_X^{-1} ...

Inverse CDF method: Example

Let $X \sim \exp(\lambda)$, i.e. with pdf

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x} & x \ge 0\\ 0 & x < 0 \end{cases}$$

implying $(SHOW\ THIS)$

$$F_X(x) = \int_{-\infty}^{x} f_X(s) ds = 1 - e^{-\lambda x}, \quad x \ge 0$$

QUESTIONS:

What is $F_X(x)$ for x < 0? What is E[X]?

Inverse CDF method: Example

Find F_X^{-1}

$$y = 1 - e^{-\lambda x}$$

$$e^{-\lambda x} = 1 - y$$

$$x = -\frac{1}{\lambda} \ln(1 - y)$$

$$F_X^{-1}(y) = -\frac{1}{\lambda} \ln(1 - y)$$

Hence, if
$$U \sim U(0,1)$$
, then

$$-\frac{1}{\lambda}\ln(1-U) = X \sim \exp(\lambda)$$

Inverse CDF method

• When F_X^{-1} can be derived: **EASY**

• When **NOT**: numerical solution

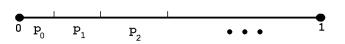
time-consuming

numerical errors?

Situation 2 is common ... e.g. $\mathcal{N}(0,1)$

Generating discrete RVs

- Define distribution $P(X = x_i) = p_i$
- Generate $U \sim \text{Unif}(0,1)$
- If $U \le p_0$, set $X = x_0$
- Else if $U \leq p_0 + p_1$, set $X = x_1$
- **5** . . .

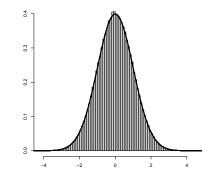


Generating $\mathcal{N}(0,1)$

Assume

- $\theta \in \mathrm{Unif}(0,2\pi)$
- $D \in \mathrm{Unif}(0,1)$

- 1: Generate θ , D
- 2: Generate X_1 and X_2 as



$$X_1 = \sqrt{-2\ln D}\cos\theta$$

$$X_2 = \sqrt{-2\ln D}\sin\theta$$

 X_1 and X_2 are independent and normally distributed

But finding such transformations is not easy

Acceptance/rejection methods

- IDEA: generate $Y \sim f_Y$ similar to some known PDF f_X
- IDEA: f_Y is easy to generate from
- \bullet REQUIREMENT: there exists a constant c

$$\forall_x c f_Y(x) \ge f_X(x)$$

- f_Y : majorizing density, proposal density
- f_X : target density
- c: majorizing constant

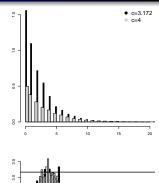
Acceptance/rejection methods

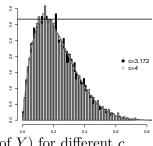
1: while X not generated do 2: Generate $Y \sim f_Y$ 3: Generate $U \sim \text{Unif}(0, 1)$ 4: if $U \leq f_X(Y)/(cf_Y(Y))$ then 5: X = Y6: Set X is generated 7: end if 8: end while

- $X \sim f_X$ CHECK THIS
- Larger c: larger rejection rates—c as small as possible number of draws \sim Geometric(1/c) mean: c
- Can work in higher dimensions—but high rejection rate

Acceptance/rejection methods: Example

```
Generate beta(2,7)
y < -dbeta(seq(0,2,0.0001),2,7)
\mathbf{c} < -\mathbf{max}(\mathbf{y}) : \mathbf{c}
[1] 3.172554
 1: while X not generated do
       Generate Y \sim \text{Unif}(0,1)
 2:
       Generate U \sim \text{Unif}(0,1)
 3:
      if U \leq dbeta(Y,2,7)/(c\cdot 1) then
 4:
         X = Y
 5:
         Set X is generated
 6:
      end if
 7:
 8: end while
 QUESTION:
```





Compare acceptance and rejection regions (of Y) for different c.

Acceptance/rejection methods:

• Acceptance/rejection is difficult to apply

- Difficult to find majorizing density
 - can always take $\sup(f_X) \cdot \operatorname{Unif}(0,1)$
 - but what is the problem?

Acceptance/rejection methods: Example

Truncated to positive half–axis $\mathcal{N}(0,1)$

$$f(x) = \sqrt{\frac{2}{\pi}} \exp\left(-x^2/2\right) \mathbf{1}_{[0,\infty)}(x).$$
$$\mathbf{1}_A(x) = \begin{cases} 1 & x \in A \\ 0 & x \notin A. \end{cases}$$

or equivalently as a mixture density

$$f(x) = \alpha_1 f_1(x) g_1(x) + \alpha_2 f_2(x) g_2(x),$$

where

$$\alpha_{1} = \sqrt{\frac{2}{\pi}} \qquad \qquad \alpha_{2} = \frac{1}{\sqrt{2\pi}}$$

$$f_{1}(x) = \mathbf{1}_{[0,1]}(x) \qquad \qquad f_{2}(x) = 2 \exp(-2(x-1)) \mathbf{1}_{(1,\infty)}(x)$$

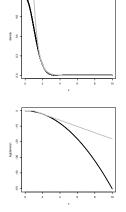
$$g_{1}(x) = \exp(-x^{2}/2) \qquad \qquad g_{2}(x) = \exp(-(x-2)^{2}/2)$$

Acceptance/rejection methods: Example

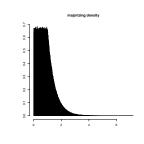
Direct sampling: x < -rnorm(N); x < -x[x > = 0]

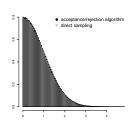
Majorizing density, mixture of uniform and exponential:

$$g(x) = \sqrt{\frac{2}{\pi}} \cdot \mathbf{1}_{[0,1]}(x) + \frac{1}{\sqrt{2\pi}} \cdot 2\exp(-2(x-1)) \, \mathbf{1}_{(1,\infty)}(x)$$



Truncated normal and majorizing densities





Sampling: 732A90_ComputationalStatisticsHT2022_Lecture03codeSlide22.R

Generating multivariate normal

Generate $\mathcal{N}(\vec{\mu}, \mathbf{\Sigma}) \in \mathbb{R}^n$

- 1: Generate n i.i.d. $\mathcal{N}(0,1)$ r.vs. $\vec{X} = (X_1, \dots, X_n)$ {We know how to do this, see slide 16}
- 2: Compute Cholesky decomposition (a.k.a. matrix square root) of Σ , i.e. find \mathbf{A} , lower triangular s.t. $\mathbf{A}\mathbf{A}^T = \Sigma$, $\{\text{in R: chol}(\underline{)}\}$
- 3: $\vec{Y} = \mu + \mathbf{A}\vec{X}$

QUESTION:

what is the expectation and variance–covariance of \vec{Y} ?

Random numbers in R

(from ?RNGversion), see also

- ddistribution name(): density of distribution
- 2 pdistribution name(): CDF of distribution
- 3 qdistribution name(): quantiles of distribution
- 4 rdistribution name(): simulate from distribution

As of R 3.6.0 there is a change in the random number generator, seeds are not compatible between versions < 3.6.0 and $\geq 3.6.0$. Use RNGversion("R version string") to set random number generator, see also ?RNGkind. Due to "sample noticeably non-uniform on large populations"

 $\verb|https://bugs.r-project.org/bugzilla/show_bug.cgi?id=17494|.$

Summary

- Computers generate pseudo-random numbers
- We draw from pseudo-uniform and transform to desired distribution
- Analytical methods for transforming exist but are distribution specific