



# An introduction to Monte Carlo methods

Elena Akhmatskaya and Enrico Scalas

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# (Pseudo-)random number generators

Enrico Scalas

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# (Pseudo-)random number generators

Pre-requisites:

- Elementary probability theory
- Random variables
- Discrete distributions (Bernoulli, Binomial, Poisson, ...)
- Continuous distributions (Uniform, Normal, Exponential, ...)

# (Pseudo-)random number generators

## History

The Monte Carlo method was introduced in connection to the development of nuclear weapons, especially to study the trajectory of neutrons through materials interacting with nuclei along the way. Part of the work leading to thermonuclear bombs is still classified. The Monte Carlo method was declassified in the 1950s. (see Harlow and Metropolis 1983).

# (Pseudo-)random number generators

Two problems:

1. Generate a sequence of i.i.d. random numbers distributed according to  $U[0,1]$ ;
2. Given an i.i.d. sequence  $U_1, U_2, \dots \sim U[0,1]$  and a target distribution  $F$  on  $\mathbb{R}^k$  find  $m \geq k$  and a deterministic function  $h: [0,1]^m \rightarrow \mathbb{R}^k$  such that  $h(U_1, \dots, U_m) \sim F$ . This means: generate a random variable or vector with distribution  $F$ .

# (Pseudo-)random number generators

Problem 1 can be further specified.

1a. The relative frequency

$$\frac{N(\{1 \leq i \leq n : U_i \in [0, b]\})}{n}$$

must converge to  $b$  for  $n \rightarrow \infty$ .

1b. The pairs  $(U_1, U_2), \dots, (U_n, U_{n+1}), \dots$  should be uniformly distributed in  $[0, 1]^2$ .

1c. For every  $k \geq 1$ , the  $k$ -tuples

$$\{(U_i, U_{i+1}, \dots, U_{i+k-1})\}_{i \geq 1}$$

should be uniformly distributed in  $[0, 1]^k$ .

# (Pseudo-)random number generators

Problem 1 can be tackled by means of a deterministic recurrence relation

$$X_{i+1} = f(X_i, X_{i-1}, \dots, X_{i-s}), i \geq s, s \geq 0$$

starting from a *seed*

$$(X_s, X_{s-1}, \dots, X_0) \in \mathbb{R}^{s+1}.$$

If  $0 \leq X_i \leq K, \forall i$ , one takes  $U_i = X_i/K$ .

A *good* pseudo-random number generator must satisfy statistical tests of uniformity and independence.

# (Pseudo-)random number generators

Example: **The midsquare method** (by Von Neumann)

Take an integer between 0 and 10000 and square it. The next number consists of the middle four digits of the square. If necessary add zeros to the left of the square, in order to get an 8-digit integer.

$$0 \leq X_i \leq 10^5, X_0 = 3457, (X_0)^2 = 11950849, X_1 = 9508, U_1 = 9508/10000 = 0.9508$$

$$X_1 = 9508, (X_1)^2 = 90402064, X_2 = 4020, U_2 = 4020/10000 = 0.4020$$

Many problems: 3792 is a fixed point (it has other fixed points). Many seeds lead to convergence to very short cycles. Seeds smaller than 100 converge to 0.



# (Pseudo-)random number generators

Example: **Fibonacci generators**

$$X_{i+1} = (X_i + X_{i-1}) \bmod m, m \in \mathbb{N}, m \gg 1$$
$$U_i = X_i / m$$

In this case, one can prove that

$$\Pr(X_i < X_{i+1} < X_i) = 0$$

but this probability should be  $1/6$  for i.i.d. uniform random variables.

# (Pseudo-)random number generators

Example: Linear congruential generators I

The (infamous) IBM RANDU algorithm

$$\begin{aligned} X_0 &: \text{random seed} \\ X_{i+1} &= 65539 X_i \bmod 2^{31}, \\ U_i &= X_i / 2^{31}. \end{aligned}$$

belongs to this class. In general

$$\begin{aligned} X_0 &: \text{random seed} \\ X_{i+1} &= (a X_i + c) \bmod m, \\ a, m &\in \mathbb{N}^+, c \in \mathbb{N} \\ U_i &= X_i / m. \end{aligned}$$

These generators cannot have a period larger than  $m$ .

# (Pseudo-)random number generators

Example: Linear congruential generators II

## Theorem (Knuth, 1981)

The period of a linear congruential generator is  $m$  if and only if the following conditions hold true:

1.  $c$  and  $m$  are relatively prime,
2. every prime factor of  $m$  divides  $a-1$ , and
3. if 4 divides  $m$ , then 4 divides  $a-1$ .

So, if  $m = 2^{31}$ , to have this period,  $c$  must be odd and  $a = 4k+1$ , for some integer  $k$  greater than 1.

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Example: Linear congruential generators III

Knuth proved that the period of RANDU is  $2^{29}$  if one starts from an odd seed. But RANDU fails to satisfy condition 1.c.

$$65539 = 2^{16} + 3$$
$$X_{i+1} = (2^{16} X_i + 2 X_i + X_i) \bmod 2^{31},$$
$$X_{i+2} = (6 X_{i+1} - 9 X_i) \bmod 2^{31}$$

Therefore  $X_{i+2} - 6 X_{i+1} + 9 X_i$  is always divisible by  $2^{31}$ .

Hence, one has  $U_{i+2} - 6 U_{i+1} + 9 U_i \in \{-5, -4, \dots, 9\}$ .

The triples  $(U_i, U_{i+1}, U_{i+2})$  lie in one of 15 parallel hyperplanes in  $[0, 1]^3$ .

# (Pseudo-)random number generators

Example: Marsaglia's generators

In 1995, Marsaglia suggested *multiply-with carry generators*.

$$\begin{aligned}X_{i+1} &= (a X_i + C_i) \bmod m, \\C_{i+1} &= \text{floor}[(a X_i + C_i) / m]\end{aligned}$$

as well as

$$X_{i+1} = 2^{13} (X_i + X_{i-1} + X_{i-2}) \bmod (2^{32} - 5),$$

a generator whose period is approximately  $2^{96}$ .

# (Pseudo-)random number generators

Problem 2 can be solved in several ways. Here is a list of strategies:

- Inversion method
- Rejection method
- Special methods
- Markov chain Monte Carlo (MCMC)

# (Pseudo-)random number generators

## Inversion method I

Suppose we are given a random variable with cumulative distribution function  $F_X(x) = \Pr(X \leq x)$ .

If  $U \sim U[0,1]$ , setting  $X = F_X^{-1}(U)$  solves the problem.

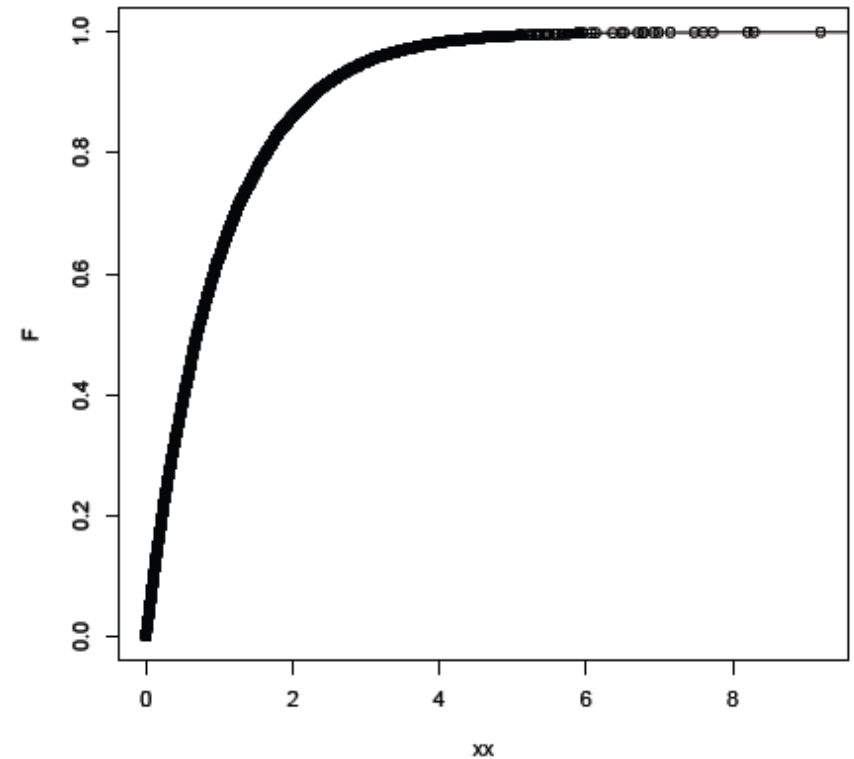
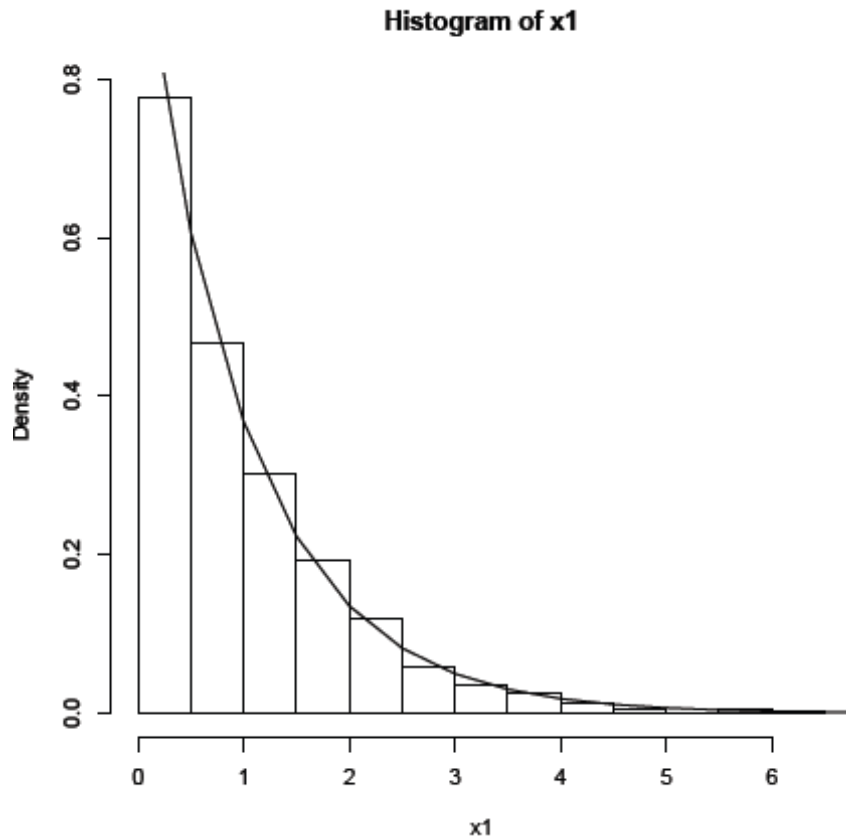
Example: **The exponential distribution**

$$F_X(x) = 1 - \exp(-\lambda x), x \geq 0$$
$$F_X^{-1}(u) = -\frac{1}{\lambda} \log(1 - u), 0 \leq u \leq 1$$
$$F_X^{-1}(1 - u) = -\frac{1}{\lambda} \log(u)$$

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## Inversion method II

### Example: The exponential distribution





# (Pseudo-)random number generators

## Inversion method III

If the inverse cumulative distribution function is not available analytically, one can

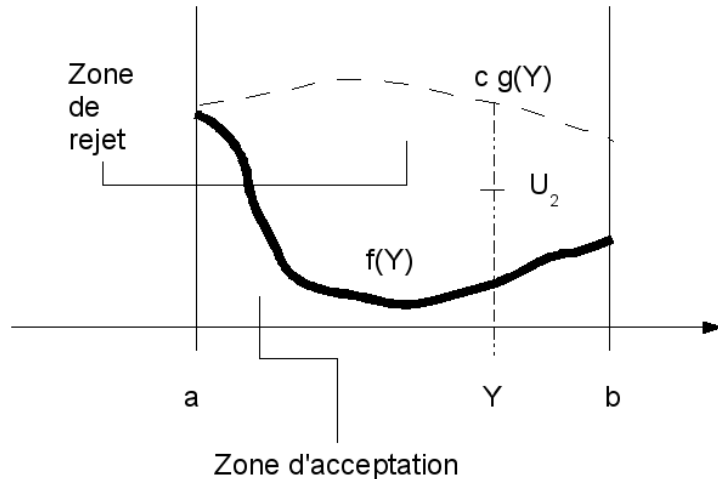
- Try to find a uniform approximant
- Use Newton's inversion method
- Use tables and linear (or other) interpolation

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## Rejection method I

It is due to Von Neumann (again). The probability density function is needed.

$$c = \sup \{ f_X(x) : x \in [a, b] \}$$



Step 1: Generate  $Y \sim U[a, b]$

Step 2: Generate  $P \sim U[0, c g(Y)]$

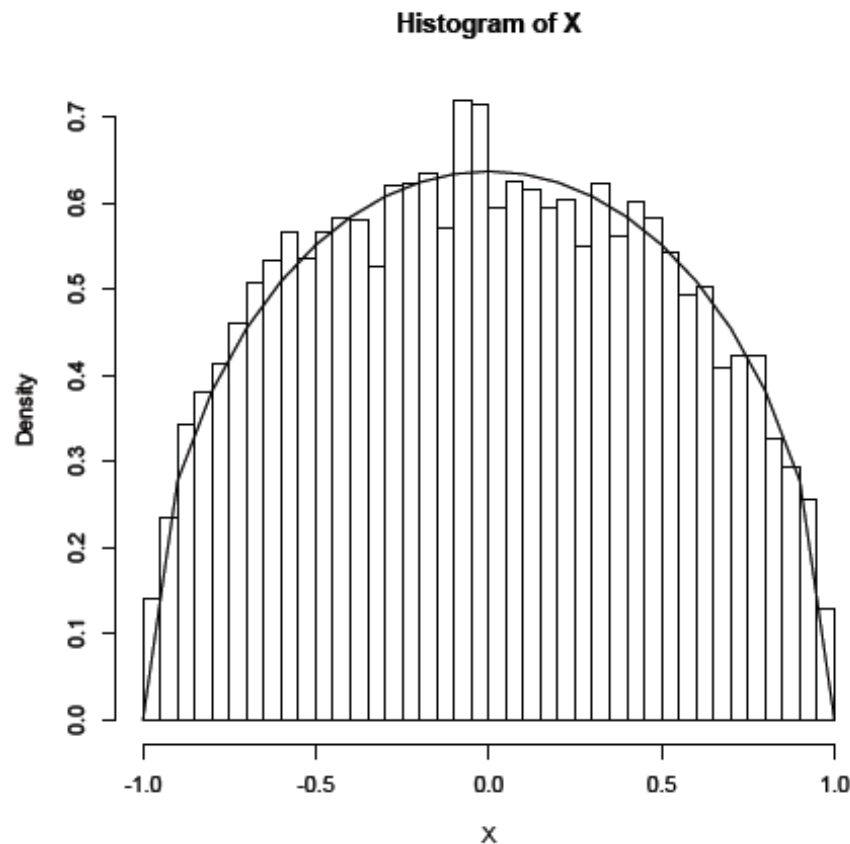
Step 3: If  $P \leq f_X(Y)$  set  $X \leftarrow Y$  and stop, otherwise reject and go to Step 1.

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## Rejection method II

Example: **Wigner semi-circle law**

$$f_X(x) = \frac{2}{\pi} \sqrt{1-x^2}, x \in [-1, 1]$$



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## Special methods I

For several important distributions, one can use special methods based on their properties and their relation with the uniform distribution.

We shall see two examples

- The Gamma distribution
- The normal distribution

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## Special methods II

### Example: The Gamma distribution

$$X \sim \text{Gamma}(a, b), a, b > 0$$

$$f_X(x; a, b) = b^a x^{a-1} \exp(-bx) / \Gamma(a), x \geq 0$$

$$f_X(x; n, b) = b^n x^{n-1} \exp(-bx) / (n-1)!, x \geq 0, n \in \mathbb{N}$$

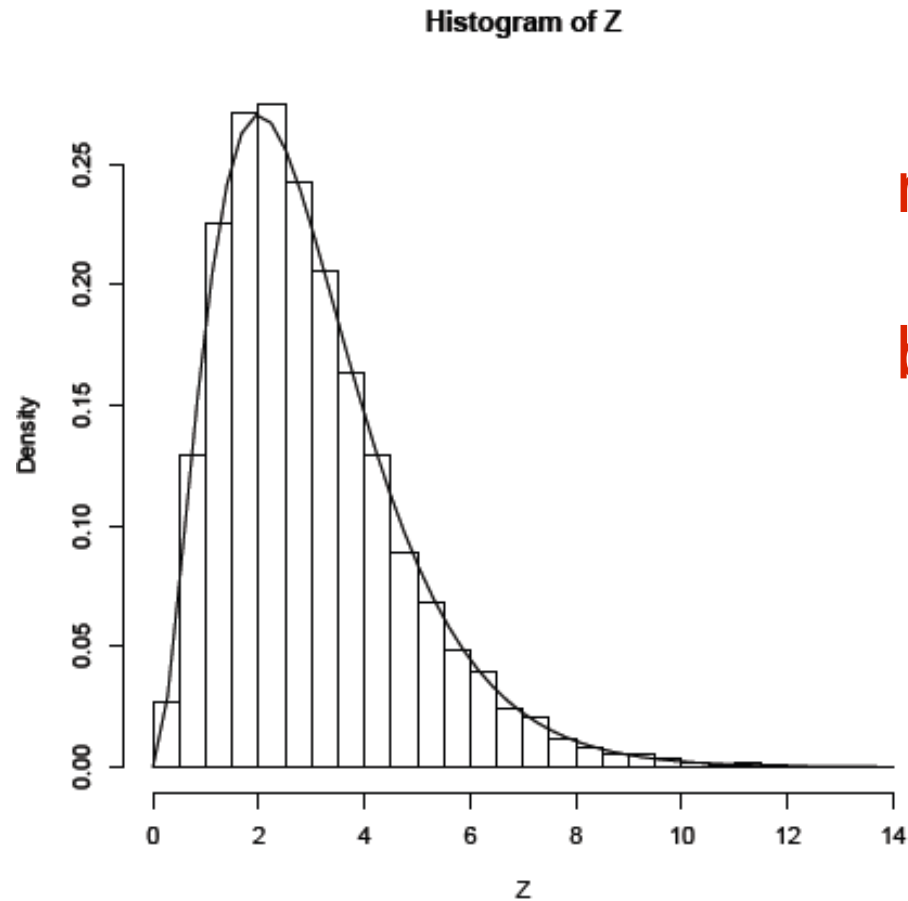
$$X \sim \text{Gamma}(1, b) \sim \text{Exp}(b)$$

**Proposition:** Let  $X_1, \dots, X_k$  be a sequence of r.v.s s.t.  $X_i \sim \text{Gamma}(a_i, b)$  then  $Z = X_1 + \dots + X_k \sim \text{Gamma}(a_1 + \dots + a_k, b)$ .  
**If**  $X_i \sim \text{Exp}(b), \forall i$  **then**  $Z \sim \text{Gamma}(n, b)$ .

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## Special methods III

### Example: The Gamma distribution



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## Special methods IV

Example: **The normal distribution**

$$X \sim N(\mu, \sigma), \sigma > 0$$
$$f_X(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right), x \in \mathbb{R}$$
$$X \sim N(0, 1)$$
$$f_X(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right), x \in \mathbb{R}$$

**Proposition:** Assume  $X \sim N(0, 1)$  then  $X^2 \sim \text{Gamma}(1/2, 1/2)$ .

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## Special methods V

### Example: Box-Muller method

$$X_1 \perp X_2, X_1, X_2 \sim \mathbf{N}(0,1),$$

$$f_{X_1, X_2}(x_1, x_2) = \frac{1}{2\pi} \exp\left(\frac{-(x_1^2 + x_2^2)}{2}\right), x_1, x_2 \in \mathbb{R}$$

$$R = \sqrt{X_1^2 + X_2^2}, \Theta = \widehat{(X_1, X_2)}$$

$$g_{R, \Theta}(r, \theta) = \frac{1}{2\pi} r \exp\left(\frac{-r^2}{2}\right), r > 0, \theta \in [0, 2\pi)$$

$$R^2 = X_1^2 + X_2^2 \sim \text{Gamma}(1, 1/2), \Theta \sim U[0, 2\pi]$$

$$R \leftarrow \sqrt{-2 \log U_1}, \Theta \leftarrow 2\pi U_2$$

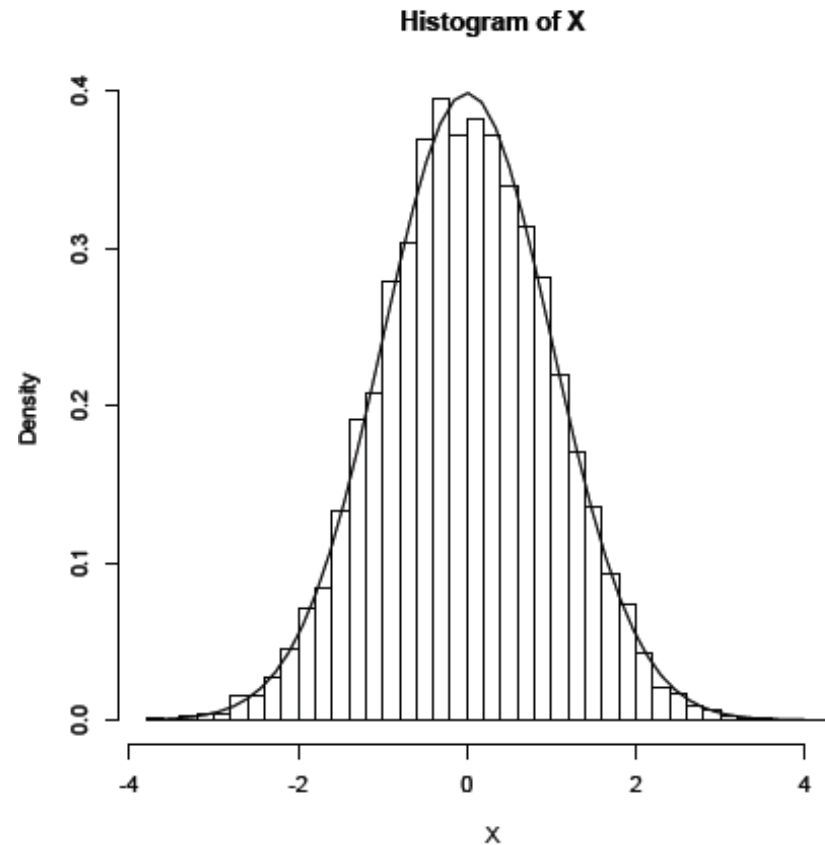
$$X_1 \leftarrow \sqrt{-2 \log U_1} \cos(2\pi U_2), X_2 \leftarrow \sqrt{-2 \log U_1} \sin(2\pi U_2).$$



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## Special methods VI

Example: **Box-Muller method**



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## Conclusions

The basic ingredients for Monte-Carlo simulations are

- A *good* pseudo-random number generator for uniform deviates in the interval  $[0, 1]$ ;
- Efficient methods to generate deviates for any distribution of interest.

Both problems are still open to new research contributions

**Exercise: What about discrete distributions?**

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## References

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