

# Scientific Computing: An Introductory Survey

## Chapter 13 – Random Numbers and Stochastic Simulation

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1 / 17

Stochastic Simulation and Randomness  
Random Number Generators  
Quasi-Random Sequences

## Stochastic Simulation, continued

- Two main requirements for using stochastic simulation methods are
  - Knowledge of relevant probability distributions
  - Supply of random numbers for making random choices
- Knowledge of relevant probability distributions depends on theoretical or empirical information about physical system being simulated
- By simulating large number of trials, probability distribution of overall results can be approximated, with accuracy attained increasing with number of trials

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3 / 17

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## Repeatability

- In addition to unpredictability, another distinguishing characteristic of true randomness is lack of *repeatability*
- However, lack of repeatability could make testing algorithms or debugging computer programs difficult, if not impossible
- Repeatability is desirable in this sense, but care must be taken to ensure independence among trials



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5 / 17

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## Random Number Generators

Properties of good random number generator as possible

- Random pattern*: passes statistical tests of randomness
- Long period*: goes as long as possible before repeating
- Efficiency*: executes rapidly and requires little storage
- Repeatability*: produces same sequence if started with same initial conditions
- Portability*: runs on different kinds of computers and is capable of producing same sequence on each



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7 / 17

## Stochastic Simulation

- Stochastic simulation* mimics or replicates behavior of system by exploiting randomness to obtain statistical sample of possible outcomes
- Because of randomness involved, simulation methods are also known as *Monte Carlo* methods
- Such methods are useful for studying
  - Nondeterministic (stochastic) processes
  - Deterministic systems that are too complicated to model analytically
  - Deterministic problems whose high dimensionality makes standard discretizations infeasible (e.g., Monte Carlo integration)

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2 / 17

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## Randomness

- Randomness* is somewhat difficult to define, but we usually associate randomness with unpredictability
- One definition is that sequence of numbers is *random* if it has no shorter description than itself
- Physical processes, such as flipping coin or tossing dice, are deterministic if enough is known about equations governing their motion and appropriate initial conditions
- Even for deterministic systems, extreme sensitivity to initial conditions can make their chaotic behavior unpredictable in practice
- Whether deterministic or not, highly complicated systems are often tractable only by stochastic simulation methods



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4 / 17

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## Pseudorandom Numbers

- Although random numbers were once supplied by physical processes or tables, they are now produced by computers
- Computer algorithms for generating random numbers are in fact deterministic, although sequence generated may *appear* random in that it exhibits no apparent pattern
- Such sequences of numbers are more accurately called *pseudorandom*
- Although pseudorandom sequence may appear random, it is in fact quite predictable and reproducible, which is important for debugging and verifying results
- Because only finite number of numbers can be represented in computer, any sequence must eventually repeat



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6 / 17

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## Random Number Generators, continued

- Early attempts at producing random number generators on computers often relied on complicated procedures whose very complexity was presumed to ensure randomness
- Example is “midsquare” method, which squares each member of sequence and takes middle portion of result as next member of sequence
- Lack of theoretical understanding of such methods proved disastrous, and it was soon recognized that simple methods with well-understood theoretical basis are far preferable



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8 / 17

## Congruential Generators

- **Congruential** random number generators have form

$$x_k = (ax_{k-1} + c) \pmod{M}$$

where  $a$  and  $c$  are given integers

- Starting integer  $x_0$  is called **seed**
- Integer  $M$  is approximately (often equal to) largest integer representable on machine
- Quality of such generator depends on choices of  $a$  and  $c$ , and in any case its period cannot exceed  $M$



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9 / 17

## Fibonacci Generators

- **Fibonacci** generators produce floating-point random numbers on interval  $[0, 1)$  directly as difference, sum, or product of previous values

- Typical example is subtractive generator

$$x_k = x_{k-17} - x_{k-5}$$

- This generator is said to have *lags* of 17 and 5
- Lags must be chosen carefully to produce good subtractive generator
- Such formula may produce negative result, in which case remedy is to add 1 to get back into interval  $[0, 1)$



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11 / 17

## Sampling on Other Intervals

- If we need uniform distribution on some other interval  $[a, b)$ , then we can modify values  $x_k$  generated on  $[0, 1)$  by transformation

$$(b - a)x_k + a$$

to obtain random numbers that are uniformly distributed on desired interval



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13 / 17

## Normal Distribution

- Important example is generation of random numbers that are normally distributed with given mean and variance
- Available routines often assume mean 0 and variance 1
- If some other mean  $\mu$  and variance  $\sigma^2$  are desired, then each value  $x_k$  produced by routine can be modified by transformation  $\sigma x_k + \mu$  to achieve desired normal distribution



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15 / 17

## Congruential Generators, continued

- It is possible to obtain reasonably good random number generator using this method, but values of  $a$  and  $c$  must be chosen *very* carefully
- Random number generators supplied with many computer systems are of congruential type, and some are notoriously poor
- Congruential generator produces random integers between 0 and  $M$
- To produce random floating-point numbers, say uniformly distributed on interval  $[0, 1)$ , random integers must be divided by  $M$  (*not* integer division!)

< interactive example >



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10 / 17

## Fibonacci Generators, continued

- Fibonacci generators require more storage than congruential generator, and also require special procedure to get started
- Fibonacci generators require no division to produce floating-point results
- Well-designed Fibonacci generators have very good statistical properties
- Fibonacci generators can have much longer period than congruential generators, since repetition of one member of sequence does not entail that all subsequent members will also repeat in same order



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12 / 17

## Nonuniform Distributions

- Sampling from nonuniform distributions is more difficult
- If cumulative distribution function of desired probability density function is easily invertible, then we can generate random samples with desired distribution by generating uniform random numbers and inverting them
- For example, to sample from exponential distribution

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

we can take

$$x_k = -\log(1 - y_k)/\lambda$$

where  $y_k$  is uniform on  $[0, 1)$

- Unfortunately, many important distributions are not easily invertible, and special methods must be employed to generate random numbers efficiently for these distributions



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14 / 17

## Quasi-Random Sequences

- For some applications, achieving reasonably uniform coverage of sampled volume can be more important than whether sample points are truly random
- Truly random sequences tend to exhibit random clumping, leading to uneven coverage of sampled volume for given number of points
- Perfectly uniform coverage can be achieved by using regular grid of sample points, but this approach does not scale well to higher dimensions
- Compromise between these extremes of coverage and randomness is provided by **quasi-random** sequences



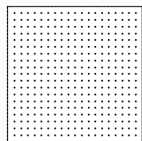
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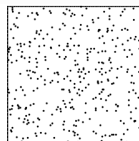
16 / 17

## Quasi-Random Sequences, continued

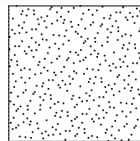
- Quasi-random sequences are not random at all, but are carefully constructed to give uniform coverage of sampled volume while maintaining reasonably random appearance
- By design, points tend to avoid each other, so clumping associated with true randomness is eliminated



Grid



Random



Quasi-random

[< interactive example >](#)