Numerical Simulation and Scientific Computing I

Lecture 7: Random Numbers & Monte Carlo Integration



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Q1: Represent the following matrix in the CRS format

$$\begin{bmatrix} 1 & 4.6 & 0 & 0 & 0 \\ 0 & 0 & 8.5 & 3.7 & 0 \\ 0 & 6 & 2.7 & 0 & 0 \\ 0 & 4.6 & 0 & 4.8 & 9.4 \\ 0 & 0 & 5.6 & 0 & 1 \end{bmatrix}$$

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• 1st step: Put the values in row-major order

$$V = \begin{bmatrix} 1 & 4.6 & 8.5 & 3.7 & 6 & 2.7 & 4.6 & 4.8 & 9.4 & 5.6 & 1 \end{bmatrix}^T$$

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2nd step: Assign the corresponding column indices

$$V = \begin{bmatrix} 1 & 4.6 & 8.5 & 3.7 & 6 & 2.7 & 4.6 & 4.8 & 9.4 & 5.6 & 1 \end{bmatrix}^T$$

$$JA = \begin{bmatrix} 0 & 1 & 2 & 3 & 1 & 2 & 1 & 3 & 4 & 2 & 4 \end{bmatrix}^T$$

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• 3rd step: Identify the indices in V where a new row starts

$$V = \begin{bmatrix} 1 \end{bmatrix} 4.6 \quad 8.5 \quad 3.7 \quad 6 \quad 2.7 \quad 4.6 \quad 4.8 \quad 9.4 \quad 5.6 \quad 1]^T$$

$$JA = \begin{bmatrix} 0 & 1 & 2 & 3 & 1 & 2 & 1 & 3 & 4 & 2 & 4]^T$$

$$IA = \begin{bmatrix} 0 & 2 & 4 & 6 & 9 & 11\end{bmatrix}^T$$

- Q2: Under which conditions would you use the CG method instead of GMRES?
- A) The matrix is indefinite
- B) The problem benefits from preconditioning
- C) The problem is ill-posed
- D) All eigenvalues are positive
- E) The LU factorization is known

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 Q3: What information from a matrix A could be useful to help choosing an adequate solver?

- A) Maximum norm
- B) Set of eigenvalues
- C) QR decomposition
- D) Transpose

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Outline

- Introduction to Randomness
- Random Number Generators (RNGs)
 - Linear Congruential Generators
 - Mersenne Twister
 - Hardware
- C++11 < random>
- Monte Carlo Integration

Take-home message

- Be careful with your choice of RNG
- Seeding is a consequence of pseudo-RNG
- Watch out for pitfalls on parallel systems

Main References

- Random Numbers and Computers
 - Author: Ronald T. Kneusel
 - eBook available: https://catalogplus.tuwien.ac.at:443/UTW:UTW:TN_springer_s978-3-319-77697-2_453445

Additional References

- Handbook of Monte Carlo Methods
 - Authors: D. P. Kroese, T. Taimre, Z. I. Botec
 - eBook available: https://catalogplus.tuwien.ac.at:443/UTW:UTW:TN_scopus2-s2.0-84949783693
- Monte Carlo Strategies in Scientific Computing
 - Author: Jun S. Liu
 - https://catalogplus.tuwien.ac.at:443/UTW:UTW:UTW_alma214661572 0003336

Randomness

- How to formally define randomness?
- Philosophical conundrum: does randomness even exist?
 - Good thing that it is not our job to figure it out!
- Too hard operational definition of a random sequence [Kneusel]:
 - a sequence of numbers n, within some bounded range, where it is not possible to predict n_{k+1} from any combination of preceding values n_i , $i=0,1,\ldots,k$.

"True" Random vs. Pseudorandom

"True" Randomness

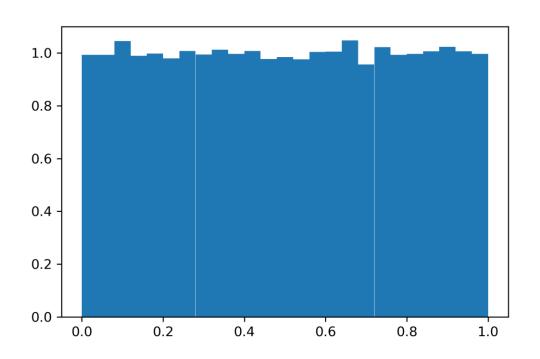
- From here on, we will assume that these exist
- Found in the physical world
- Examples?

Pseudorandomness

- [Kneusel]: A pseudorandom sequence is a deterministically generated sequence of numbers that is indistinguishable from a true random sequence of numbers
- Perfect indistinguishability is impossible but how much is enough?
- Determinism: introduces the concept of a seed
 - Seed: starting point of the deterministic sequence

Uniform Random Numbers

- Even if n_{k+1} is truly non-predictable, it can still have a distribution shows up in a histogram
 - Drawing from a parent distribution
- Uniform (real) Distribution: $n_k \in [0,1)$
 - Unless otherwise stated, it is often the default



Linear Congruential Generators

Nomenclature

- a: multiplier
- c: increment
- m: modulus
- *x*₀: seed

$$x_{n+1} = (ax_n + c) \bmod m$$

Notes

- Generates integers $\in [0, m)$. Floats: $f_n = \frac{x_n}{m}$
- Periodicity is a big problem can be lower than m
- If $x_n = x_m$ then $x_{n+1} = x_{m+1}$
- The method is defined by the choice of a, c and m

Examples

- GCC: a = 1103515245, c = 12345, $m = 2^{31} 1$
- C++11 minstd_rand: a = 48271, c = 0, $m = 2^{31} 1$

LCGs - Poll 3

• What is the issue of using this generator with $m=2^{31}-1$ to generate a double?

$$x_{n+1} = (ax_n + c) \mod m$$

- A) The periodicity is not high enough to cover the 53-bit significand
- B) It is impossible to seed this generator with a double
- C) You cannot generate a double from an integer
- D) The equation $f_n = \frac{x_n}{m}$ doesn't hold anymore

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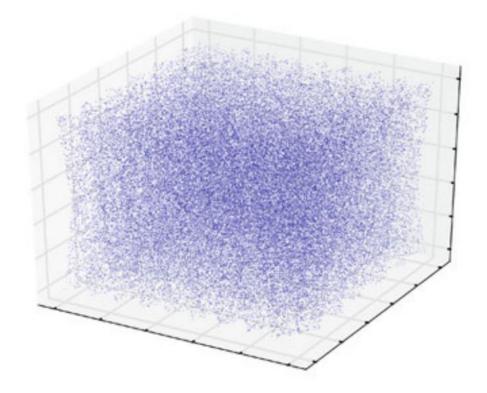
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A Lesson from History: RANDU

- How bad can it be if we choose poorly?
 - RANDU: a = 65593, c = 0, $m = 2^{31}$

$$x_{n+2} = 6x_{n+1} - 9x_n$$

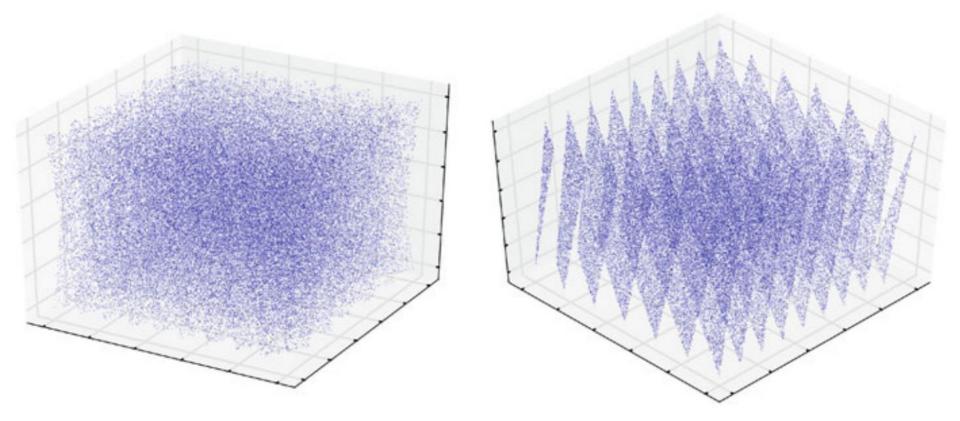


Source: Kneusel: Random Numbers and Computers, 1st ed., 2018, Springer

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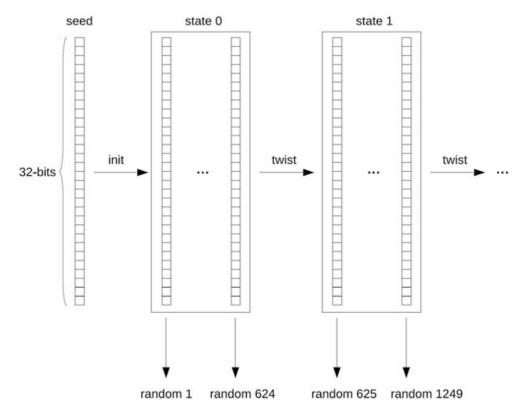
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Mersenne Twister

 MT is the current de facto standard for non-cryptographic applications



Larger memory and construction requirements!

Source: Kneusel: Random Numbers and Computers, 1st ed., 2018, Springer

Choosing your RNG

Performance is only part of the equation

- MINSTD is only 32 bits
 - a, c and m are linked
 - Don't mess around with constants!
- The performance penalty of MT can be mild (up to 50%)

| Generator | Time (s) |
|------------------|--------------------|
| MINSTD | 9.164 ± 0.006 |
| xorshift32 | 11.097 ± 0.004 |
| xorshift128+ | 11.853 ± 0.028 |
| CMWC | 12.671 ± 0.003 |
| Middle Weyl | 12.849 ± 0.028 |
| xorshift1024* | 12.985 ± 0.004 |
| Mersenne Twister | 14.353 ± 0.007 |
| KISS64 | 17.252 ± 0.015 |
| Philox | 18.097 ± 0.048 |
| Threefry | 32.442 ± 0.010 |

- Other RNG may be available!
 - May involve other performance tradeoffs...

Source: Kneusel: Random Numbers and Computers, 1st ed., 2018, Springer

- C rand()
 - NOOOOOO (RAND_MAX \geq 32767)

https://channel9.msdn.com/Events/GoingNative/2013/rand-Considered-Harmful

- How does MT compare wrt. MINSTD?
 - Higher performance: lower time to generate 1 RN
- A) Higher performance, higher periodicity, higher memory requirements
- B) Lower performance, higher periodicity, higher memory requirements
- C) Lower performance, lower periodicity, higher memory requirements
- D) Lower performance, higher periodicity, lower memory requirements
- E) Higher performance, lower periodicity, lower memory requirements

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- For a certain random sequence, in the past we drew the number 189 immediately after the number 25. Now in the same sequence, we just drew the number 25 again.
- A) MT: the next number will be 189. LCG: the next number will be 189
- B) MT: the next number will be random. LCG: the next number will be 189
- C) MT: the next number will be 189. LCG: the next number will be random
- D) MT: the next number will be random. LCG: the next number will be random

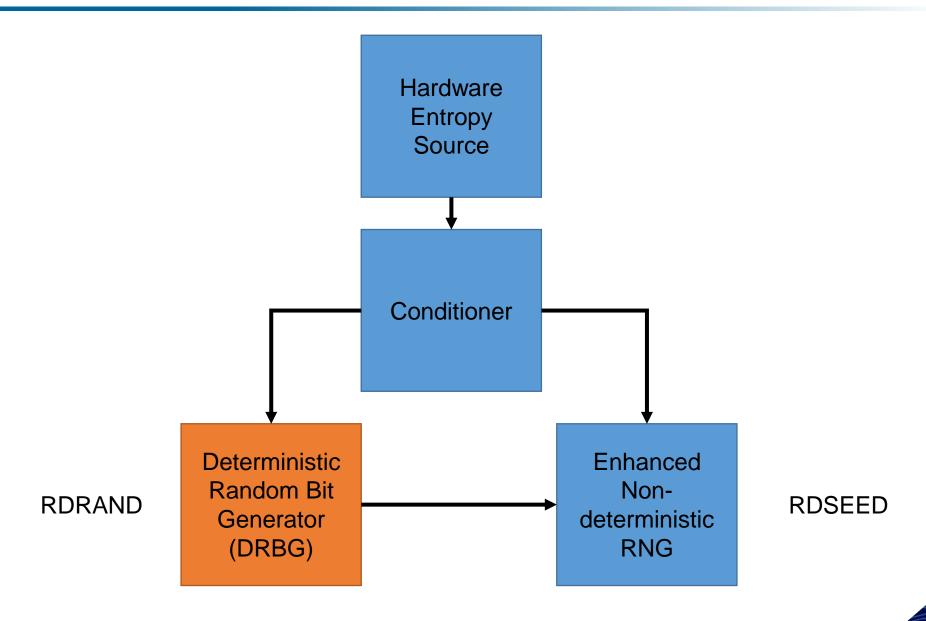
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- D) MT: the next number will be random. LCG: the next number will be random

Quiz Q4 – Poll 6

• Is it possible to generate true random numbers from a digital computer (e.g. x86 architecture)?

- Yes
- No

Intel DRNG



Entropy Pool

- Entropy pool: where you store the true randomness
 - E.g.: hardware, /dev/random
- Depletion:
 - Every time you use the pool to generate a RN, you gain information about it
 - The next query might not be random!
 - The pool usually "knows" it is depleted -> needs more randomness (time) to replenish

RDRAND - Example

```
#include <iostream>
int main() {
    unsigned long long int random;

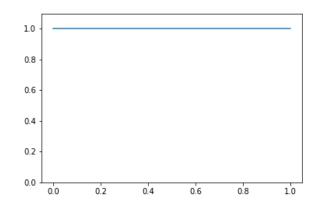
    for (int i = 0; i < 10; ++i) {
        if (_builtin_ia32_rdrand64_step(&random)) break;
    }

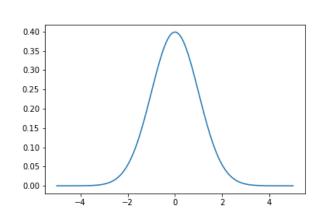
    std::cout << random << std::endl;
}</pre>
```

- GCC specific: compilation with g++ -mrdrnd
- Available in Intel Ivy Bridge and AMD Zen onwards
- Downside: lack of seeding means losing reproducibility

Generating Other Distributions

- The basic algorithms generate a uniform $u \in [0,1)$
- What if we need other distributions?
 - Common example: normal (Gaussian) distribution $N(\mu, \sigma)$
 - $N(\mu, \sigma) = \sigma * N(0,1) + \mu$
- We would like a map $u \to z \in N(0,1)$
- Very common trick: map $u_1, u_2 \in [0,1) \rightarrow z_1, z_2 \in N(0,1)$





Normal Distribution - Box-Muller Algorithm

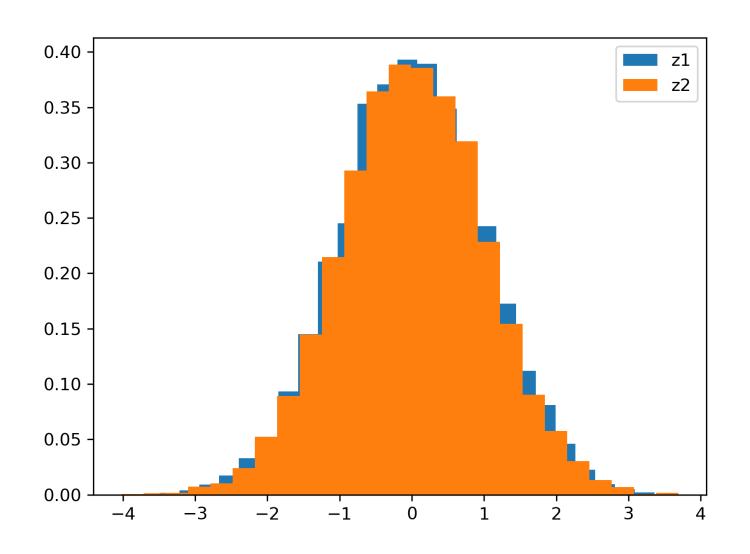
• Draw 2 uniform samples u_1 and u_2

$$z_1 = \sqrt{-2\ln(u_1)}\cos(2\pi u_2)$$

$$z_2 = \sqrt{-2\ln(u_1)}\sin(2\pi u_2)$$

```
import matplotlib.pyplot as plt
import numpy as np
u1 = np.random.random(10000)
u2 = np.random.random(10000)
z1 = np.sqrt(-2*np.log(u1))*np.cos(2*np.pi*u2)
z2 = np.sqrt(-2*np.log(u1))*np.sin(2*np.pi*u2)
fig, ax = plt.subplots()
ax.hist(z1, 25, density=1, label="z1")
ax.hist(z2, 25, density=1, label="z2")
ax.legend()
plt.savefig('boxmuller.png', dpi=300)
```

Normal Distribution - Box-Muller Algorithm



Random Numbers in C++11

- C++11 introduced the <random> header
 - https://www.youtube.com/watch?v=6DPkyvkMkk8
- Random number engines and engine adaptors
 - E.g. std::mersenne twister engine
 - These folks mess around with the constants and the internal state of the RNGs
 - Don't mess around with the given constants
- Predefined RNGs
 - E.g. std::mt19937_64 is an instantiation of the engine with the correct constants for a 64-bit random number
 - A collection of popular RNGs including both 32 and 64-bit Mersenne Twister

Random Numbers in C++11

Random Number Distributions

- E.g. std::uniform_int_distribution
- It can be imagined as a view of the RNG
- Given a certain generator, extract a new random number according to the distribution
- Many common choices, including Gaussian, Poisson...

Non-deterministic Random Numbers

- std::random_device generates a non-deterministic uniform 32-bit int
- It may use hardware-specific RNG.
- Does your implementation actually use RDRAND? ¯_(ツ)_/¯
- Common application: generate a good seed for your RNG
- It can be used for general purpose, but might become slower

Random Numbers in C++11 - Example

```
#include <iostream>
#include <random>
int main()
    std::random device rd;
    unsigned int rd seed = rd();
    std::mt19937 64 gen(rd seed);
    std::normal distribution<double> d(0,1);
    for (int i=0; i<5; ++i) {</pre>
        std::cout << d(gen) << std::endl;</pre>
```

Poll 7

• In which line might there be a problem?

```
#include <iostream>
#include <random>
int main()

    A

    std::random device rd;

    B

    unsigned int rd seed = rd();
                                                   • C
    std::mt19937 64 gen(rd seed);
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Random Numbers in a Parallel System – Poll 7

- What happens when different RNGs are initialized in a parallel system with the same seed?
- A) Each stream generates different, independent RNs
- B) The result of each stream is random, depending on initialization
- C) All threads read from the same RNG, leading to data races
- D) All streams generate the same sequence of RNs

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Random Numbers in a Parallel System

Random number server

- The program only has a single RNG and all threads and processes draw numbers from it
- Commonly used for GPUs: the CPU generates a list of random numbers which is then loaded to the GPU

Per-stream generator

- Assign a different RNG per thread or process
- Pay attention to the seeds!
- One approach: 1 master generator with 1 seed -> 1 seed per process/thread

Sidenote: CSRNG

- Working definition [Kneusel] of Cryptographically Safe RNG:
 - A CSPRNG is a random number generator that passes the next-bit test and one where an attacker's knowledge of the state of the generator at time t makes knowing the state at any previous time impossible.
- Irrelevant for simulations
- But a requirement for cryptography!
- MT is NOT cryptographically safe

Rules of Thumb

- If you do not want to think, use the Mersenne Twister
 - Consider the 64-bit version when generating doubles...
- Each thread or process needs to have its own RNG
 - With different seed!
- Avoid LCG if possible
 - Every time you use C-style rand(), a transistor cries
 - In general, their period is too short for large scale simulations
- Hardware RNGs might make sense in many applications!
 - Watch out for entropy pool depletion
- Correct seeding can be hard but allows for reproducibility!

Monte Carlo

- What is/Where is Monte Carlo?
- Term dates to the Manhattan Project
- Very loosely defined: any type of algorithm which uses random sampling to achieve a numerical result
 - The problem itself might be deterministic!
 - Las Vegas methods (subclass): uses randomness but achieves a deterministic result
- "Monte Carlo" has in practice many definitions for each field

Quiz – Question 5

• How would you estimate the value of π using random numbers?

Monte Carlo Integration – one way

Draw a circle inside the unit square

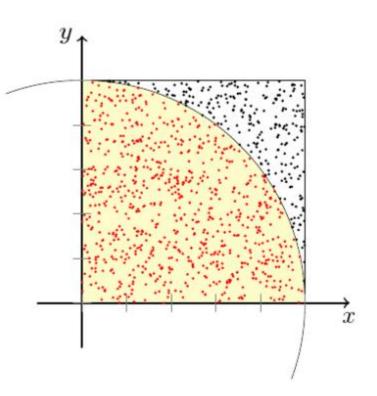
•
$$g(x) = \sqrt{1 - x^2}$$

- Generate pairs of random numbers
 - $x, y \in [0,1)$
- Count the number of hits inside

•
$$y < g(x)$$



•
$$\frac{\pi}{4} \approx \frac{\#_{inside}}{\#_{total}}$$



Monte Carlo Integration – another way

$$I = \int_{D} g(\mathbf{x}) d\mathbf{x}$$

$$\downarrow$$

$$\hat{I}_{m} = \frac{1}{m} \{ g(\mathbf{x}^{(1)}) + \dots + g(\mathbf{x}^{(m)}) \}$$

- Where $x^{(n)}$ are drawn uniformly from D
- For the circle, $D: x \in [0,1)$ and $g(x) = \sqrt{1-x^2}$

Take-home message – version 2

- Be careful with your choice of RNG
 - The Mersenne Twister is the standard for a reason
 - Hardware RNGs are becoming more useful
 - Older LCG are to be avoided whenever possible
- Seeding is a consequence of pseudo-RNG
 - Not always a bad thing reproducibility!
- Watch out for pitfalls on parallel systems
 - Usually, you must make sure that each process/thread is generating a different random number sequence

Quiz

- Q1: Consider a 32-bit LCG. How many random numbers can you generate before the sequence repeats?
- Q2: What are the consequences of entropy pool depletion?
 How would you handle it?
- Q3: What are the requirements to initialize correctly one RNG per thread?
- Q4: What is a different between a process and a thread?
 Which resources can be shared among them?
- Q5: What does the directive #pragma omp atomic do?

Next stop

- Shared Memory Parallel Optimization
- OpenMP