

Artificial Randomness for Simulation

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- ▶ Requirements, applications, multiple streams and substreams.
- ▶ Design principles and quality criteria.
- ▶ Examples: linear recurrences modulo m (large) and modulo 2.
- ▶ Statistical tests. Empirical evaluation of widely-used generators.

Articles and software: <http://www.iro.umontreal.ca/~lecuyer>

What do we want?

Sequences of numbers that **look** random.

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Example: 8 possibilities for the 3 bits **???**:

000, 001, 010, 011, 100, 101, 110, 111

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For s bits, probability of $1/2^s$ for each of the 2^s possibilities.

Sequence of integers from 1 to 6:



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Sequence of integers from 1 to 100: 31, 83, 02, 72, 54, 26, ...



Random permutation:

1 2 3 4 5 6 7

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Random permutation:

1	2	3	4	5	6	7	
1	2	3	4	6	7	5	
1	3	4	6	7	5	2	
3	4	6	7	5	2	1	

For n objects, choose an integer from 1 to n ,
 then an integer from 1 to $n - 1$, then from 1 to $n - 2$, ...
 Each permutation should have the same probability.

To shuffle a deck of 52 cards: $52! \approx 2^{226}$ possibilities.



Uniform distribution over $(0, 1)$

For simulation in general, we want (to imitate) a sequence U_0, U_1, U_2, \dots of independent random variables **uniformly distributed over $(0, 1)$** .

We want $\mathbb{P}[a \leq U_j \leq b] = b - a$.



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To generate X such that $\mathbb{P}[X \leq x] = F(x)$:

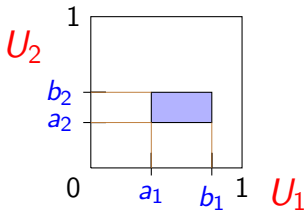
$$X = F^{-1}(U_j) = \inf\{x : F(x) \geq U_j\}.$$

Independence:

In s dimensions, we want

$$\mathbb{P}[a_j \leq U_j \leq b_j \text{ for } j = 1, \dots, s] = (b_1 - a_1) \cdots (b_s - a_s).$$

We want this for any s and any choice of box.

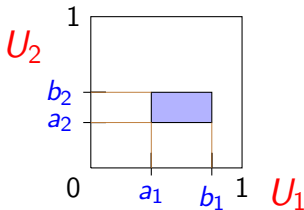


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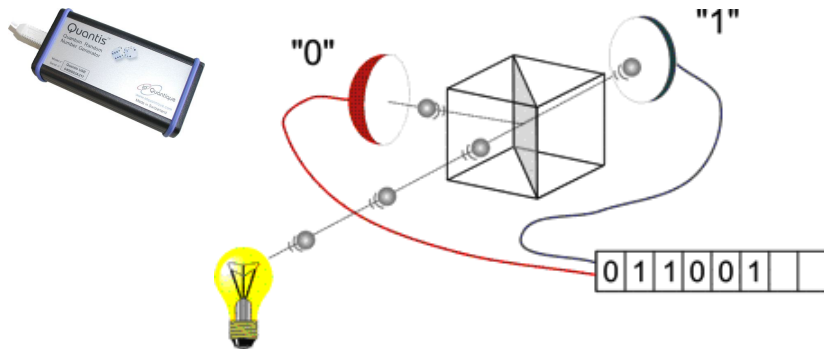
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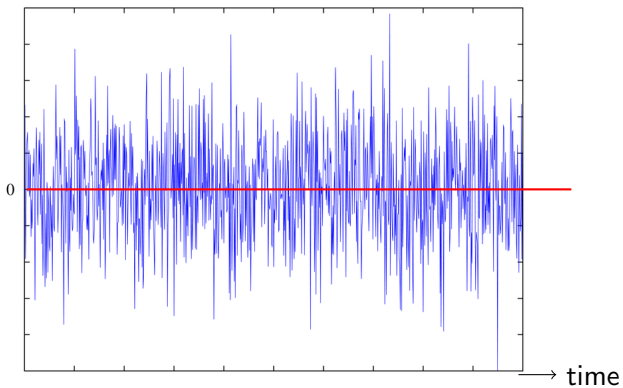
This notion of independent uniform random variables is only a **mathematical abstraction**. Perhaps it does not exist in the real world!

Physical devices for computers

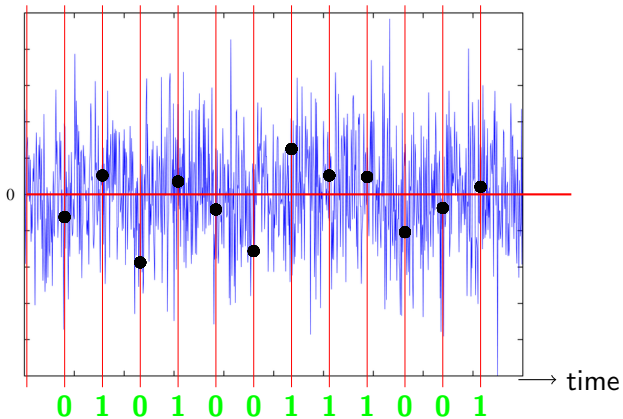
Photon trajectories (sold by **id-Quantique**):



Thermal noise in resistances of electronic circuits

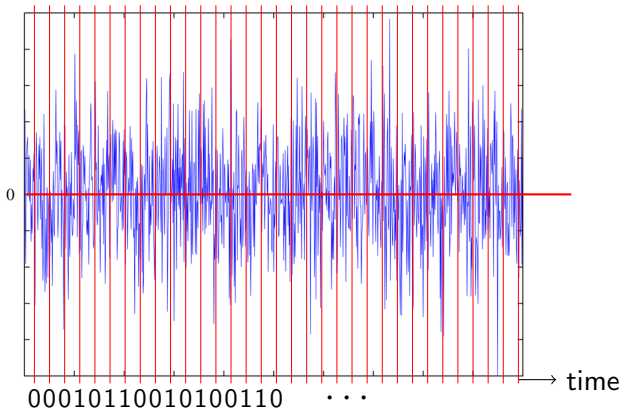


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None is perfect. Can reduce the bias and dependence by combining bits.

E.g., with a XOR:

$$\begin{array}{cccccccccc} 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 0 \\ \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} & \underbrace{\hspace{1em}} \\ 1 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 0 \end{array}$$

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1	1	0	1	1	1	1	0	1	0	0	1	0	1	0	0	0	0

or (this eliminates the bias):

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Physical devices are essential for cryptology, lotteries, etc.

But **not for simulation**.

Inconvenient, not reproducible, not always reliable, and no (or little) mathematical analysis.

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Visits all numbers from 1 to 100 exactly once before returning to x_0 .

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For real numbers between 0 and 1:

$$\begin{aligned} u_1 &= x_1/101 = 12/101 \approx 0.11881188\dots, \\ u_2 &= x_2/101 = 43/101 \approx 0.42574257\dots, \\ u_3 &= x_3/101 = 11/101 \approx 0.10891089\dots, \quad \text{etc.} \end{aligned}$$

A Larger Linear Recurrence

Choose 3 integers x_{-2}, x_{-1}, x_0 in $\{0, 1, \dots, 4294967086\}$ (not all 0).

For $n = 1, 2, \dots$, let

$$x_n = (1403580x_{n-2} - 810728x_{n-3}) \bmod 4294967087,$$

$$u_n = \lfloor x_n \bmod 4294967087 \rfloor / 4294967087.$$

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The sequence x_0, x_1, x_2, \dots is periodic, with cycle length $4294967087^3 - 1 \approx 2^{96}$, and (x_{n-2}, x_{n-1}, x_n) visits each of the $4294967087^3 - 1$ nonzero triples exactly once when n runs over a cycle.

A better (recommended) generator: MRG32k3a

Choose 6 integers:

x_{-2}, x_{-1}, x_0 in $\{0, 1, \dots, 4294967086\}$ (not all 0) and

y_{-2}, y_{-1}, y_0 in $\{0, 1, \dots, 4294944442\}$ (not all 0). For $n = 1, 2, \dots$, let

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The sequence u_0, u_1, u_2, \dots is periodic, with 2 cycles of period

$$\approx 2^{191} \approx 3.1 \times 10^{57}.$$

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Robust and reliable generator for simulation.

Used by SAS, R, MATLAB, Arena, Automod, Witness, Spielo gaming, ...

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Simulate a mathematical model of the behavior of a complex system (hospital, call center, logistic system, financial market, etc.). Must reproduce the relevant statistical properties of the mathematical model.

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4. **Cryptology**: Even stronger requirements. Observing any part the output should not help guessing (with reasonable effort) any other part. Often: very limited computational power and memory.

Nonlinear algorithmic generators with random parameters.

Algorithmic generator

\mathcal{S} , finite state space;

$f : \mathcal{S} \rightarrow \mathcal{S}$, transition function;

$g : \mathcal{S} \rightarrow [0, 1]$, output function.

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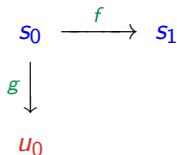
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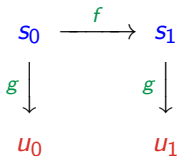
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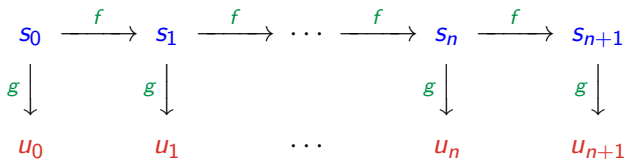
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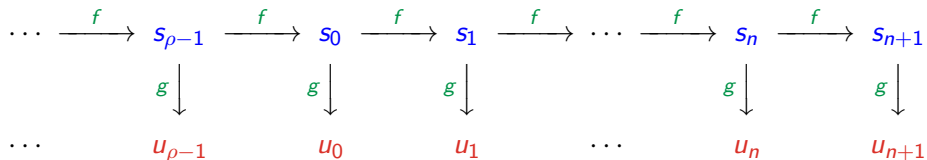
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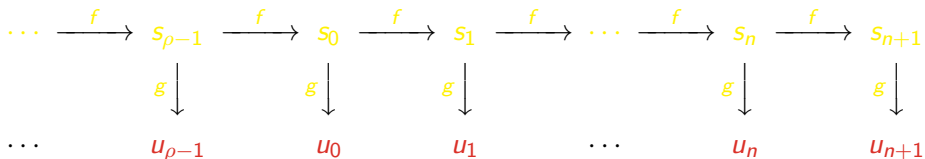


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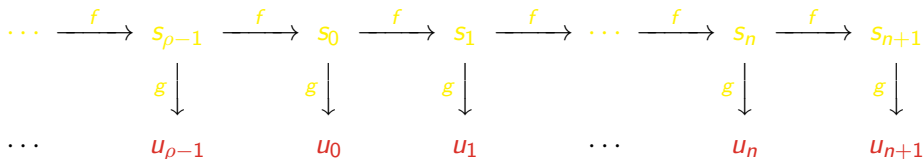
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Period of $\{s_n, n \geq 0\}$: $\rho \leq$ cardinality of \mathcal{S} .



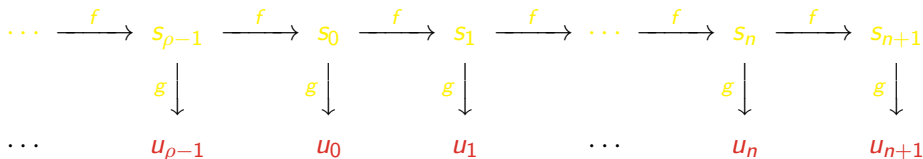
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Utopia: passes **all** statistical tests. Impossible!

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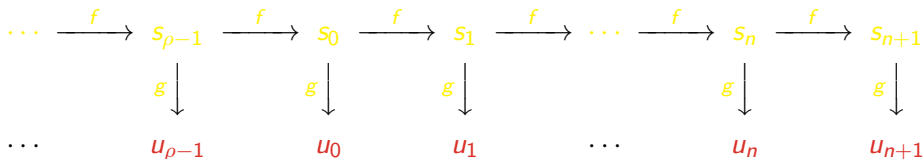
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With random seed s_0 , an RNG is a **gigantic roulette wheel**.

Selecting s_0 at random and generating s random numbers means spinning the wheel and taking $\mathbf{u} = (u_0, \dots, u_{s-1})$.

Number of possibilities cannot exceed $\text{card}(\mathcal{S})$. Ex.: shuffling 52 cards.

Lottery machines: modify the state s_n frequently.



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Uniform distribution over $[0, 1]^s$.

If we choose s_0 randomly in \mathcal{S} and we generate s numbers, this corresponds to choosing a random point in the **finite set**

$$\Psi_s = \{\mathbf{u} = (u_0, \dots, u_{s-1}) = (g(s_0), \dots, g(s_{s-1})), s_0 \in \mathcal{S}\}.$$

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Design and analysis:

1. Define a **uniformity measure** for Ψ_s , computable without generating the points explicitly. Linear RNGs.
2. Choose a parameterized family (fast, long period, etc.) and search for parameters that “optimize” this measure.

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Example 1. $u_n = (n/2^{1000}) \bmod 1$ for $n = 0, 1, 2, \dots$

Example 2. Subtract-with-borrow.

A single RNG does not suffice.

One often needs several **independent streams** of random numbers, e.g., to:

- ▶ Run a simulation on **parallel processors**.
- ▶ Compare similar systems with well synchronized **common random numbers** (for sensitivity analysis, derivative estimation, optimization). The idea is to simulate the two configurations with the same uniform random numbers U_j used at the same places, as much as possible. This requires good synchronization of the random numbers. Can be complicated to implement and manage when the two configurations do not need the same number of U_j 's.

A solution: RNG with [multiple streams and substreams](#).

We have developed software tools that permit one to create [RandomStream](#) objects at will.

Integrated in the [SSJ](#) (“Stochastic Simulation in Java”) library.

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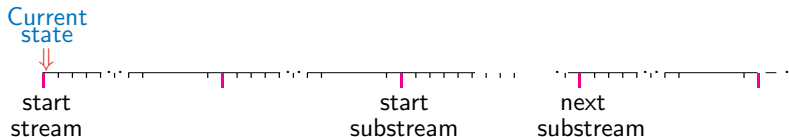
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Each **stream** is a virtual RNG, also partitioned in **substreams**.

Can create as many “independent” streams as we want.

In SSJ, a stream (RandomStream object) can also be an iterator on a **RQMC** point set.



Example of “poor” multiple streams: Image synthesis on GPUs.
(Thanks to Steve Worley, from [Worley Laboratories](#)).





Linear multiple recursive generator (MRG)

$$x_n = (a_1 x_{n-1} + \cdots + a_k x_{n-k}) \bmod m, \quad u_n = x_n / m.$$

State: $s_n = (x_{n-k+1}, \dots, x_n)$. Max. period: $\rho = m^k - 1$.

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State: $s_n = (x_{n-k+1}, \dots, x_n)$. Max. period: $\rho = m^k - 1$.

Numerous variants and implementations.

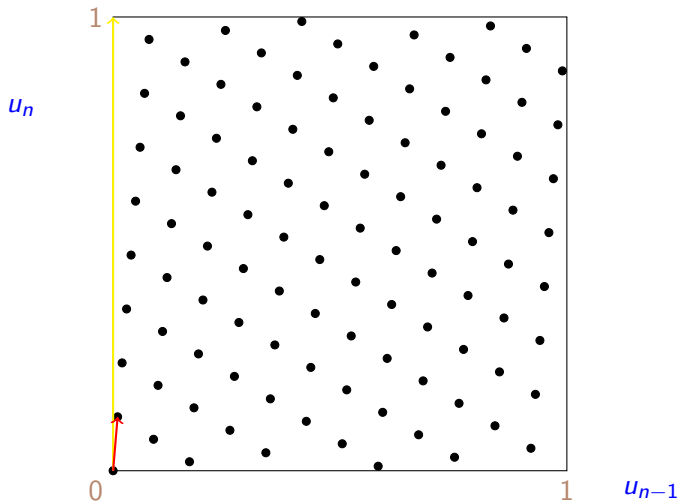
For $k = 1$: classical **linear congruential generator** (LCG).

Structure of the points Ψ_s :

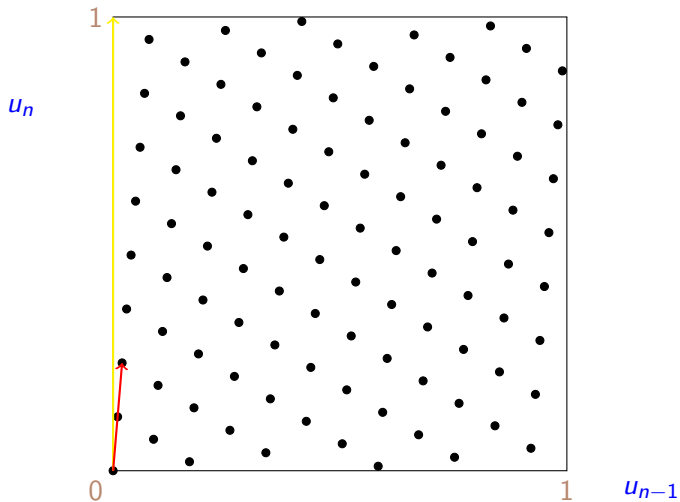
x_0, \dots, x_{k-1} can take any value from 0 to $m - 1$, then x_k, x_{k+1}, \dots are determined by the linear recurrence. Thus,

$(x_0, \dots, x_{k-1}) \mapsto (x_0, \dots, x_{k-1}, x_k, \dots, x_{s-1})$ is a **linear mapping**.

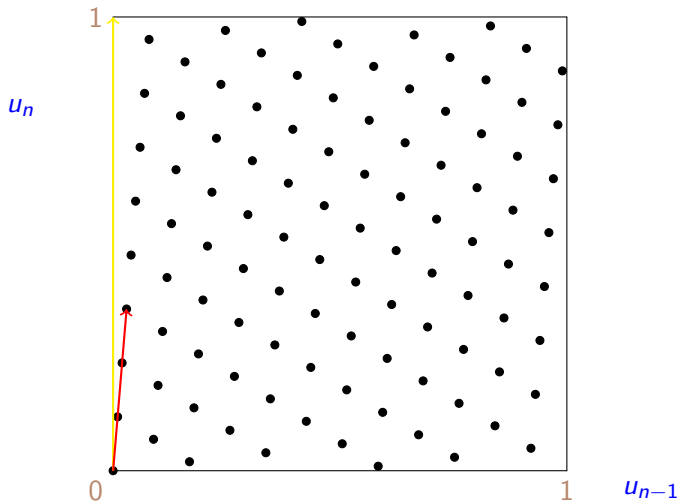
It follows that Ψ_s is a linear space; it is the intersection of a lattice with the unit cube.



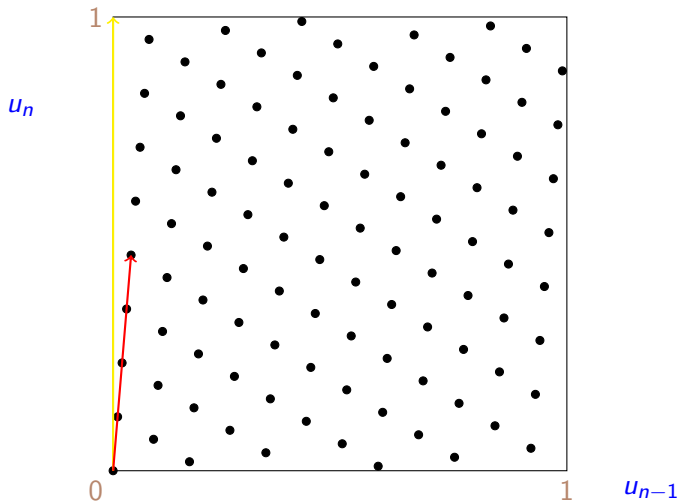
$$x_n = 12 x_{n-1} \bmod 101; \quad u_n = x_n/101$$



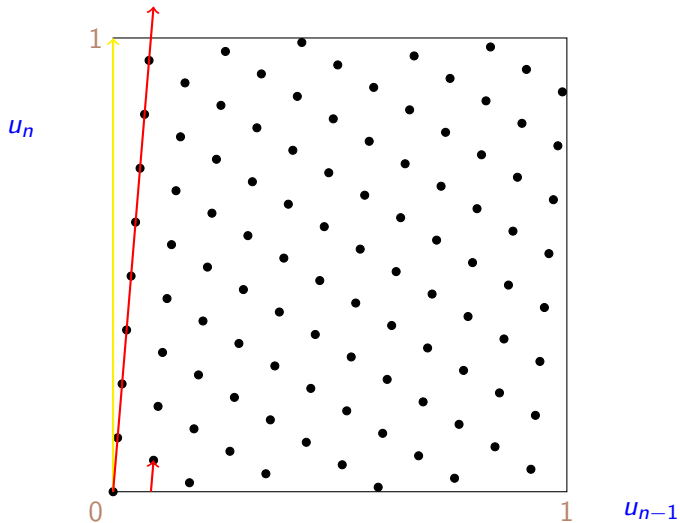
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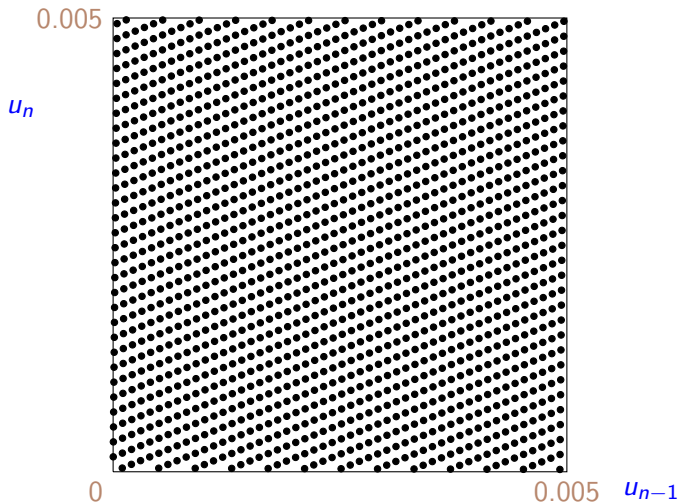
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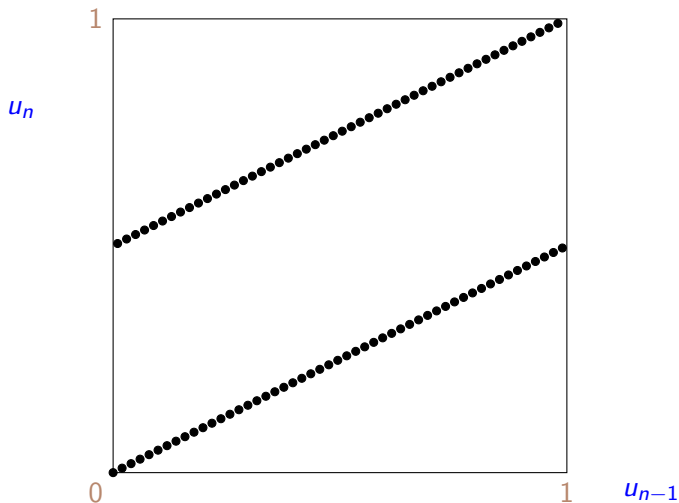
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$$x_n = 4809922 x_{n-1} \bmod 60466169 \text{ and } u_n = x_n / 60466169$$



$$x_n = 51 x_{n-1} \bmod 101; \quad u_n = x_n/101.$$

Good uniformity in one dimension, but not in two!

Example: lagged-Fibonacci

$$x_n = (x_{n-r} + x_{n-k}) \bmod m.$$

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Very fast, but bad. All points $(u_n, u_{n+k-r}, u_{n+k})$ belong to only two parallel planes in $[0, 1)^3$.

Example: subtract-with-borrow (SWB)

State $(x_{n-48}, \dots, x_{n-1}, c_{n-1})$ where $x_n \in \{0, \dots, 2^{31} - 1\}$ and $c_n \in \{0, 1\}$:

$$x_n = (x_{n-8} - x_{n-48} - c_{n-1}) \bmod 2^{31},$$

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Period $\rho \approx 2^{1479} \approx 1.67 \times 10^{445}$.

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In **Mathematica** versions ≤ 5.2 :

modified SWB with output $\tilde{u}_n = x_{2n} / 2^{62} + x_{2n+1} / 2^{31}$.

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Too obvious dependence between successive values.

All points $(u_n, u_{n+40}, u_{n+48})$ belong to **only two parallel planes** in $[0, 1)^3$.

Ferrenberg et Landau (1991). “Critical behavior of the three-dimensional Ising model: A high-resolution Monte Carlo study.”

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Tezuka, L'Ecuyer, and Couture (1993). “On the Add-with-Carry and Subtract-with-Borrow Random Number Generators.”

Couture and L'Ecuyer (1994) “On the Lattice Structure of Certain Linear Congruential Sequences Related to AWC/SWB Generators.”

Combined.

Two [or more] MRGs in parallel:

$$x_{1,n} = (a_{1,1}x_{1,n-1} + \cdots + a_{1,k}x_{1,n-k}) \bmod m_1,$$

$$x_{2,n} = (a_{2,1}x_{2,n-1} + \cdots + a_{2,k}x_{2,n-k}) \bmod m_2.$$

One possible **combinaison**:

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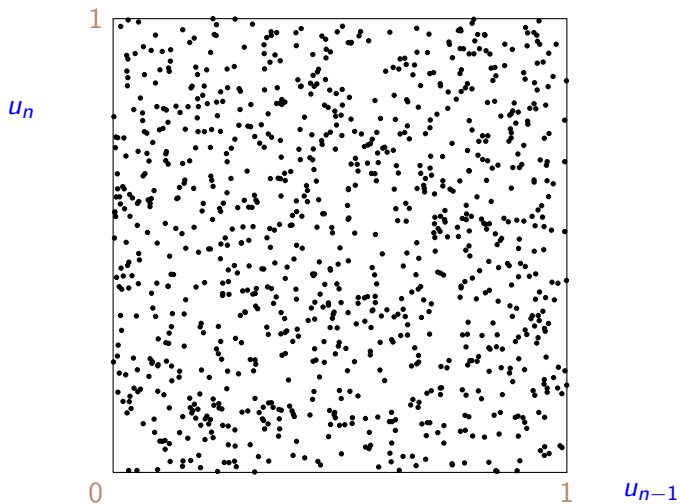
$$z_n := (x_{1,n} - x_{2,n}) \bmod m_1; \quad u_n := z_n/m_1;$$

L'Ecuyer (1996): the sequence $\{u_n, n \geq 0\}$ is also the output of an MRG of modulus $m = m_1 m_2$, with small added “noise”. The period can reach $(m_1^k - 1)(m_2^k - 1)/2$.

Permits one to implement efficiently an MRG with large m and several large nonzero coefficients.

Parameters: L'Ecuyer (1999); L'Ecuyer et Touzin (2000).

Implementations with multiple streams.



1000 points generated by MRG32k3a

Faster RNG: operations on blocks of bits.

Example: Choose $x_0 \in \{2, \dots, 2^{32} - 1\}$ (32 bits). Evolution:

$$x_{n-1} = \text{00010100101001101100110110100101}$$

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$$B = ((x_{n-1} \ll 6) \text{ XOR } x_{n-1}) \gg 13$$

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00010100101001101100110110100101	
00101001101100110110100101	100101
00111101000101011010010011100101	

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	0011110100010101101	0010011100101
--	---------------------	---------------

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$B =$	<div style="text-align: right; padding-right: 10px;">0011110100010101101</div> 0010011100101
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For real numbers in $(0, 1)$: $u_n = x_n / (2^{32} + 1)$.

More realistic: LFSR113

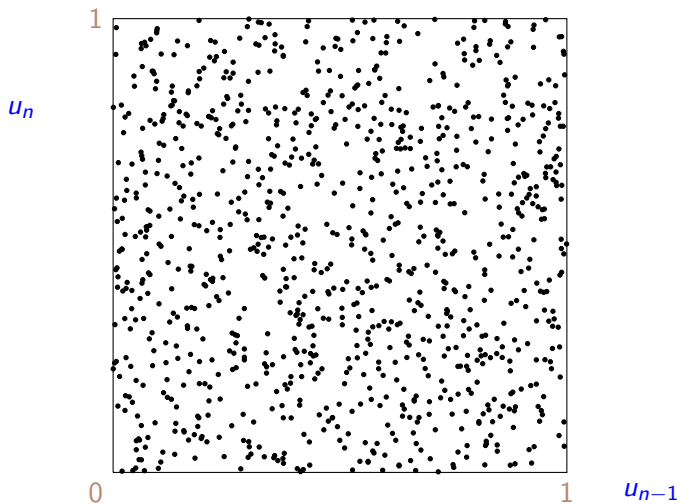
Take 4 recurrences on blocks of 32 bits, in parallel.

The periods are $2^{31} - 1$, $2^{29} - 1$, $2^{28} - 1$, $2^{25} - 1$.

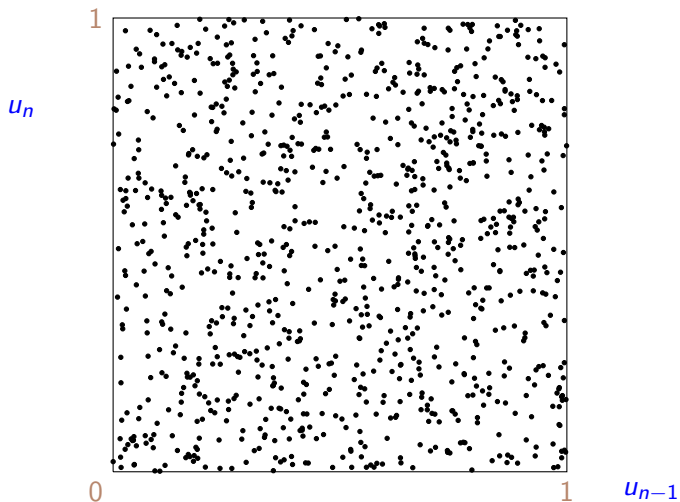
We add these 4 states by a XOR, then we divide by $2^{32} + 1$.

The output has period $\approx 2^{113} \approx 10^{34}$.

Good generator, faster than MRG32k3a, although successive values of bit i of the output obey a linear relationship of order 113, for each i .



1000 points generated by LFSR113



1000 points generated by MRG32k3a + LFSR113 (add mod 1)

General linear recurrences modulo 2

$$\begin{aligned}
 \mathbf{x}_n &= \mathbf{A} \mathbf{x}_{n-1} \bmod 2 &= (x_{n,0}, \dots, x_{n,k-1})^t, & \text{(state, } k \text{ bits)} \\
 \mathbf{y}_n &= \mathbf{B} \mathbf{x}_n \bmod 2 &= (y_{n,0}, \dots, y_{n,w-1})^t, & \text{(} w \text{ bits)} \\
 u_n &= \sum_{j=1}^w y_{n,j-1} 2^{-j} &= .y_{n,0} y_{n,1} y_{n,2} \dots, & \text{(output)}
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Special cases: Tausworthe, LFSR, GFSR, twisted GFSR, Mersenne twister, WELL, xorshift, etc.

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Each coordinate of \mathbf{x}_n and of \mathbf{y}_n follows the recurrence

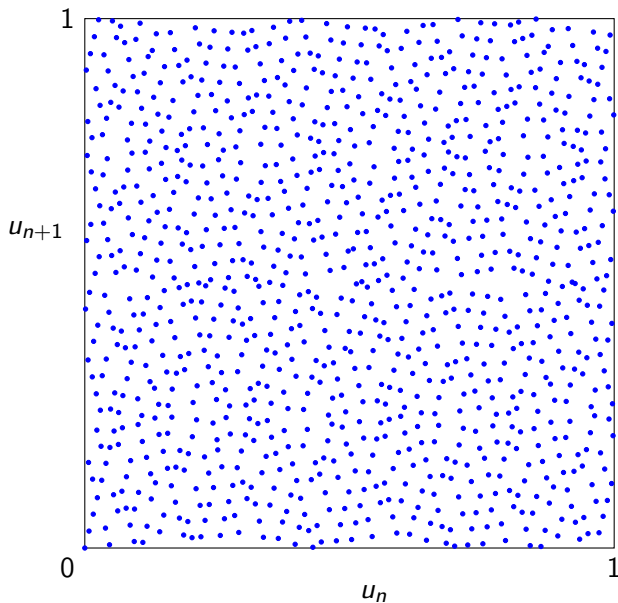
$$x_{n,j} = (\alpha_1 x_{n-1,j} + \dots + \alpha_k x_{n-k,j}),$$

with **characteristic polynomial**

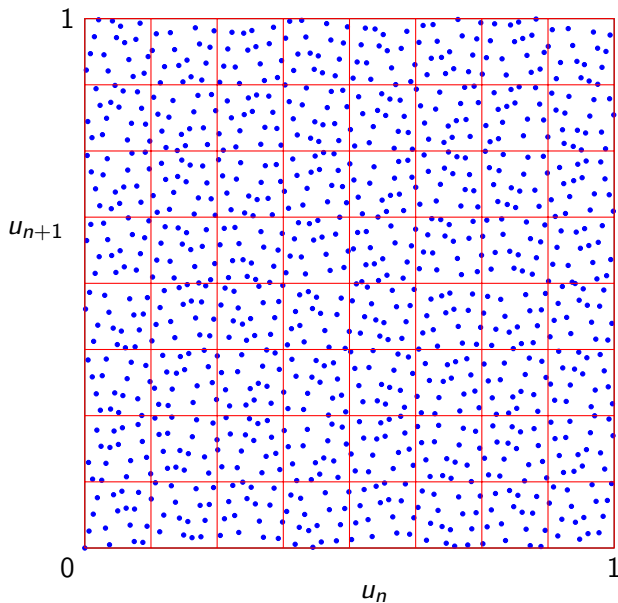
$$P(z) = z^k - \alpha_1 z^{k-1} - \dots - \alpha_{k-1} z - \alpha_k = \det(\mathbf{A} - z\mathbf{I}).$$

Max. period: $\rho = 2^k - 1$ reached iff $P(z)$ is primitive.

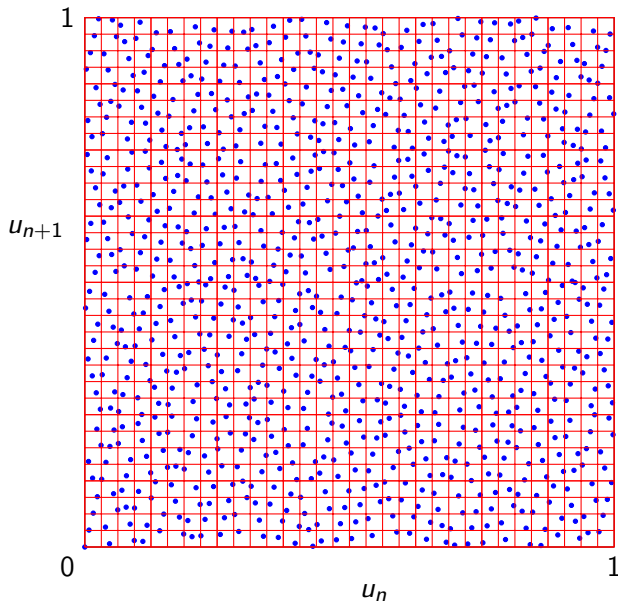
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Can be generalized to rectangular boxes...

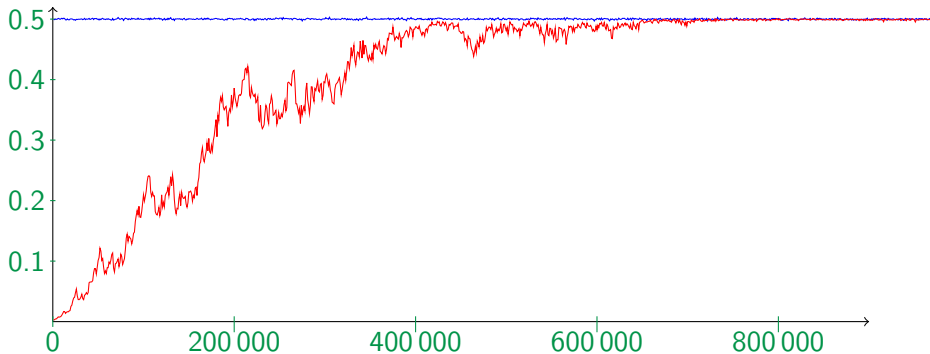
Examples: LFSR113, Mersenne twister (MT19937), the WELL family, ...

Impact of a matrix A that changes the state too slowly.

Experiment: take an initial state with a single bit at 1.

Try all k possibilities and take the average of the k values of u_n obtained for each n .

WELL19937 vs MT19937; moving average over 1000 iterations.



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Empirical tests: excellent behavior, more robust than linear generators.

Speed of some generators in SSJ

gen. time: CPU time to generate 10^9 uniform random numbers.

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Java JDK 1.5, 2.4 GHz 64-bit computer

RNG	period	gen. time	jump time
LFSR113	2^{113}	31	0.1
WELL512	2^{512}	33	234
WELL1024	2^{1024}	34	917
LFSR258	2^{258}	35	0.2
MT19937	2^{19937}	36	* 46
MRG31k3p	2^{185}	51	0.9
MRG32k3a	2^{191}	70	1.1
RandRijndael	2^{130}	127	0.6

Empirical statistical Tests

Hypothesis \mathcal{H}_0 : “ $\{u_0, u_1, u_2, \dots\}$ are i.i.d. $U(0, 1)$ r.v.'s”.

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- Define a statistic T , function of the u_i , whose distribution under \mathcal{H}_0 is known (or approx.).
- **Reject** \mathcal{H}_0 if value of T is too extreme. If suspect, can repeat.

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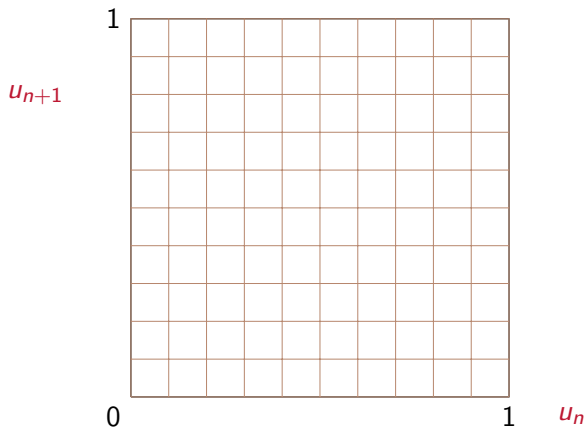
Ultimate **dream**: Build an RNG that passes **all** the tests? Formally impossible.

Compromise: Build an RNG that passes most **reasonable** tests.

Tests that fail are hard to find.

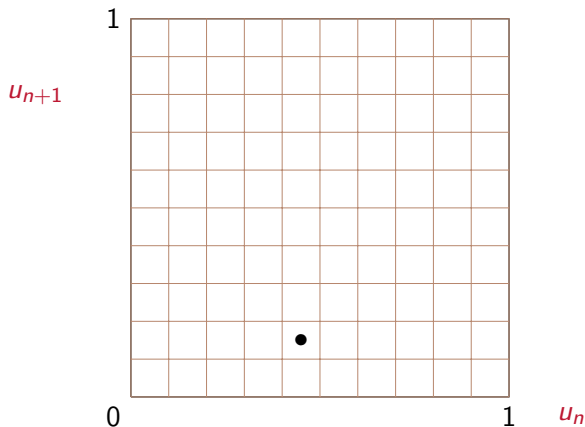
Formalization: computational complexity framework.

Example: A collision test



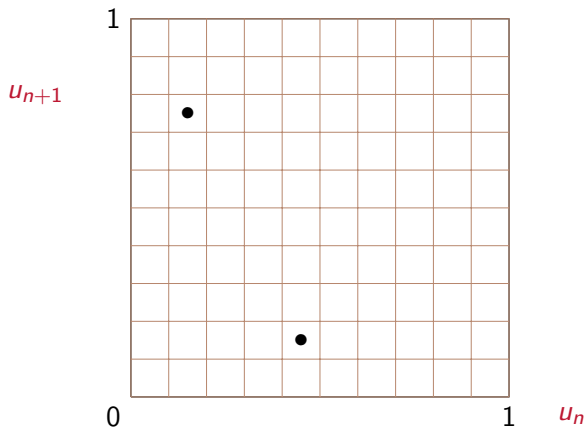
Throw $n = 10$ points in $k = 100$ boxes.

Example: A collision test



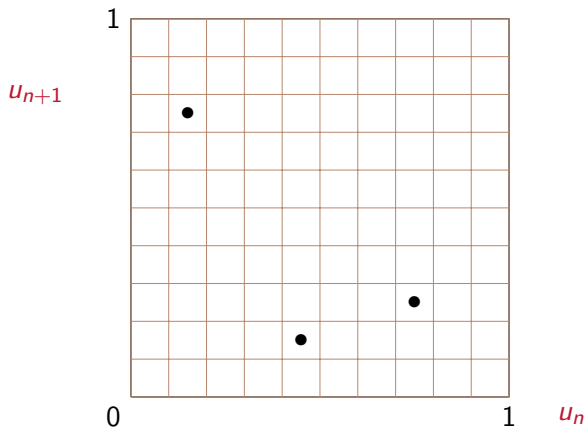
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Example: A collision test



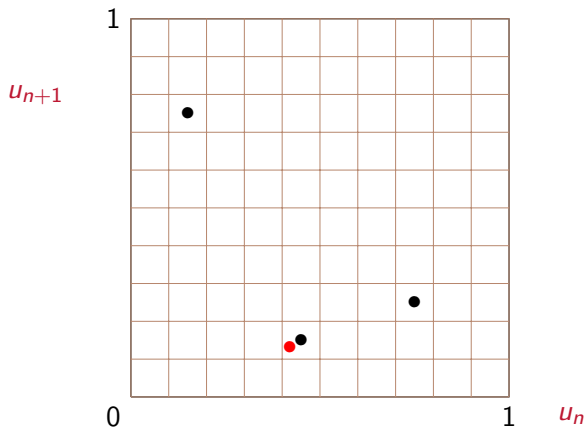
Throw $n = 10$ points in $k = 100$ boxes.

Example: A collision test



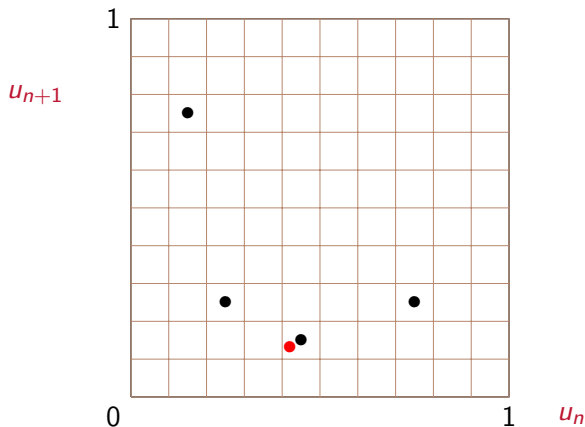
Throw $n = 10$ points in $k = 100$ boxes.

Example: A collision test



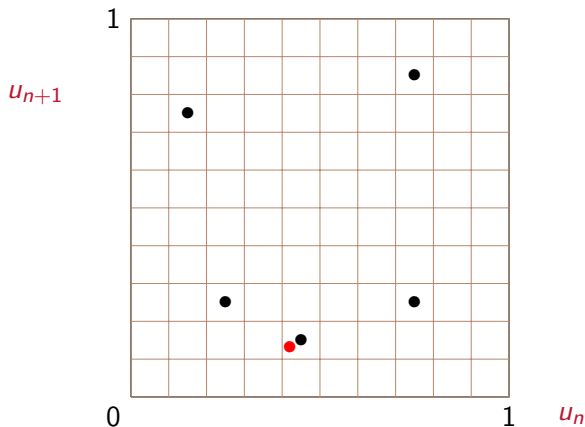
Throw $n = 10$ points in $k = 100$ boxes.

Example: A collision test



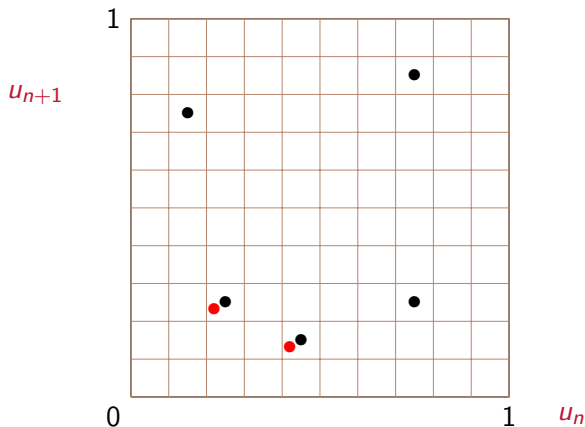
Throw $n = 10$ points in $k = 100$ boxes.

Example: A collision test



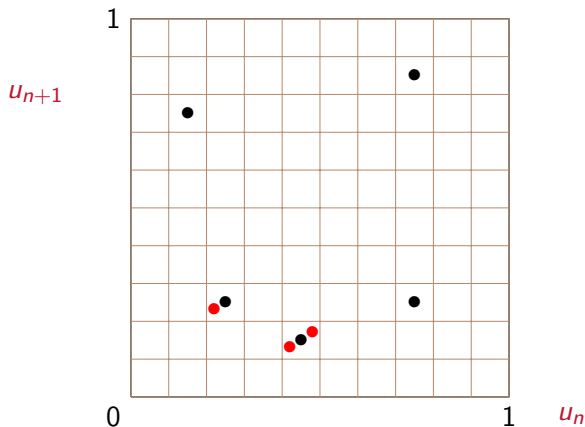
Throw $n = 10$ points in $k = 100$ boxes.

Example: A collision test



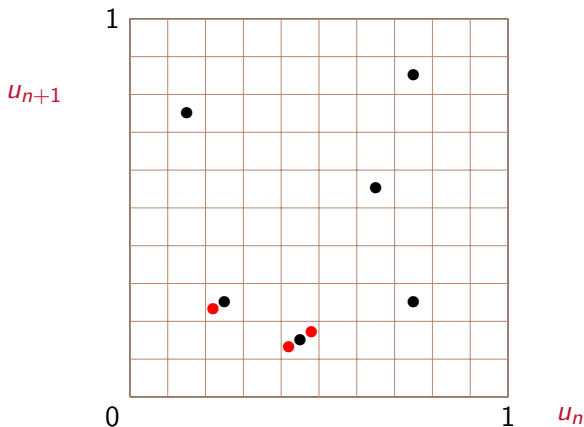
Throw $n = 10$ points in $k = 100$ boxes.

Example: A collision test



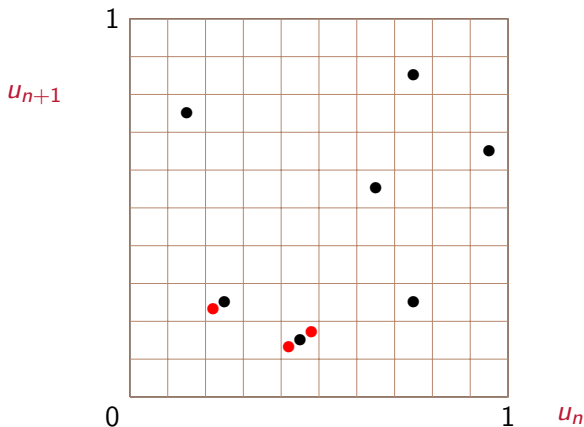
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Example: A collision test



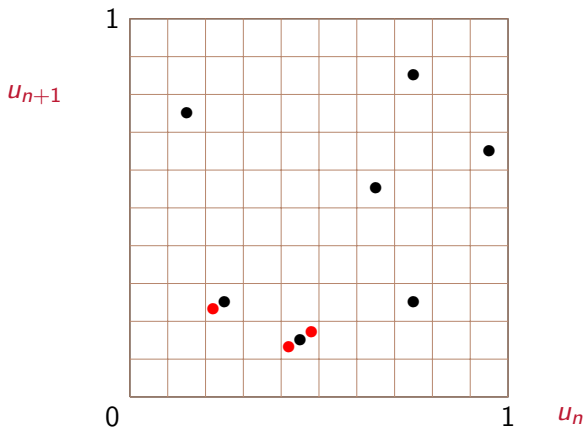
Throw $n = 10$ points in $k = 100$ boxes.

Example: A collision test



Throw $n = 10$ points in $k = 100$ boxes.

Example: A collision test



Throw $n = 10$ points in $k = 100$ boxes.

Here we observe 3 collisions. $\mathbb{P}[C \geq 3 \mid \mathcal{H}_0] \approx 0.144$.

Collision test

Partition $[0, 1)^s$ in $k = d^s$ cubic boxes of equal size.

Generate n points $(u_{i_1}, \dots, u_{i_{s+1}})$ in $[0, 1)^s$.

C = number of collisions.

Collision test

Partition $[0, 1]^s$ in $k = d^s$ cubic boxes of equal size.

Generate n points $(u_{i_1}, \dots, u_{i_1+s-1})$ in $[0, 1]^s$.

C = number of collisions.

Under \mathcal{H}_0 , $C \approx$ Poisson of mean $\lambda = n^2/(2k)$, if k is large and λ is small.

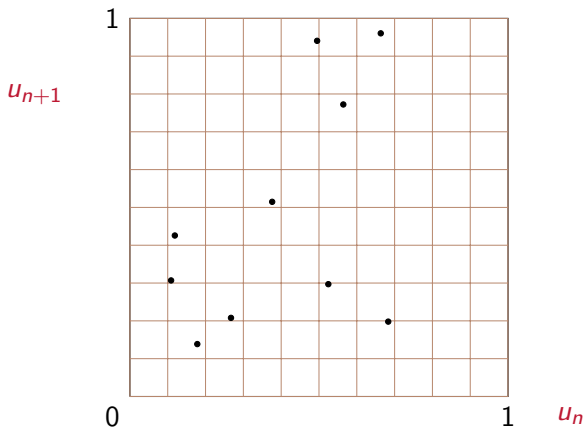
If we observe c collisions, we compute the p -values:

$$p^+(c) = \mathbb{P}[X \geq c \mid X \sim \text{Poisson}(\lambda)],$$

$$p^-(c) = \mathbb{P}[X \leq c \mid X \sim \text{Poisson}(\lambda)],$$

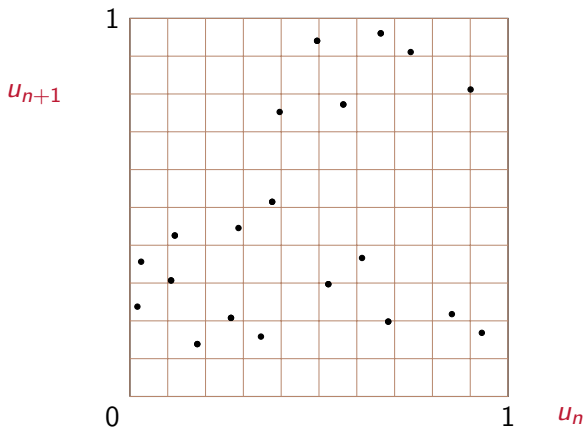
We reject \mathcal{H}_0 if $p^+(c)$ is too close to 0 (too many collisions) or $p^-(c)$ is too close to 1 (too few collisions).

Example: LCG with $m = 101$ and $a = 12$:



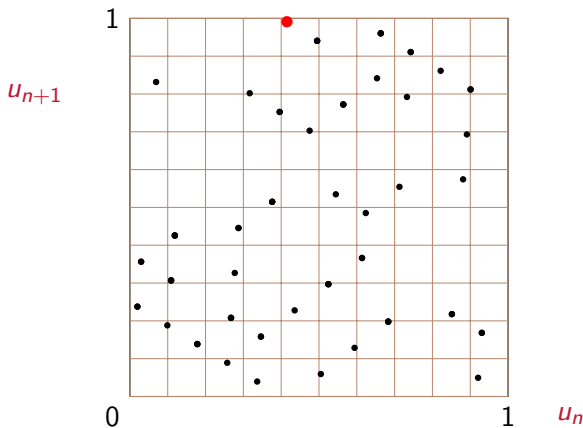
n	λ	C	$p^-(C)$
10	1/2	0	0.6281

Example: LCG with $m = 101$ and $a = 12$:

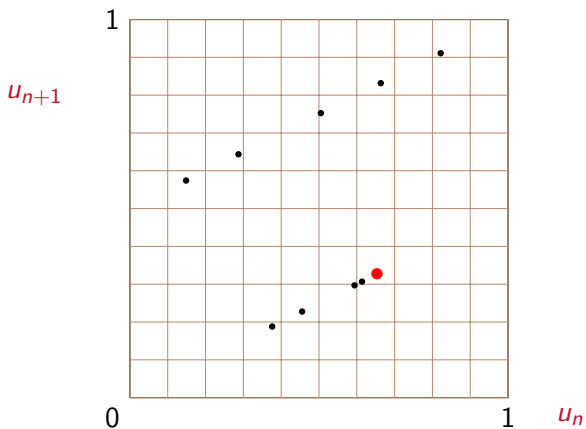


n	λ	C	$p^-(C)$
10	$1/2$	0	0.6281
20	2	0	0.1304

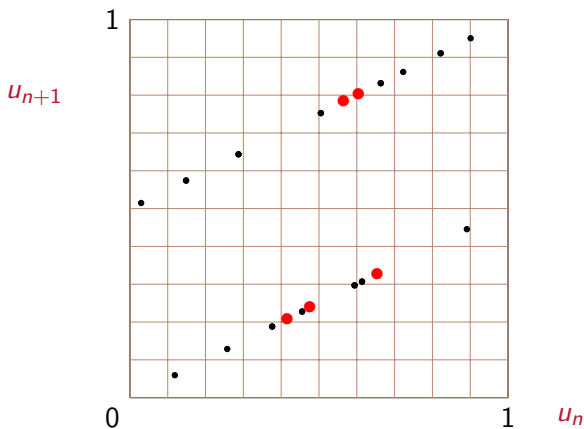
Example: LCG with $m = 101$ and $a = 12$:



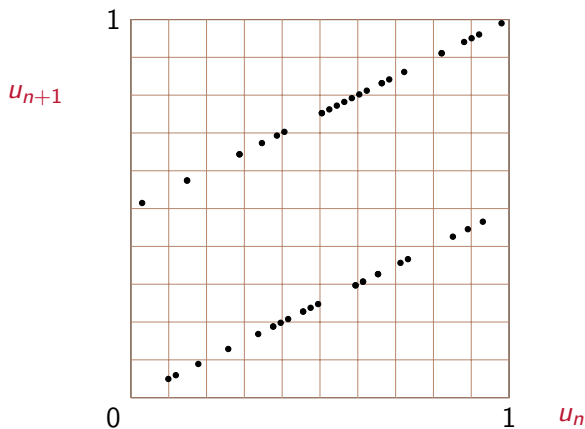
n	λ	C	$p^-(C)$
10	$1/2$	0	0.6281
20	2	0	0.1304
40	8	1	0.0015



n	λ	C	$p^+(C)$
10	$1/2$	1	0.3718



n	λ	C	$p^+(C)$
10	$1/2$	1	0.3718
20	2	5	0.0177



n	λ	C	$p^+(C)$
10	$1/2$	1	0.3718
20	2	5	0.0177
40	8	20	2.2×10^{-9}

SWB in Mathematica

For the unit cube $[0, 1)^3$, divide each axis in $d = 100$ equal intervals. This gives $k = 100^3 = 1$ million boxes.

Generate $n = 10\,000$ vectors in 25 dimensions: (U_0, \dots, U_{24}) .

For each, note the box where (U_0, U_{20}, U_{24}) falls.

Here, $\lambda = 50$.

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With MRG32k3a: $C = 41, 66, 53, 50, 54, \dots$

Other examples of tests

Nearest pairs of points in $[0, 1)^t$.

Sorting card decks (poker, etc.).

Rank of random binary matrix.

Linear complexity of binary sequence.

Measures of entropy.

Complexity measures based on data compression.

Etc.

The TestU01 software

[L'Ecuyer et Simard, ACM Trans. on Math. Software, 2007].

- ▶ Large variety of statistical tests.
For both algorithmic and physical RNGs.
Widely used. On my web page.
- ▶ Some predefined batteries of tests:
 - SmallCrush: quick check, 15 seconds;
 - Crush: 96 test statistics, 1 hour;
 - BigCrush: 144 test statistics, 6 hours;
 - Rabbit: for bit strings.
- ▶ Many widely-used generators fail these batteries unequivocally.

Results of test batteries applied to some well-known RNGs

ρ = period length;

t-32 and t-64 gives the CPU time to generate 10^8 random numbers.

Number of failed tests (p -value $< 10^{-10}$ or $> 1 - 10^{-10}$) in each battery.

Generator	$\log_2 \rho$	t-32	t-64	S-Crush	Crush	B-Crush
LCG in Microsoft VisualBasic	24	3.9	0.66	14	—	—
LCG(2^{32} , 69069, 1), VAX	32	3.2	0.67	11	106	—
LCG(2^{32} , 1099087573, 0) Fishman	30	3.2	0.66	13	110	—
LCG(2^{48} , 25214903917, 11), Unix	48	4.1	0.65	4	21	—
Java.util.Random	47	6.3	0.76	1	9	21
LCG(2^{48} , 44485709377909, 0), Cray	46	4.1	0.65	5	24	—
LCG(2^{59} , 13^{13} , 0), NAG	57	4.2	0.76	1	10	17
LCG($2^{31}-1$, 16807, 0), Wide use	31	3.8	3.6	3	42	—
LCG($2^{31}-1$, 397204094, 0), SAS	31	19.0	4.0	2	38	—
LCG($2^{31}-1$, 950706376, 0), IMSL	31	20.0	4.0	2	42	—
LCG($10^{12}-11$, ..., 0), Maple	39.9	87.0	25.0	1	22	34

Generator	$\log_2 \rho$	t-32	t-64	S-Crush	Crush	B-Crush
Wichmann-Hill, MS-Excel	42.7	10.0	11.2	1	12	22
CombLec88 , boost	61	7.0	1.2		1	
Knuth(38)	56	7.9	7.4		1	2
ran2 , in Numerical Recipes	61	7.5	2.5			
CombMRG96	185	9.4	2.0			
MRG31k3p	185	7.3	2.0			
MRG32k3a SSJ + others	191	10.0	2.1			
MRG63k3a	377	—	4.3			
LFib(2^{31} , 55, 24, +), Knuth	85	3.8	1.1	2	9	14
LFib(2^{31} , 55, 24, -), Matpack	85	3.9	1.5	2	11	19
ran3 , in Numerical Recipes		2.2	0.9		11	17
LFib(2^{48} , 607, 273, +), boost	638	2.4	1.4		2	2
Unix-random-32	37	4.7	1.6	5	101	—
Unix-random-64	45	4.7	1.5	4	57	—
Unix-random-128	61	4.7	1.5	2	13	19

Generator	$\log_2 \rho$	t-32	t-64	S-Crush	Crush	B-Crush
Knuth-ran_array2	129	5.0	2.6		3	4
Knuth-ranf_array2	129	11.0	4.5			
SWB(2^{24} , 10, 24)	567	9.4	3.4	2	30	46
SWB($2^{32} - 5$, 22, 43)	1376	3.9	1.5		8	17
Mathematica-SWB	1479	—	—	1	15	—
GFSR(250, 103)	250	3.6	0.9	1	8	14
TT800	800	4.0	1.1		12	14
MT19937, widely used	19937	4.3	1.6		2	2
WELL19937a	19937	4.3	1.3		2	2
LFSR113	113	4.0	1.0		6	6
LFSR258	258	6.0	1.2		6	6
Marsaglia-xorshift	32	3.2	0.7	5	59	—

Generator	$\log_2 \rho$	t-32	t-64	S-Crush	Crush	B-Crush
Matlab-rand, (until 2008)	1492	27.0	8.4		5	8
Matlab in randn (normal)	64	3.7	0.8		3	5
SuperDuper-73, in S-Plus	62	3.3	0.8	1	25	—
R-MultiCarry, (changed)	60	3.9	0.8	2	40	—
KISS93	95	3.8	0.9		1	1
KISS99	123	4.0	1.1			
AES (OFB)		10.8	5.8			
AES (CTR)	130	10.3	5.4			
AES (KTR)	130	10.2	5.2			
SHA-1 (OFB)		65.9	22.4			
SHA-1 (CTR)	442	30.9	10.0			

Conclusion

- ▶ A flurry of computer applications require RNGs.
A poor generator can severely bias simulation results, or permit one to cheat in computer lotteries or games, or cause important security flaws.
- ▶ Don't trust blindly the RNGs of commercial or other widely-used software, especially if they hide the algorithm (proprietary software...).
- ▶ Some software products have good RNGs; check what it is.
- ▶ RNGs with multiple streams are available from my web page in Java, C, and C++. Just Google "[pierre lecuyer](#)."
- ▶ Examples of work in progress:
Fast nonlinear RNGs with provably good uniformity;
RNGs based on multiplicative recurrences;
RNGs with multiple streams for GPUs.