

RANDOM NUMBER GENERATION

Quantitative Risk Management project work

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- Computer-generated numbers are pseudo-random: deterministic and predictable
- Quasi-random numbers prevent potential lack of equidistributedness
- **Definition.** (sample) a sequence of number is called a sample from the distribution F if the numbers are independent realizations of a random variable with distribution function F
- Uniform deviates: samples from $\sim \mathcal{U}[0, 1]$
- Normal deviates: samples from $\sim \mathcal{N}(0, 1)$
- Drawing uniform deviates is the basis of random number generation

- N_0 is chosen arbitrarily
- $N_i = (aN_{i-1} + b) \bmod M$ for $i > 0$

Requirements:

1. Large period: small set of numbers makes the outcome easier to predict (choose M as large as possible)
2. Statistical tests to verify that the distribution is the intended one
 - Comparison of sample mean and variance μ, σ^2 with desired values
 - Correlation between sample values
 - Quality of approximation of the distribution
3. Distribution in higher dimensional spaces: lattice structure

- Sequences of random numbers can be arranged in m -dimensional vectors
- The vectors lie on a number of parallel $(m - 1)$ -dimensional hyperplanes
- The ideal condition is that the number of parallel hyperplanes is maximized: number of hyperplanes is a measure of equidistributedness
- Family of parallel lines in the (U_{i-1}, U_i) -plane

$$z_0 U_{i-1} + z_1 U_i = c + \frac{z_1 b}{M} \quad \text{where} \quad c := N_{i-1} \frac{z_0 + a z_1}{M} - z_1 k$$

for each tuple (z_0, z_1) and for all cs .

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- Inversion and transformation methods generate numbers distributed according to an arbitrary distribution from uniformly distributed samples

IMPLEMENTATIONS - LINEAR CONGRUENTIAL GENERATOR

```
1  function [ rn ] = LCG( x )
2
3      if(nargin == 0)
4          x = 1;
5      end
6
7      rn = zeros(x,1);
8
9      for i = 1:x
10         rn(i) = LCGstep();
11     end
12
13 end

14 function [ rnStep ] = LCGstep()
15
16     persistent seed;
17     M = 244944;
18     a = 1597;
19     b = 51749;
20
21     if isempty(seed)
22         seed = 0;
23     end
24
25     seed = mod(seed * a + b, M);
26
27     rnStep = seed / M;
28
29 end
```

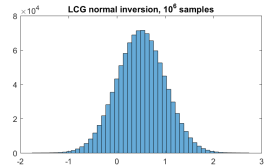
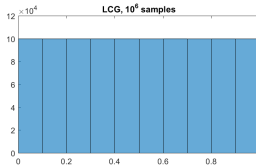
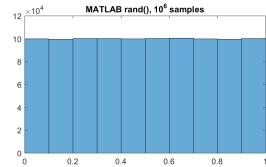
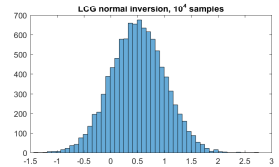
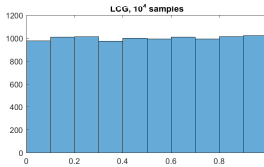
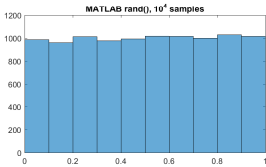
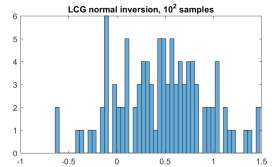
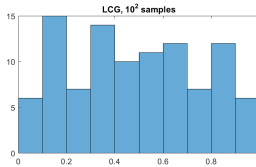
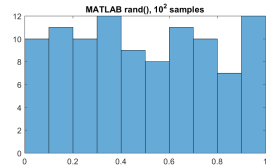

IMPLEMENTATIONS - BOX-MULLER METHOD

```
1  function [ Z ] = BoxMuller( x )
2
3      if(nargin == 0)
4          x = 1;
5      end
6
7      U = rand(x, 2);
8
9      theta = 2 .* pi .* U(:, 2);
10     rho    = sqrt( -2 .* log( U(:, 1) ) );
11
12     Z = [ rho .* cos(theta), rho .* sin(theta) ];
13
14 end
```

IMPLEMENTATIONS - MARSAGLIA POLAR ALGORITHM

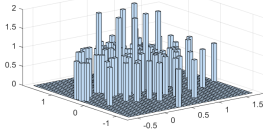
```
1  function [ Z ] = Marsaglia( x )
2
3      if(nargin == 0)
4          x = 1;
5      end
6
7      Z = zeros(x,2);
8
9      for i = 1 : x
10         W = 1;  V = [ 1, 1 ];
11         while not (W < 1)
12             V = 2 * rand(1, 2) - 1;
13             W = V(1) .^ 2 + V(2) .^ 2;
14         end
15
16         Z(i, :) = V .* sqrt(-2 * log(W) / W);
17     end
18 end
```

PLOTS - UNIVARIATE METHODS

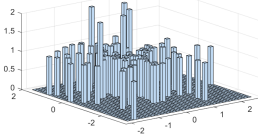


PLOTS - BIVARIATE METHODS

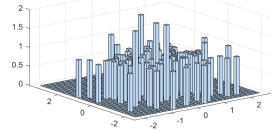
norminv(rand()), 10^2 samples



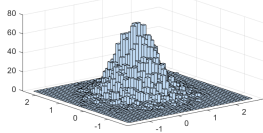
Box-Muller, 10^2 samples



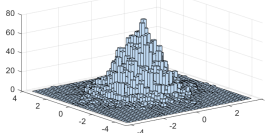
Marsaglia, 10^2 samples



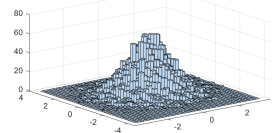
norminv(rand()), 10^4 samples



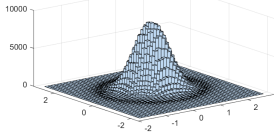
Box-Muller, 10^4 samples



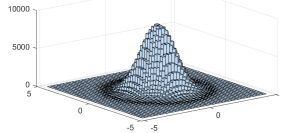
Marsaglia, 10^4 samples



norminv(rand()), 10^6 samples



Box-Muller, 10^6 samples



Marsaglia, 10^6 samples

