

# Quasi-random number generator

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## 1 Pseudo-random vs. quasi-random

Pseudo-random number:

- a computer-generated number
- appears to be random but is generated by an entirely deterministic process
- a pseudo-random process is easier to produce than a genuinely random one
- the benefit of a pseudo-random process is that it can be used again and again to produce exactly the same numbers, which is useful for testing and fixing software

Quasi-random number:

- also called low-discrepancy numbers
- the discrepancy is a measure of how inhomogeneously a set of  $d$ -dimensional vectors are distributed in the unit hypercube
- low-discrepancy means the points are distributed more uniformly, with less clusters and gaps that are typical for pseudo-random numbers
- unlike pseudo-random numbers, low-discrepancy numbers aim not to be serially uncorrelated but instead to take the previous draws into account when determining the next number in the sequence

If we take a uniform random generator on  $[0, 1)$  and halve the interval, for each trial there is a probability of  $\frac{1}{2}$  that the generated point will be in the left interval and a probability of  $\frac{1}{2}$  that the point will be in the right

interval. generating a point on each of these subintervals. Therefore, it is possible for first  $n$  generated points to coincidentally all lie in the first half of the interval, while the next point still falls within the other of the two halves with probability  $\frac{1}{2}$ . This is not the case with the quasirandom sequences because of the low-discrepancy requirement that has an effect of points being generated in a highly correlated manner (i.e., the next point “knows” where the previous points are).

## 2 Quasi-random numbers – usage

Quasi-random numbers are useful in computational problems and are especially popular for financial Monte Carlo calculations. Quasi-Monte Carlo calculations (using sequences of quasi-random numbers to compute the integral) asymptotically converge faster than normal Monte Carlo calculations using pseudo-random numbers, even for large dimensionality of drawn vectors  $d$ .

## 3 Sobol’ numbers

- we need a new unique generating integer  $\gamma(n)$  for each new draw
- easy choice is  $\gamma(n) = n$ , another possibility is the Gray code  $\gamma(n) = G(n)$ , which I will not be discussing
- the generation is carried out on a set of integers in the interval  $[1, 2^b - 1]$
- $b$  represents the number of bits in an unsigned integer on the given computer and is typically 32
- denote  $x_{nk}$  as the  $n$ th draw of Sobol’ integer in dimension  $k$
- a set of  $b$  *direction integers* for each dimension  $k$ , which are the basis of the number generation
- there are some additional constraints on the direction integers which I will not discuss
- for each dimension, we select a primitive polynomial modulo two and calculate the direction integers using the coefficients of the polynomial and binary addition

- from there, we calculate  $x_{nk}$ : depending on which bits in the binary representation of  $\gamma(n)$  are set, the direction integers are XORed to produce the Sobol' integer  $x_{nk}$

## 4 Project timeline

Work done so far:

- reading the source material
- getting familiar with C++

Plan for the rest of the project:

- implement Sobol' number generator with Gray code
- test the generator with quasi-Monte Carlo integration
- compare results with the parallel version