



The Monte Carlo method

EUTEMPE-RX module 03

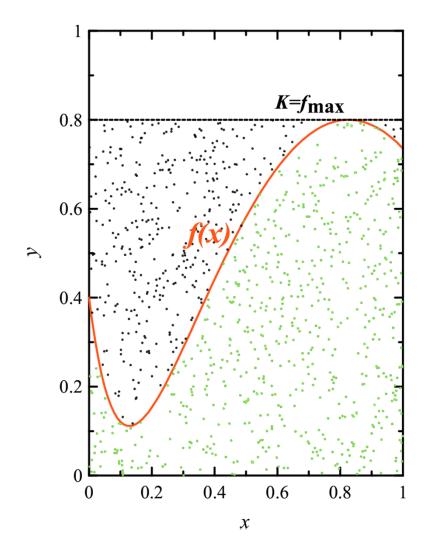
Monte Carlo simulation of x-ray imaging and dosimetry

Barcelona, June 2017

What is Monte Carlo?

- MC methods are a class of numerical techniques distinguished by the use of stochastic (i.e. non-deterministic) algorithms to simulate the behaviour of physical or mathematical systems.
- Based on the modelling of individual object-object relationships (conceptual simplicity and flexibility).
- It involves random sampling of many individual object-object interactions to find the average value of some quantity of interest (**repetitive** calculation). Computers are well suited for this task.
- There are applications in game theory, traffic flow, social science, mathematics, finance, quantum chemistry, radiation physics, etc.

An example: MC integration



$$I = A \frac{N_{\mathrm{hits}}}{N} = A \frac{\sum_{i=1}^{N} q_i}{N}$$
 q_i = 0 or 1

I is a random variable

$$\langle I \rangle = A \frac{\sum \langle q_i \rangle}{N} = A \langle q \rangle$$

$$\sigma^{2}(I) = A^{2} \frac{\sum \sigma^{2}(q_{i})}{N^{2}} = A^{2} \frac{\sigma^{2}(q)}{N}$$

uncertainty
$$\sim \frac{1}{\sqrt{N}}$$

A little bit of history

The underlying concept of using random numbers can be traced back to the early pioneers of prob. theory (Buffon, Gosset).



Georges L Leclerc (Comte de Buffon) 1707 (France) - 1788

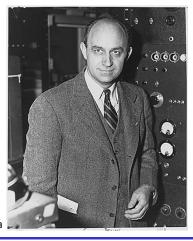
Source: Wikipedia

Fermi used random numbers in the 30s to evaluate some properties of the newly discovered neutron.

William S Gosset (a.k.a. Student) 1876 (UK) - 1937



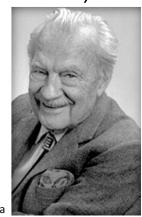
Source: Wikipedia



Enrico Fermi 1901 (Italy) - 1954

Source: Wikipedia

- Simulations during the Manhattan Project (WW2), limited by computing power.
- With the advent of electronic computers (1945) MC methods were taken seriously.
- In the 50's MC was used at Los Alamos for early work on the H-bomb.
- The invention of the Monte Carlo method is attributed to Stanislaw Ulam, a Polish-born mathematician who worked for John von Neumann on the Manhattan Project (Ulam is primarily known, with Edward Teller, for the Hbomb design in 1951).



Nicholas C. Metropolis 1915 (USA) - 1999



Source: Wikipedia

Stanislaw M. Ulam 1909 (Austria-Hungary)-1984



Source: Wikipedia

John von Neumann 1903 (Austria-Hungary)-1957

MC method

Random number generators

• Truly RNGs can be based on random processes, like thermal noise, radioactive decay, coin flipping...



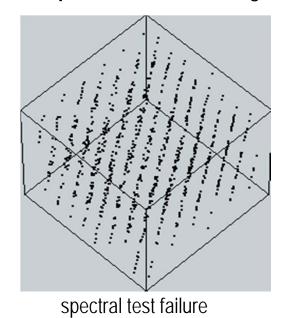
There are good reasons not to do it in this way: computing speed and repeatability.

Or on arithmetic, and therefore deterministic, algorithms: pseudo-random.

Multiplicative Linear Congruential (MLCG)

An MLCG is defined by
$$S_{i+1} = (aS_i) \operatorname{MOD} m$$
 , $u_i = \frac{S_i}{m}$

- Cyclical, with a period $T \leq (m-1)$. For 32-bit-long signed integers, $T \sim 2 \times 10^9$ at most, insufficient for present-day applications.
- \bullet and m must be chosen carefully to ensure good random properties.
- The **spectral test** (Marsaglia 1968) is of particular interest.



A bad example: RANDU (SSP package):

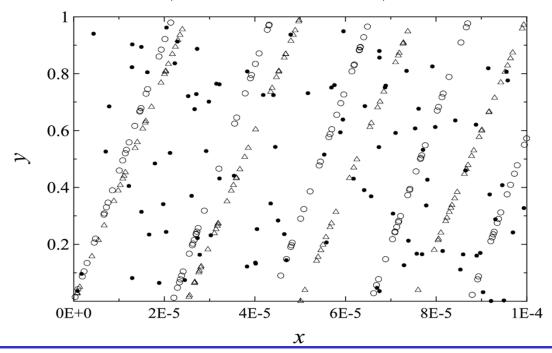
$$S_{i+1} = (65539 \, S_i) \, \text{MOD} \, 2^{31}$$

Combines two MLCGs :
$$S_i = (S_i^{(1)} - S_i^{(2)}) \text{ MOD } (m^{(1)} - 1)$$

Parameters of the MLCGs that are used in RANECU

	Modulus (m)	Multiplier (a)	
1st generator	2 147 483 563	40 014	
2nd generator	2 147 483 399	40 692	

$$T = \text{lcm}(m^{(1)} - 1, m^{(2)} - 1) \sim 2 \times 10^{18}$$



good spectral properties

Some other good RNGs

• RANLUX (Lüscher 1994), based on a lagged Fibonacci algorithm called subtract-and-borrow (c_i is the carry bit, 1 or 0):

$$S_i = (S_{i-10} - S_{i-24} - c_{i-1}) \text{ MOD } 2^{24}, \quad i > 23$$

Some elements are discarded to eliminate short-ranged correlations

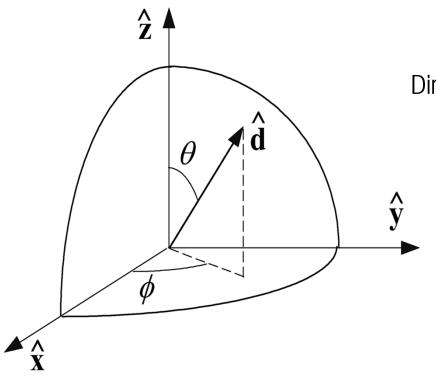
- High-quality, with a period $T \sim 10^{171}$ (!), but slow.
- Mersenne Twister (M Matsumoto et al 2000), based on a linear feedback shift register, which involves binary operations with the seed bits
 - considerably faster than RANLUX and RANECU.
 - has passed the most relevant random tests.
 - cycle period ~ 10⁶⁰⁰¹ (!!!)
 - lack of a theoretical basis for its weaknesses.

All the previous RNGs can be "parallelized".

Elements of probability theory

- Understand underlying concepts and simulation results.
- Prepare/adapt your own routines (e.g. radiation sources).

Example: isotropic source



Direction of motion: $\hat{\mathbf{d}} = (u, v, w)$

- Prob. of u_i v and w?
- Sampling algorithm?

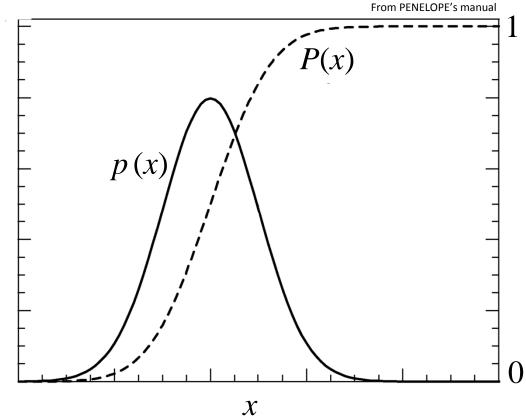
Probability distribution function (PDF)

$$p_{\eta}(x) = \frac{\mathcal{P}(x < \eta < x + \mathrm{d}x)}{\mathrm{d}x}$$

$$p(x) \ge 0$$

$$\int_{-\infty}^{+\infty} \mathrm{d}x \ p(x) = 1$$

$$P(x) \equiv \int_{-\infty}^{x} \mathrm{d}x' \ p(x')$$



For discrete variables

$$p(x) = \sum_{i} p_{i} \, \delta(x - x_{i})$$

Moments of a random variable

$$\langle x \rangle = \int \mathrm{d}x \ p(x)x$$

PDF of a dependent r.v.

$$p(y) = p(x) \left| \frac{\mathrm{d}x}{\mathrm{d}y} \right|$$

Expected value of a derived r.v.

$$\langle y(x) \rangle = \int dy \ p(y)y = \int dx \ p(x)y(x)$$

Variance

$$\sigma^2(x) \equiv \langle (x - \langle x \rangle)^2 \rangle = \langle x^2 \rangle - \langle x \rangle^2$$

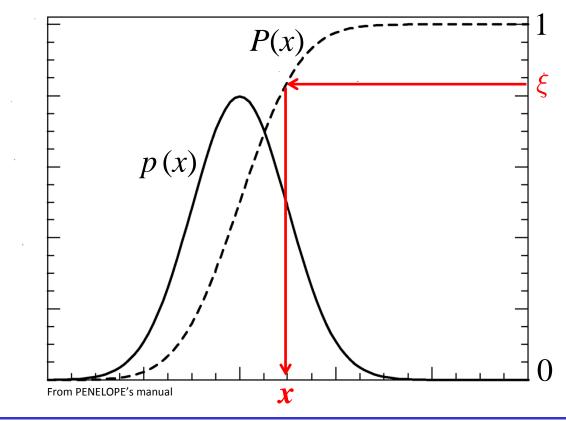
Can be readily extended to multiple r.v.'s using marginal PDFs

$$p(x_i) = \int \left(\prod_{j \neq i} dx_j\right) p(x_1, \dots, x_n)$$

Random sampling

Inverse transform

Define
$$\xi(x) = \int_{-\infty}^{x} \mathrm{d}x' \ p(x')$$
 then $p(\xi) = p(x) \left| \frac{\mathrm{d}x}{\mathrm{d}\xi} \right| = p(x) \frac{1}{p(x)} = 1$



Examples

$$p(\phi) = \frac{1}{2\pi} \qquad \phi \in (0, 2\pi)$$

$$\xi = \int_0^\phi d\phi' \, \frac{1}{2\pi} = \frac{\phi}{2\pi} \quad \Rightarrow \quad \phi = 2\pi\xi$$

Exponential PDF
$$p(s) = \frac{1}{\lambda} \exp(-s/\lambda)$$
 $s \in (0, +\infty)$

$$s = -\lambda \ln(1 - \xi) = -\lambda \ln \xi$$

Rejection

Consider a PDF p(x)

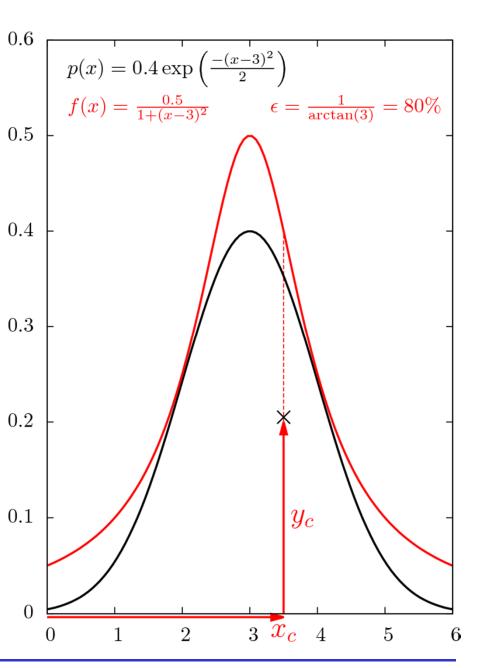
Define an arbitrary function $f(x) \ge p(x)$ that can be sampled easily (e.g., inversion).

To sample p(x) perform these steps:

- 1. Generate $x_c = \text{sample } \{f(x)\}$
- 2. Sample $y_c = \xi \cdot f(x_c)$
- 3. If $y_c > p(x_c)$ go to 1 (x_c rejected)
- 4. Deliver x_c

The ratio of success ("efficiency") of the process is

$$\epsilon = \frac{\operatorname{area}\{p(x)\}}{\operatorname{area}\{f(x)\}} = \frac{1}{\operatorname{area}\{f(x)\}} \le 1$$



Gaussian: Box-Müller method

G. E. P. Box and M. E. Muller Ann. Math. Statist. 29 (1958)

Of particular interest is the sampling of a Gaussian PDF,

$$G(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right)$$

$$G(x,y) = \frac{1}{2\pi} \exp\left(-\frac{x^2+y^2}{2}\right)$$
 (originally proposed by Laplace)

$$G(r,\theta) = rG(x,y) = \frac{r}{2\pi} \exp\left(-\frac{r^2}{2}\right) = \left[\frac{1}{2\pi}\right] \left[r \exp\left(-\frac{r^2}{2}\right)\right]$$

Sampling algorithm (Box-Müller method):

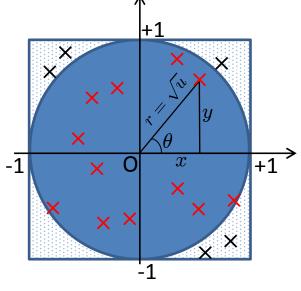
$$x = r\cos\theta = \sqrt{-2\ln\xi_1} \cos(2\pi\xi_2)$$

$$y = r\sin\theta = \sqrt{-2\ln\xi_1} \sin(2\pi\xi_2)$$

Polar method

1. Sample (x, y) in a unit circle using a rejection method:

$$x = 1 - 2\xi_1$$
, $y = 1 - 2\xi_2$
if $u \equiv x^2 + y^2 > 1 \Rightarrow \text{reject}$; $(\epsilon = \frac{\pi}{4} = 78.5\%)$



2. In the (r, θ) and (u, θ) spaces the PDFs are

$$p(r,\theta) = p(x,y) \left| \det \frac{\partial(x,y)}{\partial(r,\theta)} \right| = \frac{r}{\pi} = \left(\frac{1}{2\pi}\right) (2r) = p(\theta) p(r)$$

$$p(u,\theta) = p(r,\theta) \left| \frac{\mathrm{d}r}{\mathrm{d}u} \right| = \frac{p(r,\theta)}{2r} = \left(\frac{1}{2\pi}\right) (1) = p(\theta) p(u)$$

Note that: (i) u and θ are independent; and (ii) u is uniformly distributed in (0,1). The polar method takes advantage of these two facts.

Marsaglia & Bray's polar method avoids (expensive) computations of trigonometric functions.

Box-Müller:

$$v_1 = r\cos\theta = \sqrt{-2\ln\xi_1}\cos(2\pi\xi_2)$$

$$v_2 = r\sin\theta = \sqrt{-2\ln\xi_1}\sin(2\pi\xi_2)$$

Polar method: (Recall that $u \equiv x^2 + y^2$ for (x, y) inside the unit circle.)

$$v_1 = \sqrt{-2 \ln u} \; \frac{x}{\sqrt{u}} = x \, \sqrt{\frac{-2 \ln u}{u}}$$
 (we have used $\cos \theta = \frac{x}{\sqrt{u}}$)

$$v_2 = \sqrt{-2\ln u} \, \frac{y}{\sqrt{u}} = y \, \sqrt{\frac{-2\ln u}{u}}$$

Timings

- Intel Core i7 @ 2GHz running OSX v.10.10.2
- gfortran 4.9.0 with optimization -O
- RNGs are RANECU or simpleRNG (T=1e9)
- Speed is in ns per RNG call

Method	RANECU	sRNG	
Polar	2.93	1.92	(ns per RNG)
Polar-single	5.53	3.46	•
BoxMuller	3.40	2.53	
BoxMuller-single	6.22	4.32	
LorentzReject	11.75	10.08	
CentralLimit	11.92	3.51	

Estimators, uncertainties and efficiency

• MC estimate of $\langle E \rangle$ after N independent histories :

$$\bar{E} = \frac{1}{N} \sum_{i=1}^{N} e_i$$

- $ar{E}$ is a random variable:
 - Gaussian distributed (central limit theorem)
 - Unbiased: $\langle \bar{E} \rangle = \langle E \rangle$
 - Consistent: tends to $\langle E \rangle$ in probability (law of large numbers)
 - Efficient: lowest possible variance
- Statistical uncertainty: $\sigma^2(\bar{E}) = \frac{\sigma^2(\bar{E})}{2}$

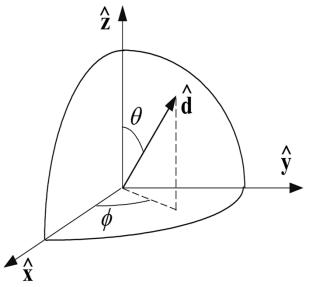
$$\sigma^2(\bar{E}) = \frac{\sigma^2(E)}{N} \simeq \frac{1}{N} \left[\frac{\sum e_i^2}{N} - \bar{E}^2 \right]$$

$$\sigma(\bar{E}) \sim N^{-1/2}$$

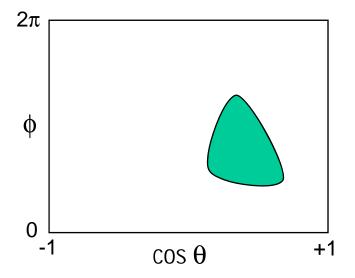
• Simulation efficiency :

$$\epsilon = \frac{1}{t\sigma^2}$$

Isotropic source — the solution



$$dS = r^2 d\phi d\cos\theta \implies d\Omega = d\phi d\cos\theta$$



Therefore, the problem can be readily solved in polar coordinates.

$$p(\phi, \cos \theta) = \left[\frac{1}{2\pi}\right] \left[\frac{1}{2}\right] = p(\phi) \ p(\cos \theta)$$

$$\phi = 2\pi\xi_1 \quad , \quad \cos\theta = -1 + 2\xi_2$$

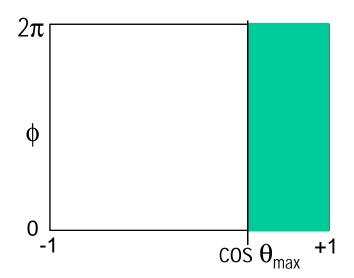
$$\hat{\mathbf{d}} = (u, v, w) = (\sin \theta \cos \phi, \sin \theta \sin \phi, \cos \theta)$$

Other useful exercises

Initial direction uniformly distributed in a cone

Sol:
$$\phi = 2\pi \xi_1$$

$$\cos \theta = \cos \theta_{\rm max} + \xi_2 (1 - \cos \theta_{\rm max})$$



Homogeneous radioactive source on a circle

Sol:
$$r = R\sqrt{\xi_1}$$
 , $\phi = 2\pi\xi_2$

Homogeneous radioactive source in a sphere

Sol:
$$r = R\xi_1^{1/3}$$
 , $\phi = 2\pi\xi_2$, $\cos\theta = -1 + 2\xi_3$

Thank you.