

A decorative frame consisting of blue lines and corner markers. A vertical line on the left and a horizontal line at the top meet at a small circle in the top-left corner. A horizontal line below the title and a vertical line on the right meet at a small circle in the bottom-right corner.

Monte Carlo sampling

FLUKA beginners Course

Overview:

General concepts:

- Phase space
- The Boltzmann equation
- Monte Carlo foundations
- Simulation vs. integration

Sampling techniques

- discrete
- by inversion
- by rejection

Results and Errors:

- Statistical errors (single histories, batches)
- Figure of merit

Phase space:

- **Phase space:** a concept of classical Statistical Mechanics
- Each Phase Space dimension corresponds to a particle degree of freedom
- 3 dimensions correspond to **Position in (real) space:** x, y, z
- 3 dimensions correspond to **Momentum:** p_x, p_y, p_z
(or **Energy and direction:** E, θ, ϕ)
- More dimensions may be envisaged, corresponding to other possible degrees of freedom, such as **quantum numbers:** spin etc
- Each particle is represented by a **point in phase space**
- **Time** can also be considered as a coordinate, or it can be considered as an independent variable: the variation of the other phase space coordinates as a function of time constitutes a particle **"history"**

The Boltzmann equation:

- All particle transport calculations are (explicit or implicit) attempts at solving the **Boltzmann Equation**
- It is a balance **equation in phase space**: at any phase-space-point, the increment of particle phase-space-density is equal to the sum of all "production terms" minus a sum of all "destruction terms"
- **Production**: Sources, "Inscattering", Particle Production, Decay
- **Destruction**: Absorption, "Outscattering", Decay
- We can look for solutions of different type: at a number of (real or phase) space points, averages over (real or phase) space regions, projected on selected phase space hyperplanes, stationary or time-dependent

Mean of a distribution - 1

In one dimension:

Given a variable x , distributed according to $f(x)$, the mean or average of another function of the same variable $A(x)$ over $[x_{\min}, x_{\max}]$ is given by:

$$\bar{A} = \frac{\int_{x_{\min}}^{x_{\max}} A(x) f(x) dx}{\int_{x_{\min}}^{x_{\max}} f(x) dx}$$

Or, introducing the normalized distribution f' :

$$f'(x) = \frac{f(x)}{\int_{x_{\min}}^{x_{\max}} f(x) dx}$$
$$\bar{A} = \int_{x_{\min}}^{x_{\max}} A(x) f'(x) dx$$

A special case is that of $A(x)=x$:

$$\bar{x} = \int_{x_{\min}}^{x_{\max}} x f'(x) dx$$

Mean of a distribution - 2

In several dimensions:

- Given n variables, x, y, z, \dots , distributed according to the (normalized) functions $f'(x, y, z, \dots)$, $g'(x, y, z, \dots)$, $h'(x, y, z, \dots)$, the **mean** or **average** of a function of those variables $A(x, y, z, \dots)$ over an n -dimensional domain D , is given by:

$$\bar{A} = \int_x \int_y \int_z \dots \int A(x, y, z, \dots) f'(x, y, z, \dots) g'(x, y, z, \dots) h'(x, y, z, \dots) dx dy dz \dots$$

- Often impossible to calculate with traditional methods, but we can **sample** N values of A , by sampling N sets of variables x_i, y_i, z_i, \dots with probability $f' \cdot g' \cdot h' \dots$ and divide the sum of the sampled values by N :

$$S_N = \frac{\sum_{i=1}^N A(x_i, y_i, z_i, \dots)}{N}$$

- Each term of the sum is distributed like A , integration but also **simulation!**

Central limit theorem

Central limit theorem:

$$\lim_{N \rightarrow \infty} P(S_N) = \frac{1}{\sqrt{2\pi \frac{\sigma_A^2}{N}}} \exp \left[-\frac{(S_N - \bar{A})^2}{2 \frac{\sigma_A^2}{N}} \right]$$

- For large values of N , the normalized sum of N independent and identically distributed random variables tends to a normal distribution with mean \bar{A} and variance σ_A^2/N

$$\lim_{N \rightarrow \infty} S_N = \lim_{N \rightarrow \infty} \frac{\sum_{i=1}^N A(x_i, y_i, z_i, \dots)}{N} = \bar{A}$$

Monte Carlo* mathematical foundation:

Several possible ways of defining Monte Carlo (MC):

- A mathematical method for Numerical Integration
 - Random sampling techniques
 - Convergence, variance reduction techniques...
- A computer simulation of a Physical Process
 - Physics
 - Tracking
 - Scoring...

Both are valid, depending on the problem one or the other can be more effective (see the examples above)

* Monte Carlo method "inventors": Von Neumann, Ulam, Fermi, Metropolis in the late 40's

Monte Carlo* mathematical foundation:

The central limit theorem is the mathematical foundation of the Monte Carlo method:

In words:

Given any observable A , that can be expressed as the result of a convolution of random processes, the average value of A can be obtained by sampling many values of A according to the probability distributions of the random processes

MC is indeed an INTEGRATION method that allows to solve multi-dimensional integrals by sampling

The accuracy of a MC estimator depends on the number N of samples ($\propto 1/\sqrt{N}$)

Analog Monte Carlo:

In an **analog Monte Carlo calculation** ("honest" simulation), not only the **mean of the contributions** converges to the **mean of the real distribution**, but also the **variance** and all **moments** of higher order

$$\overline{\mu}^m = \int_x \int_y \int_z \dots \int [A(x, y, z, \dots) - \overline{A}]^m f'(x, y, z, \dots) g'(x, y, z, \dots) h'(x, y, z, \dots) dx dy dz \dots$$

converge as well:

$$\lim_{N \rightarrow \infty} \left[\frac{\sum_{i=1}^N (A_i - S_n)^m}{N} \right]^{\frac{1}{m}} = \overline{\mu}^m$$

and **fluctuations** and **correlations** are faithfully reproduced

Integration efficiency:

- Traditional numerical integration methods (Simpson, etc), converge to the true values as $N^{-1/n}$ where N = number of "points" (interval), and n = number of dimensions
- Monte Carlo converges instead as $1/\sqrt{N}$

| Number of dimensions | Traditional methods | Monte Carlo | Remark |
|----------------------|---------------------|--------------|---------------------|
| $n = 1$ | $1/N$ | $1/\sqrt{N}$ | MC not convenient |
| $n = 2$ | $1/\sqrt{N}$ | $1/\sqrt{N}$ | About equivalent |
| $n > 2$ | $1/n\sqrt{N}$ | $1/\sqrt{N}$ | MC converges faster |

**A typical particle transport Monte Carlo problem is a 7-D problem!
 x, y, z, p_x, p_y, p_z and t !!**

Random Sampling: the key to Monte Carlo!

The central problem of the Monte Carlo method:

Given a Probability Density Function (pdf), $f(x)$, generate a sequence of x 's distributed according to $f(x)$ (x can be multi-dimensional)



The use of random sampling techniques is the distinctive feature of Monte Carlo

The use of Monte Carlo to solve the integral Boltzmann transport equation consists of:

- Random sampling of the outcome of physical events
- Geometry and material description of the problem

(Pseudo) Random numbers:

- Basis for all Monte Carlo integrations are **random numbers**, *i.e.* values of a variable distributed according to a pdf (**probability distribution function**).
- In real world: the random outcome of a physical process
- In computer world: **pseudo-random numbers**
- The basic pdf is the **uniform distribution**:

$$f(\xi) = 1 \quad 0 \leq \xi < 1$$

- Pseudo-random numbers are sequences that reproduce the uniform distribution, constructed from mathematical algorithms.
- All computers provide a pseudo-random number generator (or even several of them). In most computer languages (e.g., Fortran 90, C) a PRNG is even available as an intrinsic routine

Sampling from a distribution:

Sampling from a discrete distribution:

- Suppose to have a *discrete* random variable x , that can assume values $x_1, x_2, \dots, x_n, \dots$ with probability $p_1, p_2, \dots, p_n, \dots$
- Assume $\sum_i p_i = 1$, or normalize it
- Divide the interval $[0,1)$ in n subintervals, with limits

$$y_0 = 0, y_1 = p_1, y_2 = p_1 + p_2, \dots$$

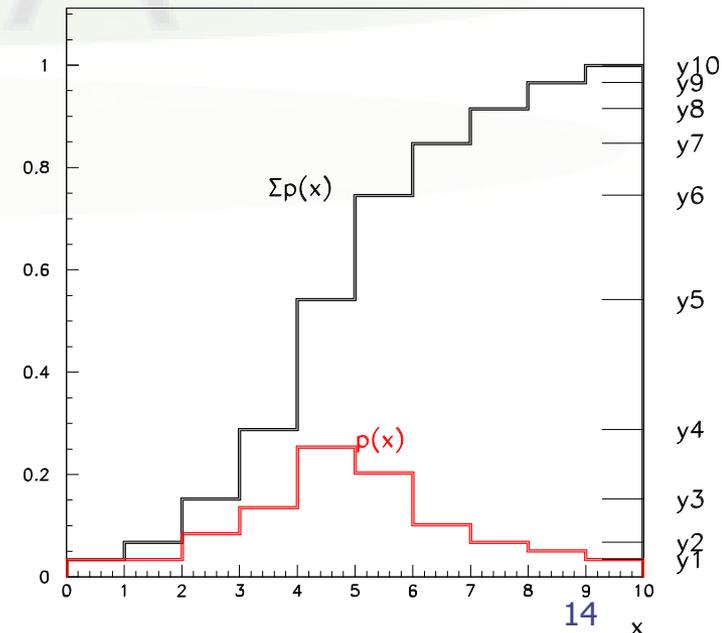
- Generate a uniform pseudo-random number ξ
- Find the interval i^{th} y -interval such that

$$y_{i-1} \leq \xi < y_i$$

- Select $X = x_i$ as the sampled value

Since ξ is uniformly random:

$$P(x_i) = P(y_{i-1} \leq \xi < y_i) = y_i - y_{i-1} = p_i$$



Sampling from a distribution:

Sampling from a generic continuous distribution:

- Integrate the distribution function $f(x)$, analytically or numerically, and normalize to 1 to obtain the **normalized cumulative distribution**

$$F(\xi) = \frac{\int_{x_{\min}}^{\xi} f(x) dx}{\int_{x_{\min}}^{x_{\max}} f(x) dx}$$

- Generate a uniform pseudo-random number ξ
- Get the desired result by finding the **inverse value** $X = F^{-1}(\xi)$, **analytically** or most often numerically, i.e. by **interpolation** (table look-up)

Since ξ is uniformly random:

$$P(a < x < b) = P(F(a) \leq \xi < F(b)) = F(b) - F(a) = \int_a^b f(x) dx$$

Example:

Take $f(x) = e^{-\frac{x}{\lambda}}$, $x \in [0, \infty)$

Cumulative distribution:

$$F(t) = \int_0^t e^{-\frac{x}{\lambda}} dx = \lambda \times \left(1 - e^{-\frac{t}{\lambda}} \right)$$

Normalized:

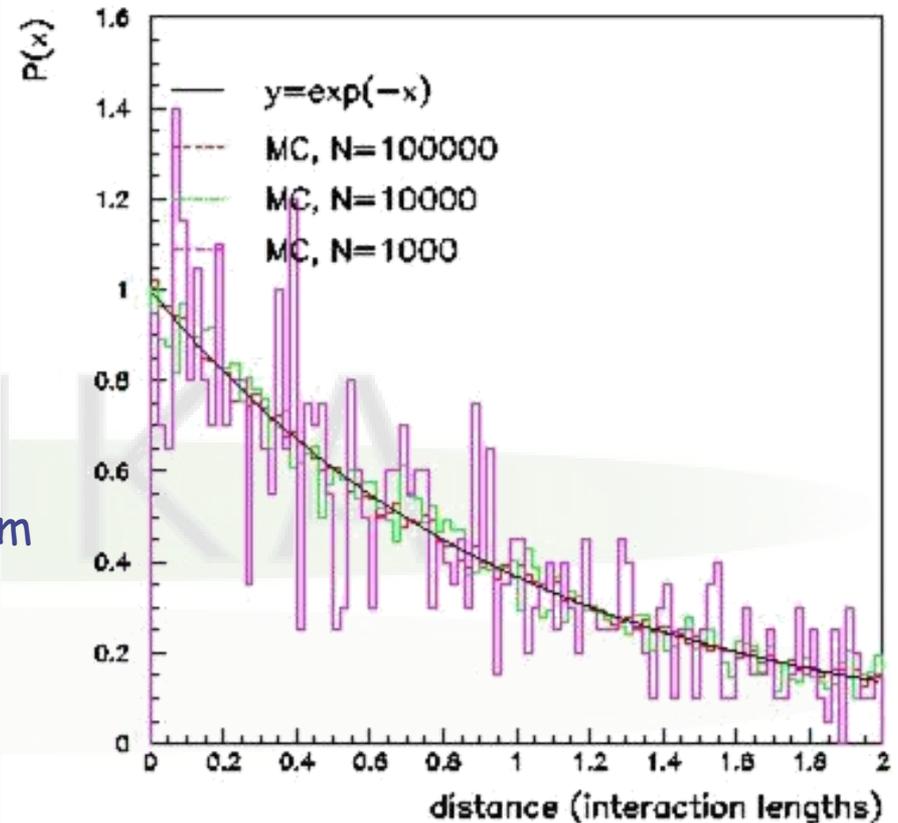
$$F'(t) = \int_0^t \frac{e^{-\frac{x}{\lambda}}}{\lambda} dx = 1 - e^{-\frac{t}{\lambda}}$$

Generate a uniform pseudo-random number $\xi \in [0, 1)$

Sample t by inverting $1 - e^{-\frac{t}{\lambda}} = \xi$

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

Repeat N times



Practical rule: a distribution can be sampled directly if and only if its pdf can be integrated and the integral inverted

Sampling from a distribution: rejection technique

Rejection procedure:

- Let be $f'(x)$, a normalized distribution function, which cannot be sampled by integration and inversion
- Let be $g'(x)$, a normalized distribution function, which can be sampled, and such that $Cg'(x) \geq f'(x), \forall x \in [x_{min}, x_{max}]$
- Sample X from $g'(x)$, and generate a uniform pseudo-random number $\xi \in [0, 1)$
- Accept X if $\xi < f'(X)/Cg'(X)$, if not repeat the previous step
- The overall efficiency (accepted/rejected) is given by:

$$R = \int \frac{f'(x)}{Cg'(x)} g'(x) dx = \frac{1}{C}$$

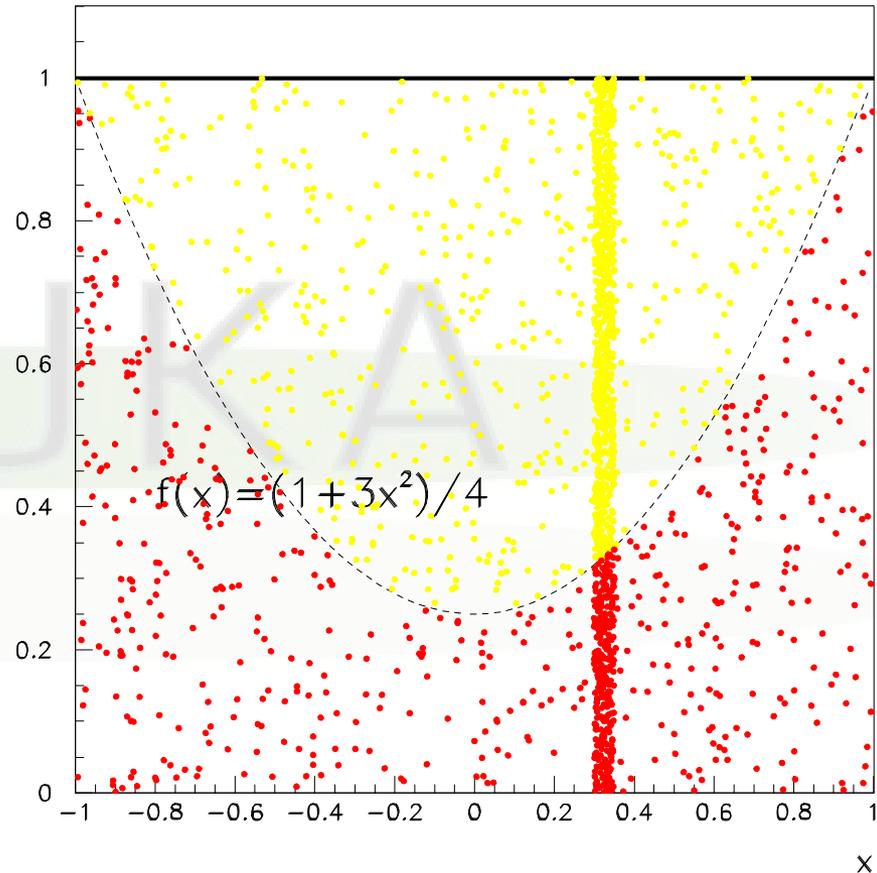
- and the probability that X is accepted is unbiased:

$$P(X) dX = \frac{1}{R} g'(X) dX \times \frac{f'(X)}{Cg'(X)} = f'(X) dX$$

Sampling from a distribution: example

Rejection procedure:

- Let be $f(x) = (1+3x^2)/4$, $x \in [-1,1]$,
- Take $g(x) = 1/2$, $C=2$
- Generate two uniform pseudo-random numbers $\xi_1, \xi_2 \in [0,1]$
- Accept $X = 2\xi_1 - 1$ if $\xi_2 < (1+3X^2)/4$, if not repeat



Particle transport Monte Carlo:

Assumptions:

- Static, homogeneous, isotropic, and amorphous media (and geometry)
- Markovian process: the fate of a particle depends only on its actual properties, not on previous events or histories
- Particles do not interact with each other
- Particles interact with individual atoms/nuclei/molecules (invalid at low energies)
- Material properties are not affected by particle reactions



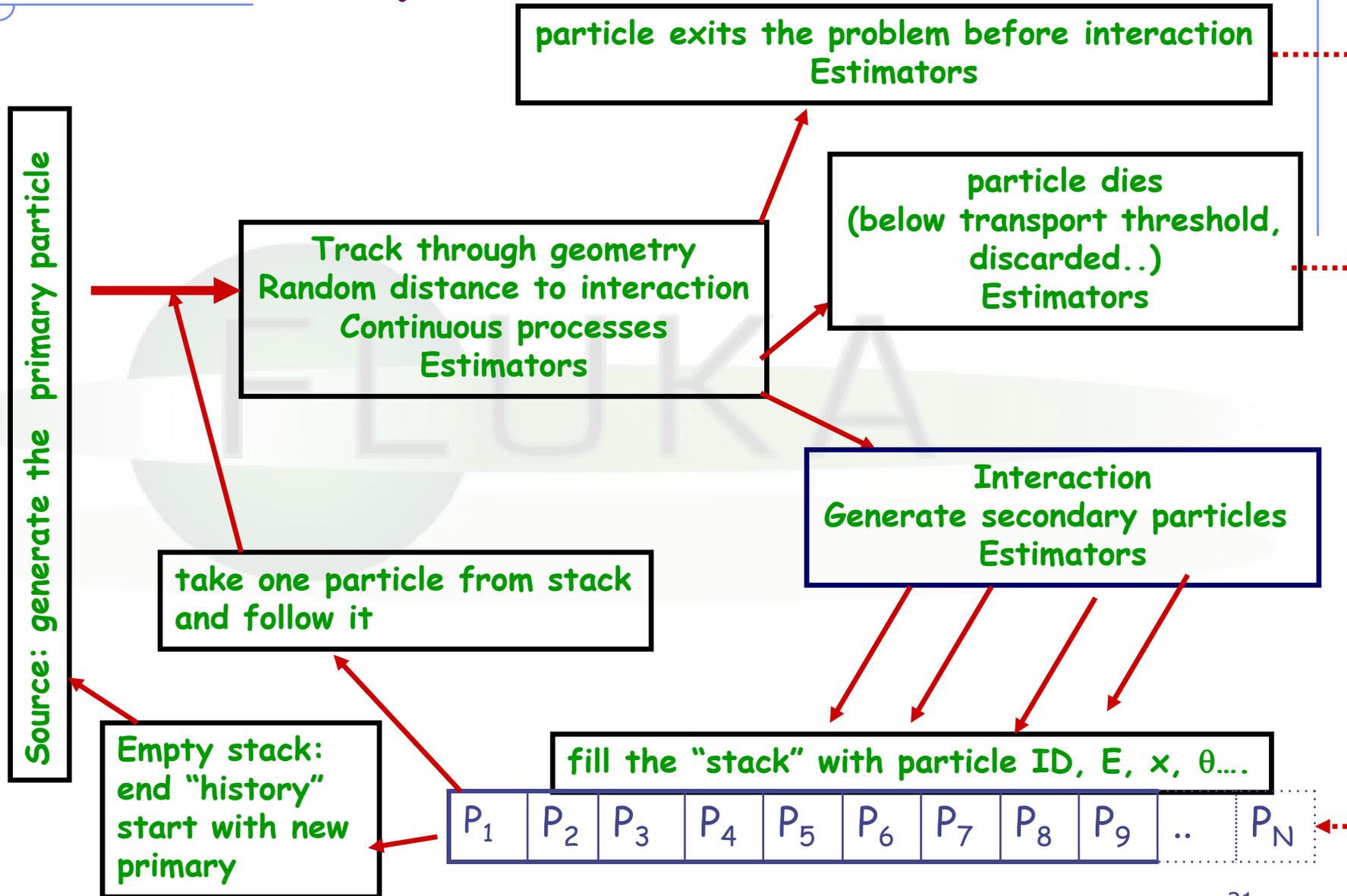
The superposition principle can be used

Particle transport Monte Carlo:

Application of Monte Carlo to particle transport and interaction:

- Each particle is followed on its path through matter.
- At each step the occurrence and outcome of interactions are decided by random selection from the appropriate probability distributions.
- All the secondaries issued from the same primary are transported before a new history is started.
- The accuracy and reliability of a Monte Carlo depends on the models or data on which the pdfs are based
- Statistical accuracy of results depends on the number of "histories"
- Statistical convergence can be accelerated by "biasing" techniques.

Practical implementations



Statistical Errors:

- Can be calculated for **single histories**, or for **batches** of several histories each
- Distribution of scoring contributions by single histories can be very asymmetric (many histories contribute little or zero)
- Scoring distribution from batches tends to Gaussian for $N \rightarrow \infty$, **provided $\sigma^2 \neq \infty$** (thanks to Central Limit Theorem)
- The standard deviation of an estimator calculated from batches or from single histories is **an estimate of the standard deviation of the actual distribution** ("error of the mean")
- How good is such an estimate depends on the type of estimator and on the particular problem (but it converges to the true value for $N \rightarrow \infty$)

| Relative error | Quality of Tally | <i>(from the MCNP Manual)</i> |
|----------------|---|-------------------------------|
| 50 to 100% | Garbage | |
| 20 to 50% | Factor of a few | |
| 10 to 20% | Questionable | |
| < 10% | Generally reliable except for point detectors | |

Statistical Errors (batch statistics)

The **variance of the mean** of an estimated quantity x (e.g., fluence), calculated out of N batches, is:

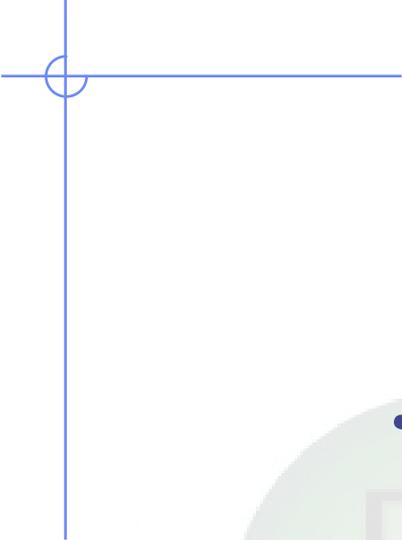
$$\sigma_{\langle x \rangle}^2 = \frac{1}{N-1} \left[\frac{1}{n} \sum_{i=1}^N n_i x_i^2 - \frac{1}{n^2} \left(\sum_{i=1}^N n_i x_i \right)^2 \right]$$

where:

- n_i is the number of histories in the i^{th} batch
- $n = \sum n_i$ is the total number of histories in the N batches
- x_i is the average of x calculated in the i^{th} batch: $x_i = \frac{\sum_{j=1}^{n_i} x_{ij}}{n_i}$
where x_{ij} is the contribution to x of the j^{th} history in the i^{th} batch
- In the limit $N=n$, $n_i=1$, the formula applies to single history statistics

Practical tips:

- Use always at least 5-10 batches of comparable size (it is not at all mandatory that they be of equal size)
- Never forget that the variance itself is a stochastic variable subject to fluctuations
- Be careful about the way convergence is achieved: often (particularly with biasing) apparently good statistics with few isolated spikes could point to a lack of sampling of the most relevant phase-space part
- Plot 2D and 3D distributions! In those cases the eye is the best tool in judging the quality of the result



Thank you for
your attention!