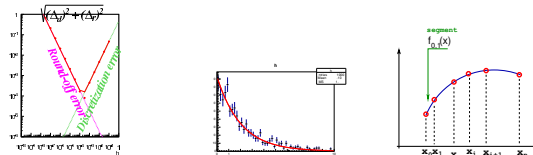




Computational Physics

numerical methods with C++ (and UNIX)



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Computational Physics

Monte-Carlo methods

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Generating random variables

- ✓ The common problem is to have a variable x distributed according a given distribution function $p(x)$ we are going to make a change of variable such that the number of events (randoms) generated is independent of the used variable

$$dN = p(x)dx = p(y)dy$$

- ✓ Suppose that y is a random variable distributed in $[0, 1]$ and x starts at x_0

$$p(y) = 1 \Rightarrow \int_0^y dy' = \int_{x_0}^x p(x')dx' \Rightarrow y = \int_{x_0}^x p(x')dx'$$

- ✓ For generating a random variable x in a interval $[x_0, x_1]$ we just make sure that:

$$\int_{x_0}^{x_1} p(x)dx = 1$$

and we invert the relation above (boxed) giving us $x(y)$.

Provided a random y in $[0, 1]$ we generate a random x in $[x_0, x_1]$.



uniform $[0, 1] \rightarrow$ uniform $[a, b]$

- ✓ Let's transform a variable y uniformly distributed in $[0, 1]$ into a variable x uniformly distributed in $[a, b]$

- ✓ Normalization of $p(x)$:

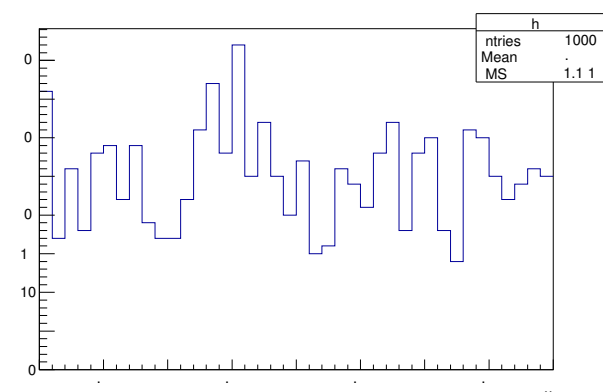
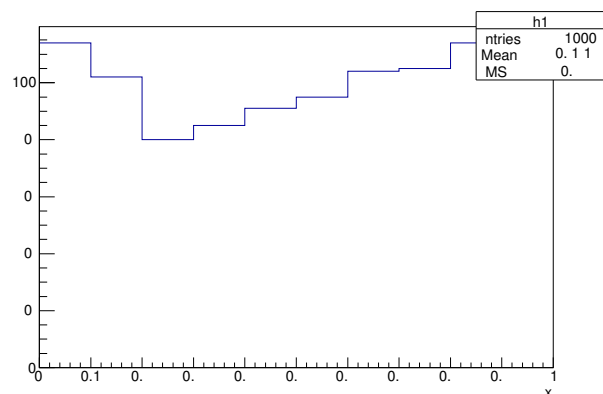
$$p(x) = \frac{1}{b-a}$$

- ✓ Transformation:

$$y = \int_a^x \frac{1}{b-a} dx' = \frac{x-a}{b-a}$$

$$\Rightarrow x - a = (b - a)y$$

$$x = a + (b - a) y$$





uniform $[0, 1] \rightarrow$ exponential $[0, \infty]$

- Let's transform a variable

☞ y uniformly distributed in $[0, 1]$
into a variable

☞ x distributed according to

$$p(x) \propto e^{-x} \text{ in } [0, \infty]$$

- Normalization of $p(x)$:

$$k \int_0^{+\infty} e^{-x} dx = 1$$

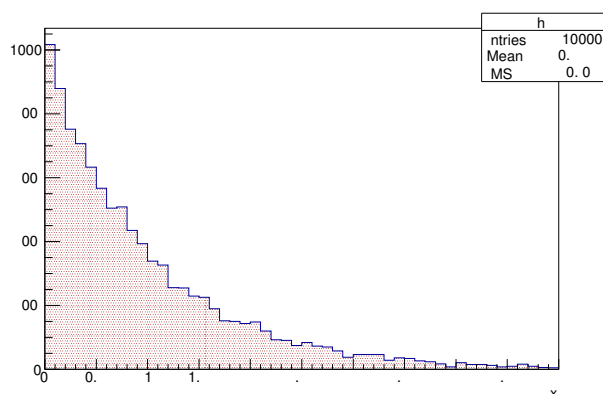
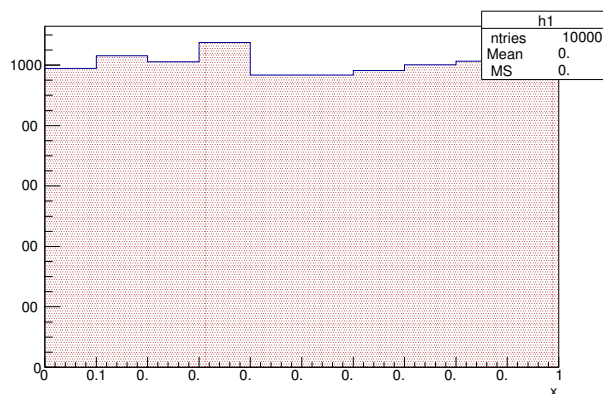
$$\Rightarrow k [-e^{-x}]_0^{\infty} = 1 \Rightarrow k = 1$$

$$p(x) = e^{-x}$$

- Transformation:

$$y = \int_0^x e^{-x'} dx' = [-e^{-x'}]_0^x = 1 - e^{-x}$$

$$x = -\ln(1 - y)$$



MC integration: acceptance-rejection

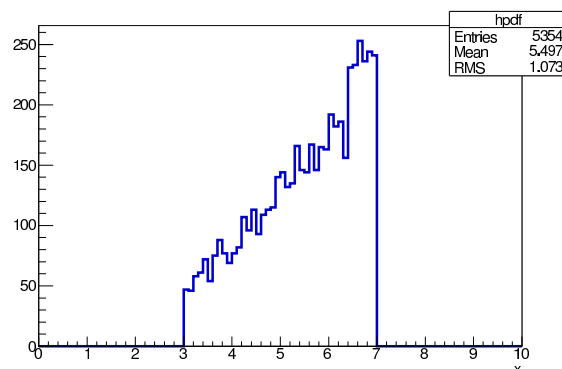
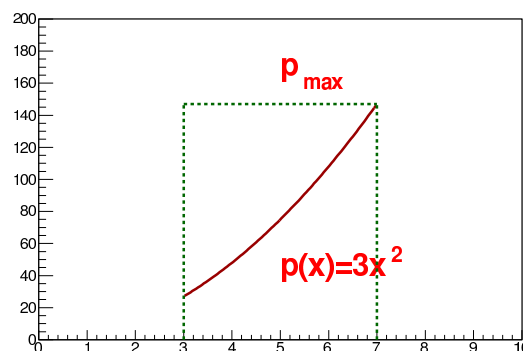
- For applying the method before said we need to integrate the pdf and invert it
- In case it is not possible we can use the more generic but less efficient method of acceptance-rejection
- For generating a x variable in the interval $[a, b]$ distributed according to a pdf $p(x)$ we do the following:

☞ generate a uniform random x_R between $[a, b]$

☞ compute $p(x_R)$ and the ratio $\frac{p(x_R)}{p_{\max}}$

☞ generate a second random u_R from $U(0, 1)$

☞ if $u_R \leq \frac{p(x_R)}{p_{\max}}$ accept the variable x_R





MC integration example: $\cos(x)$

- ✓ method introduced by von Neumann
- ✓ for integrating the function we define an envelope with an area

$$A = (x_{\max} - x_{\min}) * f_{\max}$$

- ✓ generate two random variables

☞ x_R in in range $[x_{\min}, x_{\max}]$

☞ f_R in in range $[0, f_{\max}]$

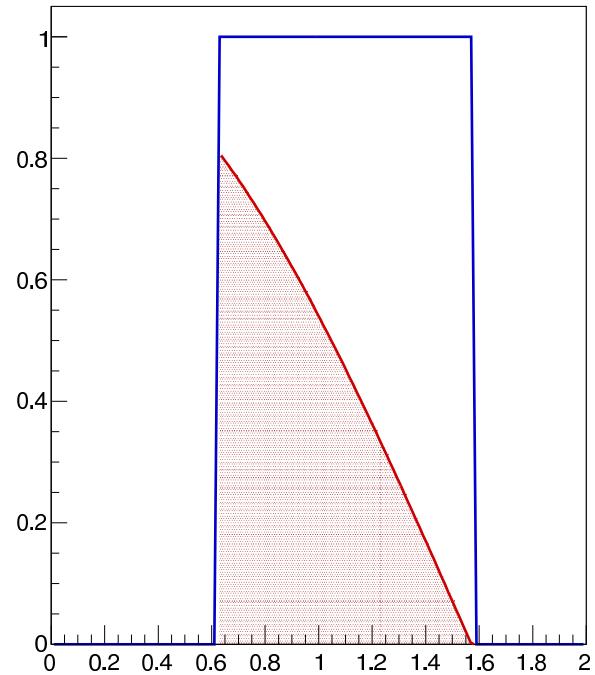
- ✓ count the number of events N_R that

$$f_R \leq f(x_R)$$

- ✓ the integral $I = (x_{\max} - x_{\min}) f_{\max} \frac{N_R}{N}$

- ✓ the integral error

$$\sigma_I = \frac{(x_{\max} - x_{\min}) f_{\max}}{N} \sqrt{N_R \left(1 - \frac{N_R}{N}\right)}$$



Using 100 randoms:

$$\int_{0.2\pi}^{0.5\pi} \cos(x) dx = 0.435 \pm 0.037$$



MC integration example: $f(x) = 3x^2$

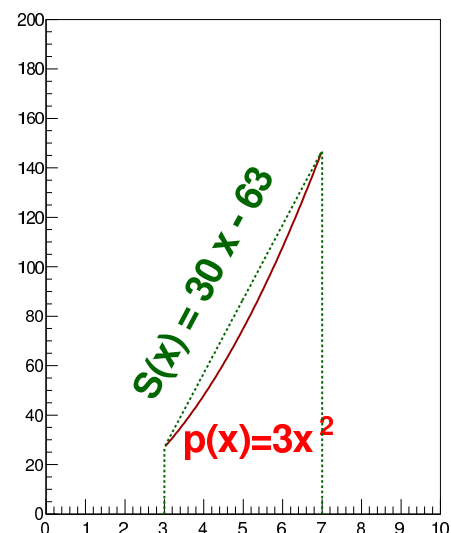
- ✓ The acceptance-rejection method is inefficient if the function varies quickly
- ✓ The number of randoms accepted (efficiency) is given by:

$$\varepsilon = \frac{\int_a^b f(x) dx}{(b - a) f_{\max}}$$

- ✓ The efficiency can be improved using an auxiliar function $S(x)$ that has a shape close to the one we want to sample

$$\varepsilon_S = \frac{\int_a^b f(x) dx}{\int_a^b q(x) dx}$$

where $q(x) = C S(x) \geq f(x)$ for x in $[a, b]$



efficiencies:

$$\varepsilon = \frac{N_R}{N} \simeq 0.535$$

$$\varepsilon_S = \frac{N_R}{N} \simeq 0.91$$

MC integration: acc-rej with auxiliar function

For generating a random variable x distributed according to $f(x)$ in the interval $[a, b]$

1. Find auxiliar function $S(x)$ with a shape close to the function $f(x)$ we want to sample

☞ integrable, invertible

☞ from $S(x)$ we define a pdf $p(x)$ and we apply the transformation
 $y \in U[0, 1] \rightarrow x \in U(p(x))$

☞ invert transformation equation: $x(y)$

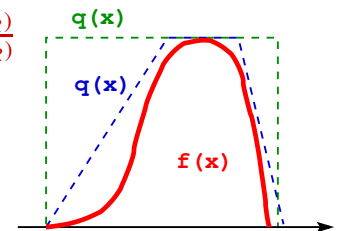
☞ using $x(y)$ and generating y uniformly between $[0, 1]$ we obtain the random variable x_R distributed according to $p(x)$

2. Define a function $q(x) = C S(x)$ such that $q(x) \geq f(x)$ in the interval $[a, b]$

3. Generate random variable x_R according to $p(x)$ and compute $\frac{q(x_R)}{f(x_R)}$

4. Generate random $u_R \in U[0, 1]$ and accept x_R if:

$$u_R \leq \frac{q(x_R)}{f(x_R)}$$



MC integration: $f(x) = 3x^2$

- ✓ We want to generate a variable according to a function

$$f(x) = 3x^2$$

1. Define the auxiliar function $S(x)$ to improve acceptance-rejection efficiency

$$S(x) = 30x - 63$$

generate random in $[3, 7]$ interval according to auxiliar function

get pdf(x): $S(x) \rightarrow p(x)$ with $\int_3^7 p(x) dx = 1$

$$k \int_3^7 S(x) dx = 348 \Rightarrow k = \frac{1}{348}$$

$$p(x) = \frac{1}{348} (30x - 63)$$

make transformation: $y[0, 1] \rightarrow x$ according to $p(x)$

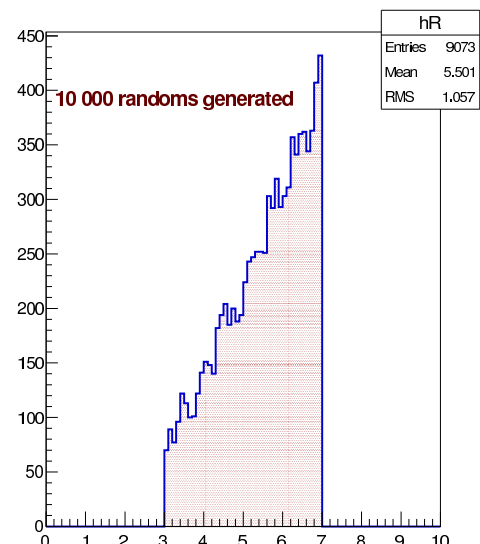
$$y = \int_3^x p(x') dx' = 348$$

$$\text{Solve } x(y): 15x^2 - 63x + 54 - 348y = 0$$

2. define $q(x)$ which in this case is $= S(x)$ and generate x_R according to $p(x)$

- 3., 4. generate $u_R \in u[0, 1]$ and accept x_R if

$$u_R \leq \frac{q(x_R)}{f(x_R)}$$





Multidimensional MC integration

A multi-dimensional integral:

$$I = \int_{a_1}^{b_1} dx_1 \int_{a_2}^{b_2} dx_2 \int_{a_3}^{b_3} \cdots \int_{a_n}^{b_n} dx_n f(x_1, x_2, \cdots, x_n)$$

✓ Brute-force

- ☞ generate random variables $x_1, x_2, \cdots, x_n \in U[0, 1]$ in the interval $[a_i, b_i]$

$$x_i = a_i + (b_i - a_i)x_R \quad \text{with } x_R \in [0, 1]$$

- ☞ calculate the function at the random variables: $f(x_1, x_2, \cdots, x_n)$

- ☞ the Monte-Carlo integration:

$$I = \frac{\prod_{k=1}^n (b_k - a_k)}{N} \sum_{i=1}^N f(x_1, x_2, \cdots, x_n)_i$$

N = number of random set of n variables



Multidimensional MC integration (cont.)

✓ Importance sampling

$$I = \int_{a_1}^{b_1} dx_1 \int_{a_2}^{b_2} dx_2 \int_{a_3}^{b_3} \cdots \int_{a_n}^{b_n} dx_n \frac{f(x_1, x_2, \cdots, x_n)}{p(x_1, x_2, \cdots, x_n)} p(x_1, x_2, \cdots, x_n)$$

