

Exercise/Hands-on #3

Generation & Interpolation with an UML fit with RooFit

Statistical Data Analysis for HEP

Prof. **Alexis Pompili** (University of Bari Aldo Moro)*

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* alexis.pompili@ba.infn.it (or alexis.pompili@cern.ch)

A very interesting feature of `Roofit` is the possibility to generate pseudo-experiments (called also MC toys), namely, sampling distributions according to a certain given model (p.d.f.).

The macro `RooConvolutionExpNew.C` ...

- generates a distribution (it is an unbinned dataset: `RooDataSet` in `Roofit`)
- executes an **Unbinned Maximum Likelihood (UML)** fit of this distribution earlier generated
- gives as output both a plot [written in `./plots/`]
... and a txt file [written in `./txt_files/`] (that can be used externally for other purposes)

Note: the # of bins is settled only for **representation purposes** (the fit is still unbinned !)

Let's inspect now the code in RooConvolutionExpNew.C

```
#include "RooPolynomial.h"
#include "RooRealVar.h"
#include "RooBreitWigner.h"
#include "RooNumConvPdf.h"
// #include "RooVoigtian.h"
#include "RooGaussian.h"
#include "RooExponential.h"
#include "RooDataSet.h"
#include "RooDataHist.h"
#include "RooAbsData.h"
#include "RooMinuit.h"
#include "RooPlot.h"
#include "RooChebychev.h"
#include "RooAddPdf.h"
#include "RooArgList.h"
#include "TH1F.h"
#include <vector>
#include "TCanvas.h"
//
#include "RooRandom.h" // needed for Randomizer
//
using namespace RooFit; //----Working in RooFit//
//
/////////////////////////////////////////////////////////////////
//
// root [0] .L RooConvolutionExpNew.C
// root [1] RooConvolutionExpNew("10000", 1010, 80)
//
//---- providing #events (as a string), seed# and #bins.
//
// Try at least 10K, 100K, 500K, 1M (it takes from about 2 t 20 minutes!).
//
// Choose the most relevant parameters and show for each of them how the best estimate
// given by the fit gets closer to the true (generated) value
//
/////////////////////////////////////////////////////////////////
```

INSTRUCTIONS HOW-TO_RUN

```

////////////////////////////////////
//
void RooConvolutionExpNew(TString argv, int seed=1000, int bins=200) {
//
//-- note: external values override those dummy initializing values!
//      (check that changing seed you get a different distribution)
//
int events = atoi(argv.Data()); // it converts string "number" into an integer
TString name = argv;
//
char bufferstring[256];
//
RooRealVar xvar("xvar", "", -10, 10);
xvar.setBins(bins);
//
// Breit Wigner Signal //
RooRealVar mean("m", "mean", 0.2, -1, 1); //Breit Wigner mean//
RooRealVar gamma("#Gamma", "gamma", 2, 0.1, 5); //Breit Wigner width//
RooBreitWigner signal("BW", "BW signal", xvar, mean, gamma); //Breit Wigner pdf//
//
// Gaussian Resolution Function //
RooRealVar zero("zero", "Gaussian resolution mean", 0.); // offset from mean
RooRealVar sigma("#sigma", "sigma", 1.5, 0.1, 5); //Gaussian sigma//
RooGaussian resol("resol", "Gaussian resolution", xvar, zero, sigma); //Gaussian pdf//
//
// Background //
RooRealVar alpha("#alpha", "Exponential Parameter", -0.05, -2.0, 0.0);
RooExponential bkg("Bkg", "Bkg", xvar, alpha);
//
// Gaussian + BW convolution // perform a numerical convolution
RooNumConvPdf convolution("convolution", "BW (X) gauss", xvar, signal, resol);
//
//-- note that alternately you can try a Voigtian
//
// TotalPdf = Gaussian + Bkg //
RooRealVar sigfrac("sigfrac", "fraction of component 1 in signal", 0.5, 0., 1.);
RooAddPdf total("totalPDF", "totalPDF", RooArgList(convolution, bkg), sigfrac);
//
cout << "\n-----Generating " << name << " events\n" << endl ;
cout << "\n-----Remember: initial values for fitting step are the generated (true) values in generation ----" << endl;
//

```

interface

Preparation step: define model

pdf modelling

- signal as convolution of a Breit-Wigner and a gaussian resolution function
- exponential background

1st step: generation

```
cout << "\n-----Generating " << name << " events\n" << endl ;
cout << "\n-----Remember: initial values for fitting step are the generated (true) values in generation ----" << endl;
//
/////////////////////////////////////////////////////////////////
// Generating data
/////////////////////////////////////////////////////////////////
//
cout << "\n-----Remember to change seed every time to get different distributions-----" << endl;
//
RooRandom::randomGenerator()->SetSeed(seed); ←
//
RooDataSet* data = total.generate(xvar,events); ←
//
sprintf(bufferstring, "./txt_files/%d_events.txt", events);
data->write(bufferstring);
//
```

In execution, we get after generation step:

```
[[pompili@vm-pompili Esercitazione-4]$ root -l
[roo [0] .L RooConvolutionExpNew.C
[roo [1] RooConvolutionExpNew("10000", 1010, 80)

-----Generating 10000 events

-----Remember: initial values for fitting step are the generated (true) values in generation ---

-----Remember to change seed every time to get different distributions-----
[#1] INFO:NumericIntegration -- RooRealIntegral::init(convolution_Int[xvar]) using numeric integrator RooIntegrator1D to calculate Int(xvar)
[#1] INFO:NumericIntegration -- RooRealIntegral::init(convolution_Int[xvar]) using numeric integrator RooIntegrator1D to calculate Int(xvar)
[#1] INFO:DataHandling -- RooDataSet::write(totalPDFData) writing ASCII file ./txt_files/10000_events.txt
```

```

cout << "\nFitting " << name << " events\n" << endl ;
//
// Fitting data
//
RooAbsReal* nll = total.createNLL(*data); // neg-log-likelihood
RooMinuit min(*nll);
//
min.migrad(); // execute MIGRAD fit
cout << "\n-----minimization done; now recalculating the uncertainties-----" << endl;
//
min.hesse(); // calculate the uncertainties in the parabolic approximation
cout << "\n-----fit done; check best estimates for the model parameters-----" << endl;
//
// Fit result and data representation
//
TCanvas *myC = new TCanvas("RooCanvas","Roofit Canvas", 1000, 750);
//
RooPlot *frame = xvar.frame("");
sprintf(bufferstring, " RooFit : %d events", events);
frame->SetTitle(bufferstring);
frame->SetYTitle("# of events");
//
data->plotOn(frame);
total.plotOn(frame, LineColor(kGreen));
total.plotOn(frame, Components(RooArgSet(convolution)), LineColor(kRed));
total.plotOn(frame, Components(RooArgSet(bkg)), LineColor(kBlue), LineStyle(kDashed));
total.paramOn(frame, Layout(0.75, 0.99, 0.99));
frame->getAttText()->SetTextSize(0.028);
//
frame->Draw();
myC->SaveAs("plots/RooConvGen_"+name+".png");
//
//
if (myC)
{
myC->Close();
delete myC;
}
//
}

```

2nd step: fitting

Fitting sequence: MIGRAD + HESSE

3rd step: plotting

In execution, we get @ fitting step (**MIGRAD**):

Fitting 10000 events

[#1] INFO:NumericIntegration -- RooRealIntegral::init(convolution_Int[xvar]) using numeric integrator RooIntegrator1D to calculate Int(xvar)

** 13 **MIGRAD** 2500 1

FIRST CALL TO USER FUNCTION AT NEW START POINT, WITH IFLAG=4.

START MIGRAD MINIMIZATION. STRATEGY 1. CONVERGENCE WHEN EDM .LT. 1.00e-03

FCN=28493.8 FROM MIGRAD STATUS=INITIAL 20 CALLS 21 TOTAL

EDM= unknown STRATEGY= 1 NO ERROR MATRIX

EXT PARAMETER		CURRENT GUESS	STEP	FIRST
NO. NAME	VALUE	ERROR	SIZE	DERIVATIVE
1 #Gamma	2.00000e+00	4.90000e-01	2.06953e-01	-2.77994e+01
2 #alpha	-5.00000e-02	2.50000e-02	8.28427e-02	3.92141e+01
3 #sigma	1.50000e+00	4.90000e-01	2.24553e-01	-2.27174e+01
4 m	2.00000e-01	2.00000e-01	2.05758e-01	3.73329e+01
5 sigfrac	5.00000e-01	1.00000e-01	2.01358e-01	8.00078e+01

ERR DEF= 0.5

MIGRAD MINIMIZATION HAS CONVERGED.

MIGRAD WILL VERIFY CONVERGENCE AND ERROR MATRIX.

COVARIANCE MATRIX CALCULATED SUCCESSFULLY

FCN=28489 FROM MIGRAD STATUS=CONVERGED 166 CALLS 167 TOTAL

EDM=4.32044e-06 STRATEGY= 1 ERROR MATRIX ACCURATE

EXT PARAMETER			STEP	FIRST
NO. NAME	VALUE	ERROR	SIZE	DERIVATIVE
1 #Gamma	3.40452e+00	5.25290e-01	5.98428e-03	2.11982e-02
2 #alpha	-5.44013e-02	4.53968e-03	1.10219e-03	8.90567e-03
3 #sigma	9.73194e-01	2.41004e-01	4.83234e-03	3.41460e-02
4 m	1.08019e-01	5.01055e-02	5.56296e-03	2.28328e-02
5 sigfrac	5.42053e-01	2.62713e-02	2.33086e-03	-3.69678e-02

ERR DEF= 0.5

EXTERNAL ERROR MATRIX. NDIM= 25 NPAR= 5 ERR DEF=0.5

2.809e-01	-1.514e-03	-1.189e-01	-1.053e-03	1.234e-02
-1.514e-03	2.061e-05	5.744e-04	-4.527e-05	-8.325e-05
-1.189e-01	5.744e-04	5.841e-02	3.025e-04	-4.698e-03
-1.053e-03	-4.527e-05	3.025e-04	2.513e-03	-5.369e-05
1.234e-02	-8.325e-05	-4.698e-03	-5.369e-05	6.908e-04

PARAMETER CORRELATION COEFFICIENTS

NO.	GLOBAL	1	2	3	4	5
1	0.97483	1.000	-0.629	-0.929	-0.040	0.886
2	0.73477	-0.629	1.000	0.524	-0.199	-0.698
3	0.94605	-0.929	0.524	1.000	0.025	-0.740
4	0.32276	-0.040	-0.199	0.025	1.000	-0.041
5	0.92525	0.886	-0.698	-0.740	-0.041	1.000

➤ In execution, we get @ fitting step (**HESSE**):

```
-----minimization done; now recalculating the uncertainties-----
*****
** 18 **HESSE          2500
*****
COVARIANCE MATRIX CALCULATED SUCCESSFULLY
FCN=28489 FROM HESSE      STATUS=OK          33 CALLS          200 TOTAL
                        EDM=4.58768e-06     STRATEGY= 1      ERROR MATRIX ACCURATE
EXT PARAMETER
NO.  NAME      VALUE      ERROR      INTERNAL  INTERNAL
      NAME      VALUE      ERROR      STEP SIZE  VALUE
 1 #Gamma      3.40452e+00  6.09271e-01  2.39371e-04  3.56273e-01
 2 #alpha      -5.44013e-02  4.87576e-03  4.40875e-05  1.23943e+00
 3 #sigma      9.73194e-01  2.77711e-01  9.66467e-04  -6.99185e-01
 4 m           1.08019e-01  5.01294e-02  1.11259e-03  1.08230e-01
 5 sigfrac     5.42053e-01  2.97534e-02  4.66172e-04  8.42046e-02
ERR DEF= 0.5
EXTERNAL ERROR MATRIX.  NDIM= 25  NPAR= 5  ERR DEF=0.5
 3.803e-01 -2.072e-03  1.628e-01 -1.392e-03  1.675e-02
-2.072e-03  2.377e-05  8.199e-04 -4.362e-05 -1.081e-04
-1.628e-01  8.199e-04  7.769e-02  4.539e-04 -6.643e-03
-1.392e-03 -4.362e-05  4.539e-04  2.515e-03 -6.751e-05
 1.675e-02 -1.081e-04 -6.643e-03 -6.751e-05  8.863e-04
PARAMETER CORRELATION COEFFICIENTS
NO.  GLOBAL  1  2  3  4  5
 1  0.98147  1.000 -0.689 -0.947 -0.045  0.912
 2  0.77533 -0.689 1.000 0.603 -0.178 -0.745
 3  0.95974 -0.947 0.603 1.000 0.032 -0.800
 4  0.32402 -0.045 -0.178 0.032 1.000 -0.045
 5  0.94225 0.912 -0.745 -0.800 -0.045 1.000
```

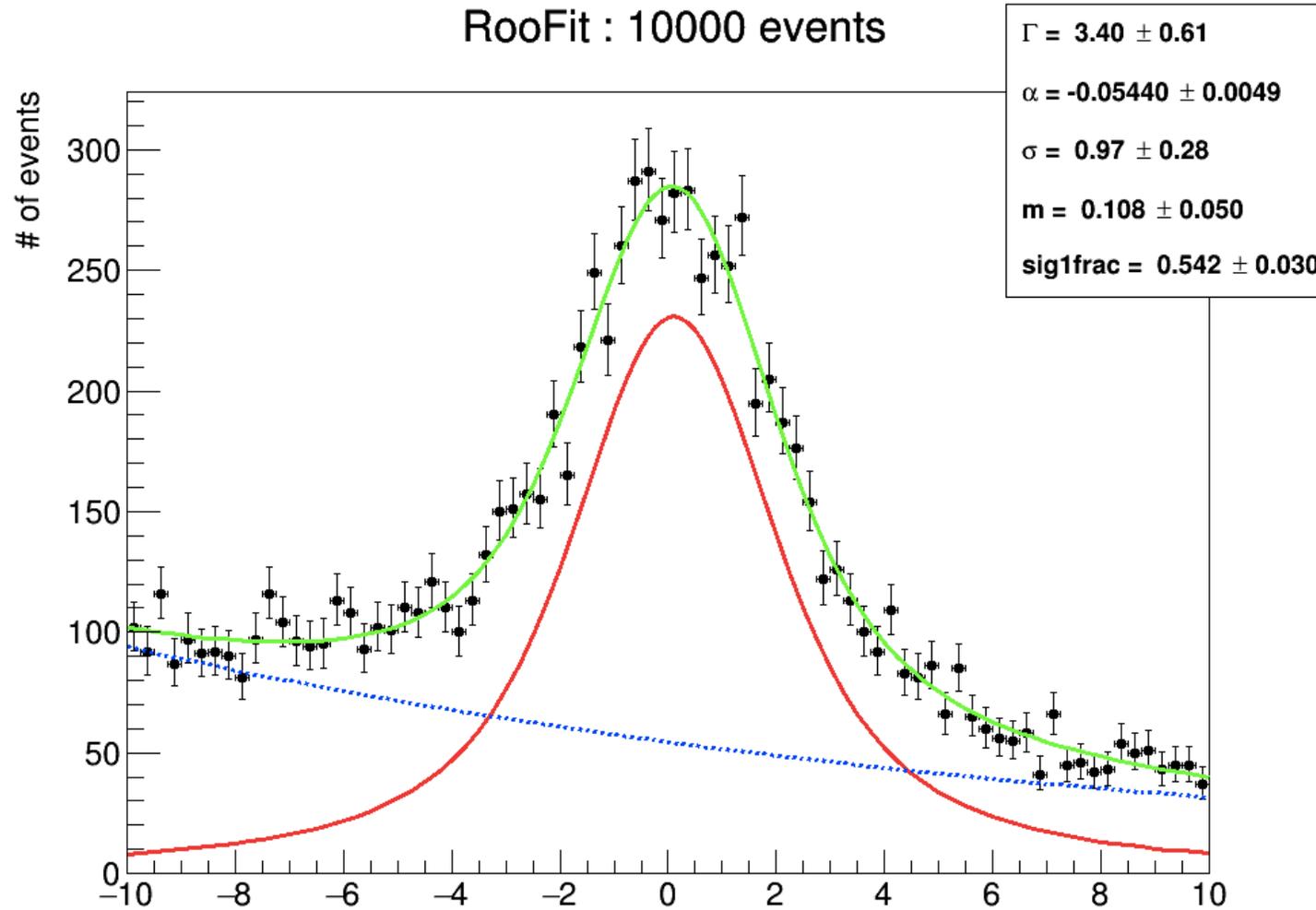
Same central values:
only uncertainties are recalculated!

➤ In execution, we get @ plotting step :

```
-----fit done; check best estimates for the model parameters-----
[#1] INFO:NumericIntegration -- RooRealIntegral::init(convolution_Int[xvar]) using numeric integrator RooIntegrator1D to calculate Int(xvar)
[#1] INFO:Plotting -- RooAbsPdf::plotOn(totalPDF) directly selected PDF components: (convolution)
[#1] INFO:Plotting -- RooAbsPdf::plotOn(totalPDF) indirectly selected PDF components: (BW,resol)
[#1] INFO:NumericIntegration -- RooRealIntegral::init(convolution_Int[xvar]) using numeric integrator RooIntegrator1D to calculate Int(xvar)
[#1] INFO:Plotting -- RooAbsPdf::plotOn(totalPDF) directly selected PDF components: (Bkg)
[#1] INFO:Plotting -- RooAbsPdf::plotOn(totalPDF) indirectly selected PDF components: ( )
[#1] INFO:NumericIntegration -- RooRealIntegral::init(convolution_Int[xvar]) using numeric integrator RooIntegrator1D to calculate Int(xvar)
Info in <TCanvas::Print>: file plots/RooConvGen_10000.png has been created
```

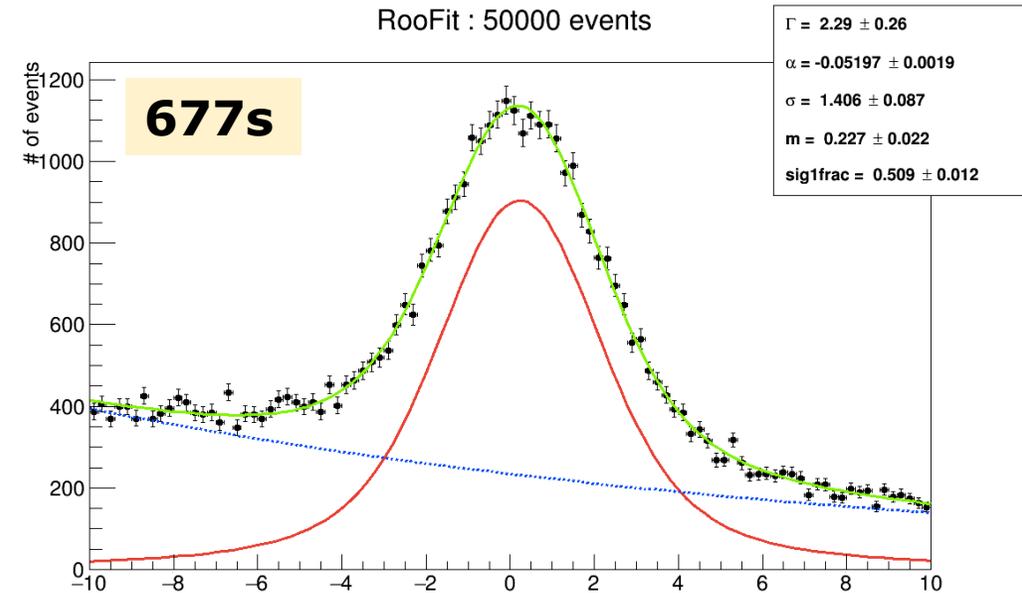
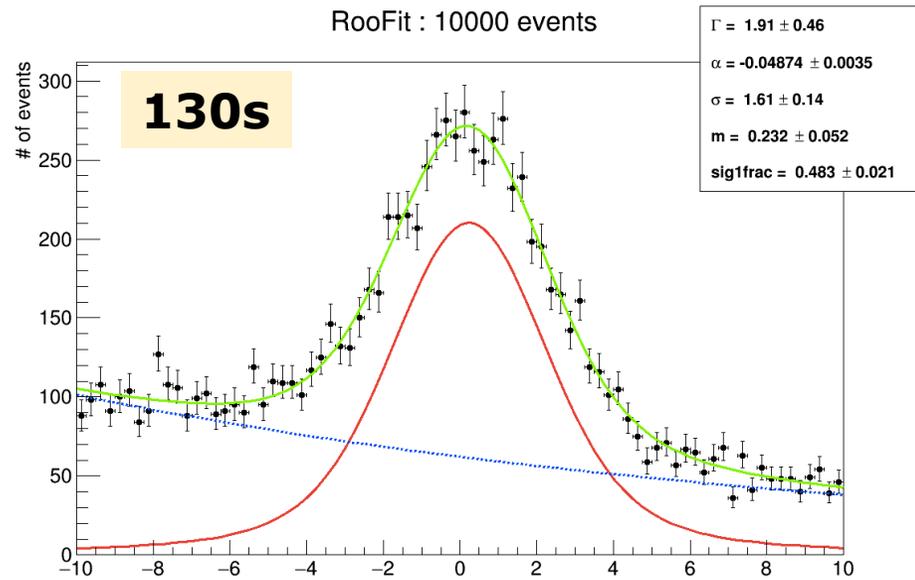
The obtained plot:

```
[[pompili@vm-pompili Esercitazione-4]$ display plots/RooConvGen_10000.png
```



CPU-time considerations - I

➤ Example of plots obtained in these 2 cases (timing info obtained from a past exercise):



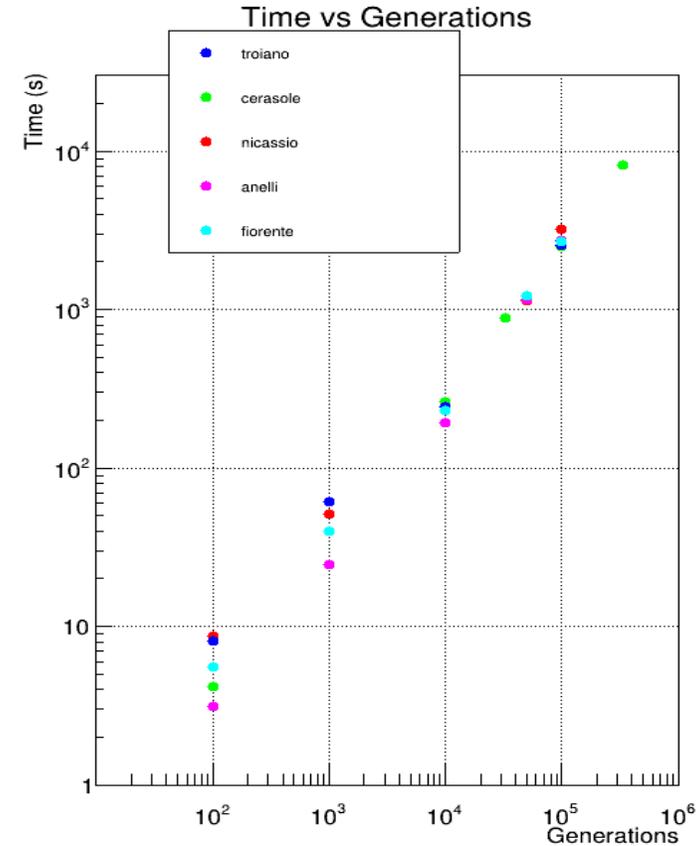
➤ Since the generation time is negligible with respect to the fitting time, the needed time refers to the UML fitting task (on some server @ ReCas, long time ago):

scaling behaviour seems to be approx. **linear**
 (see also next slide)
 [by extrapolation 1M would require ~210min]

#events	CPU-timing (sec)
10K	130
50K	677
100K	1250

CPU-time considerations - II

➤ In the course of academic year 2021-22 the students
- as an exercise - measured these CPU-timings :



➤ To shorten the CPU-timing we can exploit the **parallel computing capabilities** of RooFit; just add the following option:

```
RooAbsReal* nll = total.createNLL(*data, NumCPU(4));
```

To check how many core the VM of the course has, give the command `lscpu` or alternatively do `cat /proc/cpuinfo`

Considerations about the seed to provide to the random generator

To be sure to generate two different distributions we need to provide two different seeds with the method `SetSeed`:

```
RoRandom::randomGenerator() ->SetSeed( )
```

↑
put here an int or long int number! (*)

Note : it can be checked (from the output txt file) that:

- if you use the same seed twice the generated values are the same (and thus the two distributions)
- if you use the same seed and generate two different sequences/lists of values (A and B), with $\#A < \#B$, the first $\#A$ generated values in the list B are the same as those in list A!

(*) Ideally, the seed can be chosen as the time of the system at the start of the execution of the macro.
In this way the seed is automatically different every time you run the task.

Exercise for homework

It's a good practice to **compare the result of the fit** (best estimates of the parameters) **w.r.t. the values used at generation!**

You can verify that the agreement enhances when the number of generated events increases

(as expected from the consistency property of a maximum likelihood estimator).

1) The Monte Carlo method is well and compactly explained in chapter 3 of Cowan's textbook !

Note that RooFit uses the *acceptance-rejection method* (paragraph 3.3)

2) Being able to generate distributions according to some model can be rather useful in order to use the so called *MC toys technique*.

Have a look for instance at:

http://roofit.sourceforge.net/docs/tutorial/fitgen/roofit_tutorial_fitgen.pdf

A specific application of the MC toys is set up when one needs to estimate the *p-value* of a distribution to determine the **statistical significance of a physical signal**.

See for instance slides 5-6 of A.P. talk @ Conference ACAT2016:

https://indico.cern.ch/event/397113/contributions/1837858/attachments/1213108/1770056/pompili_acat16_final.pdf