

Laboratorio di fisica computazionale

Homework 6

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```
• begin
•   #using Pkg;Pkg.update();Pkg.add("SpecialFunctions")
•   using Random ✓
•   using Formatting ✓
•   using Printf ✓
•   using Plots ✓
•   import StatsBase ✓ as SB
•   import LinearAlgebra ✓ as LA
•   theme(:ggplot2)
•   using PlutoUI ✓
•   import SpecialFunctions ✓ as SF
•   # using LaTeXStrings
• end
```

The next function generates a random variable distributed uniformly on the interval $[-1, +1]$.

unipm1 (generic function with 1 method)

```
• function unipm1()
•   return 2*rand(Float64)-1
• end
```

The next function generates a random variable distributed according to $p(x) = \exp(-x)$ on the interval $[-1, +1]$.

e-rnd (generic function with 1 method)

```
• function e-rnd()
•   return 0. - log1p( - rand(Float64) )
• end
```

The next function generates a random variable distributed according to $p(x) = \frac{a}{\pi} \frac{1}{x^2+a^2}$.

Lorrnd (generic function with 1 method)

```
• function Lorrnd() #(a::Float64)
•   return 1. * tan(pi*(rand(Float64) - 1/2)) #1. = a
• end
```

CLT

This function produces a K-uple of averages \bar{x} of random variables distributed according to the function f .

Arguments:

- N : number of points for the average
- K : number of averages to be generated
- f : function which generates the N random variables r of which the average is calculated. If default is left, it generates a variable distributed accordingly to the uniform distribution on $[-1,1)$.
- μ : analytical average of the distribution of the random variable r , produced by $f(\text{rand}())$
- σ : analytical variance of the distribution of the random variable r , produced by $f(\text{rand}())$

-extras: boolean variable that, when "true", triggers the computation of the ratio $\langle z^4 \rangle / 3 \langle z^2 \rangle$, which is the returned as third output

Returns:

- \bar{x} : list of K averages
- σ : estimate of the standard deviation of the K averages
- ratio $\langle z^4 \rangle / 3 \langle z^2 \rangle$: ratio that should equal 1 for z according to $N(0,1)$

```
• """
• This function produces a K-uple of averages  $\bar{x}$  of random variables distributed
• according to the function  $f$ .
•
• Arguments:
•
• -  $N$ : number of points for the average
•
• -  $K$ : number of averages to be generated
•
• -  $f$ : function which generates the  $N$  random variables  $r$  of which the average is
• calculated. If default is left, it generates a variable distributed accordingly to
• the uniform distribution on  $[-1,1)$ .
•
• -  $\mu$ : analytical average of the distribution of the random variable  $r$ , produced by
•  $f(\text{rand}())$ 
•
• -  $\sigma$ : analytical variance of the distribution of the random variable  $r$ , produced by
•  $f(\text{rand}())$ 
•
• -extras: boolean variable that, when "true", triggers the computation of the ratio
•  $\langle z^4 \rangle / 3 \langle z^2 \rangle$ , which is the returned as third output
•
• Returns:
•
```

```

: - x: list of K averages
:
: -  $\sigma$ : estimate of the standard deviation of the K averages
:
: - ratio  $\langle z^4 \rangle / 3 / \langle z^2 \rangle$ : ratio that should equal 1 for z according to  $N(0,1)$ 
: """"
: function
CLT(N::Int64,K::Int64;f=unipm1::Function, $\mu_0=0$ ::Float64, $\sigma_0=1$ ::Float64,extras=false:
: Bool)
:
:     x = zeros(Float64,K)
:      $\mu = 0$ ::Float64
:      $\sigma = 0$ ::Float64
:      $\bar{z}^4 = 0$ ::Float64
:      $\bar{z}^2 = 0$ ::Float64
:     for j = 1:1:K
:         xhere = 0.
:         for i = 1:1:N
:             r = f()
:             xhere += r
:         end
:         xhere = xhere/N
:         x[j] = xhere
:          $\mu = \mu + xhere$ 
:          $\sigma = \sigma + xhere^2$ 
:
:         if (extras == true)
:             z = (xhere- $\mu_0$ )/ $\sigma_0$ 
:              $\bar{z}^4 += z^4$ 
:              $\bar{z}^2 += z^2$ 
:         end
:
:     end
:
:      $\mu = \mu/K$ 
:      $\sigma = (\sigma/K - \mu^2) * \text{sqrt}(K/(K-1))$ 
:      $\sigma = \text{sqrt}(\sigma)$ 
:
:     if (extras == true)
:          $\bar{z}^4 = \bar{z}^4/K$ 
:          $\bar{z}^2 = \bar{z}^2/K$ 
:         ratio =  $\bar{z}^4 / 3 / (\bar{z}^2)^2$ 
:         return x,  $\sigma$ , ratio
:     end
:
:     if (extras == false)
:         return x,  $\sigma$ 
:     end
:
:     # plot( $x_n$ ,seriestype = :histogram)
:
: end

```

Averages of uniform random numbers in $[-1, +1)$

```

• begin
•   N1 = 500::Int64
•   K1 = 100::Int64
•
•   x1, σ1, one1 = CLT(N1,K1;μ0 = 0.,σ0 = 1/sqrt(3*N1),extras = true)
•   x̄1 = sum(x1)/K1
• end;

```

```

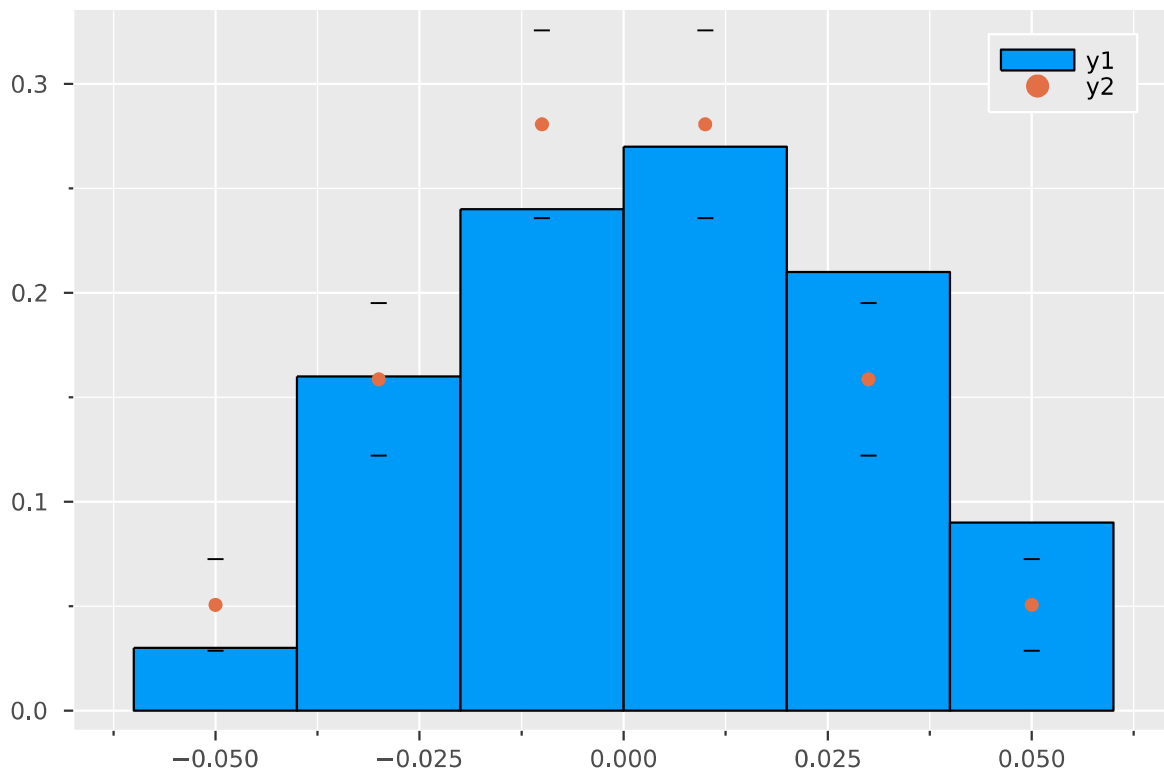
• begin
•   x1fmt = @sprintf "%.3f" x̄1
•   σ1fmt = @sprintf "%.3f" σ1
•   one1fmt = @sprintf "%.3f" one1
•
•   #theoretical value
•   σ1th = @sprintf "%.3f" 1/sqrt(3*N1)
• end;

```

The values for K averages over N uniform random numbers r in $[-1, +1)$ we obtained, written as exp. value -> theor. value are:

- average: 0.005 -> 0.0;
- std. dev.: 0.025 -> 0.026;
- $\langle z^4 \rangle / 3 \langle z^2 \rangle^2$: 0.755 -> 1;

the theoretical values having been computed respectively as the expectation value of the r s and the std. dev. of the original r s, $\sqrt{1/3}$, divided by \sqrt{N} , as required by the formula of the propagation of the variance.



```

• begin
•   # Automated histogram generation, from which we get the bins
•   local h = SB.fit(SB.Histogram, x1)#, nbins=10)
•   local plotrange = h.edges[1]
•
•   # We use the bins to construct the theoretical normalized histogram
•   # using the gaussian error function
•   local σ = 1/sqrt(3*N1)
•   local Δplot = plotrange[2]-plotrange[1]
•
•   # Broadcast the function '1/2 * (erf((x+Δplot)/(sqrt(2)*σ))-
•   erf(x/(sqrt(2)*σ)))'
•   # onto the array plotrange[1:end-1] to compute the normalized histogram
•   local plotfunc = broadcast(x -> 1/2 * (SF.erf((x+Δplot)/(sqrt(2)*σ))-
•   SF.erf(x/(sqrt(2)*σ))), plotrange[1:end-1])
•
•   local plotcentres = [(plotrange[i]+plotrange[i-1])/2 for i in
•   2:1:length(plotrange)]
•
•   # Final plot
•   h = LA.normalize(h; mode=:probability)
•   plot(h)
•   plot!(plotcentres, plotfunc, yerr = sqrt.(plotfunc .* (1 .- plotfunc)/K1),
•   seriestype = :scatter)
• end

```

One can see that the experimental values and the theoretical ones seem to be in good agreement with each other. The histogram and the function plot, too, agree within 1-2 standard deviation with each other in most runs, providing evidence for the validity of the Central Limit Theorem.

Averages of random numbers with $p(x) = e^{-x}$

```

• md"""#### Averages of random numbers with ``p(x) = e^{-x}``"""

```

```

• begin
•     N2 = 500::Int64
•     K2 = 100::Int64
•
•     x2, σ2, one2 = CLT(N2,K2;f=e-rnd,μ0 = 1.,σ0 = 1/sqrt(N2), extras = true)
•     x̄2 = sum(x2)/K2
• end;

```

```

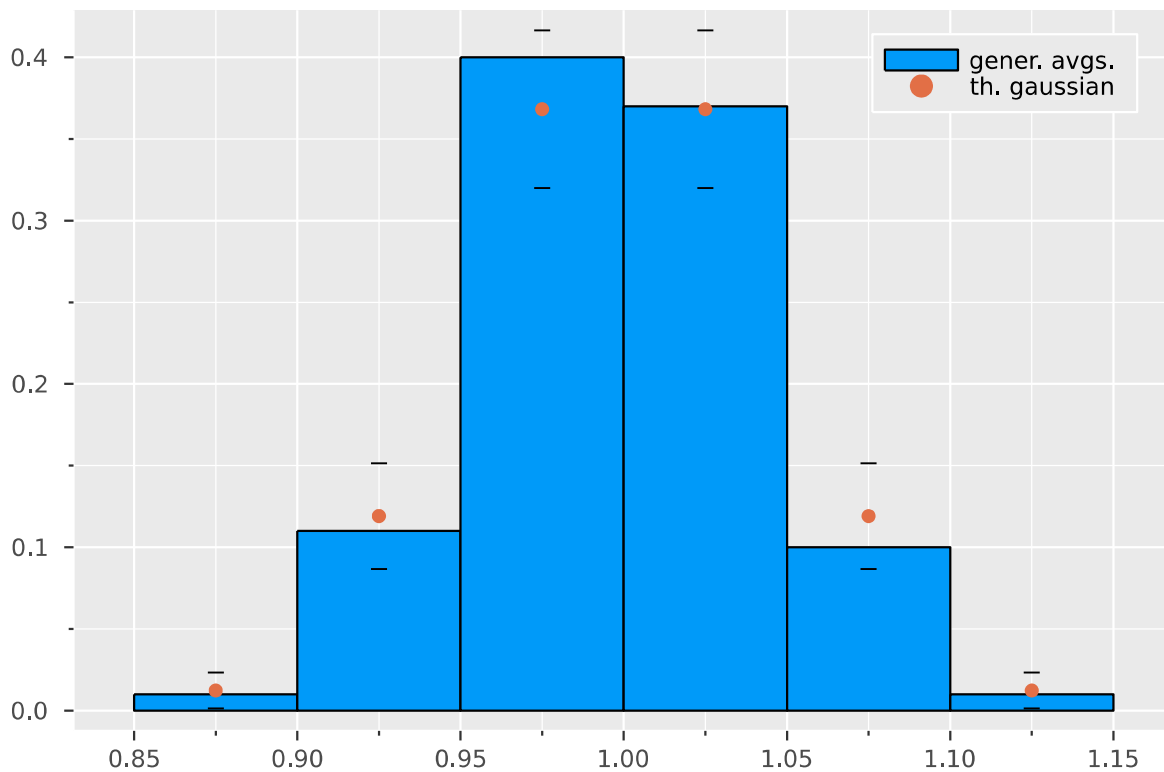
• begin
•     # Exp. values that are printed in the next cell
•     x2fmt = @sprintf "%.3f" x̄2
•     σ2fmt = @sprintf "%.3f" σ2
•     one2fmt = @sprintf "%.3f" one2
•
•     # Theoretical value for the std. dev.
•     σ2th = @sprintf "%.3f" 1. /sqrt(N2)
• end;

```

The values for K averages over N random numbers r distributed accordingly to $p(x) = e^{-x}$ we obtained, written as exp. value -> theor. value are:

- average: 0.999 -> 1.0;
- std. dev.: 0.043 -> 0.045;
- $\langle z^4 \rangle / 3 \langle z^2 \rangle^2$: 1.086 -> 1;

the theoretical values having been computed respectively as the expectation value of the r s and the std. dev. of the original r s, 1, divided by \sqrt{N} , as required by the formula of the propagation of the variance.



```

• begin
•   # Automated histogram generation, from which we get the bins
•   local h = SB.fit(SB.Histogram, x2)#, nbins=10)
•   local plotrange = h.edges[1]
•
•   # We use the bins to construct the theoretical normalized histogram
•   # using the gaussian error function
•   local σ = 1/sqrt(N2)
•   local Δplot = plotrange[2]-plotrange[1]
•
•   # Broadcast the function '1/2 * (erf((x+Δplot)/(sqrt(2)*σ))-
•   erf(x/(sqrt(2)*σ)))'
•   # onto the array plotrange[1:end-1] to compute the normalized histogram
•   local plotfunc = broadcast(x -> 1/2 * (SF.erf((x+Δplot-1.)/(sqrt(2)*σ))-
•   SF.erf((x-1.)/(sqrt(2)*σ))), plotrange[1:end-1])
•
•   local plotcentres = [(plotrange[i]+plotrange[i-1])/2 for i in
•   2:1:length(plotrange)]
•
•   # Final plot
•   h = LA.normalize(h; mode=:probability)
•   plot(h, label = "gener. avgs.")
•   plot!(plotcentres, plotfunc, yerr = sqrt.(plotfunc .* (1 .- plotfunc)/K1),
•   seriestype = :scatter, label = "th. gaussian")
• end

```

The histogram and the theoretical prediction for the counts for the new gaussian average agree with each other within 1-2 standard deviations on most runs, except for bins with very low counts, providing further evidence for the validity of the Central Limit Theorem.

Averages of random numbers with $p(x) = 1/\pi/(x^2 + 1)$

```

• begin
•     N3 = 500::Int64
•     K3 = 100::Int64
•
•     x3, σ3 = CLT(N3,K3;f = Lorrnd)
•     x̄3 = sum(x3)/K3
• end;

```

```

• begin
•     # Exp. values that are printed in the next cell
•     x3fmt = @sprintf "%.3f" x̄3
•     σ3fmt = @sprintf "%.3f" σ3
• end;

```

Using the characteristic function of the lorentzian distribution one can show that, if x is distributed accordingly to the lorentzian, which has the characteristic function

$$\Phi_X(t) = \exp(-a|t|) = E[e^{itx}] = \int_{-\infty}^{+\infty} dx \frac{a}{\pi} \frac{1}{x^2 + a^2} e^{itx},$$

the average \bar{x} on N independent x s will be distributed according to a distribution function with characteristic function

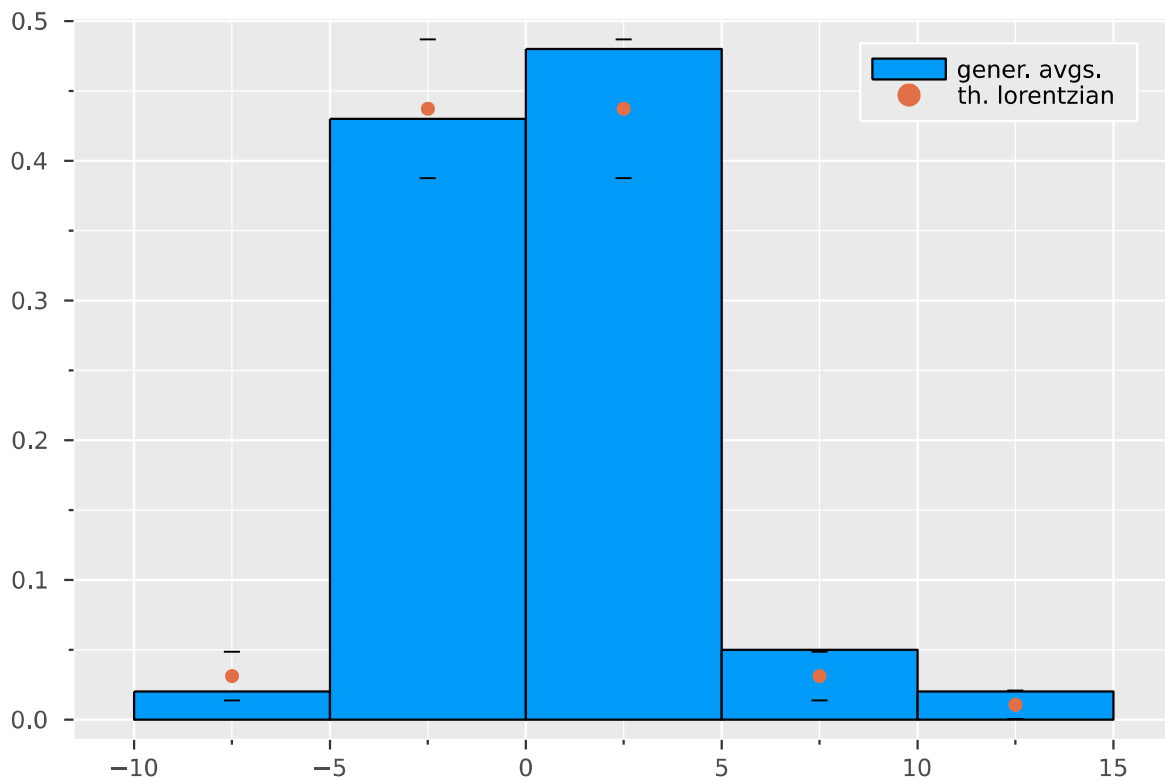
$$\begin{aligned} \Phi_{\bar{X}}(t) &= E[e^{it\bar{x}}] = E\left[e^{it \sum_{j=1}^N x/N}\right] = \left(E\left[e^{itx/N}\right]\right)^N = \\ &= \left(\int_{-\infty}^{+\infty} dx \frac{a/N}{\pi} \frac{1}{x^2 + (a/N)^2} e^{itx}\right)^N = \left(\exp\left(-\frac{a}{N}|t|\right)\right)^N = \Phi_X(t), \end{aligned}$$

which means the average itself will be a lorentzian variable with the same parametre a as the x s from which it was computed.

The values for K averages over N random numbers r distributed accordingly to the lorentzian $p(x) = \frac{1}{\pi} \frac{1}{x^2+1}$ we obtained, written as exp. value -> theor. value are:

- average: 0.526 -> 0.0;
- std. dev.: 2.634 -> Inf;

the theoretical values having been computed respectively as the expectation value of the r s and the std. dev. of the original r s, 1, divided by \sqrt{N} , as required by the formula of the propagation of the variance.



```

• begin
•   # Automated histogram generation, from which we get the bins
•   local h = SB.fit(SB.Histogram, x3), nbins=10)
•   local plotrange = h.edges[1]
•
•   # We use the bins to construct the theoretical normalized histogram
•   # using the gaussian error function
•   local σ = 1/sqrt(N3)
•   local Δplot = plotrange[2]-plotrange[1]
•
•   # Broadcast the function '1/2 * (erf((x+Δplot)/(sqrt(2)*σ))-
•   erf(x/(sqrt(2)*σ)))'
•   # onto the array plotrange[1:end-1] to compute the normalized histogram
•   local plotfunc = broadcast(x -> 1/pi * ( atan((x+Δplot)/1.) - atan(x/1.) ),
•   plotrange[1:end-1])
•
•   local plotcentres = [(plotrange[i]+plotrange[i-1])/2 for i in
•   2:1:length(plotrange)]
•
•   # Final plot
•   h = LA.normalize(h; mode=:probability)
•   plot(h, label = "gener. avgs.")
•   plot!(plotcentres, plotfunc, yerr = sqrt.(plotfunc .* (1 .- plotfunc)/K1),
•   seriestype = :scatter, label = "th. lorentzian")
• end

```

The histogram and the theoretical prediction for the counts for the lorentzian average agree within 1-2 standard deviations with each other on most of the runs, except for bins with very low counts. Comparing the theoretical values to the experimental ones, though, one gets disappointing results because of how likely results far from the average are, which is what causes the value of the variance to be high. One might expect to get better estimates of the average by increasing the number of averages that one generates, but that doesn't seem to happen.

