

```

• begin
•   using Pkg; Pkg.add(["Distributions", "LinearAlgebra", "Plots", "PlutoUI"])
•   using Distributions
•   using LinearAlgebra
•   using Plots
•   using PlutoUI
•   default(legendfontsize = 15.0, linewidth = 2.0)
• end

• # TableOfContents()

```

# Problem Sheet 1

## Inverse Transformation Method: Cauchy Distribution

The probability density function (pdf) of a cauchy distribution is defined

$$p(x|x_0, \gamma) = \frac{1}{\pi} \left( \frac{\gamma}{(x - x_0)^2 + \gamma^2} \right)$$

where  $x_0$  is the location of the mode and  $\gamma$  is a shape parameter.

Use the inverse transformation method to find a function  $f(u|x_0, \gamma)$  which generates cauchy distributed samples if  $u$  is uniformly distributed over  $[0, 1]$ .

*Fill in your answer here or on paper!*

$\gamma =$

$x_0 =$

`true_d = Distributions.Cauchy{Float64}(μ=3.0, σ=2.61)`

We sample  $N$  uniform variables and compute the inverse transform on the uniform variables

```

• function f(u, x0, γ)
•   ## !! CODE MISSING !! ##
•   ## Fill in the function correctly transforming your uniform random variables
•   here
•   ## !! CODE MISSING !! ##
• end;

• begin
•   N = 1000

```

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•     u = rand(N)
•     x = f.(u, x₀, γ) # We broadcast the transformation on all u
• end;

```

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• true_x = rand(true_d, N); # We also sample from the method in Distributions.jl

```

## Polar Box-Muller

A computational more efficient version of the Box-Muller transformation makes use of random numbers  $z_1, z_2$  which are uniformly distributed in the unit circle.

We can generate these by drawing  $z_1$  and  $z_2$  from the uniform distribution over  $[-1, 1]$  and rejecting the pairs until  $z_1^2 + z_2^2 \leq 1$  is true.

- **Show** that

$$y_1 = z_1 \sqrt{\frac{-2 \ln(r^2)}{r^2}} \quad (1)$$

$$y_2 = z_2 \sqrt{\frac{-2 \ln(r^2)}{r^2}} \quad (2),$$

with  $r^2 = z_1^2 + z_2^2$ , have the joint distribution

$$p(y_1, y_2) = \left( \frac{1}{\sqrt{2\pi}} \exp \left( \frac{-y_1^2}{2} \right) \right) \left( \frac{1}{\sqrt{2\pi}} \exp \left( \frac{-y_2^2}{2} \right) \right)$$

and therefore each has a standard normal distributio (Gaussian distribution with zero mean and unit variance).

### Tip

Use the two first equations (1) and (2) to get a formula for  $r^2$  depending only on  $y_1$  and  $y_2$ . Then you can easily get the inverted function  $z_{1/2}(y_1, y_2)$ .

You might want to use *Mathematica* or *Maple* for computing some of the derivates. If not you can use

$$[y_1^4 - 2y_2^2 + y_1^2 y_2^2][y_2^4 - 2y_1^2 + y_1^2 y_2^2] - [y_1 y_2 (2 + y_1^2 + y_2^2)]^2 = -2(y_1^2 + y_2^2)^3$$

Fill in your answers here or on paper

# Rejection Sampler: General

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We want to use a rejection sampler to sample from a target distribution  $p(x)$ . As a proposal distribution we can choose between:

- (1)  $q_1(x)$ , with  $c_1 = 1.5$ ,
- (2)  $q_2(x)$ , with  $c_2 = 2.0$ ,
- (3)  $q_3(x)$ , with  $c_3 = 4.0$ ,

where for  $i = 1, 2, 3$  the constant  $c_i$  is the smallest number which fulfills  $c_i q_i(x) \geq p(x) \forall x \in \mathcal{R}$ .

We know that on average it takes  $6 \cdot 10^{-4}$ ,  $4 \cdot 10^{-4}$  and  $3 \cdot 10^{-4}$  seconds to get one sample from  $q_1$ ,  $q_2$  and  $q_3$ , respectively.

With this information, **which proposal distribution should you use and why?**

*Fill in your answer here or on paper*

# Rejection Sampler: Rayleigh distribution

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We want to use a rejection sampler to sample from a Rayleigh distribution. The pdf of a Rayleigh distribution is

$$p(x|\sigma_R) = \begin{cases} \frac{x}{\sigma_R^2} \exp\left(-\frac{x^2}{2\sigma_R^2}\right), & x \geq 0 \\ 0, & x < 0. \end{cases}$$

We want to use a Gaussian distribution as a proposal distribution and set its mean to  $\sigma_R$  (which is the mode of the Rayleigh distribution) and its standard deviation to  $\sigma_G$ .

**a) Show that if  $\sigma_G \geq \sigma_R$ ,  $c$  has to be at least**

$$\sqrt{\frac{2\pi}{\exp(1)} \frac{\sigma_G}{\sigma_R}}$$

*Fill in your answer here or on paper*

For  $\sigma_G \geq \sigma_R$  only  $x_1$  is positive.

$$\frac{d^2 c}{dx^2}(x) = \left[ \left( \frac{2x(1 - \frac{\sigma_G^2}{\sigma_R^2}) - \sigma_R}{\sigma_G \sigma_R^2} \right) + \left( \frac{2x(\sigma_R^2 - \sigma_G^2) - 2\sigma_R^3}{2\sigma_G^2 \sigma_R^2} \right) \right] \left( \frac{x^2(1 - \frac{\sigma_G^2}{\sigma_R^2}) - x\sigma_R + \sigma_G^2}{\sigma_G \sigma_R^2} \right) \\ \times \sqrt{2\pi} \exp \left( \frac{x^2(\sigma_R^2 - \sigma_G^2) - 2x\sigma_R^3 + \sigma_R^4}{2\sigma_G^2 \sigma_R^2} \right)$$

$$\begin{aligned} \text{sign} \left( \frac{d^2 c}{dx^2}(\sigma_R) \right) &= \text{sign} \left( \left( \frac{2\sigma_R(1 - \frac{\sigma_G^2}{\sigma_R^2}) - \sigma_R}{\sigma_G \sigma_R^2} \right) + \left( \frac{2\sigma_R(\sigma_R^2 - \sigma_G^2) - 2\sigma_R^3}{2\sigma_G^2 \sigma_R^2} \right) \left( \frac{\sigma_R^2(1 - \frac{\sigma_G^2}{\sigma_R^2}) - \sigma_R + \sigma_G^2}{\sigma_G \sigma_R^2} \right) \right) \\ &= \text{sign} \left( \left( \frac{\sigma_R - \frac{\sigma_G^2}{\sigma_R}}{\sigma_G \sigma_R^2} \right) + \left( \frac{-2\sigma_G^2 \sigma_R}{2\sigma_G^2 \sigma_R^2} \right) \left( \frac{\sigma_R^2 - \sigma_G^2 - \sigma_R^2 + \sigma_G^2}{\sigma_G \sigma_R^2} \right) \right) \\ &= \text{sign} \left( \frac{\sigma_R^2 - \sigma_G^2}{\sigma_G \sigma_R^3} \right) \\ &= -1, \text{ for } \sigma_G \geq \sigma_R. \end{aligned}$$

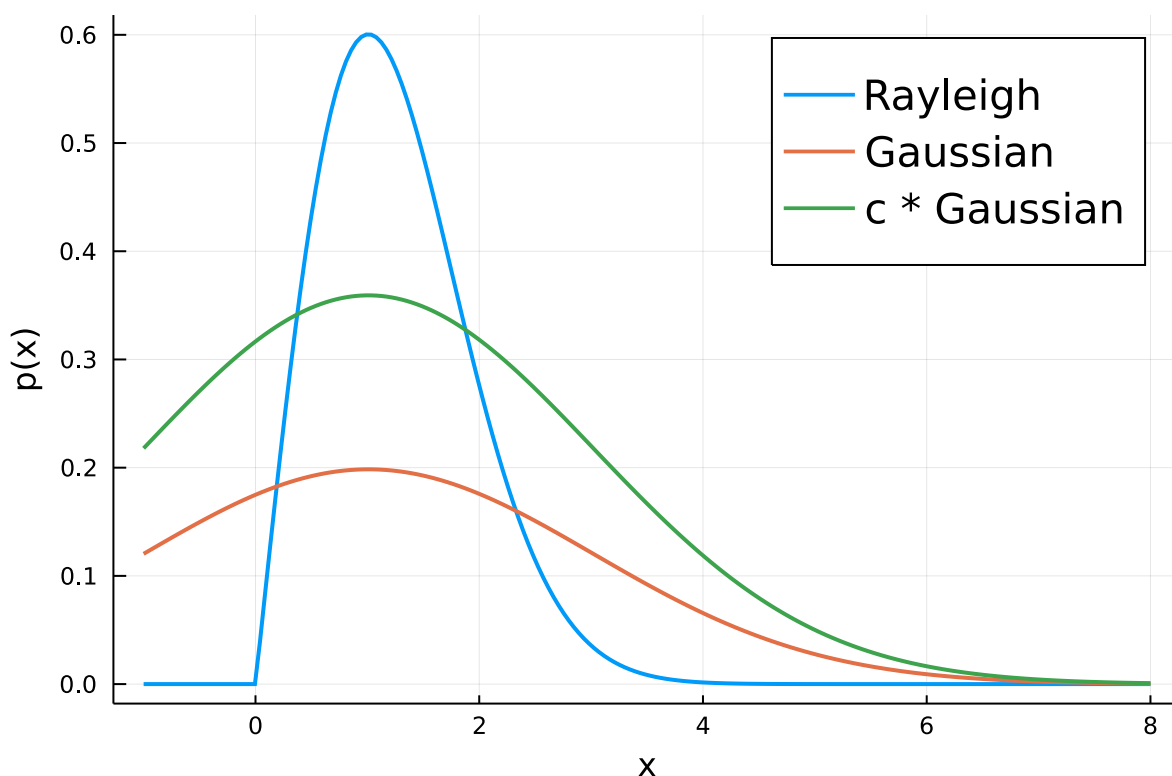
$\sigma_r =$    $\sigma_g =$

$c =$

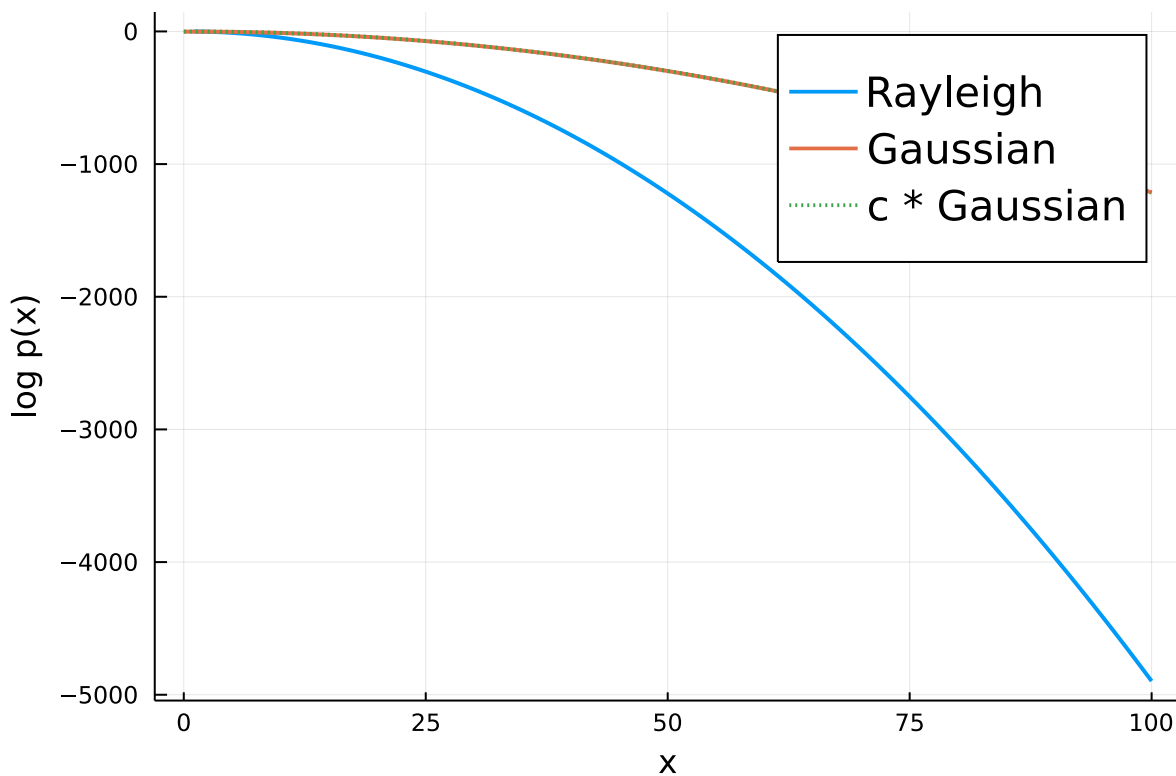
```
md"c = $(@bind c Slider(0.01:0.1:10; default=min_c, show_value=true))"
```

**min\_c = 5.0**

```
• min_c = 5.0 ## !! CODE MISSING !! ## Write here what hte minimum value of c should be
```



Let's plot the same thing but in log-space



**(b) It is obvious that  $c$  is minimal for  $\sigma_G = \sigma_R$ . Why is it not possible to use a Gaussian distribution with  $\sigma_G < \sigma_R$  as a proposal?**

*Fill in your answer here or on paper*

**(c) Program a rejection sampler for a Rayleigh distribution with an arbitrary  $\sigma_R$  and a Gaussian distribution with standard deviation and mean  $\sigma_R$  and the minimal  $c$  as computed in (a). Plot the acceptance rate against the number of drawn samples to show that it converges to  $\frac{1}{c}$ .**

**Solution**

