

Computational Numerical Statistics

PROJECT 1

Group G2 – TP1

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References

-  Sheldon M Ross.
Simulation.
Academic press, 2002.
-  Sheldon M Ross.
Introduction to Probability Models, ISE.
Academic press, 2006.

Project task 1

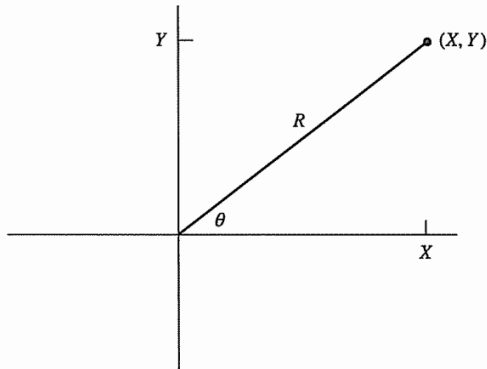
Random variable generation

- 1 Introduction
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Random variable generation

Introduction

- Mervin Edgar Muller & George Edward Pelham Box, 19th century
- Method for generating samples from two independent random variables $X, Y \sim N(0, 1)$ from the $U(0, 1)$ distribution
- Polar coordinates are created



[1]

Random variable generation

Derivation of the Box-Muller method

- $R^2 = X^2 + Y^2$ and $\theta = \tan^{-1}(\frac{x}{y})$
- Proposition: Let Z_1, \dots, Z_v be v independent random variables such that $Z_i \sim N(0, 1)$. Then $\sum_{i=1}^v Z_i^2 \sim \chi_v^2$
so in our case $X^2 + Y^2 \sim \chi_2^2$

So we have the following p.d.f.

	χ_2^2	$\Gamma(1, \frac{1}{2})$	$Exp(\frac{1}{2})$
p.d.f.	$\frac{1}{2^{\frac{k}{2}} \Gamma(\frac{k}{2})} x^{\frac{k}{2}-1} e^{-\frac{x}{2}}$	$\frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$	$\lambda e^{-\lambda x}$
	$\frac{1}{2} e^{-\frac{1}{2}x}$		

$$\Rightarrow R^2 \sim \frac{1}{2} e^{-\frac{1}{2}x}$$

Random variable generation

Derivation of the Box-Muller method: Joined density of $f(R^2, \theta)$

Let's consider the joined density:

$$f(x, y) \stackrel{X, Y \sim N(0, 1)}{=} f(x) * f(y) = \frac{1}{2\pi} e^{-\frac{1}{2}(x^2 + y^2)}$$

→ Joined density of $g(R^2, \theta)$?

given $J_{f(x,y)} = 2$ and $R^2 = X^2 + Y^2$:

$$g(R^2, \theta) = \frac{1}{|J_{f(x,y)}|} f(x, y) = \underbrace{\frac{1}{2\pi}}_I \underbrace{\frac{1}{2} e^{-\frac{1}{2}R^2}}_{II} \quad [2]$$

Random variable generation

Derivation of the Box-Muller method: ITM

- Now we want to sample R^2 and θ from $U(0, 1)$
- **Inverse Transformation Method:** generate a random variable R^2 from the continuous distribution function F by generating a random number U and then setting $R^2 = F^{-1}(U)$
- I. $u = \frac{1}{2}e^{-\frac{x}{2}} \Leftrightarrow x = -2\log(\underbrace{2u}_*)$ Remember: $R^2 \sim \frac{1}{2}e^{-\frac{1}{2}x}$
* $\sim U(0, 1)$ as well as $-2\log(u)$
- II. $g(R^2, \theta) = \frac{1}{2\pi} \frac{1}{2} e^{-\frac{1}{2}R^2} \Rightarrow \theta \in [0, 2\pi] \Rightarrow \theta = 2\pi u_2$
- once we have the radius R of the coordinates, the angle θ is uniformly distributed over the circumference with radius R .

Random variable generation

Derivation of the Box-Muller method: generating the samples

From I. and II. we get

$$R = \sqrt{-2\log(u_1)}$$

$$\theta = 2\pi u_2$$

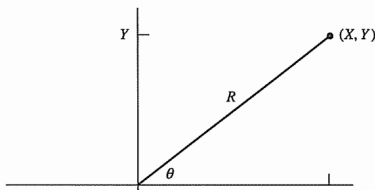
$$X = R\cos(\theta)$$

$$Y = R\sin(\theta)$$

$$\Rightarrow X = \sqrt{-2\log(u_1)}\cos(2\pi u_2)$$

$$\Rightarrow Y = \sqrt{-2\log(u_1)}\sin(2\pi u_2)$$

with $u_1, u_2 \sim U(0, 1)$



Random variable generation

Transfer to other distribution

Q.: How to generate samples from $Z \sim N(\mu, \sigma^2)$?

$$y = ax + b \quad , \quad x \sim N(0, 1)$$

$$E[Y] = E[a \cdot X + b] = aE[X] + E[b] = a \cdot \mu + b$$

$$\text{Var}[Y] = \text{Var}[a \cdot X + b] = a^2 * \text{Var}[X] = a^2 \cdot \sigma^2$$

$$\sigma[Y] = \sqrt{\text{Var}[Y]} = a \cdot \sigma$$

Note: $Y \sim N(\mu^*, \sigma^{2*})$:

$$p.d.f._Y = \frac{1}{\sigma^* \cdot \sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{y - \mu^*}{\sigma^*} \right)^2}$$

→ Find transformation that converts it to a $N(\mu^*, \sigma^{2*})$:

$$y = \sigma^* \cdot X + \mu^*$$

Random variable generation

Algorithm

- Generate two observations u_1 and u_2 from $U(0, 1)$.
- Set

$$\theta = 2\pi u_1$$

$$R = \sqrt{-2\log(u_2)}$$

- Set

$$x = R\cos(\theta)$$

$$y = R\sin(\theta)$$

- Iterate the previous steps until you reach the desired sample size.

Random variable generation

Algorithm

(a) Implement the Box-Muller method in R.

```
sim.norm<-function(n, mu, std){  
  "Box-Muller Algorithm. This function generates samples  
  from two independent random variables  $X, Y \sim N(\mu, \text{std})$ ."  
  
  x<-vector()  
  y<-vector()  
  
  # Box-Muller algorithm  
  theta=2*pi*runif(n, 0, 1)  
  R=sqrt(-2*log(runif(n, 0, 1)))  
  
  # add  $N(0, 1)$  observations to the samples  
  x=c(x, R*cos(theta))  
  y=c(y, R*sin(theta))  
  
  # convert all observations from  $N(0, 1)$  to  $N(\mu, \text{std})$   
  x=x*std+mu  
  y=y*std+mu  
  
  # return results in a table format  
}
```

Random variable generation

Implementation

(b) Use routine `sim.norm()` to generate a sample of size $m = 10000$ from $X \sim N(0, 4)$.

```
#Exercise B - generate 10k samples from  $X \sim (0, 4)$ 
set.seed(123)
mu = 0
std = 4
n = 10 * 1000

# n/2 because we can merge X and Y since their both are independent.
samples = sim.norm(n/2, 0, 4)

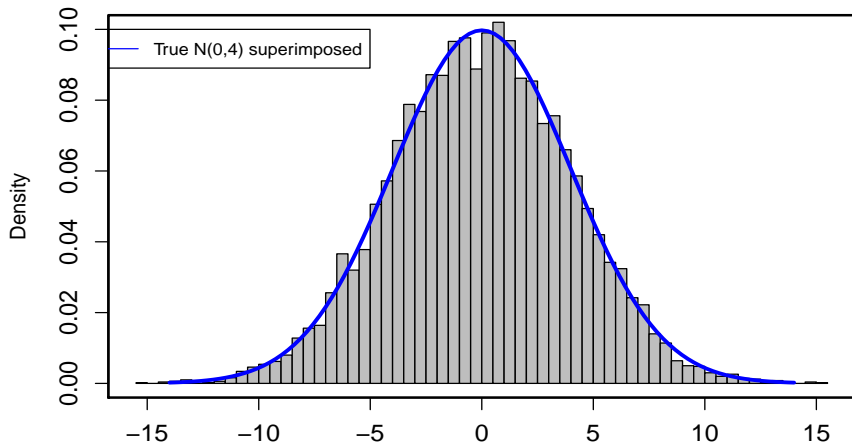
# merge the 5k samples from X with the 5k samples from Y
samples = c(samples[, "X"], samples[, "Y"])
```

Random variable generation

Visualization

(c) Plot the histogram referring to the previous exercise.

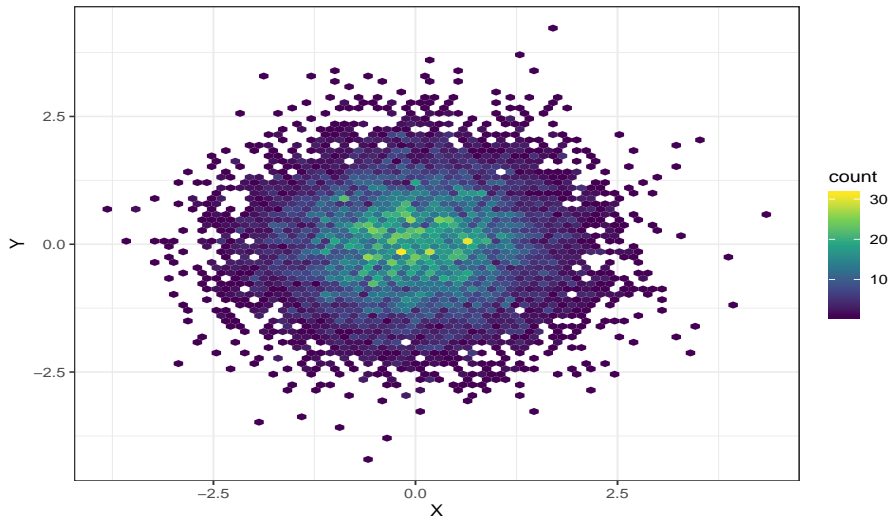
Box-Muller 10k samples from $N(0,4)$



Random variable generation

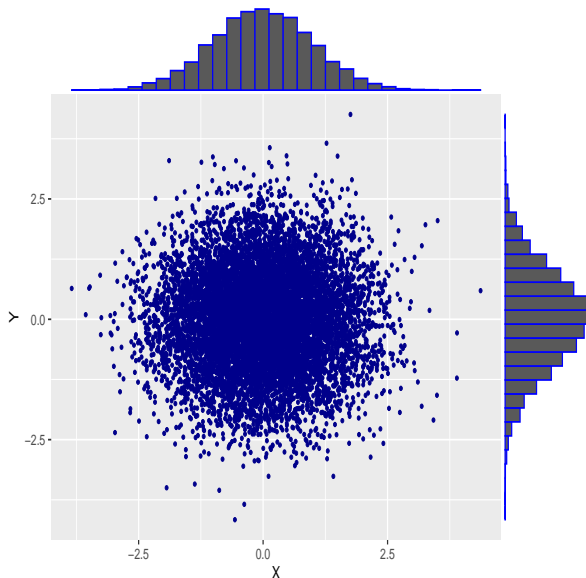
In-depth Visualization of the samples

Let's see the density of the point cloud of X and Y .



Random variable generation

In-depth Visualization of the samples



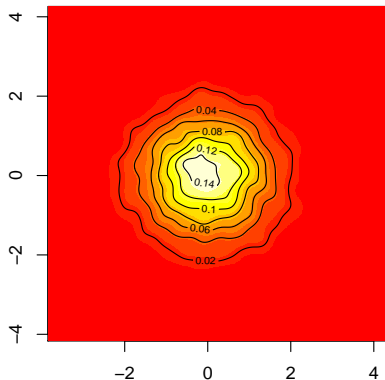
As most points are located near the origin they increase the density of $N(0,1)$ around the mean of 0.

Outlier points are barely accounted for since there are 10000 samples.

Random variable generation

In-depth Visualization of the samples

The different confidence regions, note that none of them are elliptical.



Random variable generation

In-depth Visualization of the samples

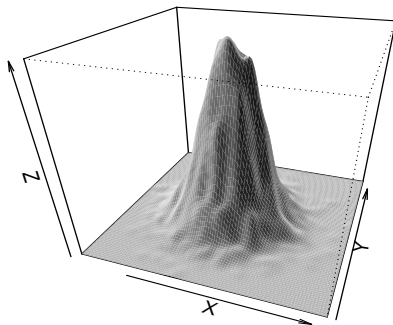
Calculating the covariance matrix and the mean of X and Y we get:

- for 10 samples, $S = \begin{bmatrix} 1.543 & -0.468 \\ -0.468 & 0.452 \end{bmatrix}$; mean = $\begin{bmatrix} 0.1303 \\ -0.4074 \end{bmatrix}$
- for 100 samples, $S = \begin{bmatrix} 0.8660 & -0.0221 \\ -0.0221 & 0.8487 \end{bmatrix}$; mean = $\begin{bmatrix} -0.1112 \\ 0.0059 \end{bmatrix}$
- for 1000 samples, $S = \begin{bmatrix} 1.02431 & 0.00116 \\ 0.00116 & 0.97704 \end{bmatrix}$; mean = $\begin{bmatrix} -0.0237 \\ -0.0341 \end{bmatrix}$
- for 10000 samples, $S = \begin{bmatrix} 1.00123 & 0.00103 \\ 0.00103 & 1.01359 \end{bmatrix}$; mean = $\begin{bmatrix} -0.0134 \\ -0.0041 \end{bmatrix}$

Random variable generation

Visualization

Bivariate Normal KDE:



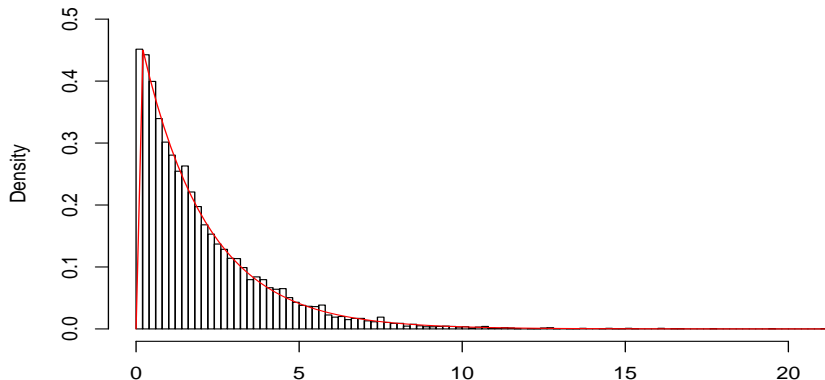
Random variable generation

Visualization

Since $X, Y \sim N(\mu, \sigma^2)$, and $R^2 = X^2 + Y^2$ then $R^2 \sim \chi_2^2$

In the special case of two degrees of freedom, the chi-squared distribution coincides with the exponential distribution.

Histogram of R^2



Random variable generation

This is the end

Questions?

If we finished the presentation on time, of course :-)