

# Simulation from Comonotonic random vectors

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## The Quantile Transform Theorem

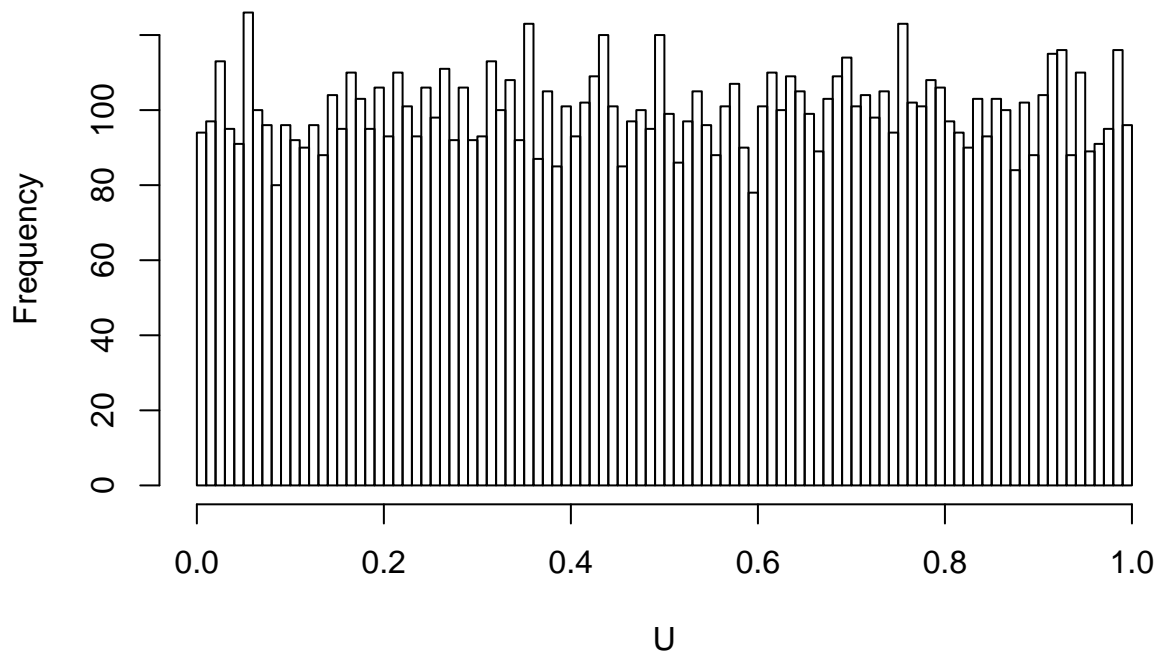
Consider a random variable  $X$  with cumulative distribution function (cdf) denoted by  $F_X$ . The **Quantile Transform Theorem** states that:

$$F_X^{-1}(U) \stackrel{d}{=} X,$$

where  $U$  is a Uniform distributed random variable. We will employ the quantile transform theorem to transform  $m$  realizations  $u_1, u_2, \dots, u_{N_{sim}}$  from  $U$  to realizations  $x_1, x_2, \dots, x_{N_{sim}}$  of  $X$ . Below, we start with simulating the realizations  $u_i, i = 1, 2, \dots, N_{sim}$  of  $U$ .

```
NSim=10000
U=runif(NSim)
#Histogram of a uniform distribution
hist(U,100, main="Histogram for Uniform realizations")
```

**Histogram for Uniform realizations**



Assume we want to transform the realizations which are stored in the vector  $U$  to realizations for an exponential distributed random variable  $X$ :

$$X \stackrel{d}{=} \text{Exp}(\lambda).$$

Then:

$$F_X(x) = 1 - e^{-\lambda x}, \quad x \geq 0.$$

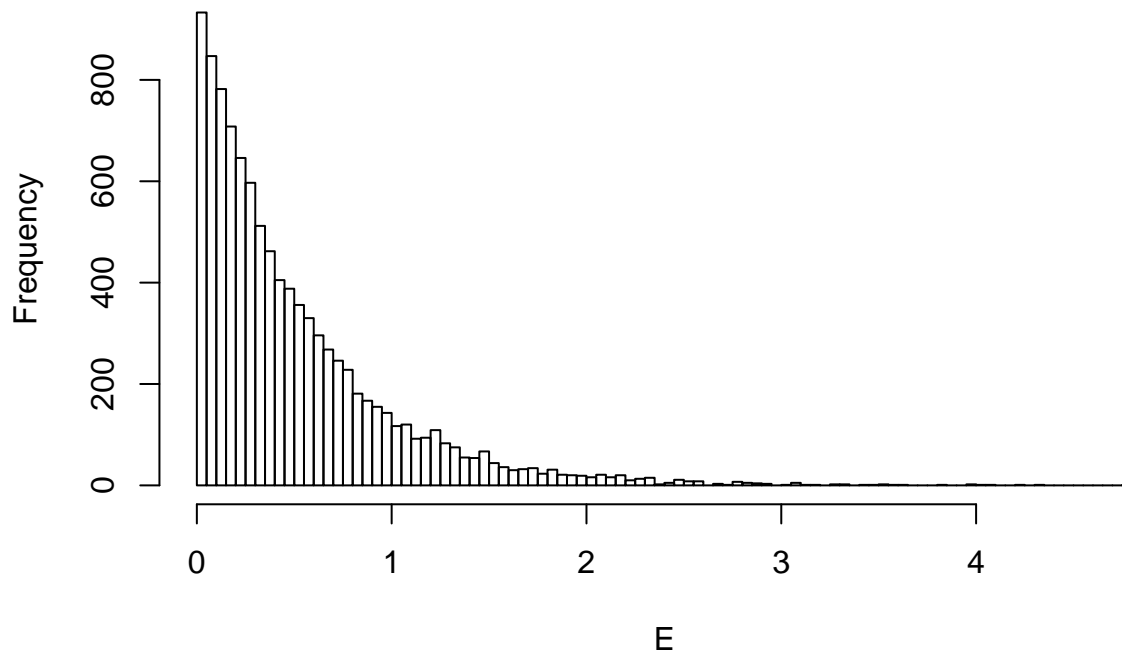
The inverse cdf of an exponential distribution is given by

$$F_X^{-1}(p) = -\frac{1}{\lambda} \log(1 - p), \quad p \in (0, 1).$$

Then, if  $u$  is a realization of the Uniform random variable  $U$ , then  $x = -\frac{1}{\lambda} \log(1 - u)$  is a realization of an exponential distribution random variable with parameter  $\lambda$ . The R code below uses the quantile transform theorem to simulate exponential distributed random variables. Because we use the same random numbers as before, there is no simulation required in this step.

```
#Transform the uniform realizations to exponential realizations  
lambda=2  
E=-(1/lambda)*log(1-U)  
hist(E,100, main="Histogram for Exponential realizations")
```

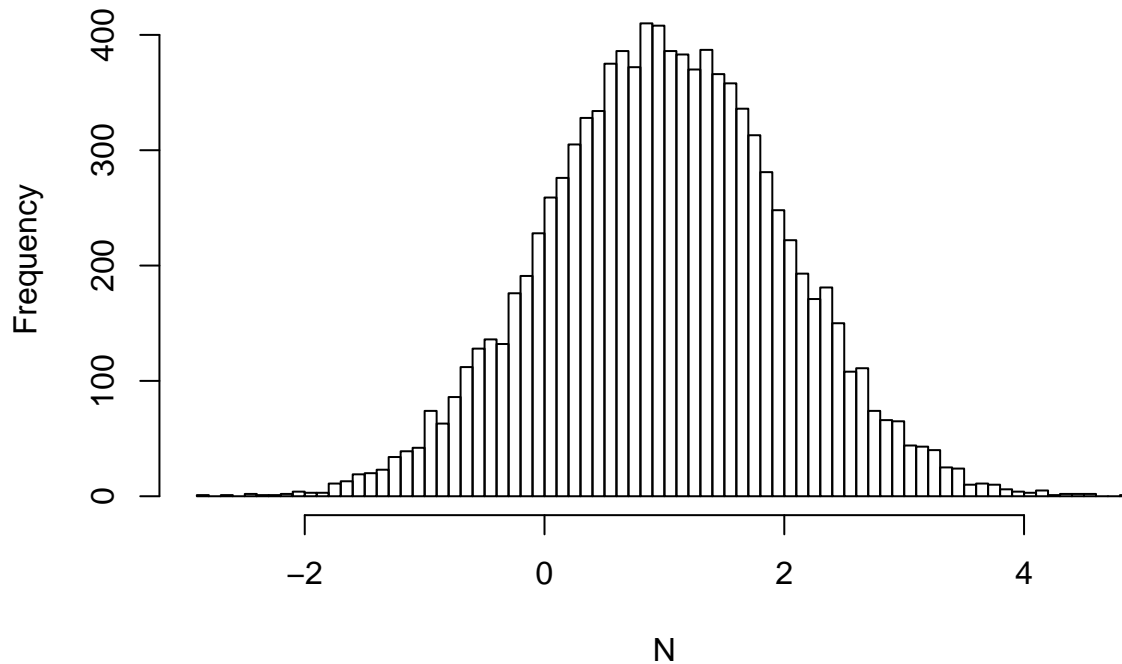
### Histogram for Exponential realizations



Above, we used the uniform realizations together with the quantile transform theorem to get exponential realizations. In the following chunk of R code, we use the same uniform realizations, but now they are transformed to normal realizations by using the inverse cdf of a normal distribution with mean  $\mu$  and variance  $\sigma^2$ .

```
#Transform the (same) uniform realizations to normal realizations  
mu=1  
sigma=1  
N=qnorm(U,mu,sigma)  
hist(N,100, main="Histogram for Normal realizations")
```

## Histogram for Normal realizations



## Simulation of comonotonic random vectors

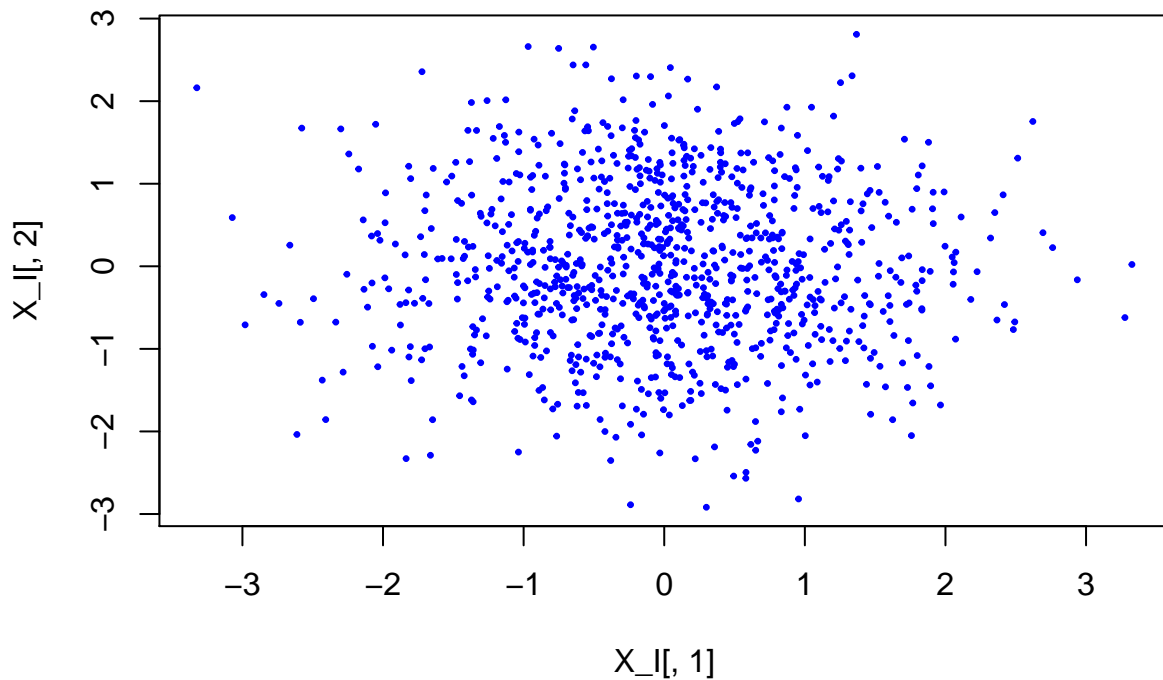
We start by showing how to simulate independent normal realizations. We assume that  $X_1$  and  $X_2$  are normally distributed:

$$X_i \stackrel{d}{=} N(\mu_i, \sigma_i), \text{ for } i = 1, 2.$$

The independent modification of  $(X_1, X_2)$  is denoted by  $(X_1^I, X_2^I)$  and  $X_i^I \stackrel{d}{=} X_i$ , for  $i = 1, 2$ . Realizations from  $(X_1^I, X_2^I)$  can be obtained by applying the quantile transform theorem twice, to get independently realizations from  $X_1^I$  and then from  $X_2^I$ . The code is illustrated below.

```
n=2
NSim=1000
mu=c(0,0)
sigma=c(1,1)
U1=runif(NSim)
U2=runif(NSim)
X_I=matrix(1,NSim,2)
X_I[,1]=mu+sigma*qnorm(U1)
X_I[,2]=mu+sigma*qnorm(U2)
plot(X_I[,1],X_I[,2],pch=20, col="blue",cex=0.5, main="Independent Realizations")
```

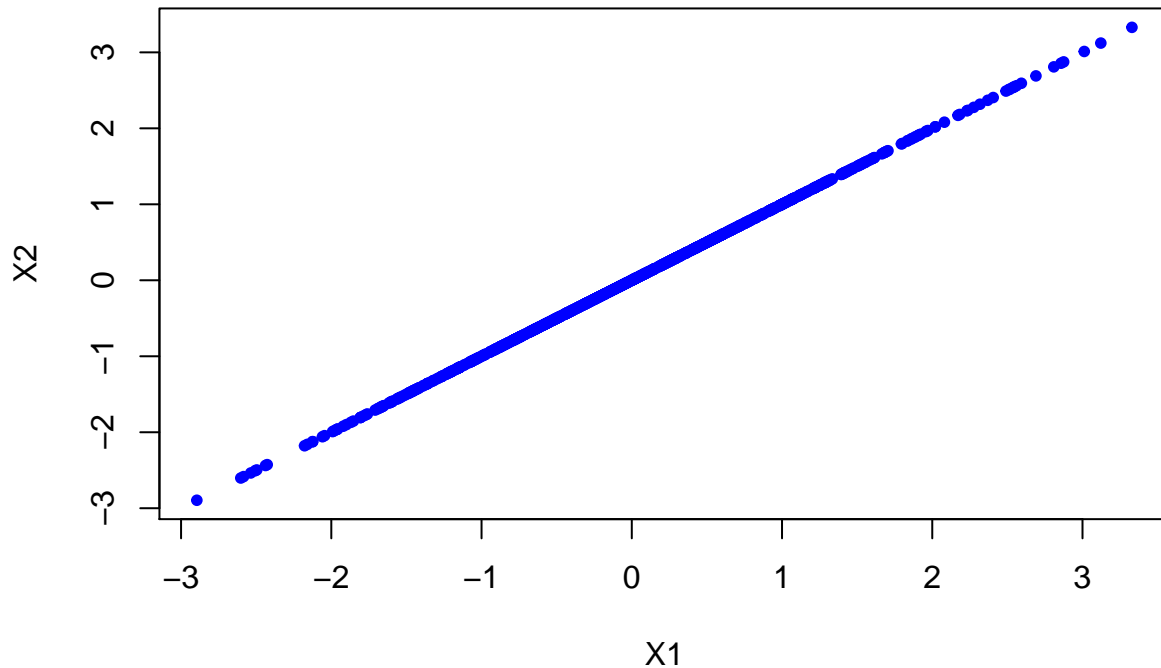
## Independent Realizations



The comonotonic modification of  $(X_1, X_2)$  is denoted by  $(X_1^c, X_2^c)$ . This comonotonic modification has the same marginals as  $(X_1, X_2)$  but a comonotonic dependence structure. Then, simulating from the comonotonic modification can be done by using the quantile transform theorem. However, when applying the quantile transform theorem to generate realizations for  $X_1^c$  and  $X_2^c$ , we have to use the *same uniform numbers*.

```
# Comonotonic random vector
U=runif(NSim)
X=rep(1,1,NSim)%o%mu+qnorm(U)%o%sigma
plot(X[,1],X[,2],pch=20, col="blue", main="Comonotonic Realizations", xlab="X1", ylab="X2")
```

## Comonotonic Realizations



Assume the random vector  $(X_1, X_2)$  has marginals given by:

$$X_1 \stackrel{d}{=} \text{Exp}(\lambda),$$

and

$$X_2 \stackrel{d}{=} N(0, 1).$$

Then we can then simulate from the comonotonic modification by changing the inverse cdfs in the R Code.

```
# Exponential/normal marginals and comonotonic dependence
lambda=1
U=runif(NSim)
E=-(1/lambda)*log(1-U) # Inverse cdf of an exponential distribution applied in U
X=qnorm(U) # Inverse cdf of a standard normal distribution applied in U
plot(E,X,pch=20, col="blue", main="Comonotonic Realizations")
```

## Comonotonic Realizations

