# Lab3

## Cui Qingxuan, Nisal Amashan

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1	Collaborations	
Ni	sal Amashan: Responsible for the question 1.	
Сι	ui Qingxuan: Responsible for the question 2.	
<b>2</b>	Question 1	
3	Question 2	
3.	1 Generate a Random Vector using the 2 Methods	
3.	1.1 Box-Muller Method	
M	easure the time for generating 10 000 000 numbers:	
## ##	•	

#### 3.1.2 Package mytnorm

#### The reason I use it:

For generating correlated multivariate normal vectors at scale, mytnorm provides a streamlined, efficient, and statistically rigorous solution. It eliminates manual matrix operations, ensures correctness, and scales effortlessly to large datasets—making it the optimal choice for this task.

#### Measure the time for generating 10 000 000 numbers:

```
## user system elapsed
## 1.08 0.32 1.53
```

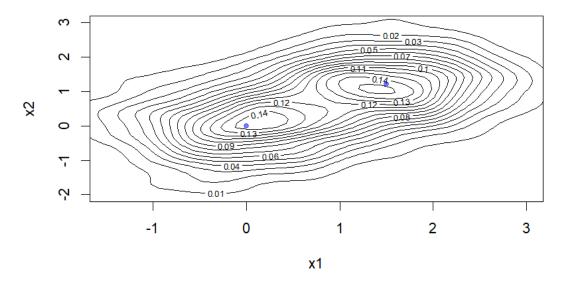
#### 3.1.3 Compare the Time of 2 Methods

Box-Muller method takes roughly 50% more time than mynorm package to generate a random variable.

#### 3.2 Generate the Random Vectors from 2 Distributions

#### 3.2.1 Plot the Random Variables

### **Bivariate Normal Distribution Contour Map**



#### 3.2.2 Discussion

#### It looks satisfactory.

Based on the contour map, we can see the contour lines in the graph are inclined ellipses, and the interval between contour lines becomes progressively wider as the height increases, and is symmetrical about the mean point (the blue point), which in summary is consistent with the properties of a Bivariate Normal Distribution image.

### 4 Appendix

```
normRVgen = function(n, mu, sigma){
  # create 2 rv vector uniformly distribute
  # u1 represents R
  # u2 represents angle
  u1 = runif(n, min=0, max=1)
  u2 = 2*pi*runif(n, min=0, max=1)
  # Generate X=[x1, x2] \sim N(0,1)
  x1 = sqrt(-2*log(u1))*cos(u2)
  x2 = sqrt(-2*log(u1))*sin(u2)
  x = rbind(x1, x2)
  # Transform to Z via Z = A.T @ X + mu
  # Cholesky Decomposition -> get A from Sigma = A.T@A
  At = t(chol(sigma))
 Z = At %*% x + mu
 return (Z)
}
n = 1000
mu = c(0,0)
sigma = matrix(c(0.6,0,0,0.6), nrow=2)
start = proc.time()
rv = normRVgen(n,mu,sigma)
end = proc.time()
print(end - start)
library(mvtnorm)
start = proc.time()
rv_buildin <- rmvnorm(n, mean = mu, sigma = sigma)</pre>
end = proc.time()
print(end-start)
# Generate 500 values for each distribution
n = 500
rv_d1 = normRVgen(n, mu, sigma)
mu_d2 = c(1.5, 1.2)
sigma_d2 = matrix(c(0.5,0,0,0.5), nrow=2)
rv_d2 = normRVgen(n, mu_d2, sigma_d2)
# Bind them and shuffle
rv_mix = as.data.frame(t(cbind(rv_d1, rv_d2)))
set.seed(123)
rv_shuffled = rv_mix[sample(nrow(rv_mix)), ]
colnames(rv_shuffled) = c("x1", "x2")
# Generate 500 values for each distribution
n = 500
rv_d1 = normRVgen(n, mu, sigma)
mu_d2 = c(1.5, 1.2)
```

```
sigma_d2 = matrix(c(0.5,0,0,0.5), nrow=2)
rv_d2 = normRVgen(n, mu_d2, sigma_d2)
# Bind them and shuffle
rv_mix = as.data.frame(t(cbind(rv_d1, rv_d2)))
set.seed(123)
rv_shuffled = rv_mix[sample(nrow(rv_mix)), ]
colnames(rv_shuffled) = c("x1", "x2")

# Plot the Function
library(MASS)
z <- kde2d(rv_shuffled$x1, rv_shuffled$x2, n = 50)
contour(z, xlab = "x1", ylab = "x2", main = "Binary Normal Distribution Contour Map")
# points(rv_shuffled$x1, rv_shuffled$x2, col = rgb(0, 0, 1, 0.5), pch = 19,cex = 0.3)</pre>
```