# Estimation theory – Laboratory 1.

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#### 1 Exercise 1

We generate a vector of  $Y \sim N(\mu = 2, \sigma^2 = 4)$  with length N = 1000:

```
Y <- rnorm(n = 1000, mean = 2, sd = 2)
# transform Y to Y1
Y1 <- 3 * (Y - 1)
```

 $Y_1$  has normal distribution, because it is a linear combination of Y. We can calculate analytical mean  $\mu_1$  and variance  $\sigma_1^2$ :

$$\mu_1 = E(Y_1) = E(3(Y - 1)) = 3E(Y - 1) = 3E(Y) - 3 = 3 \cdot 2 - 3 = 3$$

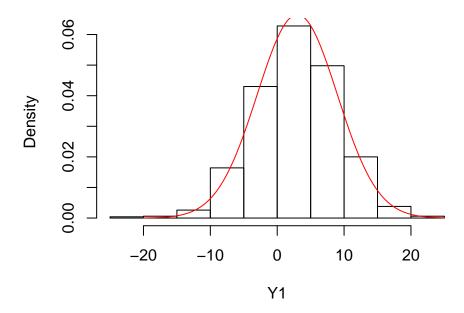
$$\sigma_1^2 = Var(Y_1) = Var(3(Y - 1)) = 9Var(Y) = 9 \cdot 4 = 36$$

We can compare numerical and analytical results:

```
Y <- rnorm(n = 1000, mean = 2, sd = 2)
Y1 <- 3 * (Y - 1)
mean(Y1)
## [1] 3.047471
var(Y1)
## [1] 34.70353
```

Now we can plot the frequency historam of  $Y_1$  and analytical normal density with  $\mu = 3$  and  $\sigma^2 = 36$ .

# Histogram of Y1



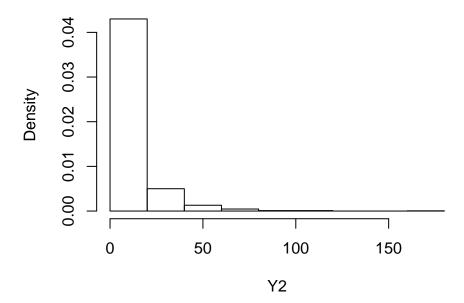
Next, we create variable  $Y_2$ 

$$Y_2 = \left(\frac{Y_1 - 2}{2}\right)^2$$

and plot its frequency historam.

```
Y <- rnorm(n = 1000, mean = 2, sd = 2)
Y1 <- 3 * (Y - 1)
Y2 <- ((Y1 - 2) / 2) ^ 2
hist(Y2, freq = FALSE)
```

#### **Histogram of Y2**



 $Y_2$  is a quadratic function of  $Y_1$ , so we know that distribution of  $Y_2$  is not normal. From the shape histogram we can assume that  $Y_2$  has exponential distribution with

$$\lambda = \frac{1}{E(Y_2)}.$$

We can obtain the analytical value of  $E(Y_2)$  in the following way

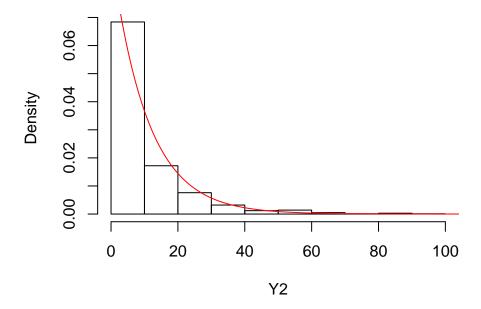
$$E(Y_2) = E\left(\left(\frac{Y_1 - 2}{2}\right)^2\right) = \frac{1}{4}E(Y_1 - 2)^2 = \frac{1}{4}E(Y_1^2 - 2Y_1 + 4) =$$

$$= \frac{1}{4}EY_1^2 - \frac{1}{2}EY_1 + 1 = \frac{1}{4}\left(VarY_1 + (EY_1)^2\right) - \frac{1}{2}EY_1 + 1 =$$

$$= \frac{1}{4}(36 + 9) - \frac{3}{2} + 1 = 10.75,$$

so 
$$\lambda = \frac{1}{10.75} \approx 0.093$$
.

### Histogram of Y2

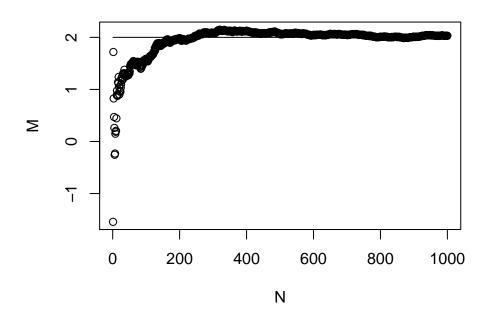


Next we will compute a sequence of means  $m_n$  and a sequence of variances  $\sigma_n^2$  for the variable Y, where

$$m_n = \frac{1}{n} \sum_{i=1}^n Y_i$$

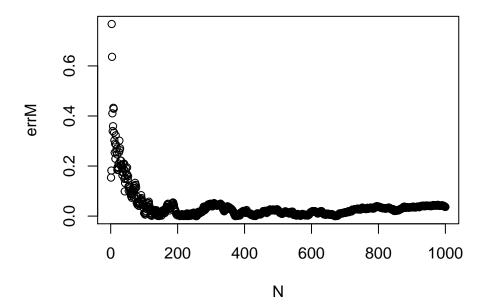
$$\sigma_n = \frac{1}{n} \sum_{i=1}^n (Y_i - m_n)^2$$

and plot the results.



The sequences  $m_n$  and  $\sigma_n^2$  converge to theoretical mean and variance, respectively. To examine the variability of the sequences we can calculate relative errors for both values.

$$err_{M_n} = \left| \frac{M_n - \mu_n}{\mu_n} \right|$$

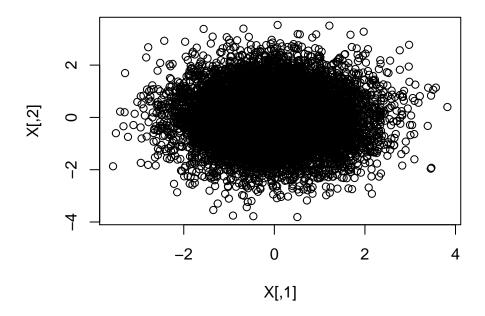


For N > 200 value of the error is less than 10% of theoretical mean.

#### 2 Exercise 2

We simulate 10000 times and then plot 2-dimensional random variable  $X \sim N(0, I_2)$ .

```
n <- 10000
mu <- c(0, 0)
Sigma <- diag(2)
X <- rmvnorm(n = n, mean = mu, sigma = Sigma)
plot(X)</pre>
```



We have to transform variable X into variable  $Y \sim N(\mu, \Sigma)$ , where

$$\mu = [0, 1]$$
 and  $\Sigma = \begin{bmatrix} 2 & 0.5 \\ 0.5 & 2 \end{bmatrix}$ 

It means that we should find vector a and matrix A, such that Y = AX + a. Expected value of Y is equal to

$$E(Y) = E(AX + a) = AE(X) + a = a,$$

and variance

$$Var(Y) = Var(AX + a) = Var(AX) = AVar(X)A' = AIA' = AA' = \Sigma = \Sigma^{0.5} \left(\Sigma^{0.5}\right)'.$$

From that we obtain  $A = \Sigma^{0.5}$ , so

$$Y = \Sigma^{0.5} X + \mu.$$

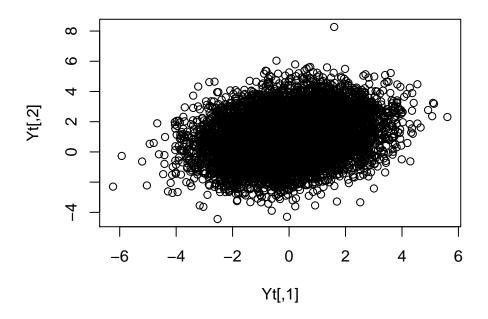
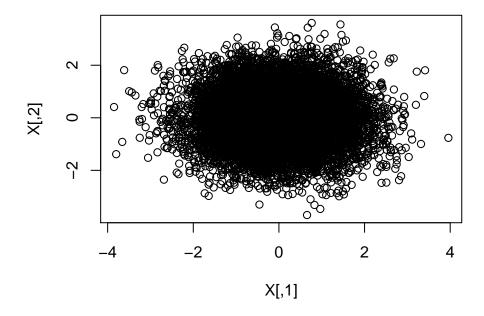


Figure 1: Random variable Y

```
## Error in eval(expr, envir, enclos): could not find function "hist3D"
```

```
n <- 10000
mu <- c(0, 0)
Sigma <- diag(2)
X <- rmvnorm(n = n, mean = mu, sigma = Sigma)
plot(X)</pre>
```



# 3 Exercise 3

When using additional source materials (books, links, etc.) do not forget to include appropriate references. For example, let us assume we want to cite Dalgard (2008). Then the bibliography section should contain:

# References

[1] Peter Dalgaard, Introductory Statistics with R, Springer-Verlag New York, 2008.