

# Simulation - Course Project - Part I

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## Requirements

Library ggplot2 is required.

```
library(ggplot2)
```

## Overview

In this report samples from a given exponential distribution with mean  $1/\lambda$  and standard deviation  $1/\lambda$  are taken in order to show the behaviour of the sample mean, the sample variance and their respective distribution.  $\lambda$  is 0.2 for the given exponential distribution. The sample mean and variance are also compared to the theoretical mean and theoretical variance.

## Exponential Distribution

The given exponential distribution has the following properties:

$$\text{Mean} = 1/\lambda$$

$$\text{Standard Deviation} = 1/\lambda$$

$$\text{with } \lambda = 0.2$$

## Simulation

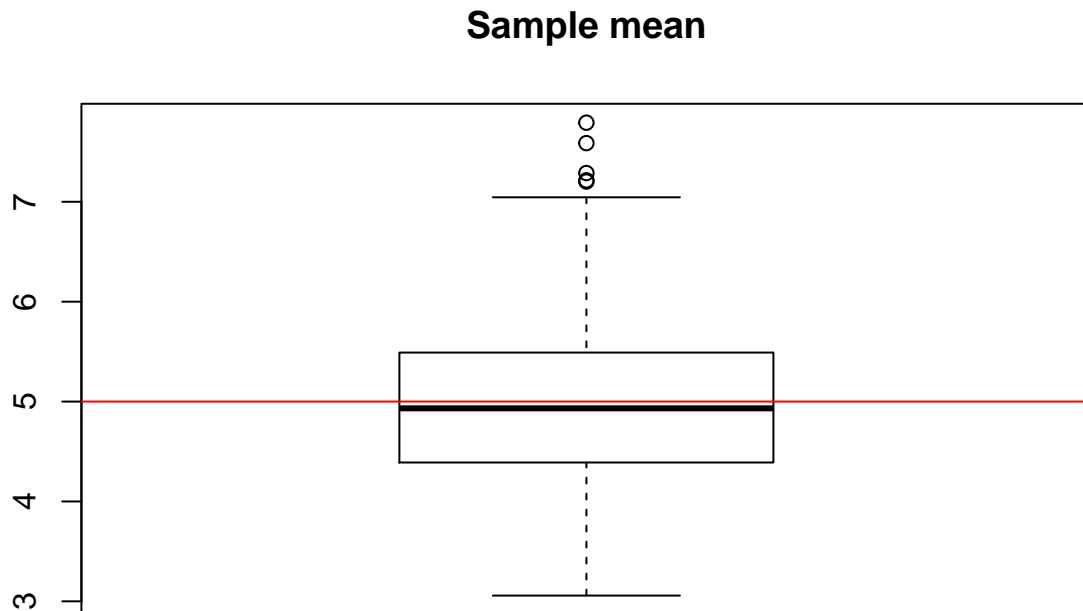
1000 simulations are run with 40 samples each. The function `rexp` is used to create the simulation of an exponential distribution using a  $\lambda$  value of 0.2. Each simulation is stored in a column of the matrix `data`.

```
numberSimulation <- 1000
numberSample <- 40
lambda <- 0.2
data <- matrix(rexp(numberSample * numberSimulation, lambda), numberSample)
```

## Sample Mean versus Theoretical Mean

In this section the sample mean of the simulation is shown and compared to the theoretical mean. The theoretical mean is equal to  $1/\lambda = 5$ . The barplot shows that the sample mean is very near to this value (marked with red line) which is confirmed by the summary calculation for the simulations

```
df <- data.frame(x=apply(data,2,mean))
boxplot(df$x,main="Sample mean")
abline(h = 1/lambda, col = "red")
```



```
summary(df)
```

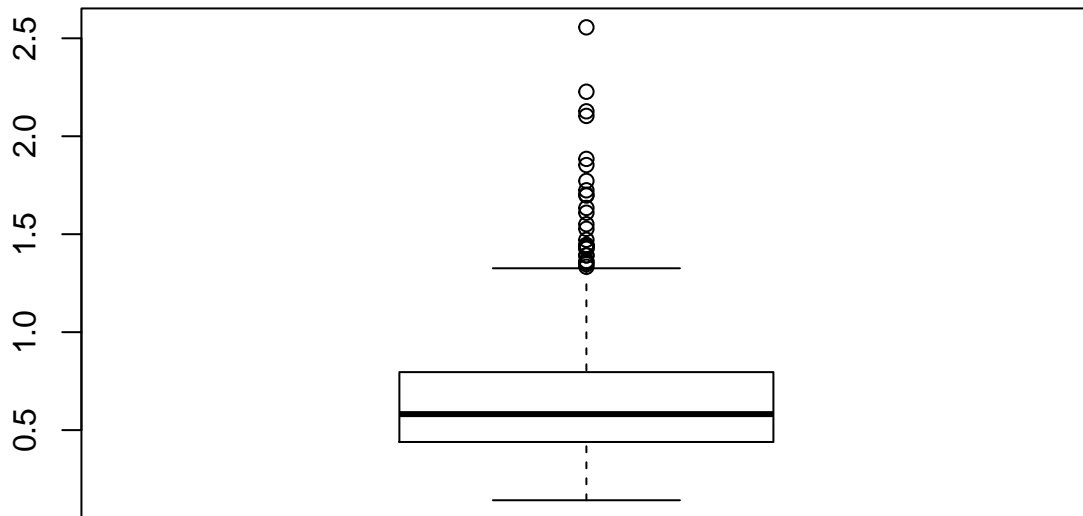
```
##          x
##  Min.   :3.058
## 1st Qu.:4.390
##  Median :4.932
##   Mean  :4.976
## 3rd Qu.:5.491
##   Max.   :7.792
```

## Sample Variance versus Theoretical Variance

The theoretical variance is given with  $1/\lambda^2$ . The sample variance is given by  $\sigma^2/(n-1)$ . As stated in the central limit theorem the variance should converge to the sample mean which is shown in the boxplot and summary statistics

```
df <- data.frame(x=apply(data,2,function(x) sd(x)^2/(numberSample-1)))
boxplot(df$x,main="Sample variance")
```

## Sample variance



```
summary(df)
```

```
##           x
##  Min.    :0.1420
## 1st Qu.:0.4394
##  Median :0.5817
##   Mean  :0.6446
## 3rd Qu.:0.7955
##   Max.   :2.5559
```

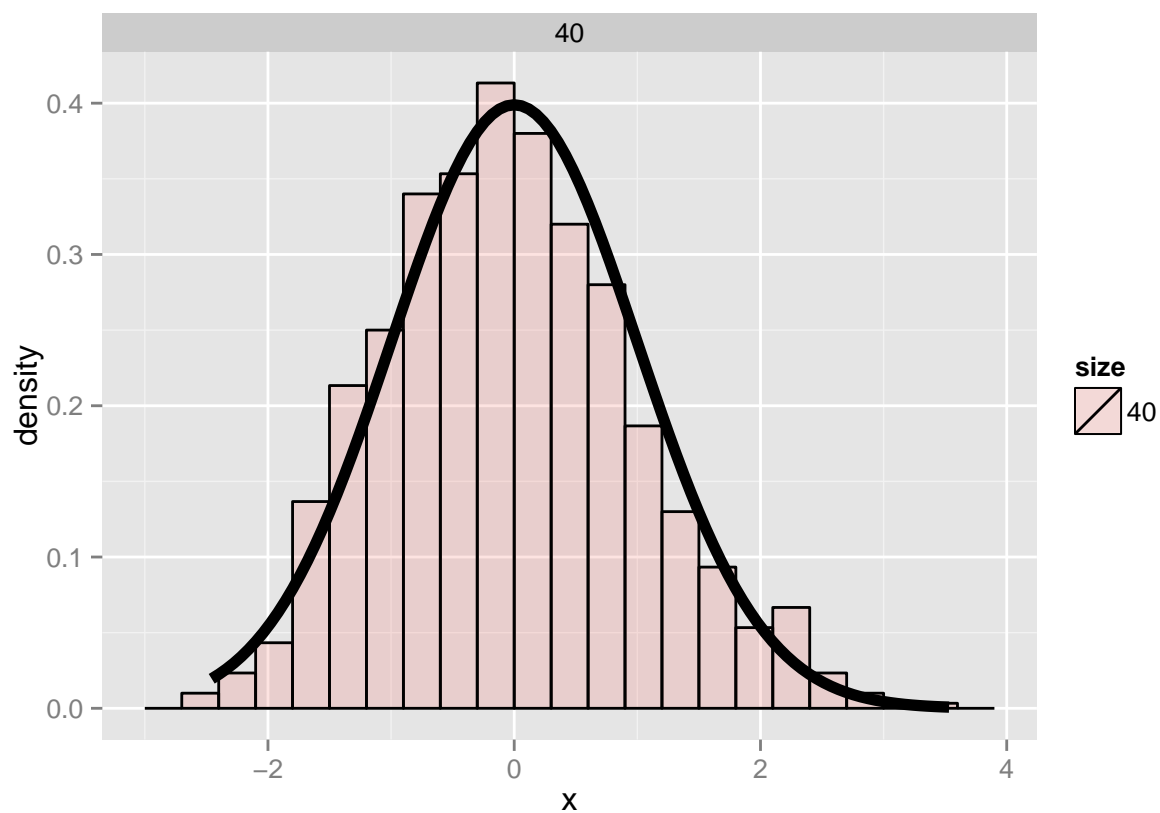
## Distribution

Based on the central limit theorem we would expect that the sample means are distributed normally. The result is that

$$\frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} = \frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} = \frac{\text{Estimate} - \text{Mean of estimate}}{\text{Std. Err. of estimate}}$$

has a distribution like that of a standard normal for large  $n$ . As shown in the diagram.

```
cfunc <- function(x, n) (sqrt(n) * (mean(x) - (1/lambda))) / (1/lambda)
dat <- data.frame(x = apply(data, 2, cfunc, 40), size = factor(rep(c(40), rep(numberSimulation, 1))))
g <- ggplot(dat, aes(x = x, fill = size)) + geom_histogram(alpha = .20, binwidth=.3, colour = "black",
g <- g + stat_function(fun = dnorm, size = 2)
g + facet_grid(. ~ size)
```



## Sources

Caffo, B. 2014. [https://github.com/bcaffo/courses/blob/master/06\\_StatisticalInference/07\\_Asymptopia/index.Rmd](https://github.com/bcaffo/courses/blob/master/06_StatisticalInference/07_Asymptopia/index.Rmd)