

Notebook for Statistical Inference Course Project 01

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PACKAGE LOADING

```
library(tidyverse)
library(ggpubr)
library(datasets)
set.seed(123456)
```

PART 01: SIMULATION EXERCISE

1.1 OVERVIEW

This report is related to course project (week 04) for Johns Hopkins Coursera Statistical Inference classes. The main object is to study the Exponential Distribution e compare it with the Central Limit Theorem.

1.2 SIMULATIONS

Below it is possible to find the code and results to simulate 1000 exponentials, all having sample size if 40 and lambda of 0.2. The result was saved at **exponentials** variable.

```
lambda <- 0.2
n <- 40 # samples for each distribution
N <- 1000 # totals of distribution
exponentials <- replicate(N, rexp(n, lambda))
```

1.3 SAMPLE MEAN VS THEORETICAL MEAN

For $\lambda = 0.2$, the exponential distributions has an theoretical mean of 5 ($1/\lambda$). To calculate the mean for all 1000 generated distributions, the *apply* function will be used.

```
sMean <- as.data.frame(apply(exponentials, 2, mean))
names(sMean) <- c("mean.exp")
summary(sMean)
```

```
##      mean.exp
## Min.      :2.527
## 1st Qu.:4.454
## Median :4.971
## Mean    :5.023
## 3rd Qu.:5.536
## Max.    :7.514
```

Comparing the sample mean of theoretical mean, they are pretty close (5.0229151 vs 5).

1.4 SAMPLE VARIANCE VS THEORETICAL VARIANCE

Using the same dataframe created at **exponentials** and the same method (*apply*), the variances for all 1000 distributions were calculated. The theoretical variance for this example is 25 ($(1/\lambda)^2$).

```
sVar <- as.data.frame(apply(exponentials, 2, var))
names(sVar) <- c("variance.exp")
summary(sVar)
```

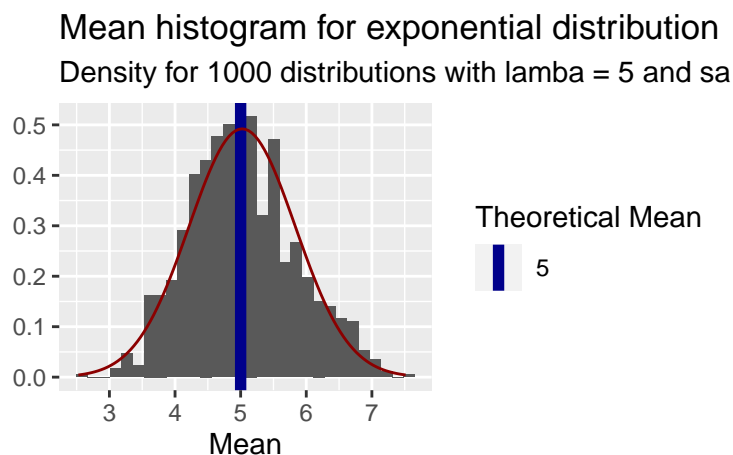
```
## variance.exp
## Min. : 6.518
## 1st Qu.:16.956
## Median :23.091
## Mean :25.242
## 3rd Qu.:30.176
## Max. :90.066
```

Comparing the sample variance with theoretical variance, they are pretty close either (25.2424913 vs 25).

1.5 DISTRIBUTION

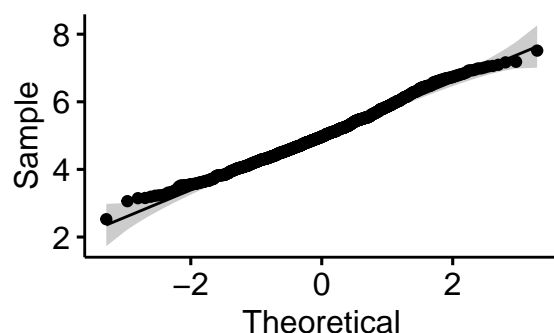
In this section, the normality of the data will be investigated. From Central Limit theorem, it is known that a distribution of means is always normal.

Sample Mean



Doing a graphical analysis, it seems that the distribution of the sample mean is practically normal. To make sure, it is necessary to run a normality test.

```
ggqqplot(sMean$mean.exp)
```



It is possible to see the data follows a normal distribution.

APPENDIX

Code for Exponential Means graphic

```
g <- ggplot(data = sMean, mapping = aes(x = mean.exp))
g + geom_histogram(aes(y = ..density..)) +
  labs (x = "Mean", y = " ", title = "Mean histogram for exponential distribution",
        subtitle = paste("Density for", N, "distributions with lambda =", 1/lambda, "and sample =",
                          N)) +
  geom_vline(aes(xintercept = 1/lambda, color = "darkblue"), size = 2) +
  scale_color_identity(guide = "legend", name = "Theoretical Mean", labels = 1/lambda) +
  stat_function(fun = dnorm, args = list(mean = mean(sMean$mean.exp), sd = sd(sMean$mean.exp)), color = "darkblue")
print("Don't run me")
```