

Statistics Assignment (Simulation)

Jayesh Gokhale

4/18/2021

Simulation Exercise for Central Limit Theorem

What we intend to do here is simulate 40 random numbers in an exponential distribution and get the means of such numbers. Repeat this experiment 1000 times and observe the distribution of means. This is called **sampling distribution of means**.

```
set.seed(100)
n <- 40
m <- 1000
lambda <- 0.2
sdom = NULL #sdom = sampling.distribution.of.means
for (i in 1 : m) sdom = c(sdom, mean(rexp(n,lambda)))

theoretical.mean <- 1/lambda
sample.mean <- mean(sdom)
diff.mean <- abs(sample.mean - theoretical.mean)
pc.diff.mean <- round(diff.mean*100/theoretical.mean,2)

population.variance <- (1/lambda)**2
theoretical.variance <- population.variance/(n)
sample.variance <- var(sdom)
diff.variance <- abs(sample.variance - theoretical.variance)
pc.diff.variance <- round(diff.variance*100/theoretical.variance,2)
```

Analysis of Means

Theoretical Mean of Distribution = Population Mean = $1/\text{Lambda} = 5$

Sample Mean = **4.9997019**

Difference (Absolute) = 2.9807313×10^{-4}

Percentage Difference (Absolute) = **0.01**

Analysis of Variance

Theoretical Variance of Distribution = (Population Variance)/n = $(1/\text{Lambda}^2)/n = 0.625$

Sample Variance = **0.6432442**

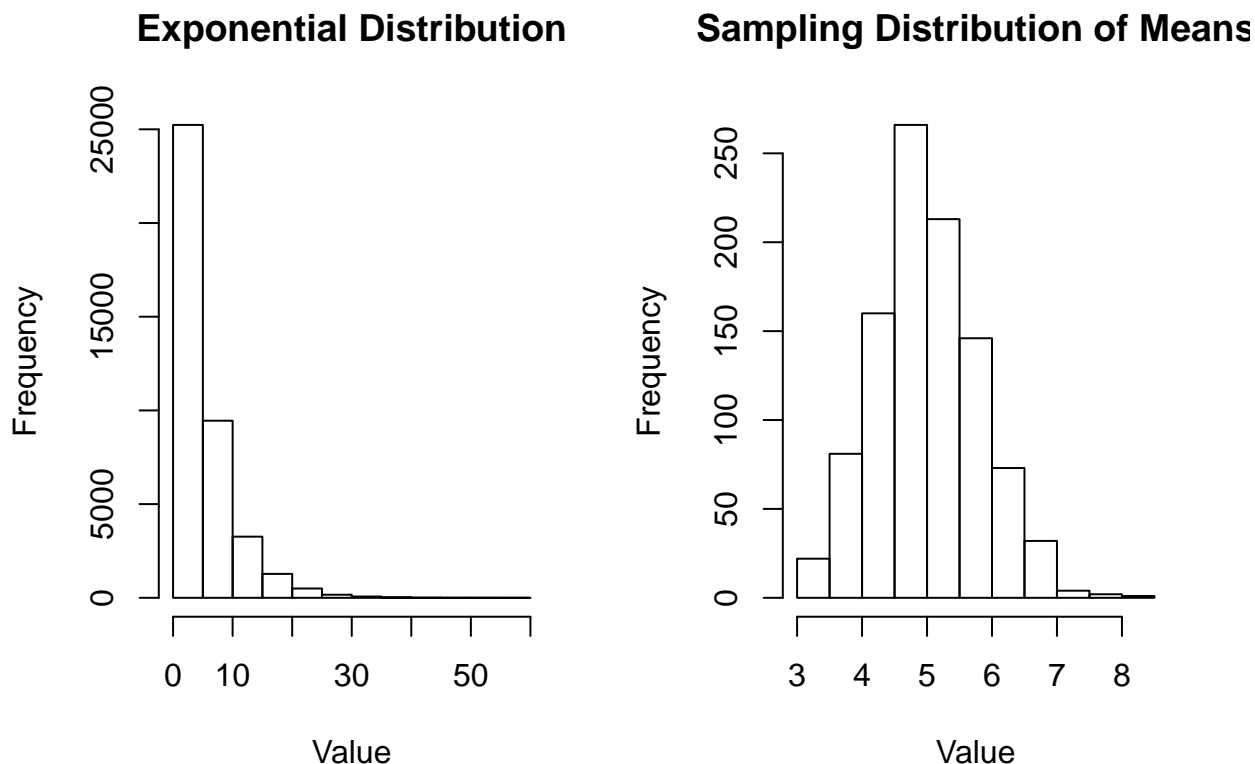
Difference (Absolute) = **0.0182442**

Percentage Difference (Absolute) = **2.92**

Analysis of Distribution

Now that we have the sampling distribution of means, let us create a histogram of it and compare it with a distribution of equivalent exponential distribution of population.

```
par(mfrow = c(1, 2))
hist(rexp(m*n,lambda),main="Exponential Distribution",xlab="Value")
hist(sdom,main="Sampling Distribution of Means",xlab="Value")
```



Now to me this right side figure looks like a Normal Distribution. But without going into any elaborate normality tests (like Anderson Darling Test), let us first do some basic checks. What we know for a fact that if the sampling distribution of means is normally distributed, it should follow the 68-95-99 rule. Let us test that out first.

```
sample.sd <- sd(sdom)
sdom.sd.1 <- sdom[(sdom >= (sample.mean - sample.sd)) & (sdom <= (sample.mean + sample.sd))]
sdom.sd.2 <- sdom[(sdom >= (sample.mean - 2 * sample.sd)) & (sdom <= (sample.mean + 2 * sample.sd))]
sdom.sd.3 <- sdom[(sdom >= (sample.mean - 3 * sample.sd)) & (sdom <= (sample.mean + 3 * sample.sd))]

fraction.sd.1 <- round(length(sdom.sd.1)*100/length(sdom),2)
fraction.sd.2 <- round(length(sdom.sd.2)*100/length(sdom),2)
fraction.sd.3 <- round(length(sdom.sd.3)*100/length(sdom),2)
```

The percentages of observations in plus/minus 1, 2 and 3 sigma range are **68**, **95.4** and **99.7**.

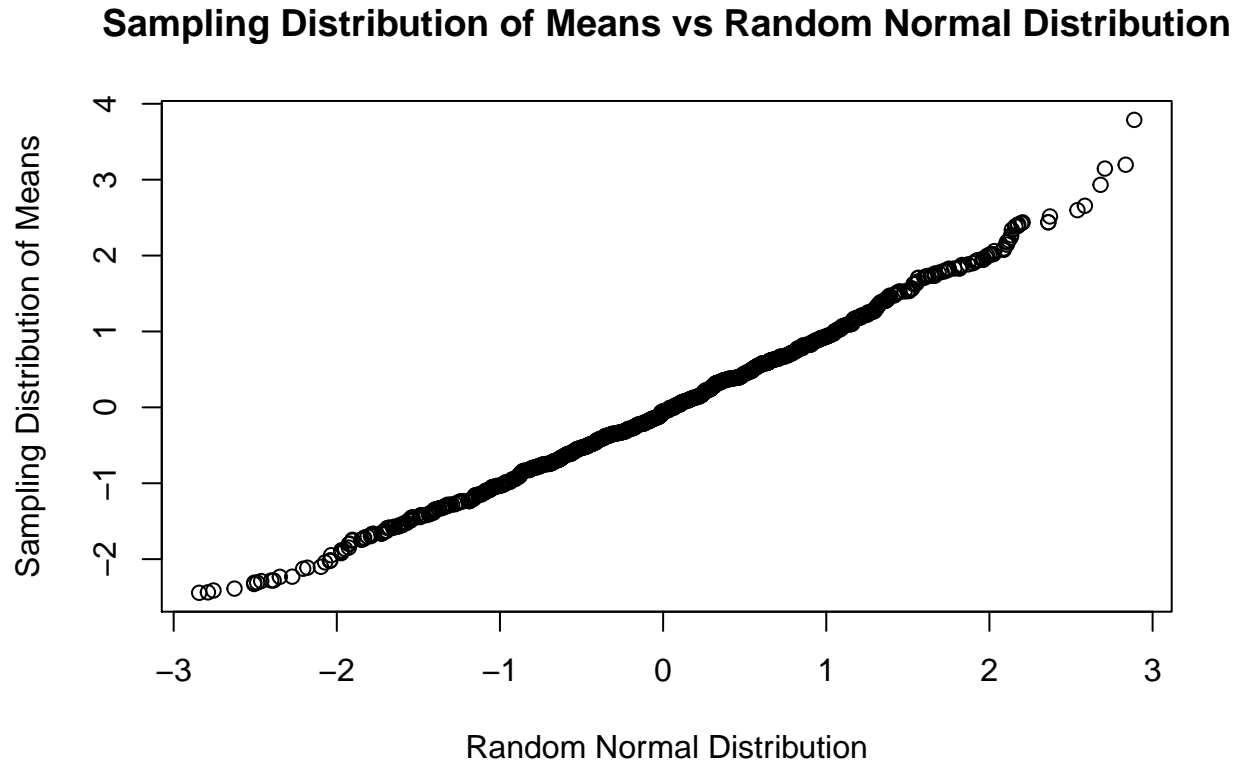
This seems to be very much in conformance to Normal Distribution. Let us do one more thing.

```
z.sdom <- (sdom - mean(sdom))/sd(sdom)
z.sdom <- sort(z.sdom)

x <- sort(rnorm(m))
```

What we have done here is scaled our distribution by subtracting the mean from it and dividing by standard deviation. For reference we take a standard normal distribution($\mu = 0$, $\sigma = 1$) of 1000 points. Now we plot with the reference standard normal distribution in X axis and our distribution (scaled). If that is close to a straight line, then we can safely conclude that our Distribution is Normal.

```
plot(x,z.sdom,main="Sampling Distribution of Means vs Random Normal Distribution",xlab="Random Normal D
```



This graph is self evident. We can see that Standard Normal Distribution and our Distribution (scaled) lie almost on one straight line.

We can hence safely conclude that the sampling distribution of 1000 means of 40 random exponentials is NORMAL