

# Exponential Distribution Simulation

Ash Chakraborty

Wednesday, June 17, 2015

## PART 1: SIMULATION - Sampling the Exponential Distribution

### Synopsis

Part 1 of this project investigates the *Exponential Distribution* and compares it to the *Central Limit Theorem*. The exponential distribution is given by the probability distribution function,  $P(x) = \lambda e^{-\lambda x}$ . We also know that it has a mean,  $\mu = 1/\lambda$ , and variance,  $\sigma^2 = 1/\lambda^2$ . This report will conduct an appropriate number of simulations on this distribution with a sample size of 40 exponentials by generating a sampling distribution of sample means. The consequences of this sampling distribution will be evaluated for adherence to the central limit theorem.

### Exponential Distribution

We are to work with a sample size,  $n = 40$  with a rate parameter,  $\lambda = 0.2$ . We first generate a sample of 40 random exponentials, and look at its central tendencies:

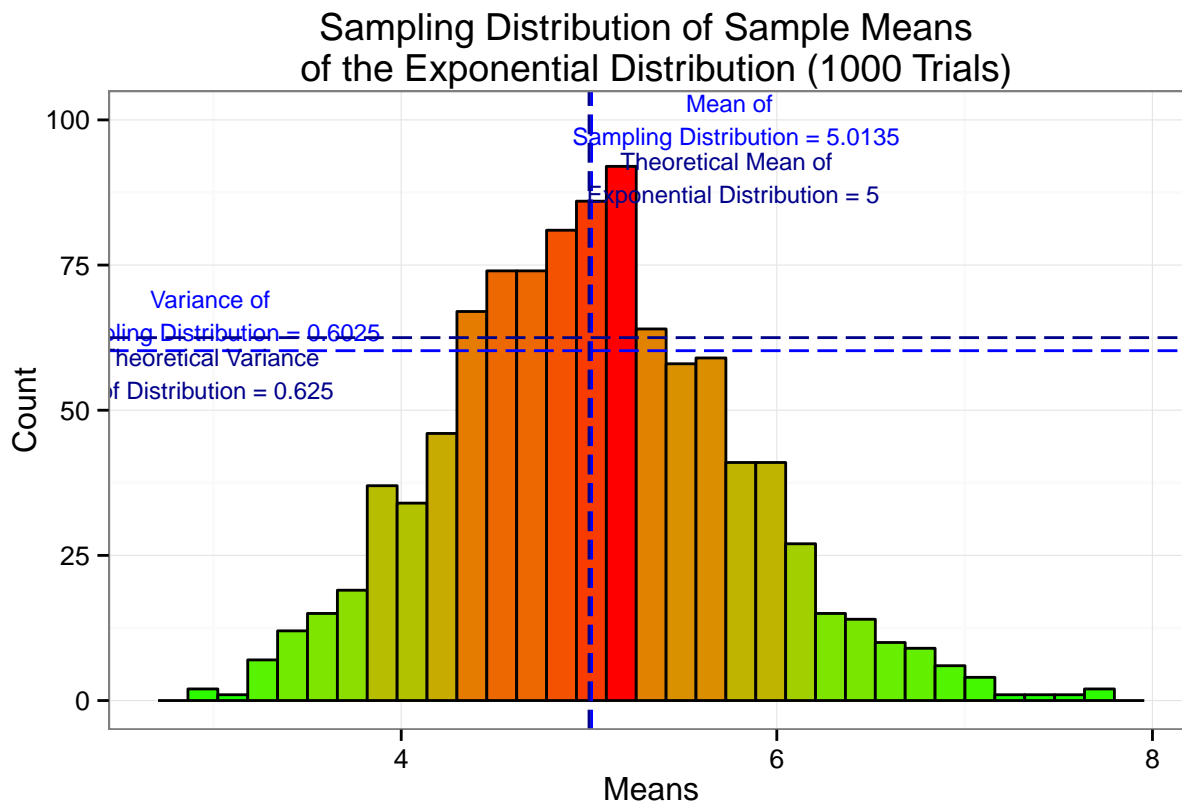
```
library(PerformanceAnalytics)
library(ggplot2)
library(gridExtra)
set.seed(123)
sample <- rexp(40, rate = 0.2)
```

### Simulating 1000 Trials

In order to understand the properties of the distribution of the mean of 40 exponentials, we conduct a 1000 simulations, and extract the mean of each sample:

```
samp.dist <- NULL
for(i in 1:1000){samp.dist <- c(samp.dist, mean(rexp(40, rate=0.2)))}
```

Now, we plot this sampling distribution:



The distribution of a 1000 means of 40 random exponentials has begun to resemble a Gaussian distribution.

### Comparing Theoretical Variance and Sample Mean

We continue to note from the earlier plot that the sampling distribution's mean and variance may be given by:

```
## [1] "Mean of Sampling Distribution: 5.0135"
```

```
## [1] "Variance of Distribution: 0.6025"
```

We noted earlier that the theoretical mean of the exponential distribution is given by  $1/\lambda$  ( $\lambda = 0.2$ ), which is equal to 5. When we compare this to sampling distribution's mean = 5.014, we see that it is a fairly good approximation.

Furthermore, the theoretical variance of the sampling distribution is given by the variance of the population mean/sample size, or  $(1/\lambda^2)/n$ , which = 0.625. Here, it seems that the variance obtained from the sampling distribution of 0.6025, is a fair approximation of the theoretical variance of the sampling distribution obtained from the population mean.

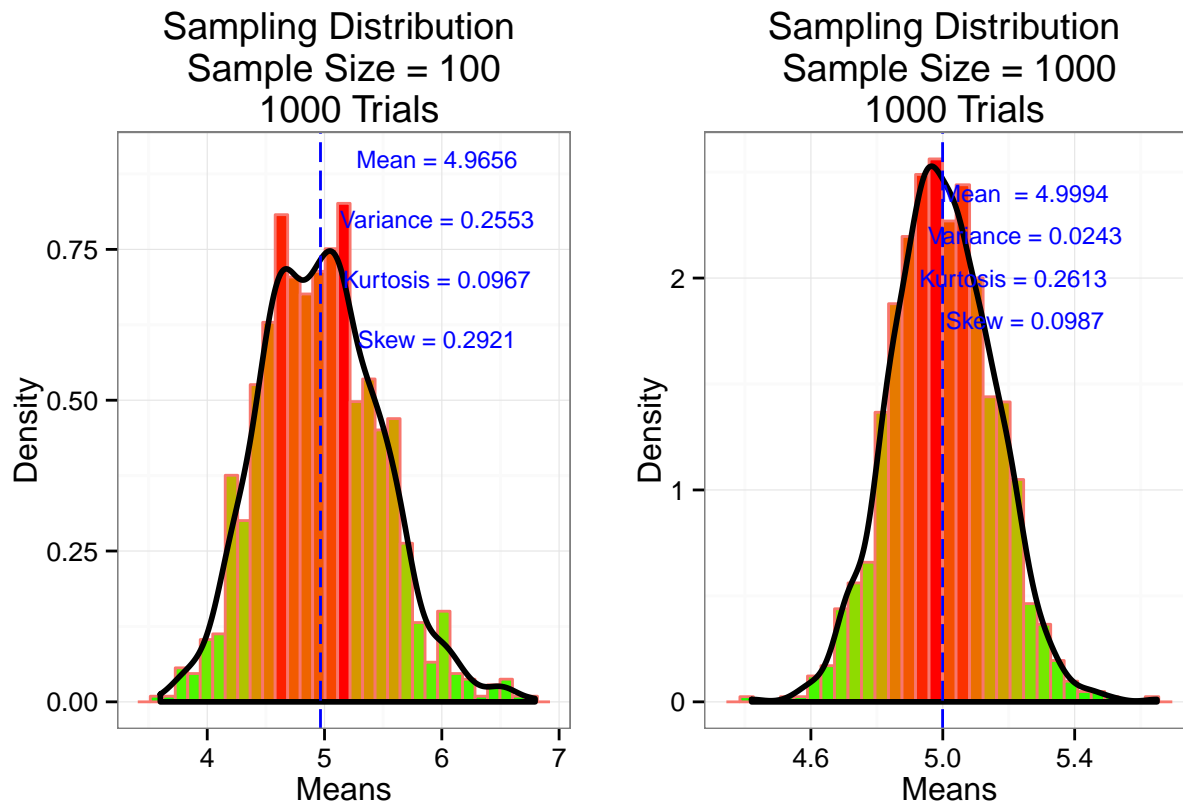
### Verifying Normality

In order to confirm that the sampling distribution obtained above is indeed normal, we will test a consequence of the central limit theorem, i.e. *as the sample size approaches infinity, the variation of the sampling*

distribution gets smaller and thus results in a closer approximation of the population mean. We will conduct two simulations with larger sample sizes,  $n = 100$  and  $n = 1000$ . We will conduct a 1000 trials and compute the variance and skew to give us an idea of the density curve.

```
#sim 1, sample size = 100
samp.dist1 <- NULL
for(i in 1:1000){samp.dist1 <- c(samp.dist1, mean(rexp(100, rate=0.2)))}

#sim 2, sample size=1000
samp.dist2 <- NULL
for(i in 1:1000){samp.dist2 <- c(samp.dist2, mean(rexp(1000, rate=0.2)))}
```



Consequently, we observe the following:

- The mean is approximated more closely as the sample size increases
- Variance of sampling distribution significantly decreases
- The skew of the density curve gets smaller

We can thus conclude that the sampling distribution of means of the exponential distribution approaches a normal distribution as the sample sizes increase.

**END OF PART 1**

## APPENDIX 1: GIT CODE

The entire markdown file can be found in this [github repo](#).

## APPENDIX 2: PLOT CODE

### Comparing Variance and Mean to Theoretical Variance and Mean

```
#sampling distribution of sample means
g3 <- ggplot()
g3+geom_histogram(aes(x=samp.dist, fill=..count..), col="black")+
  scale_fill_gradient("Count",
                      low = "green",
                      high = "red")+

#mean of sampling dist.
geom_vline(aes(xintercept=mean(samp.dist)),
           linetype="longdash",
           col="blue")+
geom_text(aes(x=mean(samp.dist)*1.15,
              y=100,
              label=paste0("Mean of \n Sampling Distribution = ",
                           round(mean(samp.dist), 4))
              ),
          col="blue", size=3
          )+

#theoretical mean
geom_vline(aes(xintercept=1/0.2),
           linetype="longdash",
           col="darkblue"
           )+
geom_text(aes(x=(1/0.2)*1.15,
              y=90,
              label=paste0("Theoretical Mean of \n Exponential Distribution = ",
                           round(1/0.2, 4))
              ),
          col="darkblue", size=3
          )+

#variance of sampling dist.
geom_hline(aes(yintercept=var(samp.dist)*100),
           linetype="longdash",
           col="blue"
           )+
geom_text(aes(y=var(samp.dist)*110,
              x=3,
              label=paste0("Variance of \n Sampling Distribution = ",
                           round(var(samp.dist), 4))
              ),
          col="blue", size=3
          )+
```

```

#theoretical variance = population variance/n
geom_hline(aes(yintercept=((1/(0.2^2))/40)*100),
            linetype="longdash",
            col="darkblue")+
geom_text(aes(y=((1/(0.2^2))/40)*90,
            x=3,
            label=paste0("Theoretical Variance \n of Distribution = ",
                        round(((1/(0.2^2))/40), 4))
            ),
            col="darkblue", size=3
        )+
labs(title="Sampling Distribution of Sample Means \n of the Exponential Distribution (1000 Trials)",
     x="Means", y="Count")+
theme_bw()+
theme(legend.position="none")

```

## Verifying Normality

```

# PLOT SIM 1
g4 <- ggplot() + geom_histogram(aes(x=samp.dist1, y=..density.., fill=..count.., col="black"))+
  scale_fill_gradient("Count", low = "green", high = "red")+
  geom_density(aes(samp.dist1), col="black", size=1)+
  #mean of sampling dist.
  geom_vline(aes(xintercept=mean(samp.dist1)),linetype="longdash", col="blue")+
  geom_text(aes(x=mean(samp.dist1)*1.2, y=.9,label=paste0("Mean = ",
                round(mean(samp.dist1), 4))), col="blue", size=3)+
  #variance of sampling dist.
  geom_text(aes(y=.8, x=mean(samp.dist1)*1.2,
                label=paste0("Variance = ", round(var(samp.dist1), 4))), col="blue", size=3)+
  #kurtosis
  geom_text(aes(y=.7,x=mean(samp.dist1)*1.2,
                label=paste0("Kurtosis = ", round(kurtosis(samp.dist1), 4))),col="blue", size=3)+
  #skew
  geom_text(aes(y=.6,x=mean(samp.dist1)*1.2,
                label=paste0("Skew = ", round(skewness(samp.dist1), 4))),col="blue", size=3)+
  labs(title="Sampling Distribution \n Sample Size = 100 \n 1000 Trials",x="Means", y="Density")+

# PLOT SIM 2
g5 <- ggplot() + geom_histogram(aes(x=samp.dist2, y=..density.., fill=..count.., col="black"))+scale_fill_gradient("Count", low = "green", high = "red")+
  geom_density(aes(samp.dist2), col="black", size=1)+
  #mean of sampling dist.
  geom_vline(aes(xintercept=mean(samp.dist2)),linetype="longdash", col="blue")+
  geom_text(aes(x=mean(samp.dist2)*1.05, y=.9+1.5,
                label=paste0("Mean = ",round(mean(samp.dist2), 4))), col="blue", size=3)+
  #variance of sampling dist.
  geom_text(aes(y=.8+1.4, x=mean(samp.dist2)*1.05,
                label=paste0("Variance = ", round(var(samp.dist2), 4))), col="blue", size=3)+
  #kurtosis
  geom_text(aes(y=.7+1.3,x=mean(samp.dist1)*1.05,
                label=paste0("Kurtosis = ", round(kurtosis(samp.dist2), 4))),col="blue", size=3)+
  #skew

```

```

geom_text(aes(y=.6+1.2,x=mean(samp.dist2)*1.05,
              label=paste0("Skew = ", round(skewness(samp.dist2), 4))),col="blue", size=3)+
labs(title="Sampling Distribution \n Sample Size = 1000 \n 1000 Trials",
      x="Means", y="Density")+theme_bw()+theme(legend.position="none")
grid.arrange(g4, g5, ncol=2)

```