Statistical Inference Assignment - Part 1

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Synopsis

In this assigment we are going to verify if the postulates of the Central Limit Theorem (CLT) stand for an exponential distribution density. That is, as we obtain a higher **N** of random samples from an an Exponention distribution, the distribution of the mean of each of these N random sampless will approximate a Normal distribution (regardless of the fact that the samples are obtained from an exponential distribution density).

We will also try to prove another of the CLT postulates: that the average of the sample means will be the population mean. In other words, we add up the means from all of the samples, find the average —-> and that average will be your actual population mean. The same can be applied for finding the standard deviation of your population (distribution, in this case)

Basic Facts

EXPONENTIAL distribution parameters

Mean = $1/\lambda$
λ (lambda) = rate parameter for the distribution St. dev. = $1/\lambda$

We will work with an exponential distribution that has λ = 0.2 Therefore, the mean of this particular distribution is 0.5 (1/0.5)

Simulation

We will simulate obtaining 1000 samples from an exponential distribution with λ=0.2, each of size 40 (n=40). So here we go:

```r
averages <- NULL

for (i in 1:1000)
{
  averages <- c(averages, mean(rexp(40, 0.2)))
}

head(averages)
```

```
## [1] 4.298304 4.770915 5.559593 4.620831 4.935799 5.865961
```

The average of the 1000 sample means is This is almost identical to the theoretical mean for an exponential distribution with $\lambda = 0.2$

Our original standard deviation is the same as the mean, 1 / lambda, so we just have to square it to get the variance for the exponential distribution with $\lambda = 0.2$:

```r
theoreticalVariance <- (1/0.2)^2 / 40
print(theoreticalVariance)
```

```
## [1] 0.625
```

If we then calculate the variance of our own sampling data, we get a close approximation:

```r
print(var(averages))
```

```
## [1] 0.5904568
```