# **Exponential Distribution Simulation; Tooth Growth Analysis**

Ash Chakraborty

Wednesday, June 17, 2015

# **PART 1: SIMULATION - Sampling the Exponential Distribution**

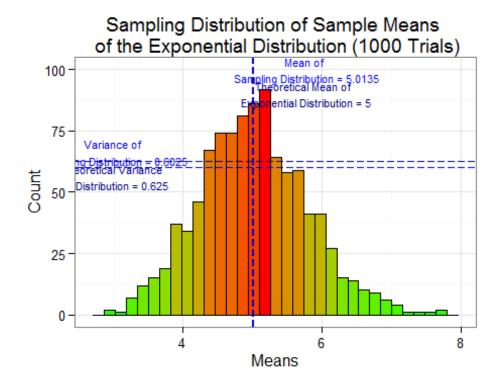
Part 1 of this report investigates the *Exponential Distribution* and compares it to the *Central Limit Theorem*. We conduct simulations on this distribution with a sample size of 40 exponentials by generating a sampling distribution of sample means. The consequences of this sampling distribution will be evaluated for adherence to the central limit theorem.

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

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)))}</pre>
```

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



The distribution has begun to resemble a Gaussian distribution.

```
## [1] "Mean of Sampling Distribution: 5.0135"
## [1] "Variance of Distribution: 0.6025"
```

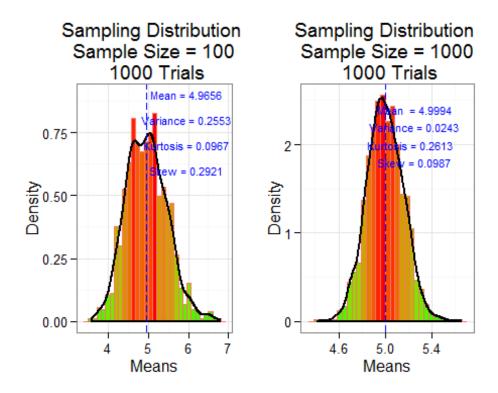
The theoretical mean of the exponential distribution is given by  $1/\lambda$  ( $\lambda = 0.2$ ) = 5. **The sampling distribution's mean is a fairly good approximation**. The theoretical variance of the sampling distribution:  $(1/\lambda^2)/n = 0.625$ . **The variance obtained from the sampling distribution is a good approximation**.

## **Verifying Distribution Normality**

We will conduct two simulations with larger sample sizes (n= 100 & 1000), conduct a 1000 trials and compute the *variance* and *skew* :

```
#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)))}</pre>
```

Plotting the resulting sampling distributions side by side:



- The mean is approximated more closely as the sample size increases (in line with CLT)
- Variance of sampling distribution significantly decreases (in line with CLT)

• The skew of the density curve get smaller, suggesting a normal curve

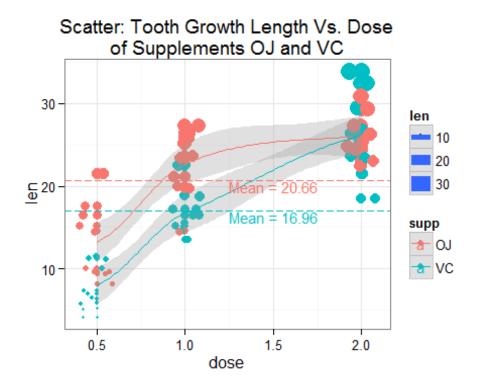
#### **END OF PART 1**

#### **PART 2: Analyzing Tooth Growth Data**

We run some summary analysis on this dataset, in addition to testing hypotheses to extract any relationships between supplement, dosage, and tooth length.

#### **Data Summary**

The scatter below shows the dataset spread out into groups by supplement and dosage:



- There is a positive correlation between length and dosage amount 0.5 and 1.0 for both supplements.
- There is *no data* for either supplement at dosage amount 1.5.
- Any effect on length at dosage amount of 2.0 for either supplement is unclear.
- Overall, the average sample tooth growth length is greater for "OJ" than it is for "VC".

## **Hypothesis Testing**

In the first test (which serves as the template for the subsequent tests), we compare the effect on tooth growth between supplements OJ and VC at dose = 0.5. We **assume** that the NULL hypothesis,  $H_0$ :  $\mu_{xOJ} = \mu_{xVC}$ , is true; independent groups, and unequal variance.

```
# Function to take in the dosage group and perform a t-test on supplement
effect on length
doseTest <- function(d) {</pre>
        testdf <- NULL
        testdf <- subset(ToothGrowth, dose==d, select=c('len', 'supp'))</pre>
        # apply t.test to compare the mean lengths by supplement at the
dosage group
        t.test(len ~ supp, paired=FALSE, data=testdf)}
doseTest(0.5)
##
   Welch Two Sample t-test
##
## data: len by supp
## t = 3.1697, df = 14.969, p-value = 0.006359
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## 1.719057 8.780943
## sample estimates:
## mean in group OJ mean in group VC
##
              13.23
                                 7.98
```

Here, we see that the 95% confidence interval is above zero. The p value of 0.64% is very unlikely, thus causing us to *reject* the NULL hypothesis. **Under a similar assumption, we repeat the** *t-test* **to get the probability of the alternate hypothesis for the other dosage groups**:

```
doseTest(1)$p.value
## [1] 0.001038376

doseTest(2)$p.value
## [1] 0.9638516
```

We note that for dose = 1.0, the p value of 0.1% is unlikely, thus causing us to **reject** the NULL hypothesis. However, for dose = 2.0, the p value of 96.39% is well within the 95th percentile of values that comply with the NULL hypothesis. In this case, then, the NULL hypothesis **stands**.

### **Assumptions and Conclusions**

The following assumptions must be restated for the tests conducted above:

- The subjects in each dosage groups are independent (not paired)
- Unequal variance between groups has been assumed

The scatter plot and the tests performed on the dataset help us conclude the following:

At dose=0.5, OJ results in higher tooth growth than VC

- At dose=1.0, OJ results in higher tooth growth than VC
- At dose=2.0, there is no discernible difference in tooth growth between the supplements
- Overall, it seems that OJ is more effective than VC at increasing tooth growth when administered at doses 0.5 or 1.0.

#### END OF REPORT

#### **APPENDIX 1: GIT CODE**

The entire markdown file can be found in this github repo.

#### **APPENDIX 2: PLOT CODE BLOCKS**

# (PART 1) 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,
                      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")
```

## (PART 1) Verifying Normality

This code chunk is quite large and may be found in its entirety in github: markdown.

## (PART 2) ToothGrowth Summary