Effect of Vitamin C on Tooth Growth of Guinea pigs

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Introduction

This assignment explores whether 3 different doses & 2 different delivery methods of Vitamin C have an influence on the tooth lengths of Guinea pigs. The dataset used is **ToothGrowth**, which comes with R as one of its practice/sample datasets.

Each animal received one of 3 doses of vitamin C, by one of 2 delivery methods: ascorbic acid (VC) versus orange juice (OJ).

This report comprises:

- A basic/descritive statistics summary of our sample data, plus an exploratory analysis.
- Use of statistical inference methods so that if any effects/conclusions are obtained from the SAMPLE data (contained in the ToothGrowth dataset), we can infer that these effects also apply to the entire population of Guinea pigs.

Summary of data & exploratory analysis

First glimpse of the ToothGrowth dataset:

```
a <- ToothGrowth %>% group_by(dose, supp) %>% summarise(n = n())
knitr::kable((a), caption = "Nr. of observations in each group")
```

Table 1: Nr. of observations in each group

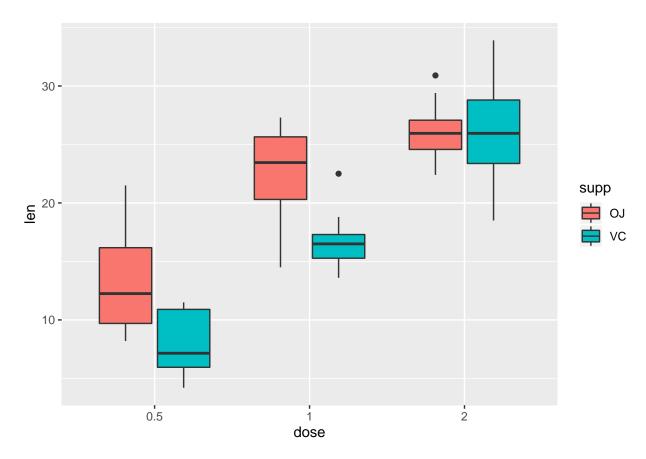
dose	supp	n
0.5	OJ	10
0.5	VC	10
1.0	OJ	10
1.0	VC	10
2.0	OJ	10
2.0	VC	10

So then -20 pigs received each of the 3 doses —> 10 via VC, 10 via OJ.

Let's have a first visualization of the data:

```
ToothGrowth$dose <- as.factor(ToothGrowth$dose)

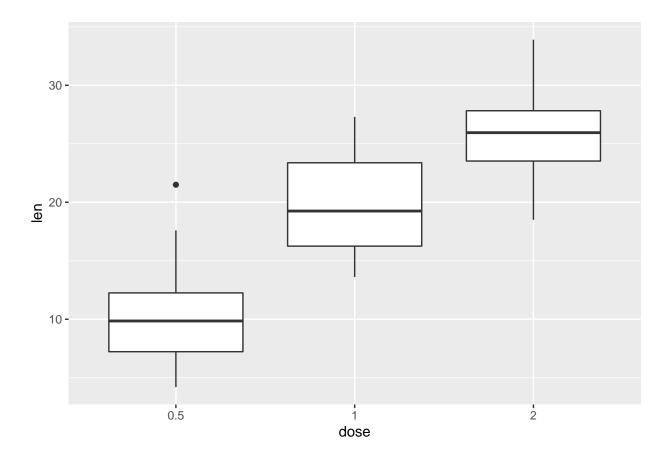
dose_supp_plot <- ggplot(ToothGrowth, aes(x = dose, y = len, fill = supp))
dose_supp_plot + geom_boxplot()</pre>
```



We can observe what could be a significant difference in Tooth Growth between the 0.5 mg/day dose versus the 1 & 2 mg/day doses. We need to test for statistical significance to ascertain this. It would also appear there is a difference between delivering Vit_C via VC vs OJ for the 0.5 and 1mg/day doses.

If we plot the tooth growth differences by Vitamin C Dose only, and obtain the means for the 3 different Vit C doses:

```
dose_plot <- ggplot(ToothGrowth, aes(x = dose, y = len))
dose_plot + geom_boxplot()</pre>
```



```
b <- ToothGrowth %>% group_by(dose) %>% summarise(Mean_Tooth_Growth = mean(len))
knitr::kable(b)
```

dose	$Mean_Tooth_Growth$
0.5	10.605
1	19.735
2	26.100

This time, it could well be that there's statistical difference between all 3 doses.

As we have > 2 groups with what appear similar intergroup variance, we use ANOVA for testing significance (equal variance).

So far, our assumptions are: - That tooth growth in Guinea pigs is normally distributed - That the 3 different DOSE groups have an equal variance

```
ANOVA_dose <- aov(len ~ dose, data = ToothGrowth)
summary.aov(ANOVA_dose)
```

```
## Df Sum Sq Mean Sq F value Pr(>F)
## dose    2   2426    1213   67.42 9.53e-16 ***
## Residuals    57   1026   18
## ---
## Signif. codes:    0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

So, per ANOVA, we have a statistically significant difference in Mean Tooth Growth between the 3 DOSES (p = 1.23e-14, thus p < 0.05).

But, ANOVA does not allow to know which of the pairwise DOSE comparisons are significant –so now we perform TUKEY TEST to determine this:

TukeyHSD(ANOVA_dose)

```
##
     Tukey multiple comparisons of means
##
       95% family-wise confidence level
##
## Fit: aov(formula = len ~ dose, data = ToothGrowth)
##
## $dose
##
           diff
                      lwr
                                upr
                                       p adj
## 1-0.5 9.130 5.901805 12.358195 0.00e+00
## 2-0.5 15.495 12.266805 18.723195 0.00e+00
          6.365 3.136805 9.593195 4.25e-05
```

Which also results in statistically significant differences between all 3 doses (p < 0.05). The differences between the mean DOSES and their confidence intervals for those mean differences are listed(provided) in the Tukey Test.

So for example, we can state that if the entire population of Guinea pigs was given Vitamin C at 3 doses, and we took random samples of these pigs, 95% of the times we would obtain a Mean difference in Tooth Growth that would be between 5.90 to 12.36 (in the 0.5 mg vs. 1.0 mg/day Vitamin C groups).

In relation to the TYPE of Vitamin C supplement, it is not advisable to test solely between VC vs OJ, as DOSE could a confounder in this relation.

So we do pairwise t-tests for each dose

```
ToothGrowth <- ToothGrowth %>% arrange(dose)
Dose0.5 <- ToothGrowth[1:20, ]
Dose1 <- ToothGrowth[21:40, ]
Dose2 <- ToothGrowth[41:60, ]

t.test(len ~ supp, data = Dose0.5)</pre>
```

```
##
## 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
```

```
t.test(len ~ supp, data = Dose1)
```

```
##
## Welch Two Sample t-test
##
## data: len by supp
## t = 4.0328, df = 15.358, p-value = 0.001038
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## 2.802148 9.057852
## sample estimates:
## mean in group OJ mean in group VC \,
              22.70
                               16.77
t.test(len ~ supp, data = Dose2)
##
## Welch Two Sample t-test
##
## data: len by supp
## t = -0.046136, df = 14.04, p-value = 0.9639
\#\# alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -3.79807 3.63807
## sample estimates:
## mean in group OJ mean in group VC \,
##
              26.06
                               26.14
```