Exploring the ToothGrowth dataset

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Load and Explore Data	
One of the standard learning data sets included in R is the "ToothGrowth" data set. The tooth growth data set is the length of the odontoblasts (teeth) in each of 10 guinea pigs at three Vitamin C dosage levels (0.5, and 2 mg) with two delivery methods (orange juice or ascorbic acid).	
The file contains 60 observations of 3 variables:	
• len: Tooth length	
• supp : Supplement type (VC or OJ)	
• dose : Dose in milligrams	
library(datasets) # convert df to tibble for tidyverse compatibility tooth = tibble(ToothGrowth)	

```
library(datasets)
# convert df to tibble for tidyverse compatibility
tooth = tibble(ToothGrowth)
# convert dose column to factor
tooth$dose = parse_factor(as.character(tooth$dose))
```

glimpse(tooth) # print the first few values

```
## 3rd Qu.:25.27
## Max. :33.90
```

count(tooth, supp, dose) # group by supp and dose, then count their observations

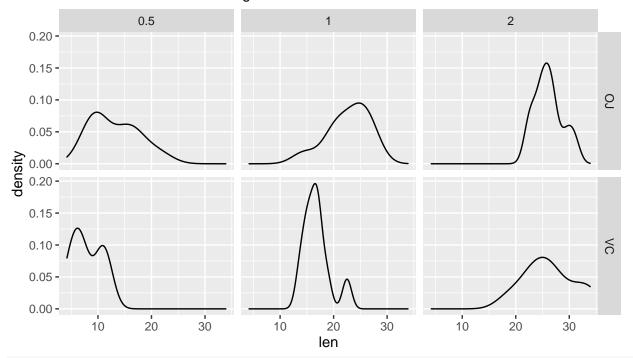
```
## # A tibble: 6 x 3
##
     supp dose
                      n
##
     <fct> <fct> <int>
           0.5
## 1 OJ
                     10
## 2 OJ
            1
                     10
## 3 OJ
            2
                     10
## 4 VC
           0.5
                      10
## 5 VC
            1
                     10
## 6 VC
           2
                     10
```

For every combination of supp and dose there are 10 observations (rows).

Now let's do some plots!

Density estimation for every combination of supp and dose

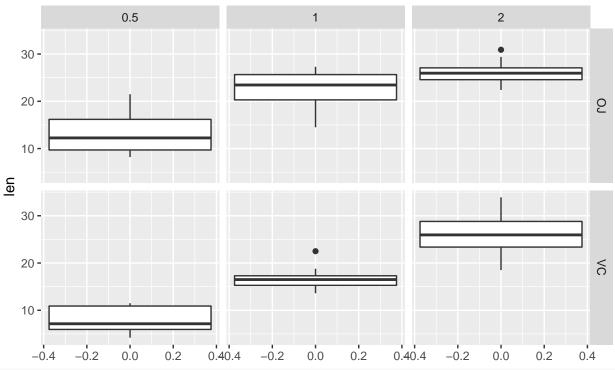
Observe that as the dose increases the distribution looks more skewed to the right. This indicates that larger doses increase the tooth length more than smaller doses.



```
# boxplot by supp and dose
ggplot(data=tooth, aes(y=len)) +
```

Boxplot for every combination of supp and dose

Observe that as the doses get higher, the distribution of the tooth length also contains larger values.



```
# mean and var by supp
tooth %>%
  group_by(supp) %>%
  summarize(mean=mean(len), var=var(len))
```

```
## # A tibble: 2 x 3
## supp mean var
## <fct> <dbl> <dbl>
## 1 DJ 20.7 43.6
## 2 VC 17.0 68.3
# mean and var by dose
tooth %>%
group_by(dose) %>%
summarize(mean=mean(len), var=var(len))
```

```
# mean and var for every combination of supp and dose
tooth %>%
    group by(supp,dose) %>%
    summarize(mean=mean(len), var=var(len))
## `summarise()` has grouped output by 'supp'. You can override using the `.groups` argument.
## # A tibble: 6 x 4
## # Groups:
               supp [2]
     supp dose
                  mean
     <fct> <fct> <dbl> <dbl>
           0.5
                 13.2 19.9
## 1 OJ
## 2 OJ
           1
                 22.7
                       15.3
## 3 OJ
           2
                 26.1
                        7.05
                  7.98 7.54
## 4 VC
           0.5
## 5 VC
           1
                 16.8
                         6.33
## 6 VC
           2
                 26.1
                       23.0
```

The mean tooth length was larger when taking the OJ supplement with .5 and 1 doses. With the 2mg dose however there is no difference in the mean tooth length between supplement types. Although, at 2mg dose, the OJ supplement is 3 times less variable on tooth length than the VC supplement.

Hypothesis & Permutation Tests

Supplement Tests

Test the null hypothesis that the supplement type does not affect tooth length. H_0 is that the difference in means is 0 and H_a that the difference in means is not 0.

```
# select len column for every supplement type
toothoj = tooth %>% filter(supp == 'OJ') %>% select(len)
toothvc = tooth %>% filter(supp == 'VC') %>% select(len)

t.test(toothoj, toothvc, alternative = 'two.sided')

##
## Welch Two Sample t-test
##
## data: toothoj and toothvc
## t = 1.9153, df = 55.309, p-value = 0.06063
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.1710156 7.5710156
## sample estimates:
## mean of x mean of y
## 20.66333 16.96333
```

The p value is very close to the rejection region and although normally we would fail to reject the H_0 , we know from the exploratory data analysis we performed, that the H_a is true. Since the p value is calculated in the direction of the H_a we hypothesize that if we perform the same test using $H_a > 0$ instead of the original $H_a \neq 0$ the p value would be smaller allowing us to reject the H_0 . This is because we observe from the data that the difference in means is greater than 0 (mean of OJ - mean of VC).

```
t.test(toothoj, toothvc, alternative = 'greater')
##
## Welch Two Sample t-test
```

Indeed, our hypothesis is correct. The p value is smaller when testing on $\mathrm{Ha} > 0$. Thus we can reject the Ho.

Dose Tests

```
# get all the observations that have doses 1 or 2
doses12 = tooth %>% filter(dose %in% c(1,2)) %>% select(len, dose)
y = doses12$len # get only len variable
dose = doses12$dose # get only dose variable
# function to calcuate differnece in means
testStat = function(y,d) mean(y[d==2]) - mean(y[d==1])
observedStat = testStat(y,dose)
# sample dose labels and calculate testStat 10000 times.
permutations = sapply(1:10000, function(i) testStat(y, sample(dose)))
observedStat
## [1] 6.365
# number of permutations that are more extreme than the observed stat
mean(permutations > observedStat)
```

[1] 0

No permutation is as or more extreme than our observed statistic (except the observed statistic itself)! We can safely conclude that a dose of 2 is associated with a larger tooth length. This is also observed in the box and density plots of the previous sections.

We will repeat the same procedure between .5 and 1 doses.

```
doses51 = tooth %>% filter(dose %in% c(.5,1)) %>% select(len, dose)
y = doses51$len
dose = doses51$dose
testStat = function(y,d) mean(y[d==1]) - mean(y[d==.5])
observedStat = testStat(y,dose)
permutations = sapply(1:10000, function(i) testStat(y, sample(dose)))
observedStat
## [1] 9.13
mean(permutations > observedStat)
```

```
## [1] 0
```

We reach the same conclusion as with the comparison between 2 and 1 doses.

Assumptions

In order to draw the conclusions in the hypothesis test section, we assume that the data is not skewed and follows a normal distribution. This is a requirement of the Student's t-test and t-confidence interval.