Pain Relief — One Way ANOVA

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Discussion: ANOVA

What is ANOVA good for?

Is a statistical method to test differences between two or more means. It is used to test general rather than specific differences among means

Why use ANOVA instead of multiple t-tests?

Every time you conduct a t-test there is a chance you will make a type 1 error. This error is usually 5%. By running two tests on the same data, you will have increased your chance of "making a mistake" to 10%. The formula for determining the new error rate for multiple t-tests are not as simple as multiplying 5% by the number of tests. ANOVA controls for these errors to that the Type 1 error remains at 5% and you can be more confident that any statistically significant result you find is not just running lots of tests.

What happens if you use ANOVA with 2 groups?

Typically, one way ANOVA is used to test for differences among at least 3 groups, since the two group case can be covered by a t test. When there are only two means to compare the t-test and f-test are equivalent; the relation between ANOVA and t is given by $F = T^2$. An extension of one way ANOVA is two way analysis of variance, that examines the difference between two different categorical variables on one dependent variable.

Is ANOVA a form of multiple linear regression? Discuss

ANOVA and linear regression are equivalent when the two models test against the same hypothesis and use an identical encoding. The models differ in their basic aim: ANOVA is mostly concerned to present differences between categories means in the data while linear regression is mostly concerned to estimate a sample mean response and an associated R^2.

What is post hoc testing in ANOVA? Discuss

Post hoc looking for patterns that were not specified a priori. Each time a pattern in the

data is considered, a statistical test is effectively performed. This greatly inflates the total number of statistical tests and necessitates the use of multiple testing procedures to compensate.

List some of the commonly used post hoc tests and compare them

Fisher's least significant difference is a technique use most commonly after a null hypothesis of ANOVA test is rejected. A significant ANOVA test only reveals that not all the means compared in the test are equal. Fisher's LSD is basically a set of individual t-tests, a pooled standard deviation is computed from only two groups being compared, while the Fisher's LSD test computes the pooled standard deviation from all groups - thus increasing power. Fisher's LSD does not correct for multiple comparisons.

Newman-Keuls method for stepwise multiple comparisons used to identify sample means that are significantly different rom each other. It is used as often as post hoc analysis whenever a significant difference between three or more sample means has been revealed by an ANOVA.

Rodger's method for omnibus analysis after carrying out ANOVA utilizes a decision-based error rate, arguing that it is not the probability of alpha of rejecting the null hypothesis in error that should be controlled, rather it is the average rate of rejecting true null contrasts that should be controlled. Meaning we should control the expected error alpha of true null contrast rejections

Summarize steps in ANOVA testing

1. Check any necessary assumptions and write null and alternative hypothesis
2. Calculate an appropriate test statistic
3. Determine p-value associated with the test statistic
4. Decide between null and alternative hypothesis
5. State a "real world" conclusion

Analysis

One Way Analysis of Variance :

- Can be used for the case of quantitative outcome with a categorical explanatory variable that has two or more levels of treatment.
- The term one way, also called one factor, indicates that there is a single explanatory variable "treatment" with tow or more levels, and only one level of treatment is applied at any time for a given subject.

- In this analysis we assume that each subject is exposed to only one treatment, in which case the treatment varaible is being applied “between subjects.”
- In ANOVA, we use variance-like quantities to study equality or non-equality of population means, therefore we are really analyzing means not variances.

Problem: Pain Relief :

In our one-way ANOVA the pain relief data is sub-divided into groups based on a single classification factor (treatment). There is variation in the measurements taken on the individual components of the data set and our ANOVA investigates whether this variation can be explained by the grouping introduced by the classification factor.

Hypothesis

H_0 : There will be no effect of the treatments on the speed to pain alleviation.

H_1 : Pain reliever treatment will significantly effect on the speed pain alleviation.

Ingest and EDA Viz

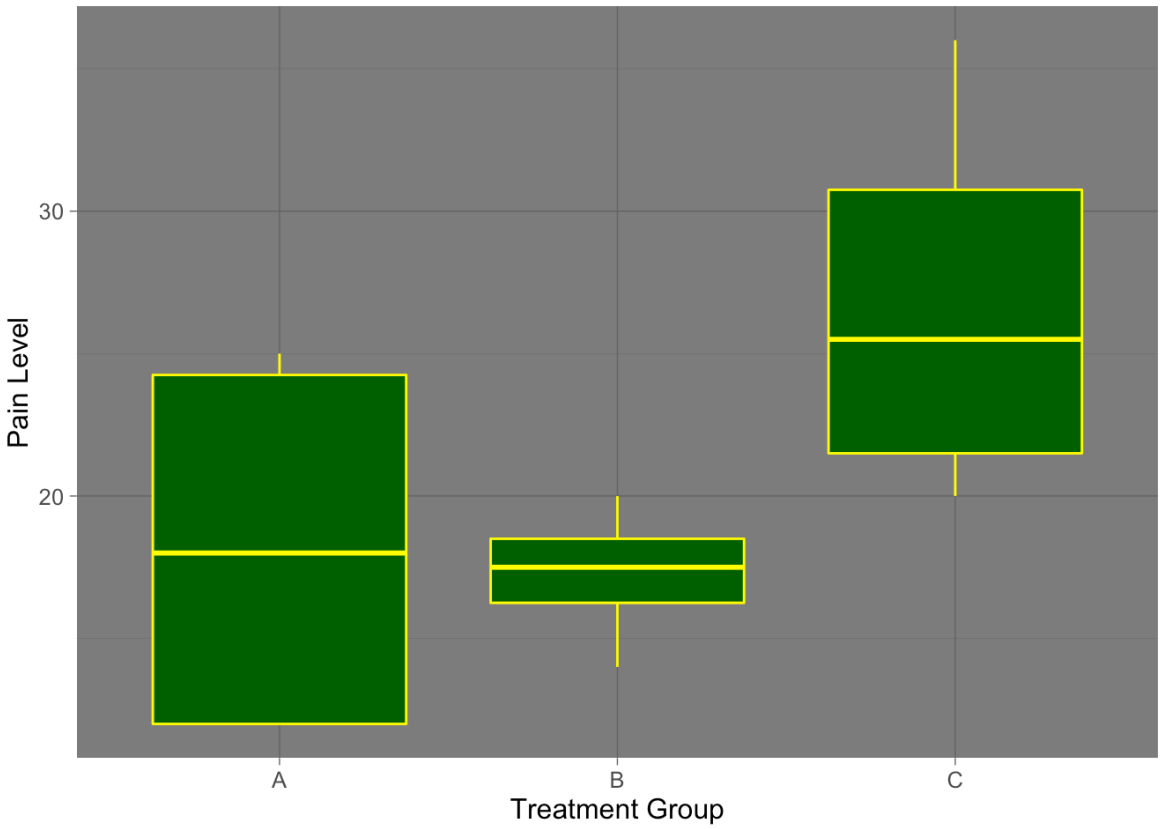
```
df <- read.csv("/Users/SeanOMalley1/Desktop/MSDS_660_Stats/pain_reli
ef_data.csv")

glimpse(df)
```

```
## Observations: 12
## Variables: 2
## $ treatment      <fctr> A, A, A, A, B, B, B, B, C, C, C, C
## $ time_to_relief <int> 12, 24, 12, 25, 20, 14, 17, 18, 22, 29, 36
, 20
```

```
summary(df)
```

```
##  treatment time_to_relief
##  A:4       Min.   :12.00
##  B:4       1st Qu.:16.25
##  C:4       Median :20.00
##            Mean   :20.75
##            3rd Qu.:24.25
##            Max.   :36.00
```

```
ggplot(df, aes(x = treatment, y = time_to_relief)) +
        geom_boxplot(fill = "#006400", colour = "yellow") +
        scale_x_discrete() +
        xlab("Treatment Group") +
        ylab("Pain Level") +
        theme_dark()
```



EDA continued...

The above visualizations suggest that treatment A shows the most promise in having the quickest time to pain relief, however we also want to look to a linear model of the treatment on the time to relief.

```
model <- lm(time_to_relief~treatment, data = df)

summary(model)
```

```
##
## Call:
## lm(formula = time_to_relief ~ treatment, data = df)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -6.750 -5.125  0.250  3.500  9.250
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   18.250      3.047   5.989 0.000205 ***
## treatmentB    -1.000      4.309  -0.232 0.821682
## treatmentC     8.500      4.309   1.973 0.080018 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.094 on 9 degrees of freedom
## Multiple R-squared:  0.3947, Adjusted R-squared:  0.2602
## F-statistic: 2.935 on 2 and 9 DF,  p-value: 0.1044
```

Simply taking note of the summary output we see that the p-value is in the range of significance on the treatment having an effect on the time to pain relief, our R^2 is fairly low. We see a negagive coeff of B, and very positive coeffiecients of C and A treatments. but nevertheless something that is good to have in mind moving forward with ANOVA.

Analysis of Variance

Build Model :

```
anova_df <- aov(time_to_relief~treatment, data = df)
```

Numerically Evaluate Model :

```
confint(anova_df)
```

```
##                 2.5 %    97.5 %
## (Intercept)  11.357017 25.142983
## treatmentB  -10.748151  8.748151
## treatmentC   -1.248151 18.248151
```

```
summary(anova_df)
```

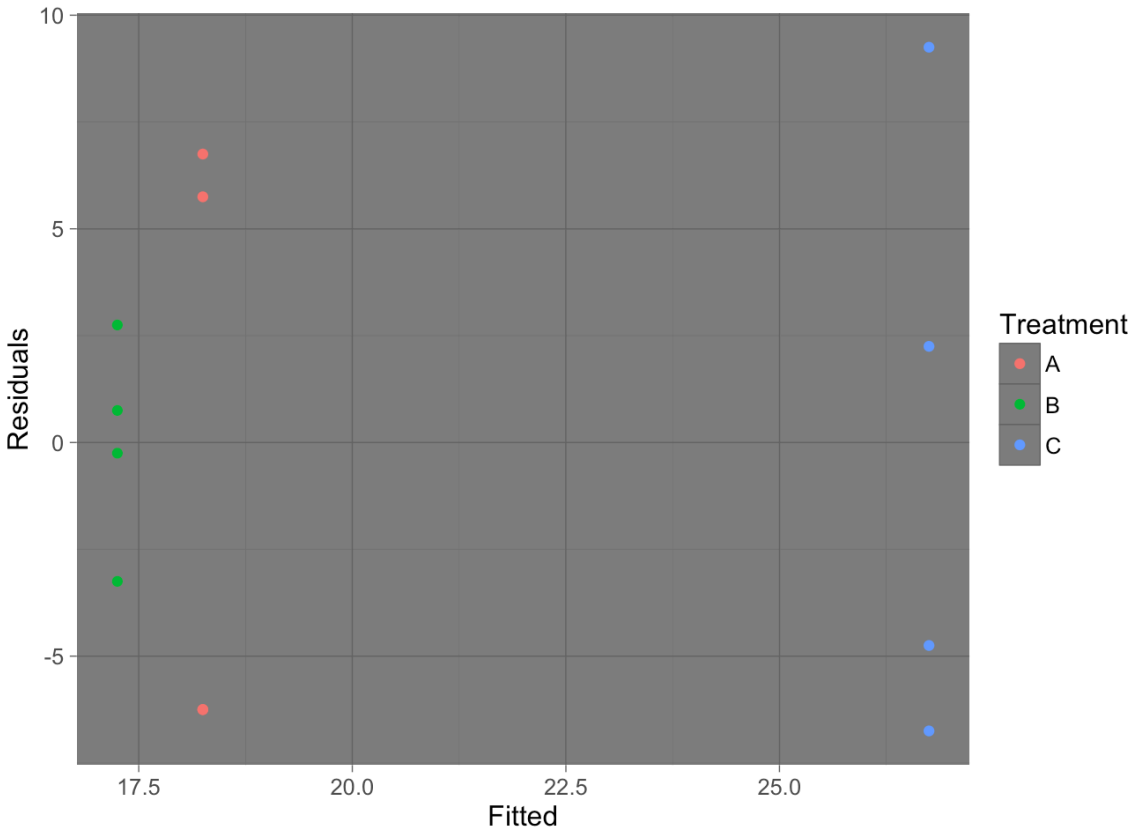
```
##             Df Sum Sq Mean Sq F value Pr(>F)
## treatment    2  218.0  109.00   2.935  0.104
## Residuals    9  334.2   37.14
```

```
resid(anova_df)
```

```
##     1     2     3     4     5     6     7     8     9    10    11
12
## -6.25  5.75 -6.25  6.75  2.75 -3.25 -0.25  0.75 -4.75  2.25  9.25
-6.75
```

Graphically Evaluate Model :

```
anova_df2 = data.frame(Fitted = fitted(anova_df),
                       Residuals = resid(anova_df),
                       Treatment = df$treatment)

ggplot(anova_df2, aes(Fitted, Residuals, color = Treatment)) +
        geom_point() +
        theme_dark()
```



Interpret Results

Hythoesis Testing :

Given a one way ANOVA test, it is fair to say that we reject the null hypothesis and say that the treatment does have a significant effect on the speed of pain relief. This has been mathematically confirmed above with the large and varying coefficients in the ANOVA testing as well as the p value above 0.05.

Visually we can see in the final graph the stark differences in time difference between the factors of treatments. The output, treatments and effects of each have had on the varaince is telling in regard to the effectiveness of these drugs.