

# STA221

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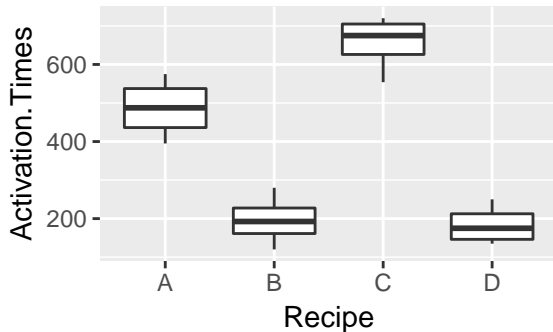
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When the null hypothesis is true,  $\frac{MS_T}{MS_E}$  lives near 1, and large values of this ratio give small p-values.

## putting it all together

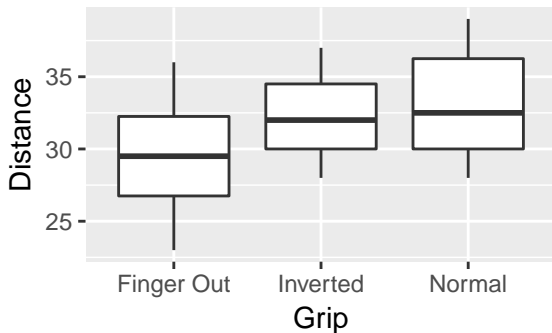
All this information is concisely displayed in what is called the “analysis of variance” table (or ANOVA table, or AOV table). Here’s the table for the Yeast example:



|    |           |    |        |         |         |             |
|----|-----------|----|--------|---------|---------|-------------|
| ## |           | Df | Sum Sq | Mean Sq | F value | Pr(>F)      |
| ## | Recipe    | 3  | 638968 | 212989  | 44.74   | 0.000000864 |
| ## | Residuals | 12 | 57128  | 4761    |         |             |

## putting it all together

And for the “probably not different” Frisbee example:



```
##           Df Sum Sq Mean Sq F value Pr(>F)
## Grip       2   58.58    29.29   2.045  0.154
## Residuals 21  300.75    14.32
```

## ANOVA table—formula version

Not explicitly appearing on the R output is  $SS_{Total} = SS_T + SS_E$  and  $N - 1 = k - 1 + N - k$ .

|            | Df | Sum Sq | Mean Sq | F value | Pr(>F) |
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| <var_name> |    |        |         |         |        |
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For example (from 25.13 “Hearing”). Four different word lists were compared for ease of hearing with background noise. 96 people were divided into four groups and the number out of 24 words understood was recorded.

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For example (from 25.13 “Hearing”). Four different word lists were compared for ease of hearing with background noise. 96 people were divided into four groups and the number out of 24 words understood was recorded.

The sample variance for all 96 people was 70.0907895. The mean squared error was 62.371. Is there a difference between the word groups?

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That's because the square of anything with a  $t_\nu$  distribution always has an  $F_{1,\nu}$  distribution.



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For example, consider the two-sample  $t$  test (equal variance version using pooled variance  $s_p^2$  - section 21.3 of the text).

Q21.20 “Hard Water” Mortality rates per county in 61 counties in England and Wales classified as “North” and “South” of Derby. Is there a difference in mean mortality rate? Here's the R output:

```
##  
## Two Sample t-test  
##  
## data: Mortality by Derby  
## t = 6.5312, df = 59, p-value = 0.00000001673  
## alternative hypothesis: true difference in means is not equal to 0  
## 95 percent confidence interval:
```

## mortality data via $F$ test

From above:

$t = 6.5312$ ,  $df = 59$ ,  $p\text{-value} = 0.00000001673$

The R ANOVA output:

| ##           | Df | Sum Sq  | Mean Sq | F value | Pr(>F)       |
|--------------|----|---------|---------|---------|--------------|
| ## Derby     | 1  | 886712  | 886712  | 42.66   | 0.0000000167 |
| ## Residuals | 59 | 1226462 | 20787   |         |              |

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Also,  $6.5312^2 = 42.6565734$ .

## the $t$ - $F$ connection - II

Recall from the Bodyfat example from regression:

```
##  
## Coefficients:  
##           Estimate Std. Error t value Pr(>|t|)  
## (Intercept) 25.58078   14.15400   1.807   0.0719  
## Height      -0.09316    0.20119  -0.463   0.6438  
##  
## Residual standard error: 8.307 on 248 degrees of freedom  
## Multiple R-squared:  0.0008637, Adjusted R-squared:  -0.003165  
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Again,  $t^2 = F$  and the p-values are identical.

The practical downside of using  $F$  is that you lose information about the sign.

## ANOVA model and calculations requirement

Look at the model again:

$$y_{ij} = \mu_i + \varepsilon_{ij}, \quad \varepsilon_{ij} \sim N(0, \sigma)$$

First, the errors are supposed to be independent, which would exclude experiments such as giving the same person different treatments over time, etc.

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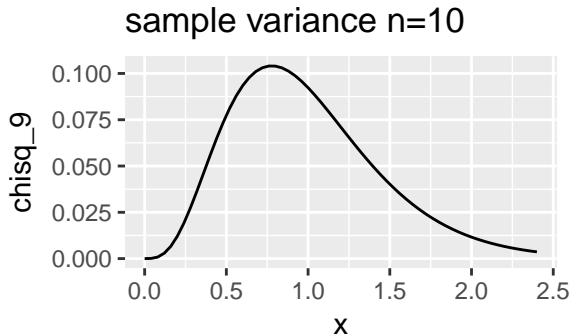
The main things to verify:

1. Do the groups come from a distribution with the same variance? (fatal if no)
2. Do the groups come from normal distributions? (OK if sample size is large enough)

## Formal test for equality of variances

For the equal variance assumptions, the book says to look at plots. Other books gives a variety of heuristics. These suggestions tend to be wildly conservative.

The problem is twofold. Within-group sample sizes tend to be small. And the sample variance itself has a very large variance.



## Levene's test

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$$H_0 : \sigma_1^2 = \cdots = \sigma_k^2$$

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The form of the test is exactly an ANOVA, but not on the original  $y_{ij}$ . Instead, it is on the *absolute differences from the group medians*:

$$Z_{ij} = |y_{ij} - \tilde{y}_i|$$

where  $\tilde{y}_i$  is the sample median of the  $i^{th}$  group.

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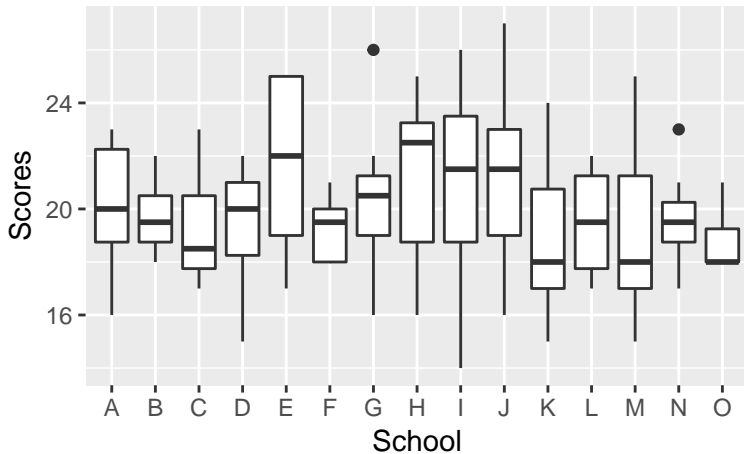
Plugging the  $Z_{ij}$  into the ANOVA formulae gives an approximate  $F_{k-1, N-k}$  distribution.

## Levene's test example - yeast

```
## Levene's Test for Homogeneity of Variance (center = median)
##      Df F value Pr(>F)
## group  3  0.2917 0.8306
##      12
```

## tougher example

From textbook question 25.18 “School System”. 15 schools selected. 8 students per school.



## tougher example - Levene

```
## Levene's Test for Homogeneity of Variance (center = median)
##           Df F value Pr(>F)
## group    14  1.2642 0.2422
##           105
```



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Technically, all the groups have to be normal. But the samples sizes are usually too small.

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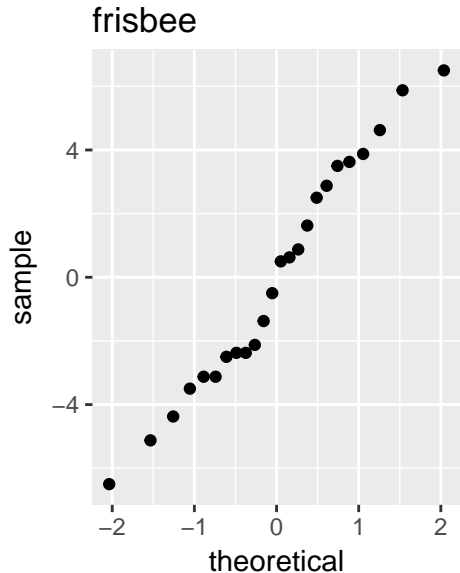
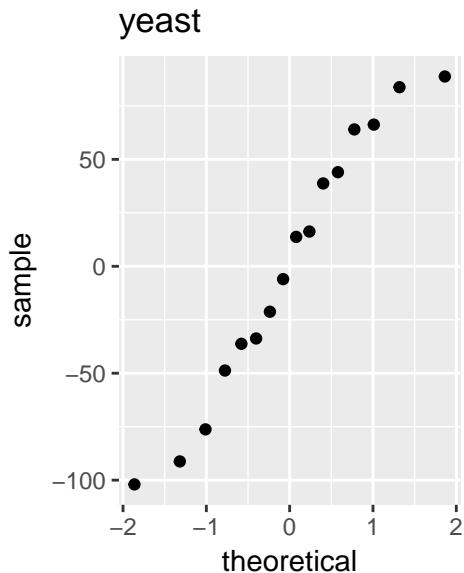
Technically, all the groups have to be normal. But the samples sizes are usually too small.

If the equal variance assumption has been satisfied (do that first), then the method is to pool all the *residuals* together:

$$y_{ij} - \bar{y}_i$$

and look at a normal quantile plot.

## normal assumption verification examples



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Or, there may be some differences between groups that are noticed after collecting data, which is gets us into dangerous territory!

The approach in any case will be to perform multiple pooled two-sample  $t$  procedures, using the overall  $MSE$  in place of the usual pooled variance:

$$\frac{\bar{y}_i - \bar{y}_j}{\sqrt{MSE} \sqrt{\frac{1}{n_i} + \frac{1}{n_j}}} \sim t_{N-k}$$

The usual technique is to produce confidence intervals for each desired pair. But at what confidence level? The usual 95% level leads to a problem. . .