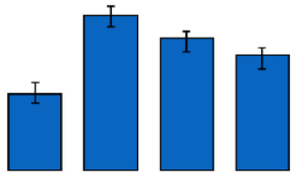
1

ANOVA: for comparing multiple means
numeric outcome, 3 or more groups

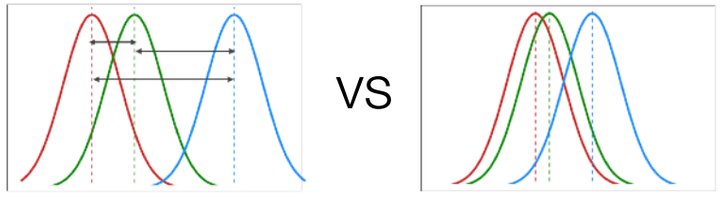


2

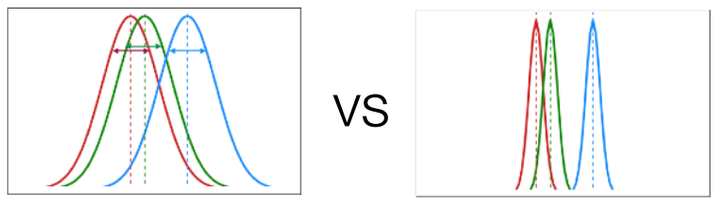
test statistic reflects the total variability SS_{tot}

$$SS_{tot} = SS_b + SS_w$$

between-groups SS_b



within-groups SS_w



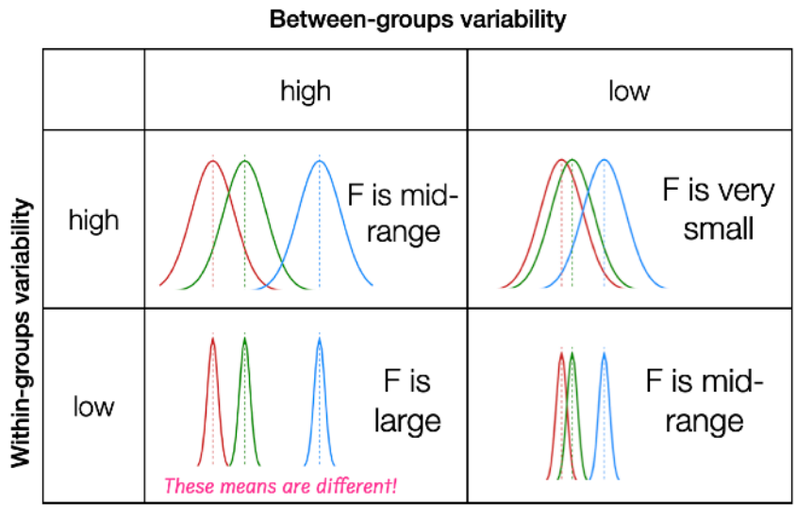
correct for **degrees of freedom**

between-groups MS_b: divide by G-1 where G=# of groups

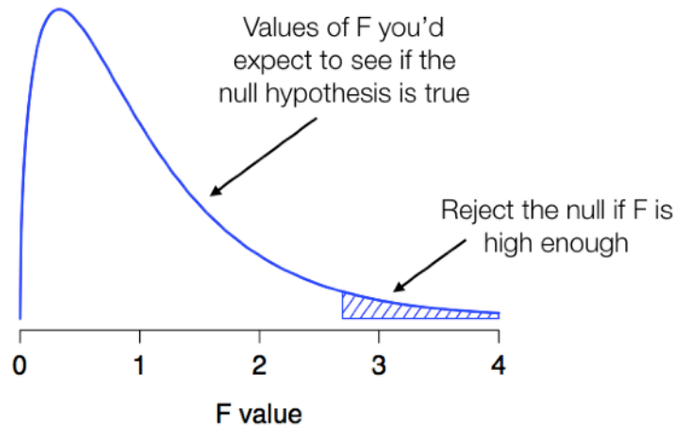
within-groups MS_w: divide by N-G where N=total sample size

F-statistic is ratio of these: MS_b/MS_w

3



So the means are more different when F is larger



4

ANOVA in R requires two commands

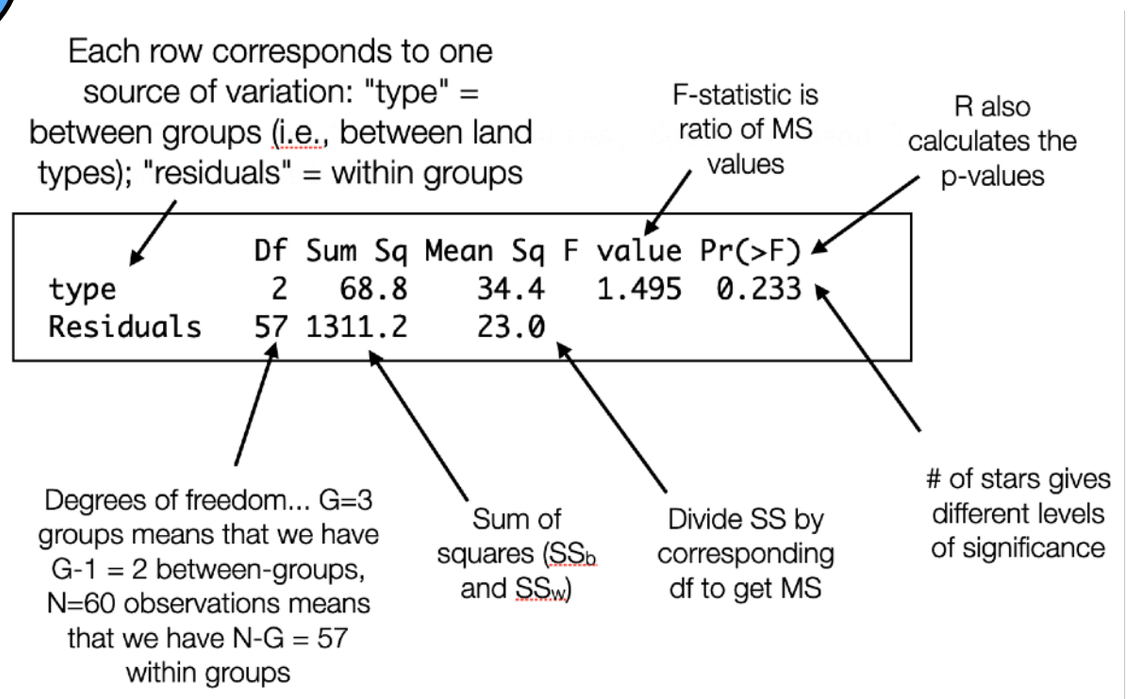
aov creates an aov object with all the info

summary runs the actual hypothesis test on that info

```
modelName <- aov( outcome ~ predictor, dataset )
summary(modelName)
```

5

ANOVA table



6

effect size eta-squared is proportion of the variance attributable to the grouping variable

$$\eta^2 = \frac{\mathrm{SS}_b}{\mathrm{SS}_{tot}}$$

```
etaSquared(modelName)
```

1 problem of multiple comparisons

ANOVA only tells you *that* there is a difference, not *which* groups are different

running many t-tests inflates Type 1 error

solve with Bonferroni or Holm corrections

Bonferroni: simple, but way conservative.

$$p' = m \times p$$

adjusted p-value ← p' = m (number of tests you're doing) × p → original p-value

Holm: better, more complicated

```
library(lsr)
posthocPairwiseT(x=modelName)
```

default: Holm
Bonferroni: `p.adjust.method = "bonferroni"`

2

posthoc test: ran after ANOVA, don't have particular hypothesis. need a correction.
planned comparison one of only a few tests you planned in advance. no correction needed but *be honest and careful!*

3 Assumption: residuals are normal

- check with Shapiro-Wilk on the residuals
- if violated, run Kruskal-Wallis

get residuals:

```
model <- aov(blahblah)
model$residuals
```

Shapiro-Wilk: `shapiro.test(model$residuals)`

Kruskal-Wallis:

```
kruskal.test(outcome ~ predictor, data=d)
```

```
library(rstatix)
kruskal_effsize(outcome ~ predictor, data=d)
```

4 Assumption: variance homogeneous

Use Levene Test to check
If violated, do Welch one-way ANOVA

Levene Test:

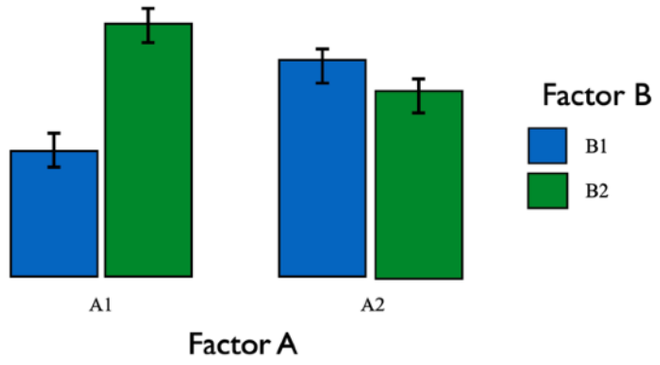
```
library(car)
LeveneTest(outcome ~ predictor, data=d)
```

Welch one-way ANOVA

```
oneway.test(outcome ~ predictor, data=d)
```

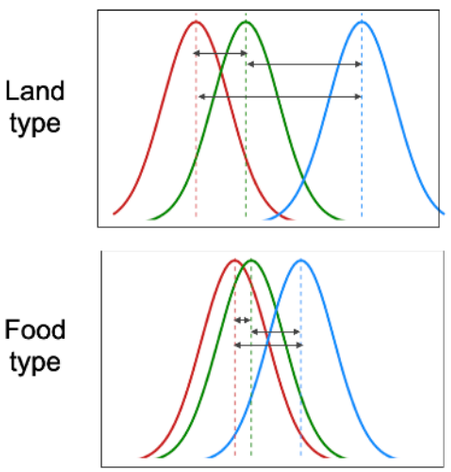
5 Two-way ANOVA

Has two factors instead of one, with a continuous outcome (comparing means)

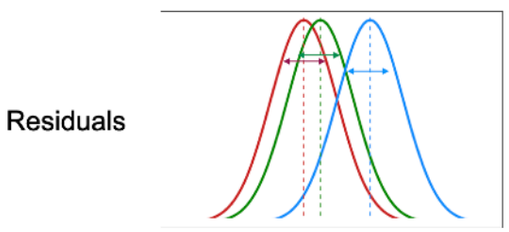


Data must be in long form!

Between groups SS (SS_A, SS_B): for each factor A and B, how different are the group means from one another?



Residual SS (SS_R): how much variation in the outcome is there after taking into account the variation associated with *both* factors?



$$MS_b = SS_b/(G-1)$$

$$MS_R = SS_R/(N-R-C+1)$$

$$F = MS_b/MS_R$$

6 Running in R

add + to formula to indicate multiple factors

```
aov(outcome ~ pred1 + pred2, data=d)
```

```
             Df Sum Sq Mean Sq F value Pr(>F)
type          2    201     100   0.887  0.414
food          2  63852   31926 282.422 <2e-16 ***
Residuals   175  19783     113
```

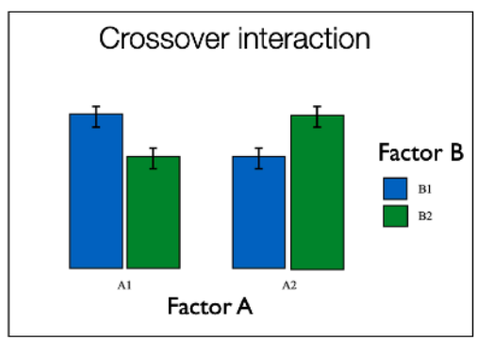
Each group has an F-statistic and can be significant or not.

If a group is significant, that's a **main effect**

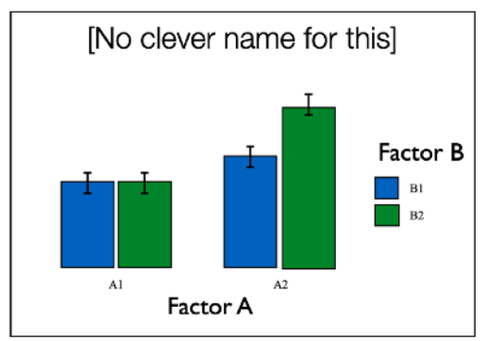
Different from testing each factor separately because the residuals are different!

7 Interactions

Occur when the effect of one factor is different depending on the level of the other



Direction of effect of a factor depends on the level of the other factor



Magnitude of effect of a factor depends on the level of the other factor

Same idea, just get an interaction sum of squares as well as for each group

8

Running interactions in R

Indicate with a : in between the two variables

```
aov(outcome ~ pred1 + pred2 + pred1:pred2, data=d)
```

Or can use shorthand to tell R to do all three:

```
aov(outcome ~ pred1*pred2, data=d)
```

```
             Df Sum Sq Mean Sq F value   Pr(>F)
type          2    201     100   1.205    0.302
food          2  63852   31926 383.612  < 2e-16 ***
type:food     4   5551    1388  16.675 1.47e-11 ***
Residuals   171  14231      83
```

Each factor *and* the interaction have an F-statistic and can be significant or not

9

Effect size for ANOVA

Same as one-way: eta-squared

But partial eta squared needs to be interpreted

```
etaSquared(model)
```

η^2: proportion of total variance due to each factor

Partial η^2: proportion of variance due to each factor assuming you pretend the effect size of all of the others is zero