Lecture 07 - Analysis of Variance

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General Outline

For this lecture, we will be discussing hypothesis testing with three or more population means, also known as analysis of variance (ANOVA).

- 1) Logic of ANOVA
- 2) Computation of ANOVA
- 3) Computing ANOVA in R
- 4) Measures of Association
- 5) Post-Hoc Tests

Inference with Three or More Sample Means

Inference with three or more sample means is a fairly simple generalization of the two-sample setup.

Now, instead of examining the difference between two specific means, we will instead ask if there is a significant amount of variability **between** the set of three or more samples means as compared to the distribution of values **about** these sample means within each sample.

Inference with Three or More Sample Means

► Research Question

- Do the differences we observe among the sample means indicate that there are significant differences across groups in the population?

Examples

- Sentence length as a function of offense type (violent, property, drug, other)
- Fear of crime as a function of residential location (urban, suburban, rural)
- Offending as a function of family structure (two-parents, single-parent, no biological parents)

Inference with Three or More Sample Means

You might ask - why not simply run t-tests between each unique group pairing?

$$t = \frac{(\overline{x}_1 - \overline{x}_2)}{\sqrt{\frac{s_1^2}{(n_1 - 1)} + \frac{s_2^2}{(n_2 - 1)}}}$$

Here's why:

- ▶ It's cumbersome
 - 3 groups: 3 tests; 4 groups: 6 tests; 5 groups: 10 tests
- Probability of committing a type I error on any given test is greater than α (.05, for example)
 - 3 groups: p=.143; 4 groups: p=.185; 5 groups: p=.226

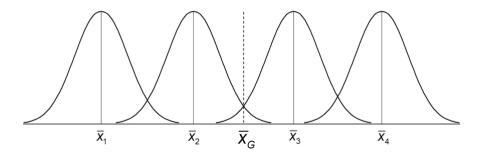
Logic of ANOVA

We want a statistical test that will help us decide whether the observed differences are the result of sampling variation or real differences.

- ightharpoonup Analysis of variance = ANOVA
 - Three or more sample means
 - Global test = joint significance of several means
 - Constant prob. of type I error (α)

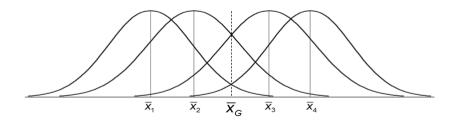
Why Variance?

- ► Analysis of Variance
 - Ratio of the variability **between** groups to the variability **within** groups
 - New test statistics the F-ratio



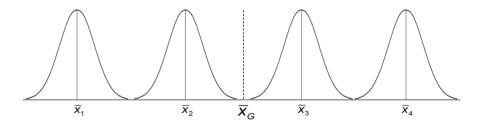
Why Variance? (cont)

- ▶ More variability within groups than between
 - F-ratio < 1.0
 - Too much overlap, there is no relationship between group membership and the outcome



Why Variance? (cont)

- ▶ More variability **between** groups than within.
 - F-ratio > 1.0
 - Little or no overlap, there is a relationship between group membership and the outcome



New Probability Distribution

- ► The F-distribution
 - The ratio of variability **between** groups to variability **within** groups.

Large F-ratios (i.e., significantly greater than 1.0) will lead us to reject the null hypothesis of no association between group membership and the outcome of interest.

New Calculations - Sum of Squares

- ► Sum of squares = numerator of variance
 - Total variation about the **grand mean** $(df_T = N 1)$

$$SS_T = \sum (\mathbf{x}_{ik} - \overline{\mathbf{x}}_G)^2 = \sum \mathbf{x}_{ik}^2 - N\overline{\mathbf{x}}_G^2$$

▶ Between-group sum of squares $(df_B = k - 1)$

$$SS_B = \sum n_k (\overline{\mathbf{x}}_k - \overline{\mathbf{x}}_G)^2 = \sum n_k \overline{\mathbf{x}}_k^2 - N \overline{\mathbf{x}}_G^2$$

▶ Within-group sum of squares $(df_W = N - k)$

$$SS_W = \sum (\mathbf{x}_{ik} - \overline{\mathbf{x}}_k)^2 = \sum \mathbf{x}_{ik}^2 - \sum n_k \overline{\mathbf{x}}_k^2 = SS_T - SS_B$$

New Calculations - Sum of Squares

- ightharpoonup Total sum of squares (SS_T)
 - $SS_T = SS_B + SS_W$
- ► Mean square (i.e., variance)
 - Mean square between: $MS_B = \frac{SS_B}{df_B}$
 - Mean square within: $MS_W = \frac{SS_W}{df_W}$
- ► F-ratio
 - $-F = \frac{MS_B}{MS_W}$

Practical Example - Offense Type and Sentence Length

Violent	Property	Drug	Other
6	4	6	1
18	6	3	3
20	3	3	1
15	10	4	1
20	12	6	6
30	8	9	9
25	6	10	3
12	10	3	6
24	8	2	2
20	15	3	4

Quick Note - How to Find F_{crit}

Much like prior distributions, there are functions in R to calculate critical scores for the F-ratio. The function takes the following form:

qf(p, df1, df2, lower.tail=TRUE/FALSE)

Where **p** is your alpha level, **df1** is the between group degrees of freedom, **df2** is the within group degrees of freedom, and **lower.tail=TRUE/FALSE** returns the upper or lower-tail F-score that leaves that cumulative probability below or above it.

- ► Step 1 Formally state hypotheses:
 - $H_1: \mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4$
 - $H_0: \mu_1 = \mu_2 = \mu_3 = \mu_4$
- ► Step 2 Obtain a probability distribution:
 - F-distribution; $df_B = k 1 = 4 1 = 3$, $df_W = N k = 40 4 = 36$
- Step 3 Make decision rules:
 - $-\alpha = .01, F_{crit} = 4.377, \text{Reject } H_0 \text{ if TS} > 4.377$

▶ Step 4 - Calculate the test statistic:

Vic	olent	Pro	perty	D	rug	Ot	her
\mathbf{x}_1	x_1^2	x_2	x_2^2	x_3	x_3^2	x_4	x_4^2
6	36	4	16	6	36	1	1
18	324	6	36	3	9	3	9
20	400	3	9	3	9	1	1
15	225	10	100	4	16	1	1
20	400	12	144	6	36	6	36
30	900	8	64	9	81	9	81
25	625	6	36	10	100	3	9
12	144	10	100	3	9	6	36
24	576	15	225	3	9	4	16
190	4030	82	794	49	309	36	194

There are several pieces of information that we need to obtain to calculate the *F*-statistic. First, we need to compute the group means as well as the grand mean.

$$\overline{x}_1 = \sum x_{i1}/n_1 = 190/10 = 19$$

$$\overline{x}_2 = \sum x_{i2}/n_2 = 82/10 = 8.2$$

$$\overline{x}_3 = \sum x_{i3}/n_3 = 49/10 = 4.9$$

$$\overline{x}_4 = \sum x_{i4}/n_4 = 36/10 = 3.6$$

$$\overline{x}_G = \sum x_i/N = \frac{190+82+49+36}{10+10+10+10} = 8.925$$

Second, we need to compute the sums of squares. This step only requires us to find the total sum of squares and between-group sum of squares, which we can use to solve for the within-group sum of squares.

$$SS_T = \sum x_{ik}^2 - N\bar{x}_G^2 = (4030 + 794 + 309 + 194) - 40(8.925)^2 = 5327 - 3168.40 = 2140.775$$

$$SS_B = \sum n_k \overline{x}_k^2 - N \overline{x}_G^2 = 10(19.0)^2 + 10(8.2)^2 + 10(4.9)^2 + 10(3.6)^2 - 40(8.925)^2 = 1465.875$$

$$SS_W = \sum_{ik} x_{ik}^2 - \sum_{ik} n_k \overline{x}_k^2 = (4030 + 794 + 309 + 194) - (10*(19.0^2)) + (10*(8.2^2)) + (10*(4.9^2)) + (10*(3.6^2)) = 5327 - 4652.1 = 674.9$$

Third, we use this information to calculate the F-statistic. It is convenient to put ANOVA data into the form of a table.

Source	SS	df	MS = SS/df	$F = MS_B/MS_W$
Between groups	1465.875	k - 1 = 3	488.62	
Within groups	674.9	N - k = 36	18.747	$\frac{488.62}{18.747} = 26.06$
Total	2140.775	N - 1 = 39	54.892	10.11

▶ Step 5 - Make a decision about the null hypothesis:

- Reject H_0 , conclude that offense type is significantly associated with sentence length.

Another Example - Residential Location and Fear of Crime

Ur	Urban		Suburban		Rural	
\mathbf{x}_U	x_U^2	\mathbf{x}_S	\mathbf{x}_S^2	\mathbf{x}_R	x_R^2	
22	484	23	529	19	361	
29	841	22	484	24	576	
31	961	26	676	24	576	
28	784	25	625	19	361	
30	900	24	576	20	400	
32	1024	25	625	24	576	
32	1024	24	576	21	441	
31	961	24	576	17	289	
28	784	27	729	23	529	
30	900	23	529	19	361	
293	8663	243	5925	210	4470	

- ► Step 1: State hypotheses
 - $H_1: \mu_U \neq \mu_S \neq \mu_R; H_0: \mu_U = \mu_S = \mu_R$
- ► Step 2: Obtain a probability distribution
 - F-distribution, $df_B = 3 1 = 2$, $df_W = 30 3 = 27$
- ► Step 3: Make decision rules
 - $-\alpha = .05 F_{crit} = 3.354$; reject H₀ if F > 3.354

- ▶ Step 4: Calculate the test statistic
- $\overline{x}_1 = \sum x_{i1}/n_1 = 293/10 = 29.3$
- $\overline{x}_2 = \sum x_{i2}/n_2 = 243/10 = 24.3$
- $\overline{x}_3 = \sum x_{i3}/n_3 = 210/10 = 21$
- $\overline{x}_G = \sum x_i/N = \frac{293 + 243 + 210}{10 + 10 + 10} = 24.87$

- ▶ Step 4: Calculate the test statistic
- $SS_T = \sum_i x_i^2 N\overline{x}_G^2 = (8663 + 5925 + 4470) 30(24.87)^2 = 502.493$
- $SS_B = \sum n_k \overline{x}_k^2 N \overline{x}_G^2 = 10(29.3)^2 + 10(24.3)^2 + 10(21.0)^2 30(24.87)^2 = 344.293$
- $SS_W = \sum_i x_i^2 \sum_i n_k \overline{x}_k^2 = SS_T SS_B = 502.493 344.293 = 158.2$

▶ Step 4: Calculate the test statistic

Source	SS	df	MS = SS/df	$F = MS_B/MS_W$
Between groups	344.293	k - 1 = 2	172.147	
Within groups	158.2	N - k = 27	5.859	$\frac{172.147}{5.859} = 29.38$
Total	502.493	N-1=29	17.327	

- ▶ Step 5: Make a decision about the null hypothesis
 - Reject H_0 , conclude that area of residence is related to fear of crime.

ANOVA Example - Sentence Length and Offense Type (but this time using R)

In this short section, I am going to show you how to calculate the F-statistic using R and then how to validate that computation with an automatic method.

Input Data

```
violent<-c(6,18,20,15,20,30,25,12,24,20)
property<-c(4,6,3,10,12,8,6,10,8,15)
drug<-c(6,3,3,4,6,9,10,3,2,3)
other<-c(1,3,1,1,6,9,3,6,2,4)</pre>
```

Obtain Means

```
viol_xbar<-sum(violent)/length(violent)
prop_xbar<-sum(property)/length(property)
drug_xbar<-sum(drug)/length(drug)
oth_xbar<-sum(other)/length(other)
grand_xbar<-(sum(violent)+sum(property)+sum(drug)+sum(other))/
  (length(violent)+length(property)+length(drug)+length(other))</pre>
```

Note - when the sample sizes are the same for each group the grand mean is the mean of the group means (19+8.2+4.9+3.6)/4 = 8.925.

Obtain Sum of Squares

```
viol_sq<-violent^2
prop_sq<-property^2
drug_sq<-drug^2
oth_sq<-other^2
## SS Total
ss_ttl<-(sum(viol_sq)+sum(prop_sq)+sum(drug_sq)+sum(oth_sq))-
  ((length(viol sq)+length(prop sq)+length(drug sq)+length(oth sq))*
     (grand xbar^2))
## SS Retween
ss_bet<-((length(violent)*viol_xbar^2)+(length(property)*prop_xbar^2) +
           (length(drug)*drug_xbar^2)+(length(other)*oth_xbar^2)) -
  ((length(viol sq)+length(prop sq)+length(drug sq)+length(oth sq))*
     (grand xbar^2))
## SS Within
ss with <- (sum (viol sq)+sum (prop sq)+sum (drug sq)+sum (oth sq)) -
  ((length(violent)*viol_xbar^2)+(length(property)*prop_xbar^2) +
           (length(drug)*drug xbar^2)+(length(other)*oth xbar^2))
```

Note: You can verify here that ss_ttl - ss_bet = ss_with.

Compute the F-ratio

```
## Mean Square Between
ms bet<-ss bet/(4-1)
ms_bet
## [1] 488.625
## Mean Square Within
ms with <- ss with / ((length(violent) + length(property) + length(drug) + length(other)) - 4)
ms with
## [1] 18.74722
## Mean Square Total
ms ttl<-ss ttl/((length(violent)+length(property)+length(drug)+length(other))-1)
ms ttl
## [1] 54.89167
## Calculate F-Ratio
f ratio <- ms bet/ms with
f_ratio
```

[1] 26.06386

ANOVA Example - Automatic R Method for Sentence Length Data

```
## Create numeric vectors
violent<-c(6.18.20.15.20.30.25.12.24.20); property<-c(4.6.3.10.12.8.6.10.8.15)
drug < c(6,3,3,4,6,9,10,3,2,3); other < c(1,3,1,1,6,9,3,6,2,4)
## Create Factor Labels
viol_label<-c(rep("Violent",10)); prop_label<-c(rep("Property",10))</pre>
drug label <-c(rep("Drug",10)); oth label <-c(rep("Other",10))
## Create Individual Variables
senlen <-c (violent, property, drug, other)
off_type<-c(viol_label, prop_label, drug_label, oth_label)
## Bind Together in One Data Frame
df <-data.frame(senlen. off type)
## Estimate and Print ANOVA Results
senlen anova<-aov(senlen~off type, data=df)
summary(senlen anova)
```

```
## Off_type 3 1465.9 488.6 26.06 0.00000000387 ***

## Residuals 36 674.9 18.7

## ---

## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

ANOVA and Measures of Association

ANOVA tells us whether there is a significant relationship between two variables, but it cannot tell us about the strength of the relationship

- ► Two measures of association
 - Eta square (η^2)
 - Epsilon square (ϵ^2)

ANOVA and Measures of Association

ightharpoonup Eta square (η^2)

$$\eta^2 = \frac{SS_B}{SS_T}$$

ightharpoonup Epsilon square (ϵ^2)

$$\epsilon^2 = 1 - \frac{MS_W}{MS_T}$$

- ► Explained variance interpretation
 - Proportion of the total variance in the dependent variable that is **explained** by variation in the independent variable.

Measures of Association - Offense Type and Sentence Length

▶ Eta square (η^2)

$$\eta^2 = \frac{SS_B}{SS_T} = \frac{1465.875}{2140.775} = 0.685$$

ightharpoonup Epsilon square (ϵ^2)

$$\epsilon^2 = 1 - \frac{MS_W}{MS_T} = 1 - \frac{SS_W/df_W}{SS_T/df_T} = 1 - \frac{18.75}{54.89} = 0.658$$

- ► Interpretation
 - Between 65.8% and 68.5% of the variance in sentence length is explained by offense type.

Measures of Association - Residential Location and Fear of Crime

▶ Eta square (η^2)

$$\eta^2 = \frac{SS_B}{SS_T} = \frac{344.293}{502.493} = 0.685$$

ightharpoonup Epsilon square (ϵ^2)

$$\epsilon^2 = 1 - \frac{MS_W}{MS_T} = 1 - \frac{SS_W/df_W}{SS_T/df_T} = 1 - \frac{5.859}{17.327} = 0.662$$

- ► Interpretation
 - Between 66.2% and 68.5% of the variance in fear of crime is explained by residential location.

Post-Hoc Tests

What if I am still interested in those individual group by group contrasts, though?

That is, knowing there's significant between-group variation is helpful, but it still doesn't tell me which groups are different from one another.

I need a way to maintain the alpha rate at my chosen level and to estimate all the potential group-by-group comparisons in the data.

Post-Hoc Tests

Luckily, there are multiple commands allow for this and we generally refer to them as **Post-Hoc** tests, or tests we estimate after the estimation of some other model.

The **Post-Hoc** tests for ANOVA models may also be referred to as multiple comparison corrections, as they *correct* for the alpha level issue we discussed earlier in lecture.

In practice, there are many different multiple comparison correction methods to choose from. I'll just discuss the Bonferroni method in this lecture as it's one of the most commonly used.

Post-Hoc Tests - Bonferroni Correction

The Bonferroni correction maintains what is known as a **Family-Wise Error Rate** at or below your selected alpha level through simple division. The correction is just this:

$$\frac{\alpha}{m}$$

Where α is your selected alpha level and m is the number of multiple comparisons you are conducting.

Post-Hoc Tests - Finding m

Remember the combination calculation we went over weeks ago? I hope so, because you'll need it here.

To find the number of multiple comparisons I need to conduct to report all group-by-group contrasts I can use the following equation:

$$m = \frac{k!}{2! * (k-2)!}$$

Where k is the total number of categories in the independent variable. Those who remember the combination equation will see that this is just a special case of it where r=2 and I have substituted k for n.

There were four groups in this example (violent, property, drug, and other) so let's calculate m.

$$m = \frac{k!}{2! * (k-2)!} = \frac{4!}{2! * (4-2)!} = 6$$

We have six total possible comparisons:

 $\begin{array}{lll} \mbox{Violent|Property} & \mbox{Property|Drug} & \mbox{Other|Drug} \\ \mbox{Violent|Drug} & \mbox{Property|Other} \\ \mbox{Violent|Other} & \end{array}$

Now, let's figure out the necessary p-value for standard alpha level.

Alpha Level	Bonferroni Correction	Corrected Alpha Level
$\alpha = .05$	$\frac{.05}{6}$	0.0083
$\alpha = .01$	$\frac{.01}{6}$	0.00167
$\alpha = .001$	$\frac{.001}{6}$	0.000167

We could apply these new alpha levels manually, run individual t-tests, then obtain probabilities for each observed test statistic or... we could use a function in R that automatically reports the results from post-hoc multiple comparisons tests.

The function to estimate a Bonferroni correction looks like this:

pairwise.t.test(x, g, p.adjust.method="bonferroni")

Where \mathbf{x} is the continuous outcome variable from the ANOVA, \mathbf{g} is the group variable from the ANOVA, and $\mathbf{p.adjust.method}$ ="bonferroni" tells R to use the Bonferroni method for multiple comparisons correction.

As noted before, the Bonferroni method is one of many, so this syntax could be used to estimate a variety of different multiple comparison corrections.

```
##
##
   Pairwise comparisons using t tests with non-pooled SD
##
## data: senlen and off type
##
##
           Drug Other Property
## Other 1.00000 -
## Property 0.22121 0.03256 -
## Violent 0.00036 0.00016 0.00373
##
## P value adjustment method: bonferroni
```

The values in the table display the adjusted p-values for each comparison. The adjusted p-values represent the probability of observing the test statistic (or a more extreme test statistic) if the null hypothesis is true, after adjusting the probability values for the Bonferroni correction.

Unfortunately, the table does not display the actual group mean differences as well (nor can I find a function that neatly does so).

The code on the following slides accomplishes this in a few steps.

First, I need to revise my data frame so that each column represents a list of sentence lengths for the different types of crimes. The rows are not meaningful at first, but will be by the end of this first block of code.

```
obs<-c(1:10)
df<-data.frame(obs, violent, property, drug, other)
df<-df %>%
  gather(key="off_type", value="senlen", violent, property, drug, other) %>%
  convert_as_factor(obs, off_type)
head(df, 5)

## obs off_type senlen
## 1 1 violent 6
## 2 2 violent 18
## 3 3 violent 20
## 4 4 violent 15
## 5 5 violent 20
```

The data are now in what is usually known as "long" format, but it's not quite the right term for what we have here.

Typically, "long" format data have multiple rows nested in some aggregated unit for example, multiple time period observations for a single person. Here, each row is just a person with columns for the offense type they were convicted of and the sentence length they received.

Terminology issues aside, we can now use a new function (pairwise_t_tests) to automatically detect all of the possible pairwise comparisons and group the results into one object.

I use this new function because the other one (pairwise.t.tests) will not work with the pipe operator (%>%) I use on the next slide to compile the results.

I don't want paired tests here (which is another way to refer to non-independent samples t-tests) so I set the paired option to FALSE.

I also do not want the test to assume the variances are equal across groups, so I set pool.sd=FALSE.

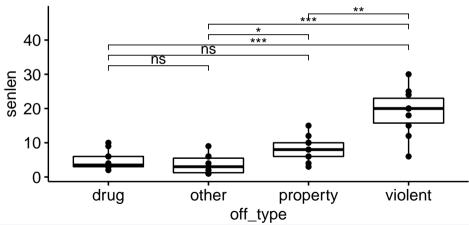
The detailed=TRUE option provides more detailed statistics in the output that you can look at after creating the option. I do not provide a summary of the object here because it does not fit properly on a slide or in a PDF - there are too many columns.

My next step is to display the results - I use a few new functions here to do so.

- ▶ The first is the ggboxplot() function,
 - A more direct way of making a box plot that includes points for the individual values.
- ► Next, the add_xy_positions() function
 - This takes the tests object I just created and adds xy coordinates to plot p-values.

```
tests_plot<- ggboxplot(df, x = "off_type", y = "senlen", add = "point")
tests<-tests %>% add_xy_position(x="off_type")
```

tests_plot+stat_pvalue_manual(tests, label="p.adj.signif")



Two Questions

What are your two questions today?

