Chapter 14: Analysis of Variance

Yu Yang

School of Statistics University of Minnesota

November 7, 2022

What is the most effective method for treating anorexia? 72 anorexic teenage girls were randomly assigned to one of three treatments.

The first treatment group received cognitive behavorial therapy in which girls are taught to identify the thinking that triggers their eating disorder and to replace it with other thoughts means to prevent this behavior.

The second treatment group attended family therapy and the third group served as a control group and did not receive any therapy. Each girl was weighed before her treatment began and weighed again upon completion of the treatment.

These data can be found at

http://stat.umn.edu/~wuxxx725/data/anorexia.txt

Let:

- μ_1 = mean weight gain after completing cognitive behavior therapy
- μ_2 = mean weight gain after completing family therapy
- μ_3 = mean weight gain with no treatment

Are any of the treatments better of worse than the others? That is, are there any significant differences among μ_1, μ_2 and μ_3 ?

Goal

Use Analysis of Variance (ANOVA) to compare the means of ${\rm more\ than\ two\ groups}$.

Why not just do a two sample *t*-test for each pair of means?

- 1. If g was the number of groups, we would have to do $\binom{g}{2}$ pairwise tests. BUT: Type I error rate increases as the number of tests increases.
- 2. This would only let us to compare 2 groups as a time, but we want know if means differ among all groups and we want to answer this with one test.

Notation:

- g = numbers of groups we are comparing
- n_i = sample size of the *i*th group
- $N = \text{overall sample size} = n_1 + n_2 + \dots n_g$
- \bar{y}_i = sample mean of the *i*th group
- \bar{y} = overall sample mean (sample mean of all the observations)
- s_i = sample standard deviation of the *i*th group

One-Way ANOVA compares population means among g different groups.

Hypotheses:

 $H_0: \mu_1 = \mu_2 = \cdots = \mu_g$

 H_a : at least 2 of the population means are unequal

To test H_0 we do an analysis of variance. That is, we compare

1. variation *between* groups, i.e. how much do $\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_g$ differ?

2. variation *within* groups, i.e. how much variability is there within each separate group?

If our goal is to compare the **means** of several populations, why are we doing analysis of **variance**? In the following box plots, the means of the groups are same between the two graphs.

If our goal is to compare the **means** of several populations, why are we doing analysis of **variance**? In the following box plots, the means of the groups are same between the two graphs.



If our goal is to compare the **means** of several populations, why are we doing analysis of **variance**? In the following box plots, the means of the groups are same between the two graphs.



- 1. Variation between groups is small compared to variability within groups
- 2. Variation between groups is large compared to variability within groups

If our goal is to compare the **means** of several populations, why are we doing analysis of **variance**? In the following box plots, the means of the groups are same between the two graphs.



- 1. Variation between groups is *small* compared to variability within groups
- 2. Variation between groups is large compared to variability within groups

Conclusions: Differences in plot 1 means are probably due to chance whereas those in plot 2 are probably due to true difference among groups and not to chance. Two means are significantly different only if their difference is large **relative** to the variability within each group.

Measuring Variability

Between Groups

 $SSG = Sum \text{ of squared deviations for groups} = \sum_{i=1}^{g} n_i (\bar{y}_i - \bar{y})^2$

 $MSG = \frac{SSG}{g-1} =$ a measure of how much means vary from group to group

Measuring Variability

Between Groups

 $SSG = Sum \text{ of squared deviations for groups} = \sum_{i=1}^{g} n_i (\bar{y}_i - \bar{y})^2$

 $MSG = \frac{SSG}{g-1} = a$ measure of how much means vary from group to group

Within Groups

SSE = Sum of Squared Deviations for Error $= \sum_{i=1}^{g} (n_i - 1)s_i^2$

 $MSE = \frac{SSE}{N-g}$ = a measure of how much observations vary within each group.

MSE is also an estimate of σ^2 , the population variance for each group.

Measuring Variability

Between Groups

 $SSG = Sum \text{ of squared deviations for groups} = \sum_{i=1}^{g} n_i (\bar{y}_i - \bar{y})^2$

 $MSG = \frac{SSG}{g-1} = a$ measure of how much means vary from group to group

Within Groups

SSE = Sum of Squared Deviations for Error $= \sum_{i=1}^{g} (n_i - 1)s_i^2$

 $MSE = \frac{SSE}{N-g}$ = a measure of how much observations vary within each group.

MSE is also an estimate of σ^2 , the population variance for each group.

Overall Variability

 $SST = SSG + SSE = \sum (y - \bar{y})^2 =$ a measure of how much observations vary from the overall mean.

Nov 7 Lecture Stopped Here

The *F* statistic measures how compatible the data is with the null $H_0: \mu_1 = \mu_2 = \cdots = \mu_g$ by comparing the variability between groups to the variability within groups.

$$F = \frac{\text{Variability Between Groups}}{\text{Variability Within Groups}} = \frac{MSG}{MSE}$$

Interpretation: When F is large, variability between groups is large compared to variability within groups. Large F suggests that at least 2 of the means are different.

Source of Variation	df	SS	MS	F
Group				
Error				
Total				

ANOVA Table

Source of Variation	df	SS	MS	F
Group	g-1	SSG	$MSG = \frac{SSG}{g-1}$	$F = \frac{MSG}{MSE}$
Error	N-g	SSE	$MSE = \frac{SSE}{N-g}$	
Total	N-1	SST		

The One-Way ANOVA F Test

Assumptions:

- 1. g independent random sample from g populations
- 2. Normality: Each population has a normal distribution with unknown mean
- 3. Equal Variance: Each population has (unknown) equal standard deviation σ .

Note:

- *F* test is robust to departures from normality and equal variance assumptions
- Graphical methods can be used to check these assumptions

Hypothesis:

 $\begin{array}{l} {\cal H}_0: \mu_1=\mu_2=\cdots=\mu_g\\ {\cal H}_a: {\rm at \ least \ 2 \ of \ the \ population \ means \ are \ unequal} \end{array}$

The One-Way ANOVA F test

Test Statistic

$$F = rac{MSG}{MSE} \sim F_{g-1,N-g}$$
 when H_0 is true

p-value

Recall that the larger F is, the more the evidence against H_0

$$\mathsf{p-value} = \mathsf{P}(\mathsf{F}_{g-1,\mathsf{N}-g} \geq \mathsf{F})$$

In R: pf(F, df1 = g-1, df2 = N-g, lower.tail = FALSE)

Conclusion:

If p-value $< \alpha$, reject H_0 If p-value $\ge \alpha$ fail to reject H_0

The F distribution

The $F_{3,60}$ density curve



- 1. Non-negative
- 2. Right Skewed
- 3. Mean is approximately 1 (exact value: $\frac{df_2}{df_2-2}$ for $df_2 > 2$)
- 4. Mode is also approximately 1 (exact value: $\frac{df_1-2}{df_1}\frac{df_2}{df_2+2}$ for $df_1 > 2$)

Calculating F values

We will only be using R to calculate p-values

 $P(F_{2,20} > 3.493)$ > pf(3.493, df1 = 2, df2 = 20, lower.tail = FALSE) [1] 0.04999364 $P(F_{5,15} > 7.42)$ > pf(7.42, df1 = 5, df2 = 15, lower.tail = FALSE) [1] 0.001103249

Recall that we want to compare anorexia treatment methods. Let

change = weight change
therapy = treatment groups (3 groups)

Assumptions

Recall that we want to compare anorexia treatment methods. Let

change = weight change therapy = treatment groups (3 groups)

Assumptions

Independent random samples, and box plot indicates assumption of normality and equal variance are OK.

Hypotheses

Recall that we want to compare anorexia treatment methods. Let

```
change = weight change
therapy = treatment groups (3 groups)
```

Assumptions

Independent random samples, and box plot indicates assumption of normality and equal variance are OK.

Hypotheses

 $H_0: \mu_1 = \mu_2 = \mu_3$ $H_a:$ at least 2 of the means are unequal

We are given SSG = 614.6 and SSE = 3910.7 and N = 72. Fill in the ANOVA Table:

We are given SSG = 614.6 and SSE = 3910.7 and N = 72. Fill in the ANOVA Table:

Source of variation	df	SS	MS	F
groups error	2 69	614.6 3910.7	307.3 56.7	5.42
Total	71	4525.3		

Test Statistic: From the table, we calculated

Test Statistic: From the table, we calculated F = 5.42

p-value

```
p-value = P(F_{2,69} > 5.42)
= pf(5.42, df1 = 2, df2 = 69, lower.tail = FALSE)
= 0.006511565
```

Conclusion:

p-value < .05, thus we reject H_0 and conclude that the mean weight gain is different for at least two of the treatment groups.

But, which ones?

Example 14.1 in R

Follow-up to the ANOVA F-Test

When we reject we do not know which groups, or even how much they differ! What do we do?

We rejected $H_0: \mu_1 = \mu_2 = \mu_3$. To determine which means are different, we could use Chapter 10 methods, making 1 - α confidence intervals for each pair:

$$\mu_1 - \mu_2$$
 $\mu_1 - \mu_3$ $\mu_2 - \mu_3$

What is the problem with this?

Follow-up to the ANOVA F-Test

When we reject we do not know which groups, or even how much they differ! What do we do?

We rejected $H_0: \mu_1 = \mu_2 = \mu_3$. To determine which means are different, we could use Chapter 10 methods, making 1 - α confidence intervals for each pair:

$$\mu_1 - \mu_2$$
 $\mu_1 - \mu_3$ $\mu_2 - \mu_3$

What is the problem with this?

Each interval has an error probability of α . Thus, the **overall** probability that at least one of the interval misses the true difference is $> \alpha$.

Multiple comparison methods perform several separate statistical analyses with a confidence level that applies simultaneously to the entire analysis.

For confidence intervals: We are $100(1 - \alpha)\%$ confident that ALL the intervals contain the truth.

A common method is the **Tukey Honest Significant Difference** (Tukey HSD) method.

Use R to construct Tukey HSD multiple comparison confidence intervals for the mean weight gain for the 3 anorexia treatments. Overall confidence level is 0.95.

```
> mod <- aov(change ~ therapy, data = dat)
> TukeyHSD(mod, "therapy", conf.level = 0.95)
Tukey multiple comparisons of means
95% family-wise confidence level
```

Fit: aov(formula = change ~ therapy, data = dat)

\$therapy

difflwruprp adjcontrol-cog-3.456897-8.3272761.4134830.2124428family-cog4.257809-1.2505549.7661730.1607461family-control7.7147062.09012413.3392880.0045127

difflwruprp adjcontrol-cog-3.456897-8.3272761.4134830.2124428family-cog4.257809-1.2505549.7661730.1607461family-control7.7147062.09012413.3392880.0045127

 $\begin{array}{l} {\rm diff} = \bar{y}_{control} - \bar{y}_{cog} \mbox{ etc} = \mbox{ difference in group sample means} \\ {\rm lwr} = \mbox{ lower bound of confidence interval} \\ {\rm upr} = {\rm upper \ bound \ of \ confidence \ interval} \\ {\rm p \ adj} = {\rm p-value \ after \ adjustment \ for \ the \ multiple \ comparisons} \end{array}$

If 0 is in the CI, there is no difference between the two groups. If 0 is not in the CI, the two groups are significantly different.

Which groups are different here?

difflwruprp adjcontrol-cog-3.456897-8.3272761.4134830.2124428family-cog4.257809-1.2505549.7661730.1607461family-control7.7147062.09012413.3392880.0045127

 $\begin{array}{l} \text{diff} = \bar{y}_{control} - \bar{y}_{cog} \ \text{etc} = \text{difference in group sample means} \\ \text{lwr} = \text{lower bound of confidence interval} \\ \text{upr} = \text{upper bound of confidence interval} \\ \text{p adj} = \text{p-value after adjustment for the multiple comparisons} \end{array}$

If 0 is in the CI, there is no difference between the two groups. If 0 is not in the CI, the two groups are significantly different.

Which groups are different here?

The mean weight gain for the **family** treatment is significantly **higher** than the mean weight gain for the **control** group.

difflwruprp adjcontrol-cog-3.456897-8.3272761.4134830.2124428family-cog4.257809-1.2505549.7661730.1607461family-control7.7147062.09012413.3392880.0045127

 $\begin{array}{l} {\rm diff} = \bar{y}_{control} - \bar{y}_{cog} \ {\rm etc} = {\rm difference \ in \ group \ sample \ means} \\ {\rm lwr} = {\rm lower \ bound \ of \ confidence \ interval} \\ {\rm upr} = {\rm upper \ bound \ of \ confidence \ interval} \\ {\rm p \ adj} = {\rm p-value \ after \ adjustment \ for \ the \ multiple \ comparisons} \end{array}$

If 0 is in the CI, there is no difference between the two groups. If 0 is not in the CI, the two groups are significantly different.

Which groups are different here? The mean weight gain for the **family** treatment is significantly **higher** than the mean weight gain for the **control** group.

Note: Hypothesis testing is not transitive!, i.e. if family is different from control, and cognitive is same as family, **it does not mean** cognitive is different from control!