

PSY 3307

Analysis of Variance (ANOVA)

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Agenda

- Review t-tests
- Overview of Analysis of Variance (ANOVA)
 - Quick Review of all the different types of ANOVA
 - One-way ANOVA
 - Two-way ANOVA
 - Factorial ANOVA
 - Repeated-measures ANOVA
 - Mixed-effect ANOVA
- Components of ANOVA
- Performing ANOVA
- Post-hoc Tests (Tukey's HSD Test)
- Effect Size and η^2
- JP is Including More

Review t-tests

- Things we need to remember
 - How to read a table (z, t, and now F)
 - Differences between within- and between-designs
 - What is an IV, DV, and conditions

Analysis of Variance (ANOVA)

- **Factor** is just another word for IV
- A **level** is the same thing as a condition (from t-tests) and similar to a t-test, ANOVA has to do with differences between or among sample means
 - however ANOVA does not have restrictions on the number of groups we can test
- **k** is the symbol for the number of levels in a factor
 - otherwise known as the number of conditions in an IV

k = number of levels in factor

Example of the Absurdity

```
## Warning: Missing column names filled in: 'X1' [1]
```

```
##
```

```
## -- Column specification -----
```

```
## cols(
```

```
##   .default = col_double(),
```

```
##   state_fips_code = col_character(),
```

```
##   county_fips_code = col_character(),
```

```
##   fips_code = col_character(),
```

```
##   state_abbreviation = col_character(),
```

```
##   county_name = col_character(),
```

```
##   reading_scores_aian = col_logical(),
```

```
##   math_scores_aian = col_logical(),
```

```
##   communicable_disease = col_logical(),
```

```
##   cancer_incidence = col_logical(),
```

```
##   coronary_heart_disease_hospitalizations = col_logical(),
```

```
##   cerebrovascular_disease_hospitalizations = col_logical(),
```

```
##   smoking_during_pregnancy = col_logical(),
```

```
##   opioid_hospital_visits = col_logical(),
```

```
##   alcohol_related_hospitalizations = col_logical(),
```

```
##   motor_vehicle_crash_occupancy_rate = col_logical(),
```

```
##   on_road_motor_vehicle_crash_related_er_visits = col_logical(),
```

```
aov_find <- aov(adult_smoking ~ state_abbreviation, data = data)
summary(aov_find)
```

```
##              Df Sum Sq Mean Sq F value           Pr(>F)
## state_abbreviation    50   2.338  0.04676    80.92 <0.00000000000000002 ***
## Residuals            3142   1.815  0.00058
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
tukey_find <- TukeyHSD(aov_find)
tukey_find$`state_abbreviation`[1:10, 1:4]
```

##		diff	lwr	upr	p adj
##	AK-CA	0.087343654	0.065752343	0.10893497	0.000000000000000
##	AL-CA	0.079242299	0.062110931	0.09637367	0.000000000000000
##	AR-CA	0.083350172	0.066642931	0.10005741	0.000000000000000
##	AZ-CA	0.043470569	0.016330229	0.07061091	0.0000002016392
##	CO-CA	0.022238079	0.004924024	0.03955213	0.0003319958281
##	CT-CA	-0.001099152	-0.035556182	0.03335788	1.000000000000000
##	DC-CA	0.038867947	-0.030362089	0.10809798	0.9909882820559
##	DE-CA	0.042165472	-0.007583593	0.09191454	0.3079515102058
##	FL-CA	0.070667490	0.053536122	0.08779886	0.000000000000000
##	GA-CA	0.061787805	0.047121974	0.07645364	0.000000000000000

Another Reason Why I Like Regression

- In a real-life scenario, you would already have a hypothesis where you would be interested in whether or not a state is different from the rest
- Therefore, you'd already have a reference group to compare everyone to and just need to run one test
- Below is the same test, just through a regression framework


```
lm_find <- lm(adult_smoking ~ state_abbreviation, data = data)
summary(lm_find)
```

```
##
## Call:
## lm(formula = adult_smoking ~ state_abbreviation, data = data)
##
## Residuals:
```

	Min	1Q	Median	3Q	Max
	-0.07620	-0.01314	-0.00115	0.01065	0.24411

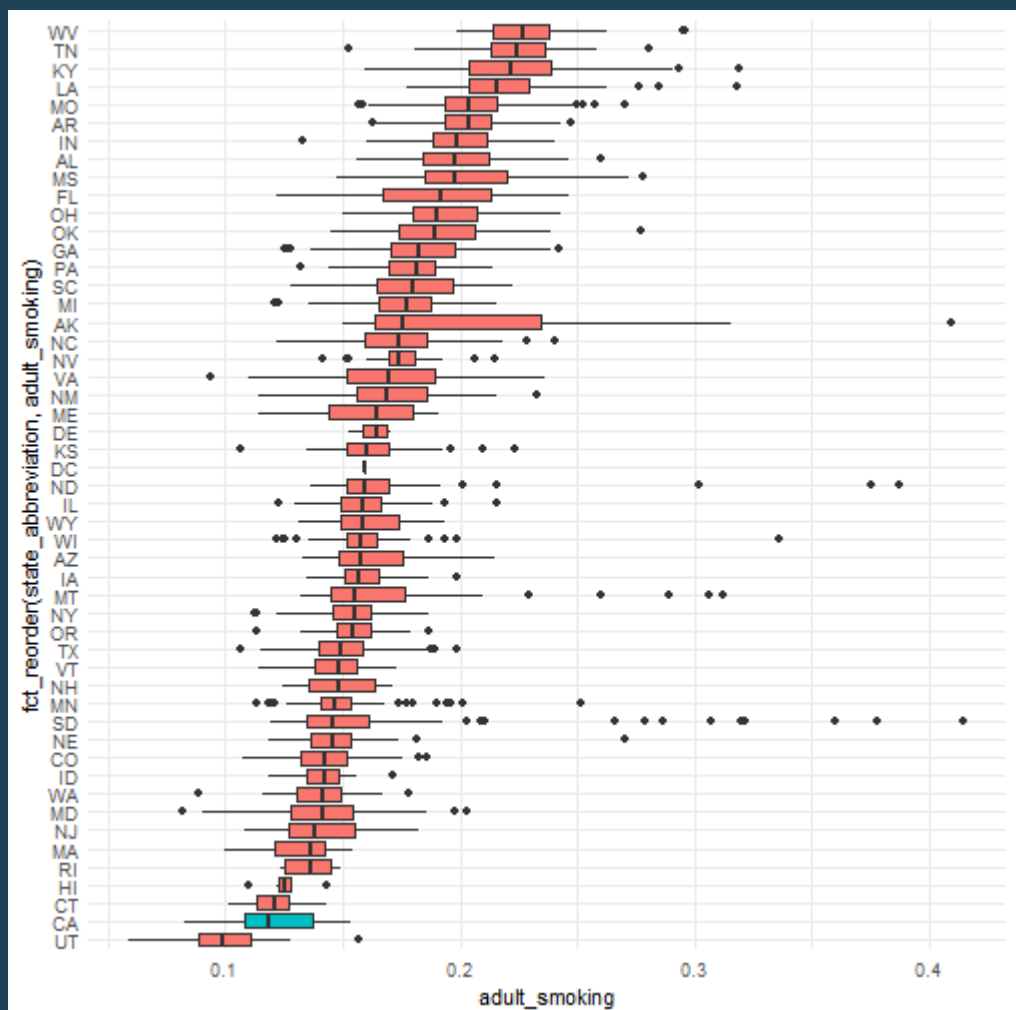
```
##
## Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	0.120788	0.003129	38.598	< 0.000000000000000002	***
state_abbreviationAK	0.087344	0.005390	16.205	< 0.000000000000000002	***
state_abbreviationAL	0.079242	0.004277	18.529	< 0.000000000000000002	***
state_abbreviationAR	0.083350	0.004171	19.984	< 0.000000000000000002	***
state_abbreviationAZ	0.043471	0.006775	6.416	0.00000000001609179	***
state_abbreviationCO	0.022238	0.004322	5.145	0.00000002839612803	***
state_abbreviationCT	-0.001099	0.008602	-0.128	0.898331	
state_abbreviationDC	0.038868	0.017283	2.249	0.024584	*
state_abbreviationDE	0.042165	0.012419	3.395	0.000694	***
state_abbreviationFL	0.070667	0.004277	16.524	< 0.000000000000000002	***
state_abbreviationGA	0.061788	0.003661	16.876	< 0.000000000000000002	***
state_abbreviationHI	0.004873	0.010300	0.473	0.636138	
state_abbreviationIA	0.037774	0.003946	9.573	< 0.000000000000000002	***
state_abbreviationID	0.020741	0.004757	4.360	0.0000134333660949	***

```
broom::tidy(lm_find)
```

```
## # A tibble: 51 x 5
```

##	term	estimate	std.error	statistic	p.value
##	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
##	1 (Intercept)	0.121	0.00313	38.6	4.13e-267
##	2 state_abbreviationAK	0.0873	0.00539	16.2	8.82e- 57
##	3 state_abbreviationAL	0.0792	0.00428	18.5	7.99e- 73
##	4 state_abbreviationAR	0.0834	0.00417	20.0	9.75e- 84
##	5 state_abbreviationAZ	0.0435	0.00678	6.42	1.61e- 10
##	6 state_abbreviationCO	0.0222	0.00432	5.14	2.84e- 7
##	7 state_abbreviationCT	-0.00110	0.00860	-0.128	8.98e- 1
##	8 state_abbreviationDC	0.0389	0.0173	2.25	2.46e- 2
##	9 state_abbreviationDE	0.0422	0.0124	3.40	6.94e- 4
##	10 state_abbreviationFL	0.0707	0.00428	16.5	7.02e- 59
##	# ... with 41 more rows				



Breaking Down A One-way ANOVA

- **One-way ANOVA** is when we have an IV that has multiple levels (3+)
 - **NOTE** if you were to go on to SPSS and run a one-way ANOVA with the **sex** variable you would get the same answer
 - Essentially the same test being run
- Similar to a t-test, this also has within- and between-subjects designs
- Now instead of a t-table, we will be using a F-table

We Are Now Working With Modeling

- There's just one problem. We have to work with ANOVA modeling
- **ANOVA** is a parametric procedure for determining whether significant differences occur in an experiment containing two or more sample means

$$X_{ij} = \mu + \gamma_j + \epsilon_{ij}$$

- μ is the grand mean
- γ_j is the specific treatment effect for group j (which group you are interested in looking at)
- ϵ_{ij} is the error/residual of a specific individual (how much an individual deviates from the group's mean)

Assumptions

- **homogeneity of variance** is the assumption that each population has the same variance

$$\sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \dots$$

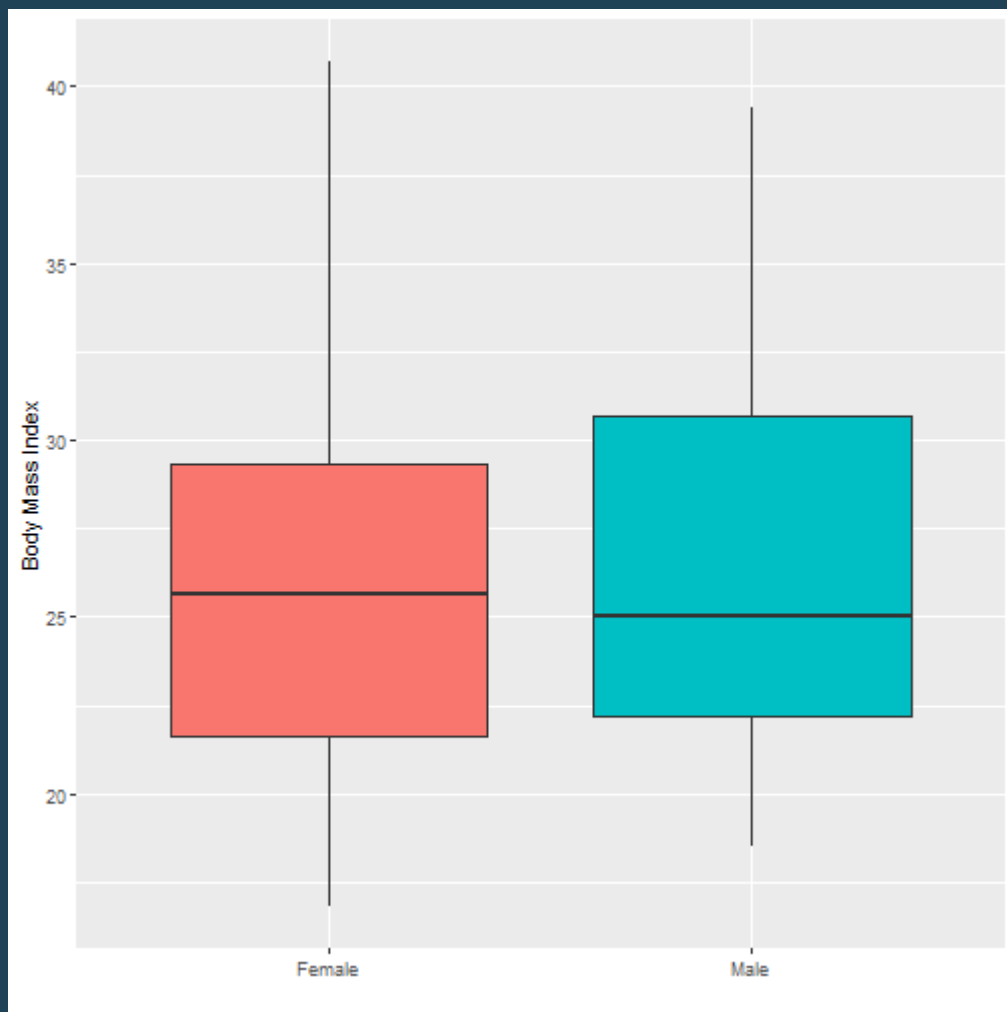
- **error variance** variance unrelated to any treatment differences
- **heterogeneity of variance** is when populations have different variances
- **normality** DV values are normally distributed
- **independence** observations are independent of one another
 - it really is that the residual/error is independent but for now we'll keep it as observations are different from one another
- The **n** in each level doesn't have to be exactly the same but they should not be drastically different

Controlling Experiment-Wise Error Rate

- I had mentioned this previously that multiple independent-samples t-tests could do the same thing as a one-way ANOVA
- **experiment-wise error rate** is the probability of making a Type I error when comparing all means in an experiment
- with an F-test we are less likely to commit a type I error because we are not running all the tests possible

Example

```
jp <- rio::import(here::here("jp_thesis_1.sav")) %>%  
  janitor::clean_names() %>%  
  rowid_to_column() %>%  
  rename(sex = ccc_gender)
```

```
bmi_aov <- aov(ccc_bmi ~ factor(sex), data = jp)
summary(bmi_aov)
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## factor(sex)    1      3    2.515   0.086  0.769
## Residuals    370  10793   29.169
```

```
TukeyHSD(bmi_aov)
```

```
##      Tukey multiple comparisons of means
##      95% family-wise confidence level
##
## Fit: aov(formula = ccc_bmi ~ factor(sex), data = jp)
##
## $`factor(sex)`
##              diff              lwr              upr              p adj
## 2-1 -0.1775135 -1.366163  1.011136  0.7691805
```

```
t.test(ccc_bmi ~ factor(sex), data = jp, var.equal = TRUE)
```

```
##  
##      Two Sample t-test  
##  
## data:  ccc_bmi by factor(sex)  
## t = 0.29366, df = 370, p-value = 0.7692  
## alternative hypothesis: true difference in means is not equal to 0  
## 95 percent confidence interval:  
##  -1.011136  1.366163  
## sample estimates:  
## mean in group 1 mean in group 2  
##      26.32931      26.15180
```

Steps to Conduct ANOVA

- Hypotheses
 - Similar to the independent-samples t-test, a one-way ANOVA's null hypothesis states that there is no difference between the levels/conditions
 - We just have more levels in a one-way ANOVA.
- our null hypothesis would be

$$H_0 : \mu_1 = \mu_2 = \mu_3$$

$$H_1 : \text{not all } \mu \text{ are equal}$$

- our alternative/research hypothesis is not that all groups would be significantly different from one another
- **JP Note** another option is to state that one group will be significantly different from the other groups

F statistic

- Steps to ANOVA
 1. Compute a F-statistic
 2. Conduct a post-hoc test

F-statistic

- we compute a F-statistic to see if any means are different
 - Significant F-statistic then there are differences somewhere between the multiple levels
 - Non-significant F-statistic means there are no differences between any levels
- The F-statistic only tells us whether or not a significant difference is found between any of the levels
- F-obtained is compared to a F-critical value to find statistical significance

Post-hoc Tests OR Planned Comparisons

- Post-hoc often refers to after the fact
- Post-hoc tests are often considered after finding a statistically significant F-statistic
- like t-tests when comparing all combinations of each levels to see if there differences between two specific levels
- Planned comparisons are when you are interested in having a specific levels being different from the other levels

Post-hoc Tests

- only look at post-hoc findings if there is a significant F-statistic
- no post-hoc tests are run when you only have two levels

Different Types of Post-hoc Tests

- **Tukey Test or Tukey's HSD (Honestly Significant Difference)**
- Fisher's Least Significant Difference (LSD) Procedure
- Newman-Keuls Test
- Scheffe Test
- Dunnett's Test
- Benjamini-Hochberg Test
- **Bonferroni Test/Correction**
 - whatever alpha you are using, you then divide by the number of tests you conduct
 - $\alpha = .05$, and you run 20 tests
- We'll get to these in the upcoming weeks (if only shortly)

Bonferroni Correction Examples

- Alpha = .05, number of tests = 20 -new p-value should be .0025

```
.05/20
```

```
## [1] 0.0025
```

- alpha = .05, number of tests = 10
 - new p-value = _

Contrasts

- **a priori comparison** or before data is collected
 - also called **contrasts**
- **post hoc comparison** after data has been collected, looked at descriptive statistics, and sometimes...
 - they've looked at their test results
- gets complicated with the type of contrast chosen
 - linear contrasts
 - orthogonal contrasts

Unequal Sample Sizes

- ANOVA is robust to slightly unequal sample sizes
 - like the example we did in SPSS
- **balanced designs** are when each level has the same amount of participants
- formula corrections are needed for unequal samples (see below)
- another option to make sure your levels are all equal in number of observations (n) is to fill in potential missing data
 - old-school methods include changing missing values to the mean or median
 - new-school methods include things like full-information maximum likelihood or multiple imputation (real fancy stuff)

Componentenets of ANOVA

$$S_x^2 = \frac{\Sigma(X - \bar{X})^2}{N - 1}$$

$$S_X^2 = \frac{\Sigma X^2 - \frac{(\Sigma X)^2}{N}}{N - 1}$$

$$S_x^2 = \frac{\text{Sum of Squares (SS)}}{\text{Degrees of Freedom (df)}}$$

Terminology

- Sum of Squares is broken down into three different categories
 - Sum of Squares Total
 - Sum of Squares Between/Treatment
 - Sum of Squares Within/Error

$$SS_{total}$$

$$SS_{bn} = SS_{treat}$$

$$SS_{wn} = SS_{error}$$

- Sum of squares (SS)/degrees of freedom (df) is equal to mean square
- mean square is often seen as MS
- when referring to ANOVA, sum of the squared deviations is called sum of squares
- this calculation of sum of squares divided by the degrees of freedom is called mean square or MS
- so our variance calculation is really our mean square in ANOVA
 - this is because we are calculating the mean square within groups and mean square between groups

Formulas for Sum of Squares

$$SS_{total} = \Sigma(X_{ij} - \bar{X})^2$$

- This means that every value (i) within each level/group/condition (j) is put into this equation and then subtracting the **grand mean**
- **the grand mean** is the mean of all the observations of each level or the mean of each level's mean

$$SS_{treat} = n\Sigma(\bar{X}_j - \bar{X})^2$$

$$SS_{error} = SS_{total} - SS_{treat}$$

- Sum of squares error is actually the sum of each score within each level minus the mean for that level and then added all together to get the final value

$$SS_{error} = \Sigma(X_{ij} - \overline{X_j})^2$$

$$SS_{wn \ level1} = \Sigma((first \ observation - level \ 1 \ mean)^2 + (second \ observation - level \ 1 \ mean)^2 + \dots)$$

Unequal Sample Size Correction

$$SS_{treat} = n \Sigma (\bar{X}_j - \bar{X})^2$$

will become

$$SS_{treat} = \Sigma [n_j (\bar{X}_j - \bar{X})^2]$$

so this would then include the n for each group/level/condition

Mean Square Within Groups

- **MS within groups** describes the variability in scores within the conditions/levels of an experiment

$$MS_{wn}$$

- we find differences among values in each level/condition and "pool" them together
- **MS within groups** is the "average" variability of scores within each level
- it is essentially a measure of variability of individual scores

Mean Square Between Groups

- **MS between groups** is the differences between the means of each condition/level in a factor/IV

$$MS_{bn}$$

- measure difference between the means by treating them as scores, with an "average" amount they deviate from their mean, which in this case is the overall mean of the experiment
- similar to how scores deviate from a mean, this is a measure of the deviations of sample means from the overall mean

The F-ratio

- MS between groups tells us whether or not the levels differ from one another and support our null/alternative hypotheses
- MS within groups estimates variability of individual scores
- if working with one population, our MS between should equal our MS within
- so if our null is true the MS between should be the same answer as the MS within
- **F-ratio** is a fraction consisting of MS between divided by the MS within or

$$F_{obt} = \frac{MS_{bn}}{MS_{wn}}$$

F-ratio

- while it is unlikely that an exact value of 1 would be a F-obtained value, a value around 1 should be supportive of the null hypothesis
- the larger the F-ratio the more likely that the result is from sampling error or from the IV
- if our F-obtained value is larger than the F-critical value then we reject the null and accept the alternative/research hypothesis

Performing an ANOVA

- before beginning, its important to note that for many of the calculations symbols will be similar like **MS** but it is important to note the subscripts

$$MS_{bn} \neq MS_{wn}$$

<i>Source</i>	<i>Sum of Squares</i>	<i>df</i>	<i>MeanSquare</i>	<i>F – ratio</i>
<i>Between</i>	SS_{bn}	df_{bn}	MS_{bn}	F_{obt}
<i>Within</i>	SS_{wn}	df_{wn}	MS_{wn}	
<i>Total</i>	SS_{total}	df_{total}		

Computing for a F-obtained value

Steps for getting the F-obtained value

1. Calculate the sum of squares
2. Calculate the degrees of freedom
3. Calculate the mean squares
4. Calculate the F-obtained value


```
difficulty <- data.frame(easy = c(9, 12, 4, 8, 7),  
                          medium = c(4, 6, 8, 2, 10),  
                          hard = c(1, 3, 4, 5, 2))
```

```
easy_sum = 9+12+4+8+7  
med_sum = 4+6+8+2+10  
hard_sum = 1+3+4+5+2
```

```
easy_sum
```

```
## [1] 40
```

```
med_sum
```

```
## [1] 30
```

```
hard_sum
```

```
## [1] 15
```

```
easy_sum2 = 9^2+12^2+4^2+8^2+7^2  
med_sum2 = 4^2+6^2+8^2+2^2+10^2  
hard_sum2 = 1^2+3^2+4^2+5^2+2^2  
  
easy_sum2
```

```
## [1] 354
```

```
med_sum2
```

```
## [1] 220
```

```
hard_sum2
```

```
## [1] 55
```

```
easy_n = 5
med_n = 5
hard_n = 5

easy_mean = easy_sum/easy_n
med_mean = med_sum/med_n
hard_mean = hard_sum/hard_n

easy_mean
```

```
## [1] 8
```

```
med_mean
```

```
## [1] 6
```

```
hard_mean
```

```
## [1] 3
```

Total Sum of all the Values

```
total_sum = easy_sum + med_sum + hard_sum  
total_sum
```

```
## [1] 85
```

Total Sum of all the Squared Values

```
total_sum2 = easy_sum2 + med_sum2 + hard_sum2  
total_sum2
```

```
## [1] 629
```

Total N

```
total_n = easy_n + med_n + hard_n  
total_n
```

```
## [1] 15
```

k or the number of levels/conditions

```
k = 3  
k
```

```
## [1] 3
```


Computing the Sums of Squares Total

$$SS_{total} = \Sigma X_{total}^2 - \frac{(\Sigma X_{total})^2}{N}$$

$$SS_{total} = 629 - \frac{(85)^2}{15}$$

```
85^2
```

```
## [1] 7225
```

$$SS_{total} = 629 - \frac{7225}{15}$$

```
## [1] 481.6667
```

$$SS_{total} = 629 - 481.67$$

```
629 - 481.67
```

```
## [1] 147.33
```

$$SS_{total} = 147.33$$

Filling in the Table

<i>Source</i>	<i>Sum of Squares</i>	<i>df</i>	<i>MeanSquare</i>	<i>F – ratio</i>
<i>Between</i>	SS_{bn}	df_{bn}	MS_{bn}	F_{obt}
<i>Within</i>	SS_{wn}	df_{wn}	MS_{wn}	
<i>Total</i>	147.33	df_{total}		

Sums of Squares Between

$$SS_{bn} = \Sigma \left(\frac{(\Sigma X \text{ in each column})^2}{n \text{ in each column}} \right) - \frac{(\Sigma X_{total})^2}{N}$$

$$SS_{bn} = \Sigma \left(\frac{(40)^2}{5} + \frac{(30)^2}{5} + \frac{(15)^2}{5} \right) - \frac{(85)^2}{15}$$

```
40^2
```

```
## [1] 1600
```

```
30^2
```

```
## [1] 900
```

```
15^2
```

```
## [1] 225
```

```
85^2
```

```
## [1] 7225
```

$$SS_{bn} = \Sigma\left(\frac{1600}{5} + \frac{900}{5} + \frac{225}{5}\right) - \frac{7225}{15}$$

```
1600/5
```

```
## [1] 320
```

```
900/5
```

```
## [1] 180
```

```
225/5
```

```
## [1] 45
```

```
7225/15
```

```
## [1] 481.6667
```

$$SS_{bn} = (320 + 180 + 45) - 481.67$$


```
(320 + 180 + 45) - 481.67
```

```
## [1] 63.33
```

$$SS_{bn} = 63.33$$

Filling in the Table

<i>Source</i>	<i>Sum of Squares</i>	<i>df</i>	<i>MeanSquare</i>	<i>F – ratio</i>
<i>Between</i>	63.33	df_{bn}	MS_{bn}	F_{obt}
<i>Within</i>	SS_{wn}	df_{wn}	MS_{wn}	
<i>Total</i>	147.33	df_{total}		

Sum of Squares Within Groups

$$SS_{wn} = SS_{total} - SS_{bn}$$

```
147.33 - 63.33
```

```
## [1] 84
```

Using the other way

$$SS_{total} = \Sigma(X_{ij} - \bar{X})^2$$

$$SS_{treat} = n\Sigma(\bar{X}_j - \bar{X})^2$$

$$SS_{error} = SS_{total} - SS_{treat}$$

```
difficulty
```

```
##      easy medium hard
## 1      9      4     1
## 2     12      6     3
## 3      4      8     4
## 4      8      2     5
## 5      7     10     2
```

```
grand_mean = (9 + 12 + 4 + 8 + 7 + 4 + 6 + 8 + 2 + 10 + 1 + 3 + 4 + 5 +
grand_mean
```

```
## [1] 5.666667
```

```
(easy_mean + med_mean + hard_mean)/3
```

```
## [1] 5.666667
```

```
ss_total = (9 - grand_mean)^2 + (12 - grand_mean)^2 + (4 - grand_mean)^2 +  
  (4 - grand_mean)^2 + (6 - grand_mean)^2 + (8 - grand_mean)^2 + (2 - gr  
  (1 - grand_mean)^2 + (3 - grand_mean)^2 + (4 - grand_mean)^2 + (5 - gr  
ss_total
```

```
## [1] 147.3333
```

```
ss_treat = 5*((easy_mean - grand_mean)^2 + (med_mean - grand_mean)^2 +  
ss_treat
```

```
## [1] 63.33333
```

```
ss_error = ss_total - ss_treat
```

```
ss_error
```

```
## [1] 84
```


Filling in the Table

<i>Source</i>	<i>Sum of Squares</i>	<i>df</i>	<i>Mean Square</i>	<i>F - ratio</i>
<i>Between</i>	63.33	df_{bn}	MS_{bn}	F_{obt}
<i>Within</i>	84	df_{wn}	MS_{wn}	
<i>Total</i>	147.33	df_{total}		

Calculating degrees of freedom

- df between groups is simply the number of groups/levels/conditions - 1

$$df_{bn} = k - 1$$

```
3 - 1
```

```
## [1] 2
```

- df within groups is $N - k$

```
15 - 3
```

```
## [1] 12
```

- df total is still $N - 1$

```
15 - 1
```

```
## [1] 14
```

Filling in the Table

<i>Source</i>	<i>Sum of Squares</i>	<i>df</i>	<i>Mean Square</i>	<i>F - ratio</i>
<i>Between</i>	63.33	2	MS_{bn}	F_{obt}
<i>Within</i>	84	12	MS_{wn}	
<i>Total</i>	147.33	14		

Computing the Mean Squares

$$MS_{bn} = \frac{SS_{bn}}{df_{bn}}$$

$$MS_{bn} = \frac{63.33}{2}$$

63.33/2

[1] 31.665

$$MS_{bn} = 31.67$$

Filling in the Table

<i>Source</i>	<i>Sum of Squares</i>	<i>df</i>	<i>MeanSquare</i>	<i>F – ratio</i>
<i>Between</i>	63.33	2	31.67	F_{obt}
<i>Within</i>	84	12	MS_{wn}	
<i>Total</i>	147.33	14		

Computing the Mean Square within Groups

$$MS_{wn} = \frac{SS_{wn}}{df_{wn}}$$

$$MS_{wn} = \frac{84}{12}$$

```
## [1] 7
```

$$MS_{wn} = 7$$

Filling in the Table

<i>Source</i>	<i>Sum of Squares</i>	<i>df</i>	<i>MeanSquare</i>	<i>F – ratio</i>
<i>Between</i>	63.33	2	31.67	F_{obt}
<i>Within</i>	84	12	7	
<i>Total</i>	147.33	14		

Calculating the F-statistic

$$F_{obt} = \frac{MS_{bn}}{MS_{wn}}$$

$$F_{obt} = \frac{31.67}{7}$$

31.67/7

```
## [1] 4.524286
```

$$F_{obt} = 4.52$$

Filling in the Table

<i>Source</i>	<i>Sum of Squares</i>	<i>df</i>	<i>MeanSquare</i>	<i>F – ratio</i>
<i>Between</i>	63.33	2	31.67	4.52
<i>Within</i>	84	12	7	
<i>Total</i>	147.33	14		

Interpreting the F-obtained value

- **F-distribution** is the sampling distribution with values of F to represent when H_0 is true and all conditions represent one population (no differences between groups/levels)
- F cannot be less than zero
- There is no limit to how large an F-obtained value can be
- the mean of the F-distribution is 1
- F-distribution shape also depends on the df

F-table

- uses alpha, df within, df between
- line up the df within with the df between and choose the value based on the alpha decided on
- the F-table only tells us one thing, *is there a statistically significant difference between the means of the three groups/conditions/levels*
- in order to see which specific group comparisons are significantly different from one another, we will rely on post-hoc tests or examination of the contrasts

Writing up Findings

- when reporting, you would first include the test that you ran and the context
 - how many groups, your IV, your DV
- you would then report the F statistic
 - $F(df \text{ between}, df \text{ within}) = F \text{ obtained value}, p \text{ value}$
- then you would report the post-hoc tests, which would include the group/level means that were statistically significant from one another
- lastly you would report the effect size/eta squared (we'll get to this next week)

Next Class

- We'll talk about:
 - effect sizes
 - calculations for post-hoc tests
 - proportions of variance accounted for
 - slight introduction to what an ANCOVA is

Practice Problems

You are interested in ways your class ($N = 30$) can increase their happiness. You are testing two methods to improve happiness and one control group. Your groups are: 1 = having plants to take care of ($n = 10$), 2 = support animal ($n = 10$), 3 = control ($n = 10$). You are interested in there is a significant difference between these three groups on your students happiness.

```
set.seed(101421)

plants <- rnorm(10, mean = 80, sd = 11)
animal <- rnorm(10, mean = 40, sd = 8.4)
control <- rnorm(10, mean = 50, sd = 2.1)

happy <- data.frame(plants,
                    animal,
                    control)

happy
```

```
##      plants  animal control
## 1  90.71611 49.36230 46.56667
## 2  62.01473 34.80282 48.64966
## 3  71.23168 38.74386 48.14495
## 4  78.82846 43.41543 50.64383
## 5  60.72292 33.21453 49.84474
## 6 107.16287 36.53926 50.35684
## 7  67.26932 32.73007 50.33949
## 8  79.73614 47.87016 49.10797
## 9  84.54266 22.45582 51.92304
## 10 86.23949 31.74746 53.10834
```

You are having a movie marathon of all your favorite spooky movies to watch. You decide to make a competition between you and your friends by seeing whose method of staying away longer will allow you to watch more movies in a weekend. You decide that you and some others ($n = 5$) are going to drink two pots of coffee each day to stay away all weekend. Another group ($n = 5$) decide that they are going to drink energy drinks to stay up. Your last group of friends ($n = 5$) are going to rely on each other to stay up by shaking each other awaken. You are interested in what group will stay up the latest.

```
set.seed(101421)

coffee <- rnorm(5, mean = 20, sd = 4.5)
energy <- rnorm(5, mean = 43, sd = 1.2)
support <- rnorm(5, mean = 10, sd = .5)

spooky <- data.frame(coffee,
                      energy,
                      support)

spooky
```

```
##      coffee  energy  support
## 1 24.38386 45.96322 10.557279
## 2 12.64239 41.61120  9.690644
## 3 16.41296 42.97121  9.925230
## 4 19.52073 43.49556 10.203300
## 5 12.11392 43.68067  9.596103
```