ANOVA

Weeks 1 – 3

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Contents

Installing the `needs` Package

- Can install packages and load them
- No longer need `install.packages()` and `library()`
- It will ask if you would like to load it every time RStudio opens. Select yes.

```
install.packages("needs")
```

Importing the Data

Normally we would use the `import()` function to import our data. However, with the SPSS `.sav` files we don't get factor labels.

```
data_import <- import(here("data/Lab2_Vocab.sav"))
head(data_import)
```

```
##   idnum vocab instruct
## 1     1    53        1
## 2     2    49        1
## 3     3    47        1
## 4     4    42        1
## 5     5    51        1
## 6     6    34        1
```

Notice how we have 1s down the instruct column.

The Fix

For now, when working with `.sav` files we will use the `read.sav` function from the `misty` package. `use.value.labels = TRUE` tells it to use the labels as the cell values.

```
needs(misty)
l2_data <- misty::read.sav(here("data/Lab2_Vocab.sav"),
                           use.value.labels = TRUE)
head(l2_data)
```

```
##   idnum vocab          instruct
## 1     1    53 physical science
## 2     2    49 physical science
## 3     3    47 physical science
## 4     4    42 physical science
## 5     5    51 physical science
## 6     6    34 physical science
```

Checking The Assumptions of ANOVA

- Independence of observations
- Normality
- Homogeneity of variance

Descriptive Statistics

Make sure the `psych` package is installed and loaded:

```
needs(psych)
```

`describe` from the `psych` package is one of the more popular functions for descriptive statistics.

```
describe(l2_data)
```

	vars	n	me...	sd	median	trimmed	mad
	<int>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
idnum	1	36	18.5	10.5356538	18.5	18.5	13.3434
vocab	2	36	33.5	12.8652355	35.5	34.2	12.6021
instruct*	3	36	2.0	0.8280787	2.0	2.0	1.4826

3 rows | 1–8 of 14 columns

Independence of Observations

- Do participants cross groups?
- We know this if we know the study design
- In this study, each student experienced one and only one lecture

Normality

- We can check the skew and kurtosis values from our `describe()` output.
- 0 ± 2 is a good rule of thumb for a tenable assumption of normality.

	vars	n	skew	kurtosis
	<int>	<dbl>	<dbl>	<dbl>
idnum	1	36	0.0000000	−1.3003629
vocab	2	36	−0.5359932	−0.8726857
instruct*	3	36	0.0000000	−1.5821759

3 rows

- Instruct is a categorical variable, so we can ignore the skew and kurtosis on that.

Visual Inspection for Normality

- For the most part, plots will be wrapped using the `ggplot()` function.

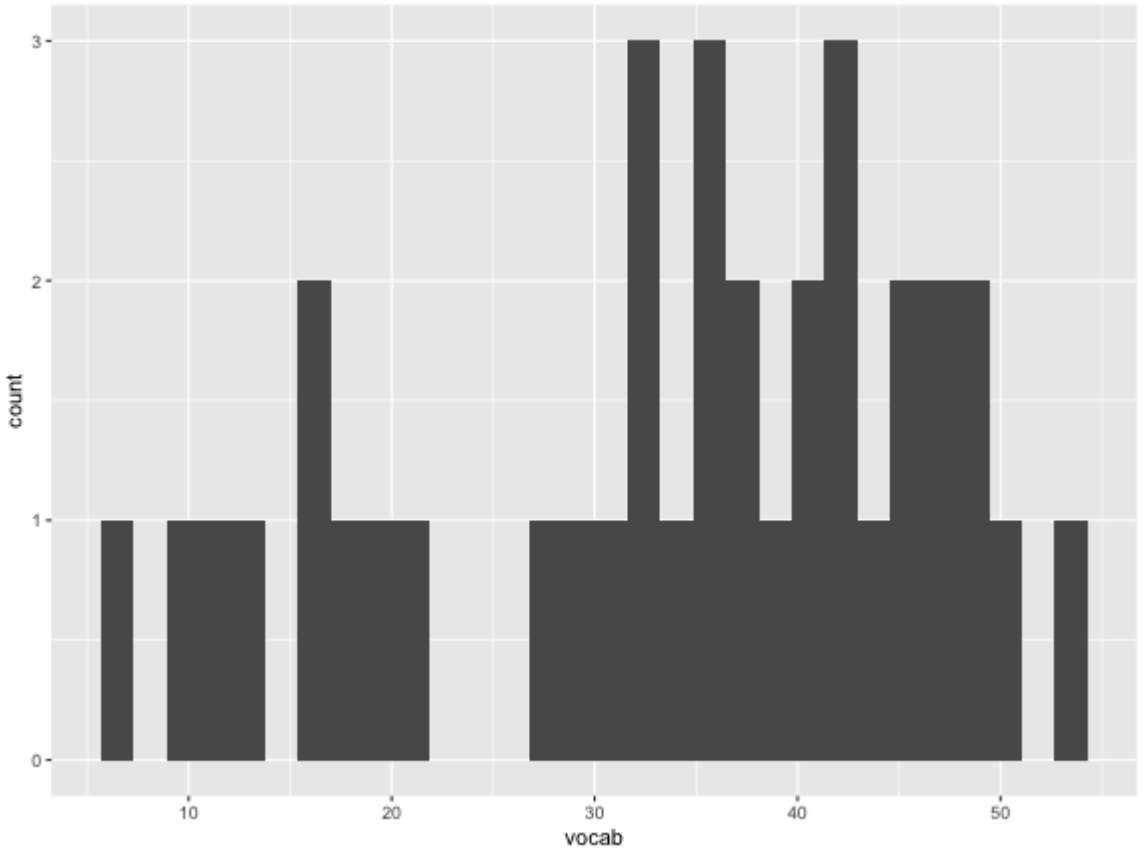
Histogram

```
ggplot(data = l2_data, aes(x = vocab)) +
  geom_histogram()
```

- `aes()` refers to aesthetics. What are the variables we want represented in our plots? Since we just want counts of a single continuous variable, we just need to specify our `x` (i.e., `x = vocab`).

Histograms

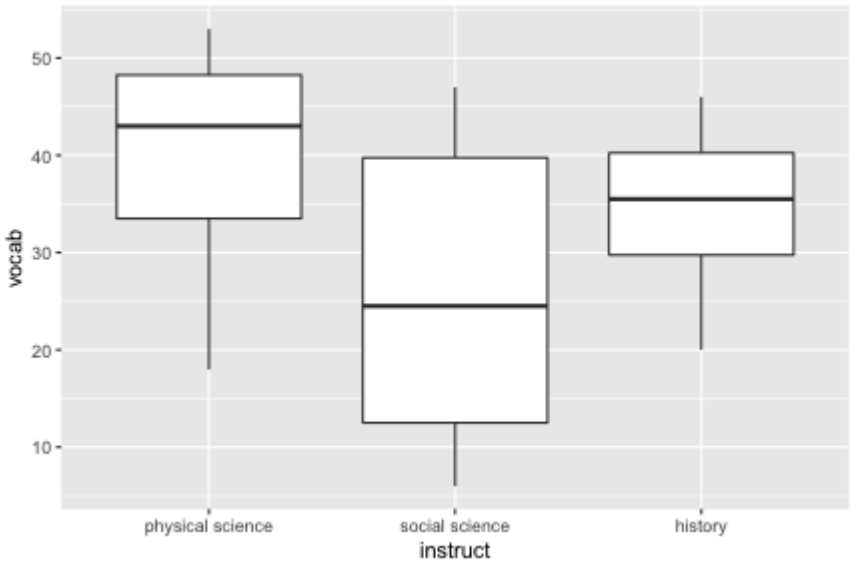
```
ggplot(data = l2_data, aes(x = vocab)) +
  geom_histogram()
```



Boxplot

- To get boxplots, we just substitute `geom_histogram()` for `geom_boxplot()` and modify our aesthetics.

```
ggplot(data = l2_data, aes(x = instruct, y = vocab)) +
  geom_boxplot()
```



Homogeneity of Variance

Homogeneity test is a separate analysis. We'll just use the `leveneTest` function for the `car` package. Formula is the same as for the ANOVA we want to run. Specify `center = "mean"` (function's default is median) to match SPSS results.

```
needs(car)
car::leveneTest(vocab ~ instruct, data = l2_data, center = "mean"
```

```
## Levene's Test for Homogeneity of Variance (center = "mean")
##       Df F value   Pr(>F)
## group  2  7.5054 0.002058 **
##       33
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Our significant result shows error variance around the *mean* is not equal across groups.

Running ANOVAs

Example here is from Lab 1 data.

ANOVAs will be run using the `anova_test()` function. Formula is specified as `DV ~ IV`. My convention is to number my model objects (e.g., m1, m2, etc.)

```
needs(rstatix)
m1 <- anova_test(data = l1_data, formula = vocab ~ instruct, deta
```

```
## Coefficient covariances computed by hccm()
```

```
m1
```

```
## ANOVA Table (type II tests)
##
##     Effect  SSn  SSd DFn DFd     F     p p<.05   ges
## 1 instruct 1176 3824   1  22 6.766 0.016     * 0.235
```

Effect Sizes

Effect sizes can be specified using `effect.size = ____` in the `anova.test()` function. Use `effect.size = "ges"` for generalized eta squared or `effect.size = "pes"` for partial eta squared. Default is "`ges`".

```
anova_test(data = l1_data, formula = vocab ~ instruct,
           effect.size = "ges")
```

```
anova_test(data = l1_data, formula = vocab ~ instruct,
           effect.size = "ges")
```

```
## Coefficient covariances computed by hccm()

## ANOVA Table (type II tests)
##
##     Effect DFn DFd     F     p p<.05   ges
## 1 instruct   1  22 6.766 0.016     * 0.235
```

```
anova_test(data = l1_data, formula = vocab ~ instruct,
           effect.size = "pes")
```

```
## Coefficient covariances computed by hccm()

## ANOVA Table (type II tests)
##
##     Effect DFn DFd     F     p p<.05   pes
## 1 instruct   1  22 6.766 0.016     * 0.235
```

Notice they are the same for a one–way between subjects ANOVA.

Posthoc Comparisons | Tukey

If you write out `"data = l2data"` the function will produce an error since it designed for multiple types of objects. Here we just type "l2data".

```
rstatix::tukey_hsd(l2_data, formula = vocab ~ instruct)
```

	term	group1	group2	null.value
	<chr>	<chr>	<chr>	<dbl>
1	instruct	physical science	social science	0
2	instruct	physical science	history	0
3	instruct	social science	history	0

3 rows | 1–5 of 10 columns

Posthoc Comparisons | Games–Howell

Remember, Games–Howell is used if the assumption of variance homogeneity is violated.

```
rstatix::games_howell_test(vocab ~ instruct, data = l2_data,
                           conf.level = 0.95,
                           detailed = FALSE)
```

	.y.	group1	group2	estimate
	<chr>	<chr>	<chr>	<dbl>
1	vocab	physical science	social science	−14.0
2	vocab	physical science	history	−5.5
3	vocab	social science	history	8.5

3 rows | 1–5 of 9 columns

Posthoc Comparisons | Bonferroni

```
pairwise_t_test(data = l2_data, vocab ~ instruct,
                p.adjust.method = "bonferroni")
```

	.y.	group1	group2	n1	n2	p
	<chr>	<chr>	<chr>	<int>	<int>	<dbl>
1	vocab	physical science	social science	12	12	0.00651
2	vocab	physical science	history	12	12	0.26200
3	vocab	social science	history	12	12	0.08700

3 rows | 1–7 of 10 columns

Specified Contrasts

(Lab 3)

- They are not automatic in R and are a bit difficult. It is not important that you understand the reasoning behind all of the following steps.

Specified Contrasts

Check the order of your levels.

```
levels(l3_data$instruct)
```

```
## [1] "physical science" "social science"   "history"
```

Make sure they are in the order that you would like and code your contrasts accordingly. As an example, If they need to be reordered use:

```
l3_data$instruct <- factor(l3_data$instruct, levels = c("social s
```

Note: We will be using the original order in the following contrasts.

Step 1: Set your contrasts. We'll do Helmert here.

```
contrast1 <- c(1, -.5, -.5) # physical science vs others
contrast2 <- c(0, 1, -1) #social science vs history
```

Step 2: Bind the vectors into a temporary matrix. Constant should be equal to 1/(length of your vectors).

```
mat.temp <- rbind(constant=1/3, contrast1, contrast2)
mat.temp
```

```
##                [,1]       [,2]       [,3]
## constant  0.3333333  0.3333333  0.3333333
## contrast1 1.0000000 -0.5000000 -0.5000000
## contrast2 0.0000000  1.0000000 -1.0000000
```

Step 3: Take the inverse of the matrix using the `solve()` function. Then we are dropping the first column with the constants.

```
mat <- solve(mat.temp)
mat
```

```
##      constant  contrast1 contrast2
## [1,]        1  0.6666667        0.0
## [2,]        1 -0.3333333        0.5
## [3,]        1 -0.3333333       -0.5
```

```
mat<- mat[ , -1]
mat
```

```
##       contrast1 contrast2
## [1,]  0.6666667        0.0
## [2,] -0.3333333        0.5
## [3,] -0.3333333       -0.5
```

Step 4: Run your model formula using `lm()` and set contrasts. Here we are linking our "instruct" variable with our contrast matrix. Remember:

- contrast1 = physical science vs others
- contrast2 = social science vs history

```
m_contrasts <- lm(vocab ~ instruct, data=l3_data, contrasts = lis
summary(m_contrasts)
```

```
##
## Call:
## lm(formula = vocab ~ instruct, data = l3_data, contrasts = list(instruct
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -22.000 -10.000   1.750   9.375  21.000
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)         33.500      1.968  17.026   <2e-16 ***
## instructcontrast1    9.750      4.174   2.336   0.0257 *
## instructcontrast2   -8.500      4.819  -1.764   0.0870 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

How do I get the SDs for calculating effect sizes?

We will use the `mutate` function to code new groupings. Then, we will run descriptives on this variable. My `case_when` function reads: If `instruct` = `social science` or `instruct` = `history`, code contrast1 as `humanities`. If `instruct` = `physical science` code as `physical science`.

```
l3_data <- l3_data %>%
  mutate(contrast1 = case_when(instruct == "social science" | ins
                               instruct == "physical science" ~ '

contrast1_desc <- describe(l3_data ~ contrast1)
```

```
rmarkdown::paged_table(contrast1_desc$humanities)
```

	vars	n	mean	sd	median	trimmed
	<int>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
idnum	1	24	24.50	7.0710678	24.5	24.50
vocab	2	24	30.25	12.7696992	34.0	30.85
instruct*	3	24	2.50	0.5107539	2.5	2.50
contrast1*	4	24	1.00	0.0000000	1.0	1.00

4 rows | 1–7 of 14 columns

```
rmarkdown::paged_table(contrast1_desc$`physical science`)
```

	vars	n	me...	sd	median	trimmed	mad
	<int>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
idnum	1	12	6.5	3.605551	6.5	6.5	4.4478
vocab	2	12	40.0	10.795622	43.0	40.9	11.8608
instruct*	3	12	1.0	0.000000	1.0	1.0	0.0000
contrast1*	4	12	1.0	0.000000	1.0	1.0	0.0000

4 rows | 1–8 of 14 columns

Pooling SDs

Here I am saving the second element of each descriptive table (since vocab is the second row in the data frame) to calculate pooled SDs.

```
sd1 <- contrast1_desc$humanities$sd[2]
sd2 <- contrast1_desc$`physical science`$sd[2]

cohens_sd <- sqrt((sd1^2 + sd2^2)/2)
cohens_sd
```

```
## [1] 11.82393
```

```
n1 <- contrast1_desc$humanities$n[2]
n2 <- contrast1_desc$`physical science`$n[2]

hedges_sd <- sqrt(((n1-1)*sd1^2 + (n2-1)*sd2^2)/(n1+n2-2))
hedges_sd
```

```
## [1] 12.16613
```

Calculate Hedges' g

Now that we have our pooled SD and coefficient, we just need to run the calculation for contrast1.

```
coefficients(m_contrasts)
```

```
##       (Intercept) instructcontrast1 instructcontrast2
##             33.50              9.75             -8.50
```

```
hedges_g <- 9.75/hedges_sd
hedges_g
```

```
## [1] 0.8014052
```

Calculate Effect Size

For an unbalanced dataset, we will use `pwr.2p2n.test` from the `pwr` package to run a power analysis on our contrast. `h` will be equal to our effect size. We already saved our n's earlier, so n1 will just be equal to n1 (same for n2).

```
needs(pwr)

pwr.2p2n.test(h = hedges_g, n1 = n1, n2 = n2, power = NULL, sig.
```

```
##
##      difference of proportion power calculation for binomial distributio
##
##               h = 0.8014052
##              n1 = 24
##              n2 = 12
##       sig.level = 0.05
##           power = 0.6204959
##     alternative = two.sided
##
## NOTE: different sample sizes
```

What about my ANOVA results?

To get the anova output, just run `rstatix::anova_test()` on your `m_contrasts` object. SPSS uses Type III SS by default, so I am matching it here.

```
contrast_anova <- anova_test(m_contrasts,
                  type="III",
                  effect.size = "ges",
                  detailed = TRUE)
```

```
## Coefficient covariances computed by hccm()
```

```
contrast_anova
```

```
## ANOVA Table (type tests)
##
##        Effect   SSn  SSd DFn DFd       F        p p<.05   ges
## 1 (Intercept) 40401 4599   1  33 289.896 6.57e-18     * 0.898
## 2    instruct  1194 4599   2  33   4.284 2.20e-02     * 0.206
```

Appendix

Contrasts

Isolated vs. Orthogonal Sets. If you are conducting an isolated contrast, or non–orthogonal set, you will need to use a different process for specifying contrasts. Here I demonstrate doing a single contrast. The primary difference is using `ginv()` from the `MASS` package rather than `solve()`.

```
contrast0 <- c(1, -.5, -.5)
mat.temp <- rbind(constant = 1/3, contrast0)
mat.temp
```

```
##                [,1]       [,2]       [,3]
## constant  0.3333333  0.3333333  0.3333333
## contrast0 1.0000000 -0.5000000 -0.5000000
```

```
mat <- MASS::ginv(mat.temp)
mat <- mat[ , -1]
mat
```

Essentially, R fills in the rest of the matrix. This means that there will be "extra" contrasts in the output that you will need to ignore. Here `instruct1` corresponds to my first and only contrast. `instruct2` can be ignored.

```
m_contrasts <- lm(vocab ~ instruct, data=l3_data, contrasts = lis
summary(m_contrasts)
```

```
##
## Call:
## lm(formula = vocab ~ instruct, data = l3_data, contrasts = list(instruct
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -22.000 -10.000   1.750   9.375  21.000
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   33.500      1.968  17.026   <2e-16 ***
## instruct1      9.750      4.174   2.336   0.0257 *
## instruct2      6.010      3.408   1.764   0.0870 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11.81 on 33 degrees of freedom
## Multiple R-squared:  0.2061,    Adjusted R-squared:  0.158
```

If you want to make it easier to refer back to your contrasts, you can rename them in your output using the following code. Here I chose to keep the name of the intercept, name my contrast, and make everything else unnamed.

```
attr(m_contrasts$coefficients, "names") <- c("Intercept", "Phys S
summary(m_contrasts)
```

```
##
## Call:
## lm(formula = vocab ~ instruct, data = l3_data, contrasts = list(instruct
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -22.000 -10.000   1.750   9.375  21.000
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## Intercept              33.500      1.968  17.026   <2e-16 ***
## Phys Sci vs. Others     9.750      4.174   2.336   0.0257 *
##                         6.010      3.408   1.764   0.0870 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11.81 on 33 degrees of freedom
## Multiple R-squared:  0.2061,    Adjusted R-squared:  0.158
```