# EDUC/PSY 6600: Unit 6 Homework

# Categorical Data - Binomial and Chi Squared Tests

# Your Name

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# NEEDS TO BE UPDATED!!!

# **PREPARATION**

# **Load Packages**

Make sure the packages are **installed** (Package tab)

```
library(tidyverse)  # Loads several very helpful 'tidy' packages

library(readxl)  # Read in Excel datasets

library(furniture)  # Nice tables (by our own Tyson Barrett)

library(afex)  # Analysis of Factorial Experiments

library(emmeans)  # Estimated marginal means (Least-squares means)

library(multcomp)  # Simultaneous Inference in General Parametric Models

library(pander)  # Make tables display nicer

library(educ6600)  # datasets for section B
```

# Other Datasets for Section B's

```
data("coupleIQs")
data("schizo_metal")
data("woman_parents")
data("react_wealth")
data("speed_voice")
data("data_12b4")
```

# Ihno's Dataset for Section C's

Import Data, Define Factors, and Compute New Variables

- Make sure the  $\mathbf{dataset}$  is saved in the same folder as this file
- Make sure the that folder is the working directory

NOTE: I added the second line to convert all the variables names to lower case. I still kept the F as a capital letter at the end of the five factor variables.

```
ihno_clean <- read_excel("Ihno_dataset.xls") %>%
  dplyr::rename_all(tolower) %>%
  dplyr::mutate(genderF = factor(gender,
                                 levels = c(1, 2),
                                 labels = c("Female",
                                             "Male"))) %>%
  dplyr::mutate(majorF = factor(major,
                                levels = c(1, 2, 3, 4,5),
                                labels = c("Psychology",
                                            "Premed",
                                           "Biology",
                                           "Sociology",
                                            "Economics"))) %>%
  dplyr::mutate(reasonF = factor(reason,
                                 levels = c(1, 2, 3),
                                 labels = c("Program requirement",
                                             "Personal interest",
                                             "Advisor recommendation"))) %>%
  dplyr::mutate(exp_condF = factor(exp_cond,
                                   levels = c(1, 2, 3, 4),
                                   labels = c("Easy",
                                               "Moderate",
                                               "Difficult",
                                               "Impossible"))) %>%
  dplyr::mutate(coffeeF = factor(coffee,
                                 levels = c(0, 1),
                                 labels = c("Not a regular coffee drinker",
                                             "Regularly drinks coffee"))) %>%
  dplyr::mutate(hr_base_bps = hr_base / 60)
```

# Chapter 9. Linear Correlation

#### Section B

# 9B-5 Calculating Pearson's r

**TEXTBOOK QUESTION:** A psychiatrist has noticed that the schizophrenics who have been in the hospital the longest score the lowest on a mental orientation test. The data for 10 schizophrenics are listed in the following table. (a) Calculate Pearson's r for the data. (b) Test for statistical significance at the .05 level (two-tailed).

#### schizo

	${\tt id}$	yr_hos	ori_test
1	1	5	22
2	2	7	26
3	3	12	16
4	4	5	20
5	5	11	18
6	6	3	30
7	7	7	14
8	8	2	24
9	9	9	15
10	10	6	19

**DIRECTIONS:** Calculate Pearson's r between  $yr_{hos}$  and  $ori_{test}$  in the schizo dataset. Also, test against the two-sided alternative.

The cor.test() function needs at least two arguments:

- 1. the formula: ~ continuous\_var1 + continuous\_var2
- 2. the dataset: data = . we use the period to signify that the datset is being piped from above

NOTE: The cor.test() function computes the Pearson correlation coefficient by default (method = "pearson"), but you may also specify the Kendall (method = "kendall") or Spearman (method = "spearman") methods. It also defauls to testing for the two-sided alternative and computing a 95% confidence interval (conf.level = 0.95). You will not need to change these options in this assignment.

# Pearson's r: yr\_hos & ori\_test

#### 9B-6 One vs. Two Sided Alternative

**TEXTBOOK QUESTION:** If a test is reliable, each participant will tend to get the same score each time he or she takes the test. Therefore, the correlation between two administrations of the test (test-retest reliability) should be high. The reliability of the verbal GRE score was tested using five participants, as shown below. (a) Calculate Pearson's r for the test-retest reliability of the verbal GRE score. (b) Test the significance of this correlation with  $\alpha = .05$  (one-tailed). Would this correlation be significant with a twotailed test?

#### GRE

	${\tt id}$	$verbalGRE\_1$	verbalGRE_2
1	1	540	570
2	2	510	520
3	3	580	600
4	4	550	530
5	5	520	520

**DIRECTIONS:** Calculate Pearson's r between verbalGRE\_1 and verbalGRE\_2 in the GRE dataset TWICE. The first time test for the **one-sided** alternative and the second time for the **two-sided** alternative.

The cor.test() function defaults to the alternative = "two.sided". If you would like a one-sided alternative, you must choose which side you would like to test: alternative = "greater" or alternative = "less"

```
# Pearson's r: verbalGRE_1 & verbalGRE_2 --> ONE tail
# Pearson's r: verbalGRE_1 & verbalGRE_2 --> TWO tails
```

# Section C

### 9C-1. Scatterplots - Eyeball method for estimating correlation

**TEXTBOOK QUESTION:** (A) Create a scatter plot of phobia versus statquiz. From looking at the plot, do you think the Pearson's r will be positive or negative? Large, medium, or small? (B) Create a scatter plot of baseline anxiety versus postquiz anxiety. From looking at the plot, do you think the Pearson's r will be positive or negative? Large, medium, or small?

**DIRECTIONS:** Create two scatter plots: the first with phobia on the horizontal axis (x) and statquiz on the vertical axis (y) and the second with anx\_base on the x-axis and anx\_post on the y-axis. Then answer the rest of the question in the printed homework packet.

**NOTE:** You may use the <code>geom\_count()</code> function instead of the <code>geom\_point()</code> function due to the high number of points that are 'over plotted' or on top of each other, since the two measures are quite coursely captured.

# Scatterplot: phobia vs. statquiz

# Scatterplot: anx\_base vs. anx\_post

# 9C-2a. Calculating Pearson's r

**TEXTBOOK QUESTION:** Compute the Pearson's r between phobia and statquiz for all students; also, find the Pearson's r between baseline and postquiz anxiety.

**DIRECTIONS:** Compute Pearson's r: first for phobia and statquiz, followed by anx\_base and anx\_post using the cor.test() function.

# Pearson's r: phobia & statquiz

# Pearson's r: anx\_base & anx\_post

# 9C-2b. Effect of Excluding Extreme Values

**TEXTBOOK QUESTION:** Use Select Cases to delete any student whose baseline anxiety is over 29, and repeat part (B) of the first exercise. Also, rerun the correlation of baseline and postquiz anxiety. What happened to the Pearson's r? Use the change in the scatter plot to explain the change in the correlation coefficient.

**DIRECTIONS:** Create a scatterplot for anx\_base and anx\_post, AFTER first using a dplyr::filter() funtion in a prepatroy step to restrict to the subsample of students with baseline anxiety of 29 and below.

# Scatterplot: anx\_base vs. anx\_post <-- restricting to baseline anxiety of 29 and lower

**DIRECTIONS:** Compute Pearson's r: for anx\_base and anx\_post, AFTER first using a dplyr::filter() funtion in a prepatroy step to restrict to the subsample of students with baseline anxiety of 29 and below.

# Pearson's r: anx\_base & anx\_post <-- restricting to baseline anxiety of 29 and lower

#### 9C-3. Reporting APA Style

**TEXTBOOK QUESTION:** (a) Compute Pearson's r's among the three measures of anxiety. Write up the results in APA style. (b) Compute the average of the three measures of anxiety, and then compute the correlation between each measure of anxiety and the average, so that the output contains a single column of correlations (do this by creating and appropriately modifying a syntax file).

**DIRECTIONS:** First, compute a new variable called anx\_mean that is the average of all three of the anxiety measures using the furniture::rowmeans() function. Then use the furniture::tableC() function to create a correlation matrix for all FOUR anxiety measures.

# Pearson's r: anx\_mean, anx\_base, anx\_pre, & anx\_post

# 9C-4. Missing Values

**TEXTBOOK QUESTION:** (a) Compute Pearson's r for the following list of variables: mathquiz, statquiz, and phobia. (b) Repeat part a after selecting exclude cases listwise. Which correlation was changed? Explain why.

**Directions:** Compute the correlation matrix between mathquiz, statquiz, and phobia using the furniture::tableC() function two times; first with all defaults and again with listwise deletion.

Note: The furniture::tableC() funtion defaults to na.rm = FALSE which displays NA for any correlation between a pair of variables where even one subject is missing one value. To use listwise deletion, specify the option na.rm = TRUE.

```
# Pearson's r: (default: na.rm = FALSE)
# Pearson's r: "complete.obs" (list-wise deletion)
```

# Chapter 10. Linear Regression

#### Section B

10B-6 Swapping x and y

**TEXTBOOK QUESTION:** A cognitive psychologist is interested in the relationship between spatial ability (e.g., ability to rotate objects mentally) and mathematical ability, so she measures 12 participants on both variables. The data appear in the following table. (a) Find the regression equation for predicting the math score from the spatial ability score. (b) Find the regression equation for predicting the spatial ability score from the math score. (c) According to your answer to part a, what math score is predicted from a spatial ability score of 20? (d) According to your answer to part b, what spatial ability score is predicted from a math score of 20?

# test\_scores

```
id spatial math
            13
                  19
1
    1
2
    2
            32
                  25
3
    3
            41
                  31
4
    4
            26
                  18
5
    5
            28
                  37
6
    6
            12
                  16
7
    7
            19
                  14
8
    8
            33
                  28
9
    9
            24
                  20
10 10
            46
                  39
            22
11 11
                  21
            17
                  15
12 12
```

**DIRECTIONS:** Use the lm() function to fit a linear model or linear regression model TWICE for math and spacial in the test\_scores dataset, specifing which is x and which is y.

The lm() function needs at least two arguments:

- 1. the formula: continuous\_y ~ continuous\_x
- 2. the dataset: data = . we use the period to signify that the datset is being piped from above

NOTE: To view more complete information, add a summary() step using a pipe AFTER the lm() step

```
# Linear model: y = math & x = spatial
# Linear model: y = spatial & x = math
```

#### 10B-9 Predictions and Residuals

**TEXTBOOK QUESTION:** If you calculate the correlation between shoe size and reading level in a group of elementary school children, the correlation will turn out to be quite large, provided that you have a large range of ages in your sample. The fact that each variable is correlated with age means that they will be somewhat correlated with each other. The following table illustrates this point. Shoe size is measured in inches, for this example, reading level is by grade (4.0 is average for the fourth grade), and age is measured in years. (a) Find the regression equation for predicting shoe size from age. (b) Find the regression equation for predicting reading level from age. (c) Use the equations from parts a and b to make shoe size and reading level predictions for each child. Subtract each prediction from its actual value to find the residual.

# child\_vars

```
child shoe read age
         5.2
               1.7
                      5
1
2
          4.7
               1.5
                      6
      2
3
      3
         7.0
               2.7
                      7
4
          5.8
               3.1
5
          7.2
      5
               3.9
                      9
6
      6
          6.9
               4.5
                     10
7
      7
         7.7
               5.1
                     11
         8.0 7.4
```

**DIRECTIONS:** Use the lm() function to fit a linear model or linear regression model TWICE for shoe and read each perdicited in turn by age in the child\_vars dataset, specifing which is x and which is y.

```
# Linear model: y = shoe & x = age
```

```
\# Linear model: y = read & x = age
```

**DIRECTIONS:** Starting with the child\_vars dataset, create four new variables, each with a seperate dplyr::mutate() function step. Pipe it all together ans save it as new dataset with the child\_new <- assignment operator to use in the next step.

- 1. shoe\_pred Use the appropriate regression equation
- 2. shoe\_resid Subtract: shoe (the original) minus shoe\_resid (the residual)
- 3. read\_pred Use the appropriate regression equation
- 4. read\_resid Subtract: read (the original) minus read\_resid (the residual)

```
# create new variables --> save as: child_new
```

Note: Remove the hashtag symbol at the first of the code line below to show your new variables.

#child\_new

#### 10B-10 Raw Correlation vs. Partial Correlation

**TEXTBOOK QUESTION:** (a) Calculate Pearson's r for shoe size and reading level using the data from Exercise 9. (b) Calculate Pearson's r for the two sets of residuals you found in part c of Exercise 9. (c) Compare your answer in part b with your answer to part a. The correlation in part b is the partial correlation between shoe size and reading level after the confounding effect of age has been removed from each variable (see Chapter 17 for a much easier way to obtain partial correlations).

 ${f DIRECTIONS}$ : Calculate Pearson's r between shoeand read in the child\_new dataset.

# Pearson's r: shoe & read

 ${f DIRECTIONS}$ : Calculate Pearson's r between shoe\_residand read\_resid in the child\_new dataset.

# Pearson's r: shoe\_resid & read\_resid

# Section C

# 10C-1. Linear Regression

**TEXTBOOK QUESTION:** Perform a linear regression to predict statquiz from phobia, and write out the raw-score regression formula. Do the slope and Y intercept differ significantly from zero? Explain how you know. What stats quiz score would be predicted for a student with a phobia rating of 9? Approximately what phobia rating would a student need to have in order for her predicted statquiz score to be 7.2?

**Directions:** Use the lm() function to fit a linear model or linear regression model predicting statquiz from phobia.

# Linear model: y = statquiz & x = phobia

#### 10C-2. Subgroups Analysis

**TEXTBOOK QUESTION:** (a) Perform a linear regression to predict pre-quiz anxiety from phobia, and write out the raw-score regression formula. (b) Repeat part a separately for men and women. For each gender, what prequiz anxiety rating would be predicted for someone reporting a phobia rating of 8? For which gender should you really not be making predictions at all? Explain.

**Directions:** Use the lm() function to fit a linear model or linear regression model predicting anx\_pre from phobia. Then repeat the same model TWICE more: first among just men and then for just women.

Note: Use the dplyr::filter() function to subset the sample BEFORE fitting the model. Also, be aware of which type of variable you are using: genderF == "Male" or gender == 2 works, but gender == male does NOT.

# Linear model:  $y = anx_pre & x = phobia <-- full sample$ 

```
# Linear model: y = anx\_pre \ \& \ x = phobia <-- subset of men
# Linear model: y = anx\_pre \ \& \ x = phobia <-- subset of women
```

# Chapter 19: Binomial Distribution

#### Section B

coupleIQs - Paired Measures: Teenage Couple IQs

19B 2: Sign Test (1-sided)

**TEXTBOOK QUESTION:** Perform the sign test on the data from Exercise 11B6 using the same alpha level and number of tails. Did you reach the same conclusion with the sign test as with the matched t test? If not, explain the discrepancy.

couple	boy	girl	sign
1	110	105	positive
2	100	108	negative
3	120	110	positive
4	90	95	negative
5	108	105	positive
6	115	125	negative
7	122	118	positive
8	110	116	negative
9	127	118	positive
10	118	126	negative

```
coupleIQs_table <- coupleIQs_wide %>%
  dplyr::select(sign) %>%
  table()

coupleIQs_table %>% pander::pander()
```

negative	positive
5	5

```
coupleIQs_table %>%
binom.test(alternative = "greater")
```

Exact binomial test

data: .
number of successes = 5, number of trials = 10, p-value = 0.623
alternative hypothesis: true probability of success is greater than 0.5

95 percent confidence interval: 0.2224411 1.0000000 sample estimates: probability of success 0.5

# schizo\_mental - Repeated Measures: Mental condition over time

# 19B 3: Sign Test

patient	year_2	year_3	sign
1	5	3	decline
2	7	6	decline
3	4	5	gain
4	2	2	NA
5	5	4	decline
6	3	4	gain
7	5	6	$_{ m gain}$
8	6	5	decline
9	4	3	decline

```
schizo_metal_table <- schizo_metal_wide %>%
  dplyr::select(sign) %>%
  table()

schizo_metal_table %>% pander::pander()
```

decline	gain
5	3

```
schizo_metal_table %>%
binom.test() # default: alternative = "two.sided"
```

Exact binomial test

# Chapter 20: Chi-Squared Tests

#### Section A

Tutorials: Chi-squared Test

Goodenss of Fit (1-way) - Equally Likely

**TEXTBOOK Example:** Often, especially in an experimental context, the expected frequencies are based on more abstract theoretical considerations. For instance, imagine that a developmental psychologist is studying color preference in toddlers. Each child is told that he or she can take one toy out of four that are offered. All four toys are identical except for color: red, blue, yellow, or green. Forty children are run in the experiment, and their color preferences are as follows: red, 13; blue, 9; yellow, 15; and green, 3. These are the obtained frequencies. The expected frequencies depend on the null hypothesis. If the null hypothesis is that toddlers in general have no preference for color, we would expect the choices of colors to be equally divided among the entire population of toddlers. Hence, the expected frequencies would be 10 for each color.

Use the chisq.test() function to perform a Goodnes-of-Fit or one-way Chi-Squared test to see if the observed counts are significantly different from being equally distributed.

**NOTE:** You do not need to declare any options inside the chisq.test() function, as the default is to use equally likely probabilities.

The following code chunk shows how to create and display a table of the observed and expected counts for any 1-way Chi-squated test.

**HINT** You may *copy-and-paste* this code for the rest of the assignment, but make sure to change the name of the model (chisq\_toy\_color appears twice before the \$-sign).

	red	blue	yellow	green
Observed	13	9	15	3
Expected	10	10	10	10

To display the full output, type and run the name the model is save as.

```
# Diplay the full output
chisq_toy_color
```

```
Chi-squared test for given probabilities
```

```
data: .
X-squared = 8.4, df = 3, p-value = 0.03843
```

# Goodenss of Fit (1-way) - Hypothesised Probabilities

**TEXTBOOK Example:** Imagine that the population of a city is made up of three ethnic groups, which I will label A, B, and C. The obtained frequencies were 28, 18, and 2. You could test the null hypothesis that sample is representative of a population proportions which is half group A and a third group B.

The chisq.test() function may also be used to perform a Goodnes-of-Fit or one-way Chi-Squared test to see if the observed counts are significantly different from those expected from a set of hypothesised probabilies.

**NOTE:** You **DO** need to declare the probabilities, as the default is to use equally likely probabilities. You may do this by including  $p = c(p_1, p_2, \ldots, p_k)$  within the chisq.test() function. The  $p_i$ 's maybe typed as decimals or fractions, but make suer they add up to exactly 1!

Use the same code chunk to display a table of the observed and expected counts for any 1-way Chi-squated test.

**HINT** You may *copy-and-paste* this code for the rest of the assignment, but make sure to change the name of the model (chisq\_ethnic appears twice before the \$-sign).

	A	В	С
Observed	28	18	2
Expected	24	16	8

To display the full output, type and run the name the model is save as.

```
# Diplay the full output chisq_ethnic
```

```
Chi-squared test for given probabilities
```

```
data: .
X-squared = 5.4167, df = 2, p-value = 0.06665
```

# Test for Independence (2-way) - vs. Association

**TEXTBOOK Example:** Suppose that the researcher has interviewed 30 women who have been married: 10 whose parents were divorced and 20 whose parents were married. Half of the 30 women in this hypothetical study have gone through their own divorce; the other half are still married for the first time. To know whether the divorce of a person's parents makes the person more likely to divorce, we need to see the breakdown in each category- that is, how many currently divorced women come from "broken" homes and how many do not, and similarly for those still married. These frequency data are generally presented in a contingency (or cross-classification) table:

```
# Display the observed counts
woman_parents %>%
  addmargins() %>%
  pander::pander()
```

	home_broken	home_complete	Sum
$\operatorname{self\_divorced}$	7	8	15
$\mathbf{self}$ _married	3	12	15
Sum	10	20	30

The chisq.test() function may also be used to perform a two-way Chi-Squared test for independence. In this case, the observed counts are compared to those expected if there is no association between the two factors.

```
# Run the 2-way chi-square test for independence
chisq_divorces <- woman_parents %>%
    chisq.test(correct = FALSE) #IF 2x2, add correct = FALSE
```

To display the counts expected if the variables are independent, start with the model name and add \$expected at the end. Then pipe on both the addmargins() and pander::pander() functions to print the counts.

```
# Request the expected counts based on "no association"
chisq_divorces$expected %>%
  pander::pander()
```

	$home\_broken$	$home\_complete$
self_divorced self_married	5 5	10 10

To display the full output, type and run the name the model is save as.

```
# Diplay the full output chisq_divorces
```

```
Pearson's Chi-squared test

data: .
X-squared = 2.4, df = 1, p-value = 0.1213
```

Blind taste test of soft drinks (given counts)

20A 3: 1-way Chi-squared Test - Goodness-of-Fit (equally likely)

**TEXTBOOK QUESTION:** A soft drink manufacturer is conducting a blind taste test to compare its best-selling product (X) with two leading competitors (Y and Z). Each subject tastes all three and selects the one that tastes best to him or her. (a) What is the appropriate null hypothesis for this study? (b) If 27 subjects prefer product X, 15 prefer product Y, and 24 prefer product Z, can you reject the null hypothesis at the .05 level?

**DIRECTIONS:** Use the chisq.test() function to perform a Goodnes-of-Fit or one-way Chi-Squared test to see if the observed counts (c(X = 27, Y = 15, Z = 24)) are significantly different from being equally distributed among the three soft drinks. Save the fitted model as chisq\_soda.

**NOTE:** You do not need to declare any options inside the chisq.test() function, as the default is to use equally likely probabilities.

**DIRECTIONS:** Follow the tutorial to create a table comparing the observed and expected counts.

**HINT** You may *copy-and-paste* the code from the chunked named tutorial\_chiSq\_GoF\_EL\_counts, but remember to change the name of the model (appears before the \$-sign in two places).

Table 9: Counts for Soda Prefereces, Observed and Expected

	X	Y	Z
Observed	27	15	24
Expected	22	22	22

**DIRECTIONS:** Place the model's name (chisq\_soda) in the following chunck, so that when run it will display the full output of the Chi-squared test.

```
# Diplay the full output chisq_soda
```

Chi-squared test for given probabilities

data:

X-squared = 3.5455, df = 2, p-value = 0.1699

# Psychiatric Hospital Admits by Season

20A 7: 1-way Chi-squared Test - Goodness-of-Fit (equally likely)

**TEXTBOOK QUESTION:** It has been suggested that admissions to psychiatric hospitals may vary by season. One hypothetical hospital admitted 100 patients last year: 30 in the spring; 40 in the summer; 20 in the fall; and 10 in the winter. Use the chi-square test to evaluate the hypothesis that mental illness emergencies are evenly distributed throughout the year.

**DIRECTIONS:** Use the chisq.test() function to perform a Goodnes-of-Fit or one-way Chi-Squared test to see if the observed counts (c(spring = 30, summer = 40, fall = 20, winter = 10)) are significantly different from being equally distributed among the four seasons. Save the fitted model as chisq\_season.

**NOTE:** You do not need to declare any options inside the chisq.test() function, as the default is to use equally likely probabilities.

# Run the 1-way chi-square test for equally likely

**DIRECTIONS:** Follow the tutorial to create a table comparing the observed and expected counts.

**HINT** You may *copy-and-paste* the code from the chunked named tutorial\_chiSq\_GoF\_EL\_counts, but remember to change the name of the model (appears before the \$-sign in two places).

# Request the observed and expected counts

**DIRECTIONS:** Place the model's name (chisq\_season) in the following chunck, so that when run it will display the full output of the Chi-squared test.

# 20A 8: 1-way Chi-squared Test - Goodness-of-Fit (hypothesised probabilities)

**TEXTBOOK QUESTION:** Of the 100 psychiatric patients referred to in the previous exercise, 60 were diagnosed as schizophrenic, 30 were severely depressed, and 10 had a bipolar disorder. Assuming that the national percentages for psychiatric admissions are 55% schizophrenic, 39% depressive, and 6% bipolar, use the chi-square test to evaluate the null hypothesis that this particular hospital is receiving a random selection of psychiatric patients from the national population.

**DIRECTIONS:** Use the chisq.test() function to perform a Goodnes-of-Fit or one-way Chi-Squared test to see if the observed counts (c(Schizophrenic = 60, Depressed = 30, Bipolar = 10)) are significantly different from being equally distributed among the three diagnoses. Save the fitted model as chisq\_rx.

**NOTE:** You **DO** need to declare the probabilities, as the default is to use equally likely probabilities. You may do this by including p = c(.55, .39, .06) within the chisq.test() function.

# Run the 1-way chi-square test for hypothesized probabilities

**DIRECTIONS:** Follow the tutorial to create a table comparing the observed and expected counts.

**HINT** You may *copy-and-paste* the code from the chunked named tutorial\_chiSq\_GoF\_EL\_counts, but remember to change the name of the model (appears before the \$-sign in two places).

# Request the observed and expected counts

**DIRECTIONS:** Place the model's name (chisq\_rx) in the following chunck, so that when run it will display the full output of the Chi-squared test.

# Section B

react wealth Reaction to Wealth

# 20B 4: 2-way Chi-squared Test - Independence

**TEXTBOOK QUESTION:** A social psychologist is studying whether people are more likely to help a poor person or a rich person who they find lying on the floor. The three conditions all involve an elderly woman who falls down in a shopping mall (when only one person at a time is nearby). The independent variable concerns the apparent wealth of the woman; she is dressed to appear either poor, wealthy, or middle class. The reaction of each bystander is classified in one of three ways: ignoring her, asking if she is all right, and helping her to her feet. The data appear in the contingency table below. (a) Test the null hypothesis at the .01 level. Is there evidence for an association between the apparent wealth of the victim and the amount of help provided by a bystander? (b) Calculate Cramer's phi for these data. What can you say about the strength of the relationship between the two variables?

# Display the observed counts
react\_wealth %>%
 addmargins() %>%
 pander::pander()

	poor	middle	wealthy	Sum
ignores	16	10	7	33
${ m ignores} \ { m talks}$	8	6	5	19
$\mathbf{helps}$	6	14	18	38
Sum	30	30	30	90

**DIRECTIONS:** Use the chisq.test() function to perform a two-way Chi-Squared test for independence to see if the observed counts provide evidence of an association between the level of wealth and reaction. Save the fitted model as chisq\_react\_wealth.

**NOTE:** You do not need to declare any options inside the chisq.test() function, as the default is test for independence when given a table. The correct = FALSE id needed only for 2x2 tables.

# Run the 2-way chi-square test for independence

**DIRECTIONS:** Display the counts expected if reaction is independent of wealth by starting with the model name chisq\_react\_wealth and adding \$expected at the end.

# Request the expected counts based on "no association"

**DIRECTIONS:** Place the model's name (chisq\_react\_wealth) in the following chunck, so that when run it will display the full output of the Chi-squared test.

speed\_voice Dichotimize Reaction Time to Voice Calling for Help

20B 8: 2-way Chi-squared Test - Independence

**TEXTBOOK QUESTION:** In Exercise 12B4, the dependent variable was the amount of time a subject listened to taperecorded cries for help from the next room before getting up to do something. If some subjects never respond within the time allotted for the experiment, the validity of using parametric statistical techniques could be questioned. As an alternative, subjects could be classified as fast or slow responders (and possibly, nonresponders). The data from Exercise 12B4 were used to classify subjects as fast responders (less than 12 seconds to respond) or slow responders (12 seconds or more). The resulting contingency table is shown in the following table:

# Display the observed counts
speed\_voice %>%
 addmargins() %>%
 pander::pander()

	child	woman	man	Sum
fast	5	3	1	9
slow	2	4	6	12
Sum	7	7	7	21

**TEXTBOOK QUESTION:** (a) Test the null hypothesis ( $\alpha = .05$ ) that speed of response is independent of type of voice heard.

**DIRECTIONS:** Use the chisq.test() function to perform a two-way Chi-Squared test for independence to see if the observed counts provide evidence of an association between the level of wealth and reaction. Save the fitted model as chisq\_speed\_voice.

**NOTE:** You do not need to declare any options inside the chisq.test() function, as the default is test for independence when given a table. The correct = FALSE id needed only for 2x2 tables.

# Run the 2-way chi-square test for independence

**DIRECTIONS:** Display the counts expected if reaction is independent of wealth by starting with the model name chisq speed voice and adding \$expected at the end.

# Request the expected counts based on "no association"

**DIRECTIONS:** Place the model's name (chisq\_speed\_voice) in the following chunck, so that when run it will display the full output of the Chi-squared test.

# Diplay the full output

**TEXTBOOK QUESTION:** (b) How does your conclusion in part a compare with the conclusion you drew in Exercise 12B4? Categorizing the dependent variable throws away information; how do you think that loss of information affects power?

data\_12b4 %>%
 pander::pander()

child	woman	man
10	17	20
12	13	25
15	16	14
11	12	17
5	7	12
7	8	18
2	3	7

```
data_12b4 %>%
 tidyr::gather(key = voice,
               value = seconds,
               child, woman, man) %>%
 dplyr::mutate(voice = factor(voice,
                              levels = c("child", "woman", "man"))) %>%
 dplyr::mutate(id = row_number()) %>%
 afex::aov_4(seconds ~ voice + (1|id),
             data = .) %>%
 summary()
Anova Table (Type 3 tests)
Response: seconds
                                     ges Pr(>F)
     num Df den Df
                      MSE
                               F
voice
               18 26.476 3.7464 0.29392 0.04362 *
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

# Section C

ihno\_clean Ihno's Dataset

20C 1a: 1-way Chi-squared Test - Goodness-of-Fit (equally likely)

**TEXTBOOK QUESTION:** (a) Perform a one-way chi square test to determine whether you can reject the null hypothesis that, at Ihno's university, there are the same number of students majoring in each of the five areas represented in Ihno's class, if you assume that Ihno's students represent a random sample with respect to major area.

**DIRECTIONS:** Use the chisq.test() function to perform a Goodnes-of-Fit or one-way Chi-Squared test to see if the observed counts are significantly different from being equally distributed among the five majors. Save the fitted model as chisq\_ihno\_major.

HINT: Since you are working from a full dataset, you will need to pipe a dplyr::select(majorF) step onto the ihno\_clean dataset to first select out just the majorF variable and then pipe on the table() function to tablulate the observed counts for each major. Then and only then, you may add the chisq.test() function.

**NOTE:** You do not need to declare any options inside the chisq.test() function, as the default is to use equally likely probabilities.

# Run the 1-way chi-square test for equally likely

**DIRECTIONS:** Follow the tutorial to create a table comparing the observed and expected counts.

**HINT** You may *copy-and-paste* the code from the chunked named tutorial\_chiSq\_GoF\_EL\_counts, but remember to change the name of the model (appears before the \$-sign in two places).

# Request the observed and expected counts

**DIRECTIONS:** Place the model's name (chisq\_ihno\_major) in the following chunck, so that when run it will display the full output of the Chi-squared test.

# 20C 1b: Repeat, separately for each gender

**TEXTBOOK QUESTION:** (b) Perform the test in part a separately for both the males and the females in Ihno's class.

**DIRECTIONS:** Perform the same test you did in part a, but separately for each level of the gender variable.

 ${f HINT}$  You may  ${\it copy-and-paste}$  the code from the chunked named  ${\tt 20c1a\_chiSq\_GoF\_EL\_test}$ , but do NOT same the model as anything.

NOTE: You will need to add a dplyr::filter(genderF == "Male") step before the selecting of major.

**HINT** You may *copy-and-paste* the code chunk directly above, changing only "Male" to "Female".

#### 20C 3: 2-way Chi-squared Test - Independence

**TEXTBOOK QUESTION:** Conduct a two-way chi-square analysis of Ihno's data to test the null hypothesis that the proportion of females is the same for each of the five represented majors in the entire university population. Request a statistic to describe the strength of the relationship between gender and major.

**NOTE:** The furniture package includes a very helpful function called tableX() which creates a nice cross-tabulation given the names of two variables.

```
ihno_clean %>%
  furniture::tableX(genderF, majorF)
        majorF
genderF Psychology Premed Biology Sociology Economics Total
                                                4
  Female 19
                            11
                                     12
                                                          57
                     11
  Male
                     14
                            10
                                     3
                                                6
                                                          43
         10
                     25
                            21
                                                          100
  Total
         29
                                     15
                                                10
```

**DIRECTIONS:** Use the chisq.test() function to perform a two-way Chi-Squared test for independence to see if the observed counts are significantly different from those expected is there is no association between gender and major.

HINT: Since you are working from a full dataset, you will need to pipe a dplyr::select(genderF, majorF) step onto the ihno\_clean dataset to first select out just the genderF and majorF variables. Then pipe on the table() function to cross-tablulate the observed counts. Then and only then, you may add the chisq.test() function.

**NOTE:** If you do not save the model to a name, the full output will be displayed.