The EMaC R Manual

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Contents

Chapter 1

How to Install R

This is the EMaC manual for how to wrangle, analyze, and visualize data in **R**. I will review a few key packages, in addition to explaing their key functions, with real data examples.

There are two things you need to do to install R on your computer. First, you would need to install the latest version of R which you would download and install from this link: R-download. Once you run and install R onto your computer, you would need to install R-Studio. R studio is the graphic user interface (GUI) where you can place all of your R-code. Follow this link: R-Studio Desktop Download. Once you have these two programs installed, all you need to do is launch R-studio Desktop and you are ready to go..

Chapter 2

Introduction to Programming in R

Before you can do data wrangling, statiscs, and visualization using R for cognitive psychology research, you need to learn the basic syntax in R. This chapter will introduce the basics.

2.1 Variables in R

R can manipulate and wrangle all kinds of data, these data could be stored in a handful of variables that we can then work with. The first one we will be talking about is numeric.

2.1.1 Numeric

a numeric is a number (including decimals) that can be stored within a variable. Here is an example:

```
x = 2
```

Here, we assigned the numeric value `2` to the variable `x`. Thus, if we were to do arithemtic, `x` will be treated as `2`. Moreover, there are specific functions in R we can use in order to do arithmetic with numeric variables. Here are a few examples:

Arithemtic	R-Input	R-Output
Addition:	`x + 2`	`4`
Substraction:	`x - 2`	`0`
Division:	`x / 2`	`1`
Multiplication:	`x * 2`	`4`

Arithemtic	R-Input	R-Output
Exponent:	`x ^ 2`	`4`

2.1.2 Character

A character is a combination of characters (either letters and/or numbers) that can be stored within a variable. Moreover, it is very important that you place the character between quotation marks. Here is an example:

`x = "Cognitive Psychology"`

Here, we assigned the character value `"Cognitive Psychology"` to the variable `x`. There are ways to manipulate character type variables, and also modify them. However, we will touch on that later.

2.1.3 Logical

A logical can only have two possible values, `TRUE` and `FALSE` that can be stored within a variable. This is not typically a varaible type that you will need to assign variable values to. However, the logical type variable is extremely important becuase a lot of functions in R return a logical variable. We will dive into some of these functions

2.1.4 Vector

A vector is multiple variables stored into one data-set. Vectors can contain any variable type: character, numeric, string, and logical. When you are declaring a a vector type variable, you typically have to use the concatenate function `c()`. Here is an example:

`x = c(1,2,3,4)`

`x = c("I", "like", "Cognitive", "Psychology")`

`x = c(TRUE, FALSE, FALSE, TRUE)`

To reference a vector varaible, you need to use `[]` and inside the brackets, you have to specify the index of where the given variable in the vector is. Here is an example

```
x = c("10", "20", "30", "40")
x[4]
```

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

Here, we assigned the numbers: `10, 20, 30, 40` to the vector `x`. `"Cognitive Psychology"` to the variable `x`. There are ways to manipulate character type variables, and also modify them. However, we will touch on that later.

2.2 Logical Operators

Now that you have a basic understanding of how variables work in R, the next step is to learn how to use logical operators in order to specifiy what are the specific conditions under which you want your variables to be manipulated. The main way to do this in R is by using logical operators.

```
x = 2
```

Here, we assigned the numeric value `2` to the variable `x`. Thus, if we were to apply logical operators to `x`, `x` will be treated as `2`. Here are examples of all of the logical operators:

Logical Operators	Description	R-Input	R-Output
<	less than	x < 10	TRUE
<=	less than or equal to	x <= 2	TRUE
>	greater than	x > 1	TRUE
>=	greater than or equal to	x >= 3	FALSE
==	exactly equal to	x == 9	FALSE
!=	not equal to	x != 10	FALSE
!x	Not x	!x	FALSE
x | y	x OR y	x == 10 | x != 10	TRUE
x & y	x AND y	x == 10 &x != 10	FALSE

Chapter 3

Introduction to Data Wrangling

To introduce data wrangling, we will be working with a dataset from a study conducted in our lab. Here are the details of the study in order to understand the data manipulation more:

3.1 The study

On each trial in this experiment (n = 174), each participant (n = 84) sees a target word very briefly (e.g., word) and then is prompted to select which of two letters was in a particular position of that word (e.g., _ _ _ ↓) - one letter was in the presented word (e.g., D) and the other letter is in an orthographic neighbor of the word (e.g., K). This is a 2 (visual field) x 3 (sentence context) experimental design: the target word is either presented in the fovea (i.e., center of the screen) or the parafovea (i.e., 3 degrees to the right of fixation). Prior to the target word, they see a sentence context presented via Rapid Serial Visual Presentation (RSVP) that constrains to target (i.e., makes the presented word predictable and the orthographic neighbor implausible), constrains to the alternative (i.e., makes the orthographic neighbor predictable and the presented word implausible), or is neutral (i.e., makes neither word predictable but both of them plausible). In addition, we collect data about the individual subjects' language ability (i.e., their z-score on some test relative to the other participants), including spelling recognition (i.e., circle which words are spelled wrong), spelling dictation (i.e., write out words that they hear said), and phonological decoding (i.e., read aloud a list of words and a list of nonwords), and information about the lexical properties of the words (e.g., word frequency, cloze probability, orthographic neighborhood size, phonological neighborhood size, clustering coefficient, orthographic similarity to other words, which of the two words is higher frequency).

3.2 Loading in Data

3.2.1 Loading Packages

Before we start wrangling the data, we need to load in the packages we are using. In this lab, most of the data wrangling tools we will be using will be located in the `tidyverse()` package. What is a package? It is simply a group of functions that group of developers made that makes computations easier. To learn more about the `tidyverse` package, you may click on this link and read on it! For the data wrangling we will be doing in this section, we will be primarily using a package within tidyverse called `dplyr`. to load in the package, simply type in the following code. What this code is saying is IF you don't have the `tidyverse` installed, THEN install the package. After that, load the `tidyverse` with the `library()` function.

```
if(!require(tidyverse)){
    install.packages("tidyverse")
}
library(tidyverse)
```

3.2.2 setting the working directory

Now that we have the packages that we need, we need to load up our directory. What is a directory? It is essentially the folder we will be using to read in files, or export files into. In this directory, we have our data set of interest, `Topgown_Data`

3.2.3 Reading in Data

Now that we have our working directory set we can use the `read_csv()` function which requires one minimum argument to work which is the name of your `.csv` file. Here we are setting the variable `mydata` to the contents within the `.csv` file. It stores the contents of `Topgown_Data.csv` in what is called a data frame. What is a dataframe? it is simply a matrix where each row constitutes a variable (which can be any type you want), and rows are observations.

```
mydata = read_csv("TopGown_Data.csv", skip_empty_rows = TRUE)
```

X1

Participants

visual_field

constrained_to

presented_word

predicted_word

question

correct_answer

item_pair

Items

probe_position

RT

accuracy

zTOWRE_Word

zTOWRE_Nonword

zSpelling_Dictation

zSpelling_Recogntion

zAll

zSpell

zTOWRE

OrthoN_T

OrthoCC_T

PhonoN_T

Freq_T

Freq_P

OrthoCC_P

OLD

Higher_Freq

1

tg011

Fovea

A

cage

cape

NA

NA

19

37

3

2986.73

1

-1.749307

0.071771

-0.0918699

1.155124

-0.1535705

0.531627

-0.838768

13

0.0000001

17

9.048

8.605

0.0000000

1.10

Target

2

tg011

Parafovea

N

ache

acne

Were they very frustrated?

Y

83

165

3

4146.67

1

-1.749307

0.071771

-0.0918699

1.155124

-0.1535705

0.531627

-0.838768

3

1.5000000

23

6.741

6.284

1.5000000

1.75

Target

3

tg011

Fovea

A

male

sale

NA

NA

37

73

1

2496.54

1

-1.749307

0.071771

-0.0918699

1.155124

-0.1535705

0.531627

-0.838768

27

0.0000000

59

10.978

11.466

0.0000000

1.00

Alternative

4

tg011

Fovea

A

leaf

loaf

NA

NA

70

139

2

1845.46

1

-1.749307

0.071771

-0.0918699

1.155124

-0.1535705

0.531627

-0.838768

9

0.0500000

29

8.861

7.109

0.5000000

1.75

Target

5

tg011

Parafovea

T

step

stop

NA

NA

7

14

3

2125.17

1

-1.749307

0.071771

-0.0918699

1.155124

-0.1535705

0.531627

-0.838768

7

0.1666667

11

10.691

11.478

0.0416667

1.50

Alternative

6

tg011

Fovea

N

mint

mind

NA

NA

24

48

4

1415.47

1

-1.749307

0.071771

-0.0918699

1.155124

-0.1535705

0.531627

-0.838768

16

0.0000005

17

11.344

11.784

0.0000001

1.25

Alternative

7

tg011

Parafovea

A

cast

case

NA

NA

20

40

4

3168.45

1

-1.749307

0.071771

-0.0918699

1.155124

-0.1535705

0.531627

-0.838768

19

0.0000000

28

10.102

12.204

0.0000000

1.00

Alternative

8

tg011

Fovea

A

golf

wolf

NA

NA

76

151

1

3765.47

1

-1.749307

0.071771

-0.0918699

1.155124

-0.1535705

0.531627

-0.838768

4

0.0000000

2

9.254

9.979

0.0000000

1.90

Alternative

9

tg011

Fovea

N

mane

maze

NA

NA

3

6

3

1503.80

1

-1.749307

0.071771

-0.0918699

1.155124

-0.1535705

0.531627

-0.838768

27

0.0000000

59

6.238

8.775

0.0000001

1.25

Alternative

10

tg011

Parafovea

N

name

fame

NA

NA

17

33

1

1565.79

1

-1.749307

0.071771

-0.0918699

1.155124

-0.1535705

0.531627

-0.838768

11

0.0041667

21

12.604

8.714

0.0000000

1.15

Target

3.3 Dplyr() Package

We will now be wrangling this new dataset we imported into R using several `dplyr` functions. These are the ones we will be covering. In the following sections I will explain what each functions does in detial.

Function	Description
select()	keeps only the variables you mention
summarize()	Create new variables summarizing the variables of an existing table
group_by()	takes an existing table and converts it into a grouped table where operations are performed "by group"
arrange()	Order table rows by an expression involving its variables
filter()	choose rows/cases where conditions are true.
mutate()	adds new variables and preserves existing ones

3.3.1 select()

For this particular experiment we have two independent variables of interest: `visual_field` and `constrained_to`; and four participant variables of interest: `zTOWRE_Word`,`zTOWRE_Nonword`, `zSpelling_Dictation`,`zSpelling_Recogntion`. What if we are only interested in these variables, and we don't particularly need word level variables such as `ortho_N`, or `phono_N`. We can then select these variables.

For this particular function, the first argument is going to be the dataset of interest. the dataset for we will be selecting from is `mydata`. The following arguments are simply the columns you would like to keep.

```
dplyr::select(mydata, Participants, visual_field, constrained_to, zTOWRE_Word,zTOWRE_No
```

Participants

visual_field

constrained_to

zTOWRE_Word

zTOWRE_Nonword

zSpelling_Dictation

zSpelling_Recogntion

tg011

Fovea

A

-1.749307

0.071771

-0.0918699

1.155124

tg011

Parafovea

N

-1.749307

0.071771

-0.0918699

1.155124

tg011

Fovea

A

-1.749307

0.071771

-0.0918699

1.155124

tg011

Fovea

A

-1.749307

0.071771

-0.0918699

1.155124

tg011

Parafovea

T

-1.749307

0.071771

-0.0918699

1.155124

tg011

Fovea

N

-1.749307

0.071771

-0.0918699

1.155124

tg011

Parafovea

A

-1.749307

0.071771

-0.0918699

1.155124

tg011

Fovea

A

-1.749307

0.071771

-0.0918699

1.155124

tg011

Fovea

N

-1.749307

0.071771

-0.0918699

1.155124

tg011

Parafovea

N

-1.749307

0.071771

-0.0918699

1.155124

3.3.1.1 The Pipe (%>*%)

However, another way I would suggest writing code like this is to use a function in the `tidyverse` called the pipe (`%>%`). Like the `select()` function, the first argument in all `tidyverse` functions will be your dataset of interest. The pipe simply gets a dataset, and pushes it into the first argument of a function. Here is an example.

```
mydata %>% dplyr::select(Participants, visual_field, constrained_to, zTOWRE_Word,zTOWRE
  dplyr::select(Participants, visual_field, constrained_to)
```

Participants

visual_field

constrained_to

tg011

Fovea

A

tg011

Parafovea

N

tg011

Fovea

A

tg011

Fovea

A

tg011

Parafovea

T

tg011

Fovea

N

tg011

Parafovea

A

tg011

Fovea

A

tg011

Fovea

N

tg011

Parafovea

N

In this regard, the pipe follows simple logic. Once a dataset is manipulated by one function, you pass it to the next function.

3.3.2 group_by() & summarise()

However, let us say we are particularly interested in the values of one variable. For example, word properties. Therefore, we would need to compile a new dataset that summarizes word properties, such as orthographic neighborhood size. So in this example we will create a dataframe summarized by the presented word.

```
mydata %>% dplyr::select(Participants, visual_field, constrained_to, presented_word, Or
  group_by(presented_word) %>%
  dplyr::summarise(OrthoN_T = mean(OrthoN_T))
```

presented_word

OrthoN_T

ache

3

acne

4

ants

7

arts

8

aunt

6

ball

20

bats

23

beef

6

bees

20

bell

15

3.3.3 arrange()

Let us say that we are still interested in neighborhood size of a particular target word. we can arrange the these variables so we can display the the words from lowest orthographic neighborhood size to higher orthographic neighborhood size. For this we can use the arrange function, which sorts a particular variable of interest in ascending or descending order.

```
mydata %>% dplyr::select(Participants, visual_field, constrained_to, presented_word, OrthoN_T, Fr
  group_by(presented_word) %>%
  dplyr::summarise(OrthoN_T = mean(OrthoN_T)) %>%
  dplyr::arrange(OrthoN_T)
```

presented_word

OrthoN_T

ache

3

film

3

gyms

3

wolf

3

womb

3

acne

4

clue

4

debt

4

drum

4

golf

4

3.3.4 filter()

Let us say that not only are we interested in orthographic neigbhorhood size, but we want to know orthographic neighborhood size for a particular condition in our study. We can then use the `filter()` function, and only keep the trails that are within the condition of interest. For this example, we are interested when the sentence is constraining toward the target word and when the target word is presented in the parafovea.

```
mydata %>% dplyr::select(Participants, visual_field, constrained_to, presented_word, O
  filter(visual_field == "Parafovea" & constrained_to == "T") %>%
  group_by(presented_word, visual_field, constrained_to) %>%
  dplyr::summarise(OrthoN_T = mean(OrthoN_T)) %>%
  dplyr::arrange(OrthoN_T)
```

presented_word

visual_field

constrained_to

OrthoN_T

ache

Parafovea

T

3

film

Parafovea

T

3

gyms

Parafovea

T

3

wolf

Parafovea

T

3

womb

Parafovea

T

3

acne

Parafovea

T

4

clue

Parafovea

T

4

debt

Parafovea

T

4

drum

Parafovea

T

4

golf

Parafovea

T

4

3.3.5 mutate()

Let us say that we are not only interested in word properties like orthographic neighborhood size, but also the spelling ability of particular participants. In this study we have four spelling tests, which were measured through the following variables: `zTowre_Word`, `zTowre_Nonword`, `Spelling_Dictation`, `Spelling_Recogntion`. However, these are a lot of measures. what if we wanted to know the average between all of these measures for each participant? we can use the mutate function to do this.

```
mydata %>% dplyr::select(Participants, zTOWRE_Word, zTOWRE_Nonword, zSpelling_Dictatio
  group_by(Participants) %>%
  dplyr::summarise(zTOWRE_Word = mean(zTOWRE_Word),
                   zTOWRE_Nonword = mean(zTOWRE_Nonword),
                   zSpelling_Dictation = mean(zSpelling_Dictation),
                   zSpelling_Recogntion = mean(zSpelling_Recogntion)) %>%
  dplyr::mutate(aggregated_spelling = ((zTOWRE_Word + zTOWRE_Nonword + zSpelling_Dicta
```

Participants

zTOWRE_Word

zTOWRE_Nonword

zSpelling_Dictation

zSpelling_Recogntion

aggregated_spelling

derp033

1.6354380

0.7156786

0.8383130

1.3936520

1.1457704

derp044

-0.6333223

0.5317050

-0.0918699

-0.7923070

-0.2464486

derp055

0.2251274

0.6236918

-0.7895071

0.2705651

0.0824693

derp066

-1.1483920

-1.1240570

-2.8824190

-1.4607150

-1.6538958

derp071

-0.3757874

-0.1122026

0.6057672

0.6449458

0.1906808

Chapter 4

Plotting

Now that we have a basic understanding of how to wrangle data, now we want to graphically explain the data we are wrangling. For this chapter we will be using `ggplot` package to further understand the data. However, before we go into plotting specific things about the data, we need to learn the grammar of plotting with `ggplot` in general

4.1 ggplot grammar

You can think of the grammar of graphics as a systematic approach for describing the components of a graph. It has seven components (the ones in bold are required to be specifed explicitly in ggplot2):

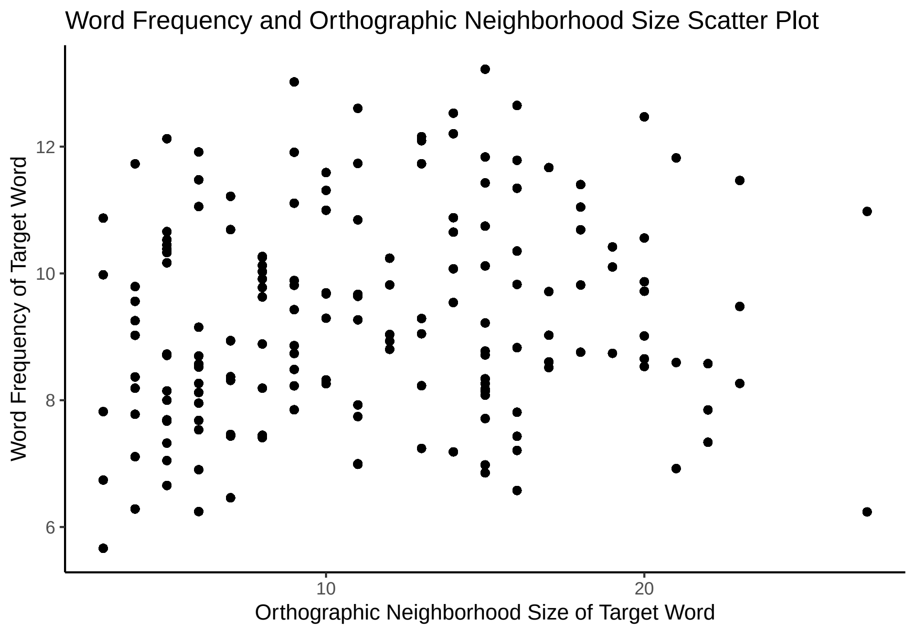
- ***Data***
  - data that you're feeding into a plot.
- ***Aesthetic mappings***
  - How are variables (columns) from your data connect to a visual dimension? Horizontal positioning, vertical positioning, size, colour, shape, etc. These visual dimensions are called "aesthetics"
- ***Geometric objects***
  - What are the objects that are actually drawn on the plot? A point, a line, a bar, a histogram, a density, etc.
- Scales
  - How is a variable mapped to its aesthetic? Will it be mapped linearly? On a log scale? Something else? This includes things like the color scale e.g., c(control, treatment_1, treatment_2) -> c("blue", "green", "red")
- Statistical transformations
  - Whether and how the data are combined/transformed before being plotted e.g., in a bar chart, data are transformed into their frequen-

cies; in a box-plot, data are transformed to a five-number summary.
- Coordinate system
  - This is a specification of how the position aesthetics (x and y) are depicted on the plot. For example, rectangular/cartesian, or polar coordinates.
- Facet
  - This is a specification of data variables that partition the data into smaller "sub plots", or panels. These components are like parameters of statistical graphics, defining the "space" of statistical graphics. In theory, there is a one-to-one mapping between a plot and its grammar components, making this a useful way to specify graphics.

4.1.1 Example: Scatterplot Grammar

Let us say that we are interested in how specific word properties relate to one another, and how correlated they are. With this information we can learn specific detials about the nature of our linguistic stimuli, which is very important in psycholinguistics. So for this example we are going to plot the orthographic neighborhood size of the target word and word frequency.

```
mydata %>% ggplot(aes(x = OrthoN_T, y = Freq_T)) + # this defines the x and y axes of
  geom_point() + # this adds geometric objects
  theme_update(plot.title = element_text(hjust = 0.5)) + # this line centers the title
  xlab("Orthographic Neighborhood Size of Target Word") + # this line sets the label f
  ylab("Word Frequency of Target Word") + # this line sets the label for y-axis
  ggtitle("Word Frequency and Orthographic Neighborhood Size Scatter Plot") + # this s
  theme_classic() # this sets the theme for the plot
```



Grammar Component	Specification
data	mydata
aesthetic mapping	x: OrthoN_T, y: Freq_T
geometric object	points
scale	x: linear, y: linear
statistical transform	none
coordinate system	rectangular
facetting	none

4.1.2 Example: Histogram Grammar

Useful for depicting the distribution of a continuous random variable. Partitions the number line into bins of certain width, counts the number of observations falling into each bin, and erects a bar of that height for each bin.

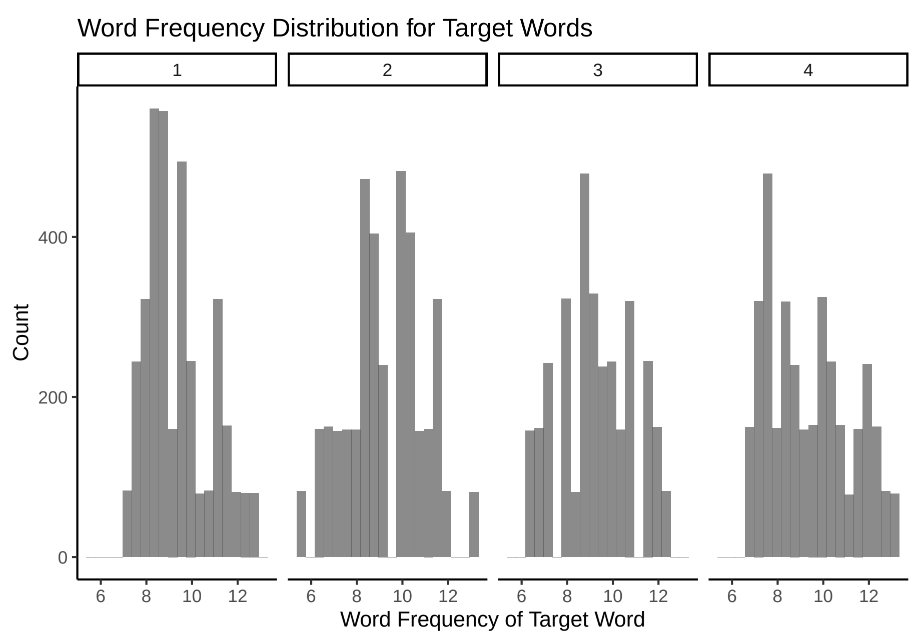
Required aesthetics:

- `x`: A numeric vector.
- By default, a histogram plots the count on the y-axis. If you want to use proportion (i.e., "density"), specify the y = ..density.. aesthetic.
- You can change the smoothness of the plot via two arguments (your choice):
- `bins`: the number of bins/bars shown in the plot.

- binwidth: the with of the bins shown on the plot.

Let us say that we want to ask very, very specific questions about how some word properties relate to other word properties. For example, in this experiment we change one letter for a given letter position. for example (word-work) pair manipulates the 4th letter position while (worm-dorm) pair manipulates the 1rst letter position. Let us explore if the words in a particular letter position category vary in word frequency. The way we can do this is by using the `facet_grid()` function in `ggplot`.

```
mydata %>% ggplot(aes(x = Freq_T)) +
  geom_histogram(bins = 20, alpha = .7) +
  xlab("Word Frequency of Target Word") +
  ylab("Count") +
  ggtitle("Word Frequency Distribution for Target Words") +
  facet_grid(~probe_position) +
  theme_classic()
```



4.1.3 Example: Density Grammar

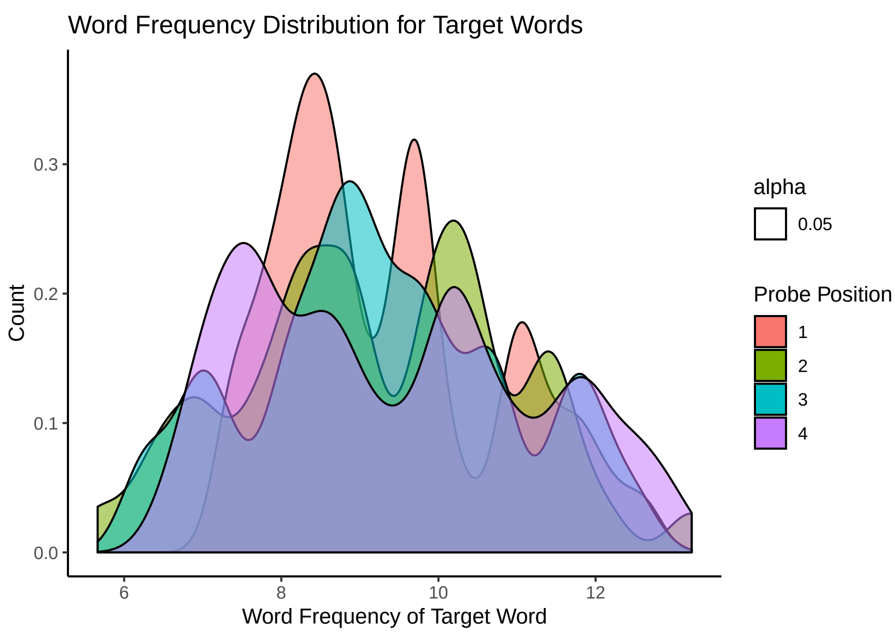
Essentially, a "smooth" version of a histogram. Uses kernels to produce the curve.

Required aesthetics:

- x: A numeric vector. Good to know:
- bw argument controls the smoothness: Smaller = rougher.

Let us say that we want to explore the same question from before, but we felt like the last graphic wasn't as clear as we would want it to be. We could use a different graphing strategy such as the density plot to make it clearer to whoever is intepreting the data. Data is only as good as you can communicate and understand it. Observe the differences between the last code's output and this code's output

```
mydata %>% ggplot(aes(x = Freq_T)) +
  geom_density(aes(fill = factor(probe_position), alpha = 0.05)) +
  xlab("Word Frequency of Target Word") +
  ylab("Count") +
  ggtitle("Word Frequency Distribution for Target Words") +
  scale_fill_discrete(name = "Probe Position", labels = c("1", "2", "3", "4")) +
  theme_classic()
```



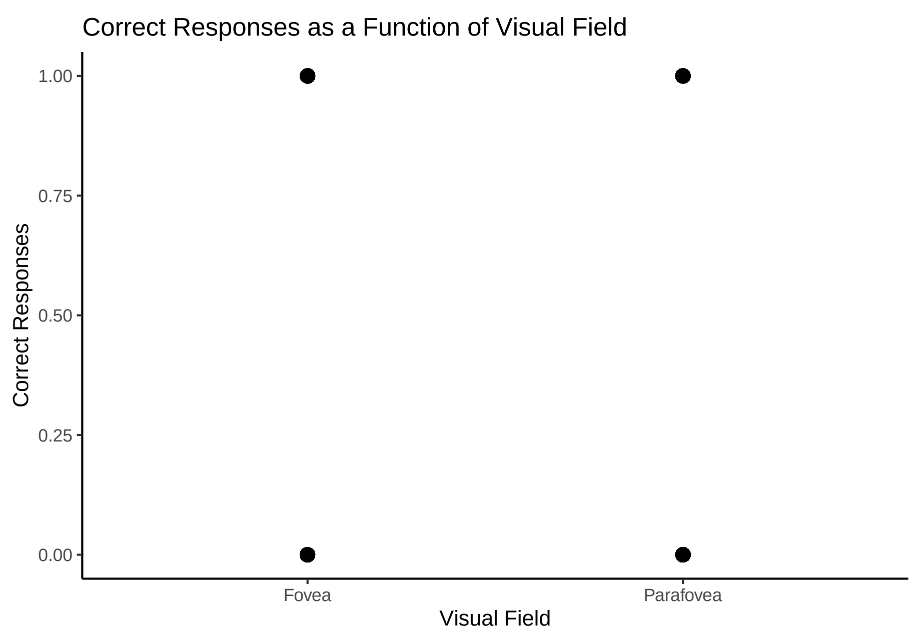
4.2 Plotting: Experimental Analysis

In cognitive psychology we are particularly interested in how our independent variables and participant variables influence performance on a particular task. In this section we are going to plot performance on this study's task. We are going to view a few ways to graphically represent how these variables influence performance.

4.2.1 Plotting Levels of One Categorical Variable

One of our manipulations for this study was visual field. Staub and Goddard (2019) argue that it is easier to identify words when they are presented in foveal vision as compared to parafoveal vision. This is ostensibly due to the fact that visual clarity drops as a function of eccentricity (how many degrees from central vision is the target word). To test this hypothesis, we will simply graph how people perform on a task across visual field. Here is an example.

```
mydata %>% ggplot(aes(x = visual_field, y = accuracy)) +
  geom_point(size = 3) +
  xlab("Visual Field") +
  ylab("Correct Responses") +
  ggtitle("Correct Responses as a Function of Visual Field") +
  theme_classic()
```

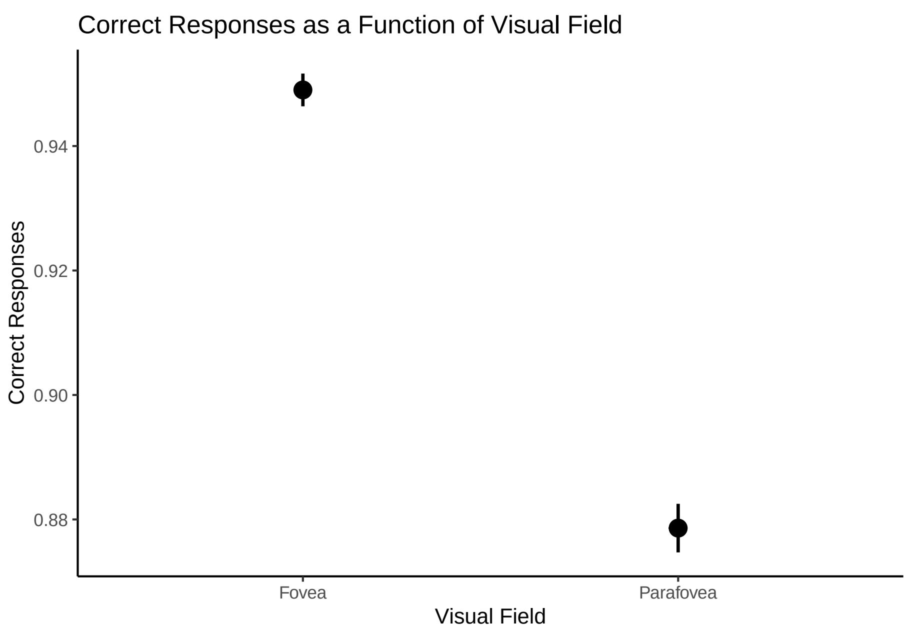



```
# stat_summary(fun.data = "mean_se", geom = "pointrange")
```

Now you may see that there is something wrong with this graph. In fact, there isn't, the problem is that all of the response data is binary: coded as (0) when you are incorrect, and (1) when you are correct. Since participants got right and wrong answers in both levels on the condition, they look identical. Thus, a better way to plot this is to create a summarized version of the data in each level of visual field. Here is an example.

```
mydata %>% ggplot(aes(x = visual_field, y = accuracy)) +
  stat_summary(fun.data = "mean_se", geom = "pointrange", size = .8) +
```

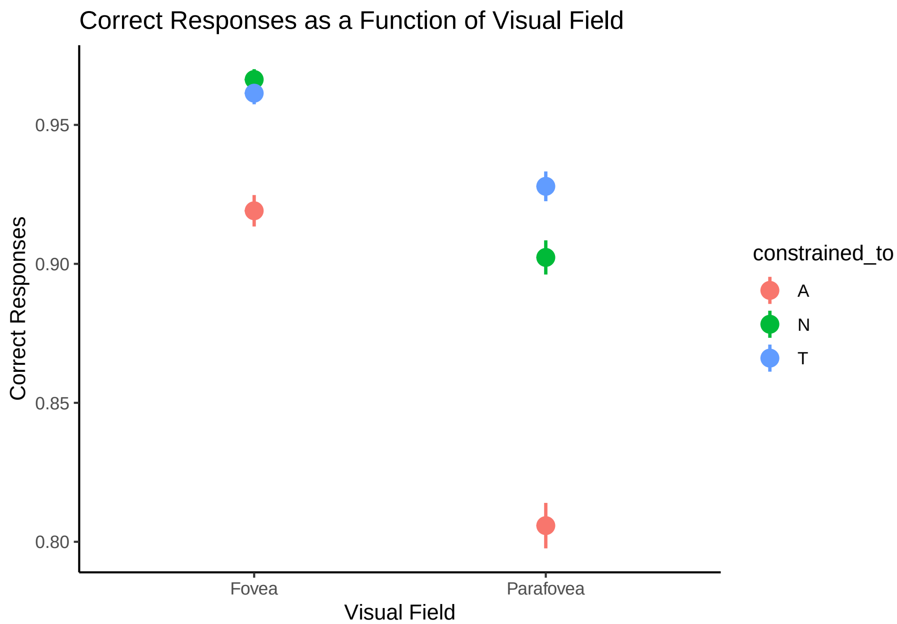
```
  xlab("Visual Field") +
  ylab("Correct Responses") +
  ggtitle("Correct Responses as a Function of Visual Field") +
  theme_classic()
```



4.2.2 Plotting Levels of Multiple Categorical Variables

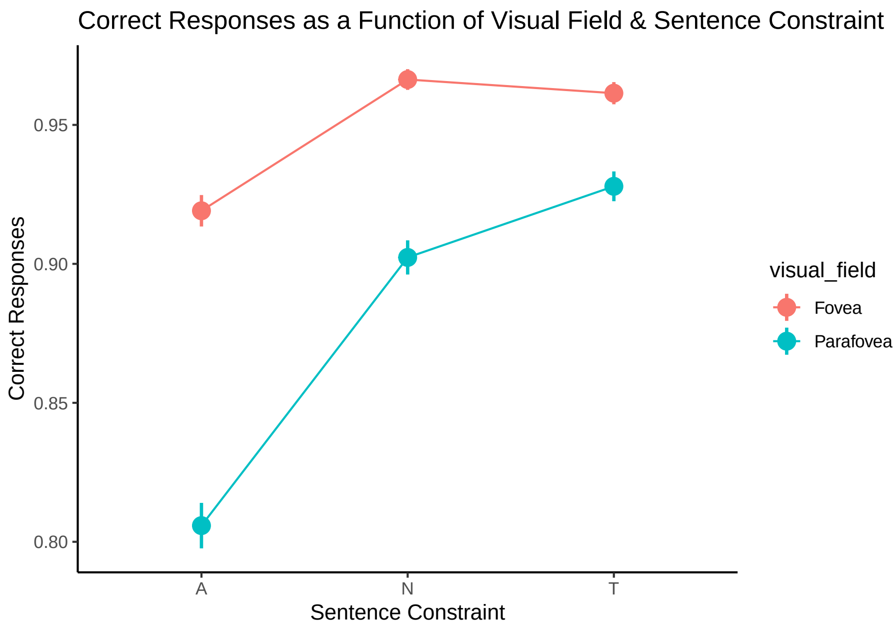
Most experiments in Cognitive dont only compare between one factor, but sometimes across many factors. For instance, with this experiment Staub and Goddard (2019) has a very specific hypothesis: When words are presented in foveal vision we are less likely to rely on sentence context for word identification, however when words are presented in parafoveal vision we are more likely to rely on sentence context for word identification. To answer this question, we need to plot both factors: visual field and sentence constraint.

```
mydata %>% ggplot(aes(x = visual_field, y = accuracy, color = constrained_to)) +
  stat_summary(fun.data = "mean_se", geom = "pointrange", size = .8) +
  xlab("Visual Field") +
  ylab("Correct Responses") +
  ggtitle("Correct Responses as a Function of Visual Field") +
  theme_classic()
```



Does this graph test for this hypothesis well? It is a little difficult to tell. Can we think of a better way to represent this? Maybe we can try to plot sentence constraint on the x-axis and our color be visual field.

```
mydata %>% ggplot(aes(x = constrained_to, y = accuracy, color = visual_field)) +
  stat_summary(fun.data = "mean_se", geom = "pointrange", size = .8) +
  stat_summary(geom = "line", fun.y = "mean", aes(group = visual_field))+
  xlab("Sentence Constraint") +
  ylab("Correct Responses") +
  ggtitle("Correct Responses as a Function of Visual Field & Sentence Constraint") +
  theme_classic()
```


Correct Responses as a Function of Visual Field & Sentence Constraint
0.95
0.90
0.85
0.80
Correct Responses
A
N
T
Sentence Constraint
visual_field
Fovea
Parafovea