The structure of data

Research Methods and Skills

27/10/2020

Writing R Scripts

Scripts are text documents that contain a sequence of commands to be executed sequentially.

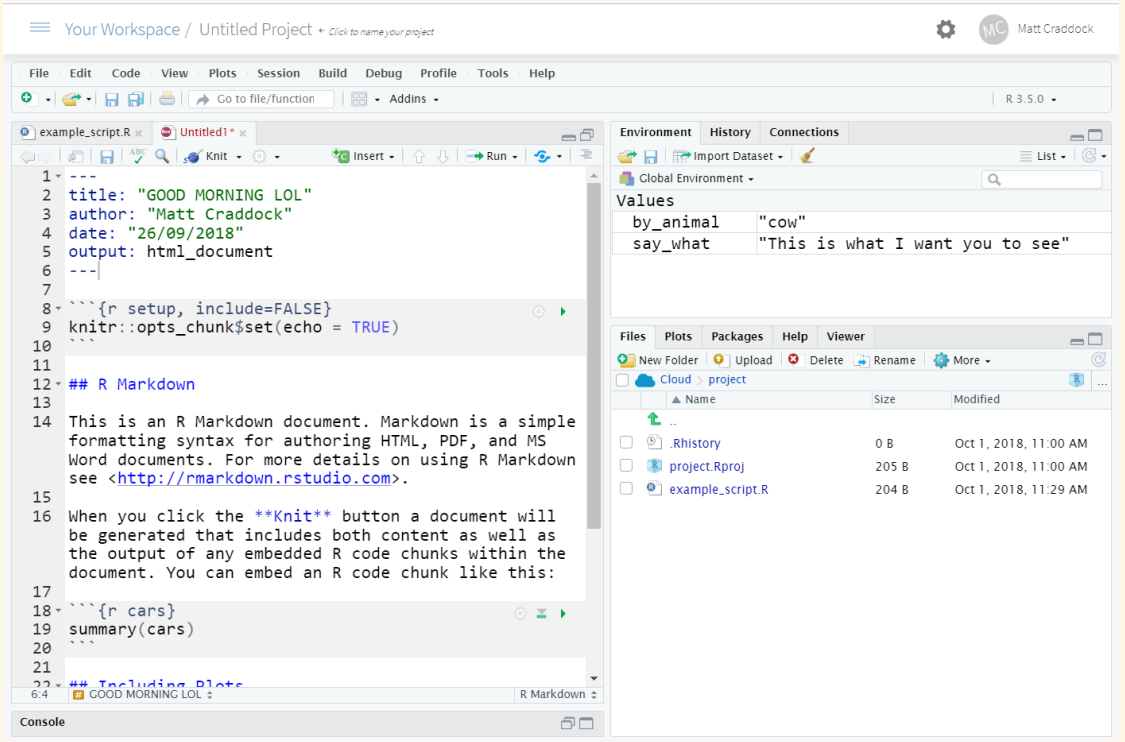
A typical script looks something like this:

```
# Load in required packages using library()
library(tidyverse)

# Define any custom functions here (we haven't covered this!)

# Now load any data you want to work on. (again, we'll cover this later!)
test_data <-
  read_csv("data/a-random-RT-file.csv") %>% # I'll explain what %>% means later
  rename(RT = `reaction times`)

# The rest of the script then runs whatever analyses or plotting you want to do
ggplot(test_data,
       aes(x = RT,
           fill = viewpoint)) +
  geom_density()
```

RMarkdown

RMarkdown documents contain a mixture of code and plain text.

They can be used to produce *reports* and fully formatted documents with whatever structure you choose.



Basic data types

There are five basic data types in R:

Type	Description	Examples
integer	Whole numbers	1, 2, 3
numeric	Any real number, fractions	3.4, 2, -2.3
character	Text	"Hi there", "8.5", "ABC123"
logical	Assertion of truth/falsity	TRUE, FALSE
complex	Real and imaginary numbers	0.34+5.3i

Containers

Vectors are one-dimensional collections of values of the same basic data type.

Matrices are two-dimensional collections of values of the same basic data type.

Lists are collections of objects of varying length and type.

Data frames are tables of data.

Accessing elements from containers

You can use the [] operator after the name of an object to extract indvidual elements from that object.

```
one_to_four
```

```
##    Monday   Tuesday Wednesday  Thursday
##         1         2         3         4
```

```
test_matrix
```

```
##             [,1]       [,2]       [,3]
## [1,]  1.3929560  0.2605482  1.3941402
## [2,] -0.8899093 -0.9559970 -0.2115673
## [3,]  1.3994929  0.7738423 -0.5347060
```

```
one_to_four["Wednesday"]
```

```
## Wednesday
##         3
```

```
test_matrix[2:3, 1:2]
```

```
##             [,1]       [,2]
## [1,] -0.8899093 -0.9559970
## [2,]  1.3994929  0.7738423
```


tidyverse
www.rstudio.com

Tidyverse

The **tidyverse** is a collection of packages that expand R's functions in a structured, coherent way.

```
install.packages("tidyverse")
```

There are eight core **tidyverse** packages loaded using **library(tidyverse)**.

- ggplot2
- **tidyr**
- dplyr
- **tibble**
- purrr
- readr
- stringr
- forcats

Tidyverse

You can load all these packages at once.

```
library(tidyverse) # This loads all the tidyverse packages at once
```

You can also load each one individually. We'll be using the **tibble** package next.

```
library(tibble)
```

Many of the *tidyverse* packages create or output *tibbles*, which are essentially a more user-friendly version of data frames.

Tibbles

You can create a *tibble* similar to how you create a data frame, using **tibble()**.

```
age_tibb <-
  tibble(Participant = 1:10,
         cond1 = rnorm(10),
         age_group = rep(c("Old", "Young"),
                         each = 5))
head(age_tibb)
```

```
## # A tibble: 6 x 3
##   Participant  cond1 age_group
##         <int>  <dbl> <chr>
## 1           1  0.653 Old
## 2           2  0.459 Old
## 3           3  1.30  Old
## 4           4 -0.776 Old
## 5           5 -1.64  Old
## 6           6  0.417 Young
```

Tibbles

```
age_tibb <-
  tibble(Participant = 1:10,
         cond1 = rnorm(10),
         age_group = rep(c("Old", "Young"), each = 5))
```

Here I used the **rep()** function to generate a character vector with the values "Old" and "Young".

```
rep(c("Old", "Young"), each = 5)
```

```
##  [1] "Old"   "Old"   "Old"   "Old"   "Old"   "Young" "Young" "Young" "Young" "Young"
```

```
rep(c("Old", "Young"), 5)
```

```
##  [1] "Old"   "Young" "Old"   "Young" "Old"   "Young" "Old"   "Young" "Old"   "Young"
```

Relating data to structure

Let's think about an *experiment*

The experiment is a reaction time experiment with a two-by-two repeated measures design.

Participants see pictures of objects twice. Sometimes they are seen from the *same* viewpoint twice, sometimes from *different* viewpoints each time.

There are two separate blocks of trials. The dependent variable is how long it takes them to name the objects, or *reaction time*.

You're interested in whether:

1. they get faster at naming object the second time

2. they are faster when the same view is presented both times.

How many variables are there?

Variables	R Data Type
Participant ID	Numeric or character
Reaction times	Numeric
Block first/second	Character/factor
Viewpoint same/different	Character/factor

The final dataset needs to be able to do several things.

1. It needs to uniquely identify each participant.
2. It needs to tie each value to the right participant.
3. It needs to identify what each value represents in terms of the design.

The many ways to structure data

One column for condition, one column for RT

```
## # A tibble: 40 x 3
## # Groups:   Participant [10]
##    Participant exp_condition       RT
##          <int> <chr>              <dbl>
##  1           1 Block1_different  407.
##  2           1 Block1_same       415.
##  3           1 Block2_different  382.
##  4           1 Block2_same       371.
##  5           2 Block1_different  420.
##  6           2 Block1_same       384.
##  7           2 Block2_different  479.
##  8           2 Block2_same       402.
##  9           3 Block1_different  368.
## 10           3 Block1_same       341.
## # ... with 30 more rows
```

This is a little awkward.

At first glance, there's no easy way to see how many variables there.

Dependent variable split across columns

```
## # A tibble: 16 x 4
## # Groups:   Participant [8]
##    Participant Viewpoint  B1RT  B2RT
##          <int> <chr>     <dbl> <dbl>
##  1           1 Different  536.  364.
##  2           1 Same       494.  450.
##  3           2 Different  511.  393.
##  4           2 Same       432.  371.
##  5           3 Different  536.  364.
##  6           3 Same       494.  450.
##  7           4 Different  511.  393.
##  8           4 Same       432.  371.
##  9           5 Different  536.  364.
## 10           5 Same       494.  450.
## 11           6 Different  511.  393.
## 12           6 Same       432.  371.
## 13           7 Different  536.  364.
## 14           7 Same       494.  450.
## 15           8 Different  511.  393.
## 16           8 Same       432.  371.
```

One column per condition

```
## # A tibble: 10 x 5
##    Participant Block1_same Block2_same Block1_different Block2_different
##          <int>       <dbl>       <dbl>             <dbl>             <dbl>
##  1           1        515.        268.              546.              413.
##  2           2        471.        249.              535.              449.
##  3           3        507.        331.              501.              386.
##  4           4        482.        312.              607.              389.
##  5           5        484.        322.              595.              431.
##  6           6        502.        301.              527.              359.
##  7           7        520.        328.              557.              398.
##  8           8        579.        272.              578.              378.
##  9           9        441.        290.              572.              401.
## 10          10        526.        285.              550.              405.
```

This is also called **wide** format.

How many *variables* are there?

```
## # A tibble: 10 x 5
##    Participant Block1_same Block2_same Block1_different Block2_different
##          <int>       <dbl>       <dbl>             <dbl>             <dbl>
##  1           1        515.        268.              546.              413.
##  2           2        471.        249.              535.              449.
##  3           3        507.        331.              501.              386.
##  4           4        482.        312.              607.              389.
##  5           5        484.        322.              595.              431.
##  6           6        502.        301.              527.              359.
##  7           7        520.        328.              557.              398.
##  8           8        579.        272.              578.              378.
##  9           9        441.        290.              572.              401.
## 10          10        526.        285.              550.              405.
```

Four... but there are five columns.

```
ncol(example_rt_df)
```

```
## [1] 5
```

How many *observations* are there?

```
## # A tibble: 10 x 5
##    Participant Block1_same Block2_same Block1_different Block2_different
##          <int>       <dbl>       <dbl>             <dbl>             <dbl>
##  1           1        515.        268.              546.              413.
##  2           2        471.        249.              535.              449.
##  3           3        507.        331.              501.              386.
##  4           4        482.        312.              607.              389.
##  5           5        484.        322.              595.              431.
##  6           6        502.        301.              527.              359.
##  7           7        520.        328.              557.              398.
##  8           8        579.        272.              578.              378.
##  9           9        441.        290.              572.              401.
## 10          10        526.        285.              550.              405.
```

40... but there are 10 rows.

```
nrow(example_rt_df)
```

```
## [1] 10
```

Your target

Switch to *RStudio.cloud* and create a *New Project*.

Your job is to try to recreate this *tibble*.

```
## # A tibble: 10 x 5
##    Participant Block1_same Block2_same Block1_different Block2_different
##          <int>       <dbl>       <dbl>             <dbl>             <dbl>
##  1           1        508.        340.              522.              295.
##  2           2        523.        268.              550.              470.
##  3           3        543.        303.              667.              476.
##  4           4        556.        408.              400.              322.
##  5           5        506.        163.              539.              269.
##  6           6        489.        287.              350.              363.
##  7           7        398.        346.              624.              392.
##  8           8        470.        494.              504.              374.
##  9           9        517.        258.              396.              422.
## 10          10        642.        348.              515.              437.
```

A shortcut to more tips

If you follow this link, you should be able to make a copy of a project I prepared for you.

This project has only one file, an RMarkdown file that has some more tips and instructions for you.

https://rstudio.cloud/project/1817564

(if you get really stuck, there is a solution to Part 1 on the next slide!)

A possible solution

```
set.seed(200) # if you want these exact numbers, use this line
example_rt_df <-
  tibble(Participant = seq(1, 10),
         Block1_same = rnorm(10, 500, 100),
         Block2_same = rnorm(10, 350, 100),
         Block1_different = rnorm(10, 500, 100),
         Block2_different = rnorm(10, 400, 100))
```

```
## # A tibble: 5 x 5
##   Participant Block1_same Block2_same Block1_different Block2_different
##         <int>       <dbl>       <dbl>             <dbl>             <dbl>
## 1           1        508.        340.              522.              295.
## 2           2        523.        268.              550.              470.
## 3           3        543.        303.              667.              476.
## 4           4        556.        408.              400.              322.
## 5           5        506.        163.              539.              269.
```

Tidy data

The three principles of tidy data

1. Each variable must have its own column.
2. Each observation must have its own row.
3. Each value must have its own cell.

Why Tidy?

1. Many functions in R operate on so-called *long* format data, requiring dependent and independent variables to be in different columns of a data frame.

2. Having a consistent way to store and structure your data makes it more *generic*. This makes it easier to use it with different functions.

3. Being *generic* also makes it easier to understand a new dataset in this format.

One column per condition

```
## # A tibble: 10 x 5
##    Participant Block1_same Block2_same Block1_different Block2_different
##          <int>       <dbl>       <dbl>             <dbl>             <dbl>
##  1           1        515.        268.              546.              413.
##  2           2        471.        249.              535.              449.
##  3           3        507.        331.              501.              386.
##  4           4        482.        312.              607.              389.
##  5           5        484.        322.              595.              431.
##  6           6        502.        301.              527.              359.
##  7           7        520.        328.              557.              398.
##  8           8        579.        272.              578.              378.
##  9           9        441.        290.              572.              401.
## 10          10        526.        285.              550.              405.
```

This is also called **wide** format.

This data is *untidy*

One variable - RT - is split across four columns.

Another variable - Block - is split across two columns.

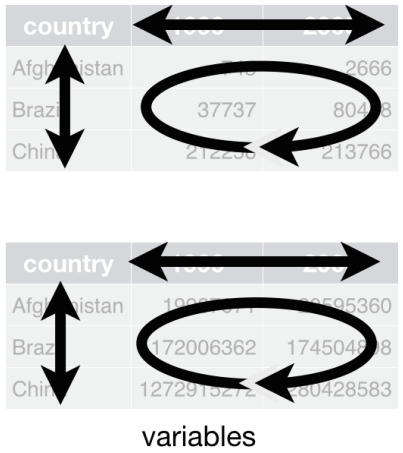
A third variable - viewpoint - is also split across two columns.

country	1999	2000
Afghanistan	745	2666
Brazil	37737	80488
China	212258	213766

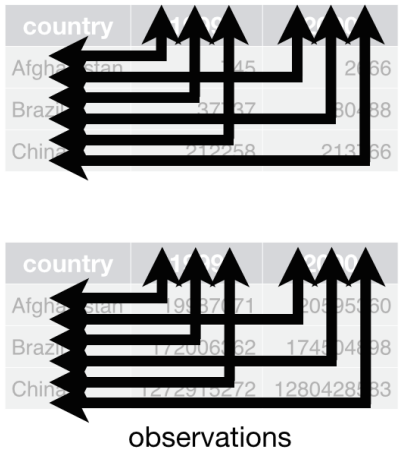
table4

country	1999	2000
Afghanistan	19987071	20595360
Brazil	172006362	174504898
China	1272915272	1280428583

table5



variables



observations

Tidying your data

Tidyr

The **tidyr** package contains functions to help tidy up your data.

We'll look now at **pivot_longer()** and **pivot_wider()**.

To start tidying our data, we need the RTs to be in a single column.

```
head(example_rt_df, n = 4)
```

```
## # A tibble: 4 x 5
##   Participant Block1_same Block2_same Block1_different Block2_different
##         <int>       <dbl>       <dbl>             <dbl>             <dbl>
## 1           1        508.        340.              522.              295.
## 2           2        523.        268.              550.              470.
## 3           3        543.        303.              667.              476.
## 4           4        556.        408.              400.              322.
```

The function **pivot_longer()** can be used to combine columns into one.

Look at the help using **?pivot_longer**

Pivoting longer

```
pivot_longer(data,
             cols,
             names_to = "key",
             values_to = "value",
             ...)
```

The first argument, *data*, is the name of the data frame you want to modify.

cols are the columns you want to combine together.

names_to is the name of the new column that will contain the values of a single categorical variable.

values_to is the name of the new column containing the values for each level of that variable.

Pivoting longer

```
long_rt <-
  pivot_longer(example_rt_df,
               cols = c("Block1_same",
                        "Block1_different",
                        "Block2_same",
                        "Block2_different"),
               names_to = "exp_cond",
               values_to = "RT")
head(long_rt)
```

```
## # A tibble: 6 x 3
##   Participant exp_cond            RT
##         <int> <chr>            <dbl>
## 1           1 Block1_same       508.
## 2           1 Block1_different  522.
## 3           1 Block2_same       340.
## 4           1 Block2_different  295.
## 5           2 Block1_same       523.
## 6           2 Block1_different  550.
```

Pivoting longer

After we specify the "key" and "value" columns, we need to specify which columns we want to be *gathered*.

```
long_rt <-
  pivot_longer(example_rt_df,
               names_to = "exp_cond",
               values_to = "RT",
               cols = 2:5) # here I use number
head(long_rt)
```

```
## # A tibble: 6 x 3
##   Participant exp_cond            RT
##         <int> <chr>              <dbl>
## 1           1 Block1_same         508.
## 2           1 Block2_same         340.
## 3           1 Block1_different    522.
## 4           1 Block2_different    295.
## 5           2 Block1_same         523.
## 6           2 Block2_same         268.
```

```
long_rt <-
  pivot_longer(example_rt_df,
               names_to = "exp_cond",
               values_to = "RT",
               cols = Block1_same:Block2_diffe
head(long_rt)
```

```
## # A tibble: 6 x 3
##   Participant exp_cond            RT
##         <int> <chr>              <dbl>
## 1           1 Block1_same         508.
## 2           1 Block2_same         340.
## 3           1 Block1_different    522.
## 4           1 Block2_different    295.
## 5           2 Block1_same         523.
## 6           2 Block2_same         268.
```

Splitting columns

We have the RTs in one column, but we still have another problem:

The "Block" and "Viewpoint" variables are combined into a single column.

```
head(long_rt)
```

```
## # A tibble: 6 x 3
##   Participant exp_cond            RT
##         <int> <chr>            <dbl>
## 1           1 Block1_same       508.
## 2           1 Block2_same       340.
## 3           1 Block1_different  522.
## 4           1 Block2_different  295.
## 5           2 Block1_same       523.
## 6           2 Block2_same       268.
```

Splitting columns

Fortunately, the values in the *exp_cond* column can be easily split:

```
unique(long_rt$exp_cond)
```

```
## [1] "Block1_same"      "Block2_same"      "Block1_different" "Block2_different"
```

The value of "Block" comes before the underscore ("_"), while the value of "viewpoint" comes after it.

Splitting columns

```
long_rt <-
  pivot_longer(example_rt_df,
               names_to = c("Block",
                            "Viewpoint"),
               names_sep = "_",
               values_to = "RT",
               cols = Block1_same:Block2_different)
head(long_rt)
```

```
## # A tibble: 6 x 4
##   Participant Block  Viewpoint    RT
##         <int> <chr>  <chr>     <dbl>
## 1           1 Block1 same       508.
## 2           1 Block2 same       340.
## 3           1 Block1 different  522.
## 4           1 Block2 different  295.
## 5           2 Block1 same       523.
## 6           2 Block2 same       268.
```

Splitting columns

Let's look at the additional syntax.

```
pivot_longer(example_rt_df,
             names_to = c("Block",
                          "Viewpoint"),
             names_sep = "_",
             values_to = "RT",
             cols = Block1_same:Block2_different)
```

`names_to` now has two entries, one for each new column that will be made.

`names_sep` is the character that *separates* the values you want to split.

Your target

```
## # A tibble: 15 x 4
##    Participant Block  Viewpoint    RT
##          <int> <chr>  <chr>     <dbl>
##  1           1 Block1 same       508.
##  2           1 Block2 same       340.
##  3           1 Block1 different  522.
##  4           1 Block2 different  295.
##  5           2 Block1 same       523.
##  6           2 Block2 same       268.
##  7           2 Block1 different  550.
##  8           2 Block2 different  470.
##  9           3 Block1 same       543.
## 10           3 Block2 same       303.
## 11           3 Block1 different  667.
## 12           3 Block2 different  476.
## 13           4 Block1 same       556.
## 14           4 Block2 same       408.
## 15           4 Block1 different  400.
```

You should specify name(s) for the column(s) that you'll create using the "names_to" and "values_to" arguments.

You'll need to add "names_sep" and the character that separates the two sides as well in order to match the target

Pivoting wider

Pivoting wider

Sometimes you want to go in the *opposite* direction.

pivot_wider() is the *opposite* of **pivot_longer()**.

```
wide_rt <-
  pivot_wider(long_rt,
              names_from = c("Block",
                             "Viewpoint"),
              values_from = "RT")
head(wide_rt, 10)
```

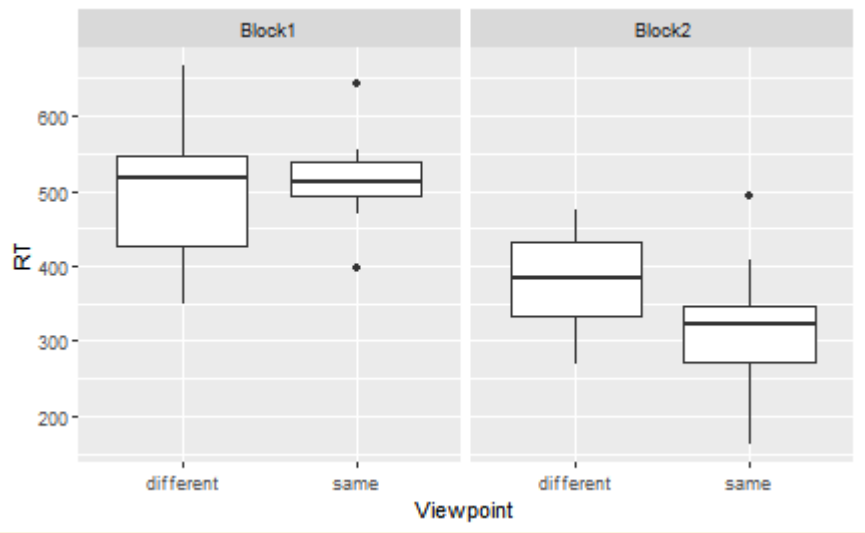
```
## # A tibble: 10 x 5
##    Participant Block1_same Block2_same Block1_different Block2_different
##          <int>       <dbl>       <dbl>             <dbl>             <dbl>
##  1           1        508.        340.              522.              295.
##  2           2        523.        268.              550.              470.
##  3           3        543.        303.              667.              476.
##  4           4        556.        408.              400.              322.
##  5           5        506.        163.              539.              269.
##  6           6        489.        287.              350.              363.
##  7           7        398.        346.              624.              392.
##  8           8        470.        494.              504.              374.
##  9           9        517.        258.              396.              422.
## 10          10        642.        348.              515.              437.
```

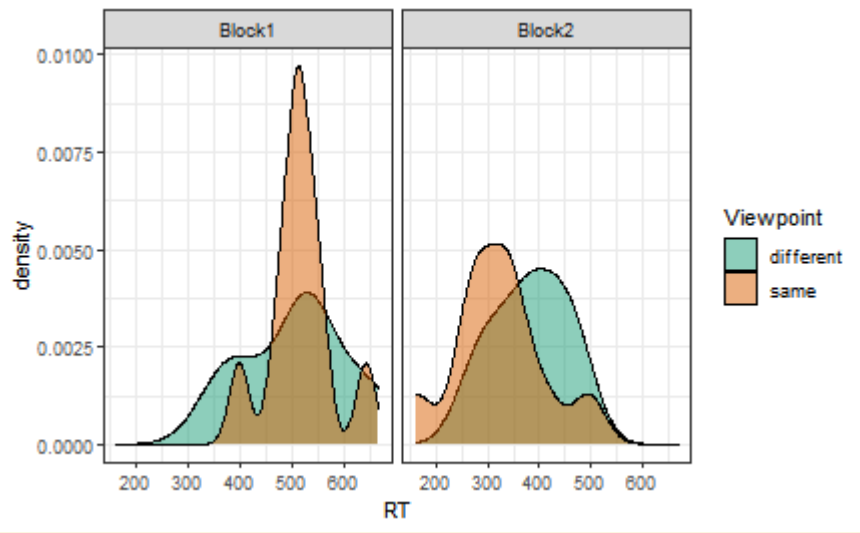
Now what?

Now that it's tidy...

Now that we've got the data in a tidy format, we can begin to use some of the more interesting features of R!

We can produce a boxplot using **ggplot2** (more next week!)





Now that it's tidy...

We can produce some summary statistics using **dplyr** (more soon!)

```
## `summarise()` regrouping output by 'Block' (override with `.groups` argument)

## # A tibble: 4 x 4
## # Groups:   Block [2]
##   Block  Viewpoint mean_RT sd_RT
##   <chr>  <chr>       <dbl> <dbl>
## 1 Block1 different    507. 100.
## 2 Block1 same         515.  62.5
## 3 Block2 different    382.  71.2
## 4 Block2 same         321.  89.7
```

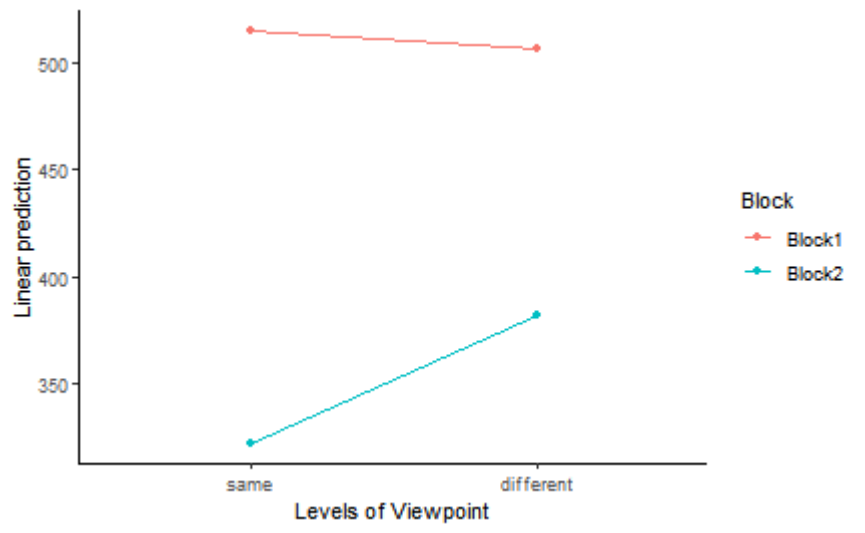
Now that it's tidy...

We can run ANOVA with **afex**.

```
## Anova Table (Type 3 tests)
##
## Response: RT
##            Effect   df     MSE         F  ges p.value
## 1           Block 1, 9 5222.72 48.56 *** .510   <.001
## 2       Viewpoint 1, 9 7794.41      0.87 .027    .376
## 3 Block:Viewpoint 1, 9 6343.29      1.87 .046    .205
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '+' 0.1 ' ' 1
```

Now that it's tidy...

We can create interaction plots using **emmeans**.




```
## Block = Block1:
##  contrast         estimate   SE   df t.ratio p.val
##  same - different     8.43 37.6 17.8  0.224  0.825
##
## Block = Block2:
##  contrast         estimate   SE   df t.ratio p.val
##  same - different   -60.45 37.6 17.8 -1.608  0.125
```

Next week

- The following chapters of R for Data Science -
  - **Data Visualization** (Chapter 1 via the library)
  - **Graphics for communication with ggplot2** (Chapter 22 via the library)

Practice some of the skills for next week:

- **RStudio.cloud Primer**
  - Visualize Data