



UNIVERSITY OF  
LINCOLN

# Structuring your data

PSY9219M - Research Methods and Skills

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# Writing R Scripts

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

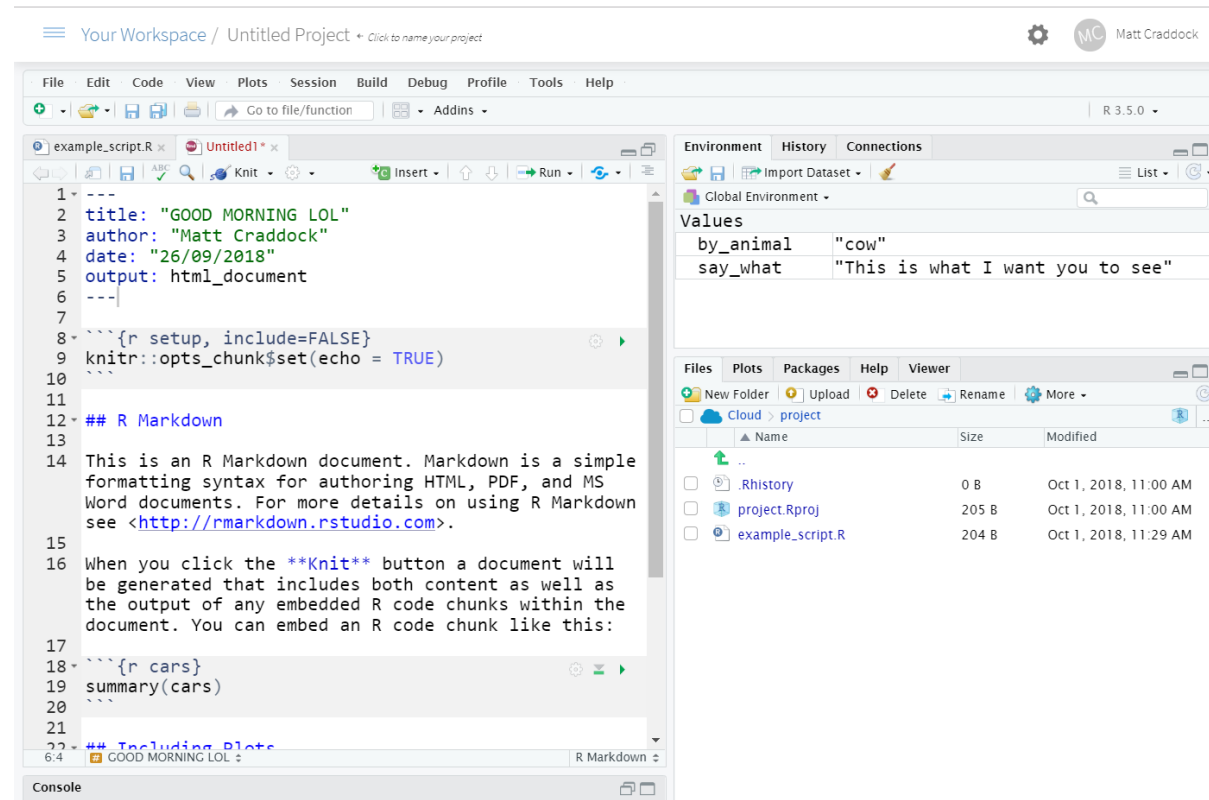
A typical script looks something like this:

```
# 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
double	Floating point value	3.12
integer	Integer	1, 2, 3
numeric	Any real number	3.4, 2, -2.3
character	Text	"Hi there", "8.5", "ABC123"
logical	Assertion of truth/falsity	TRUE, FALSE

# 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 individual elements from that object.

```
one_to_four
```

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

```
test_matrix
```

```
##           [,1]      [,2]      [,3]
## [1,]  0.45650588  1.0698847  0.8399025
## [2,] -0.47721600 -0.9100745  1.3884486
## [3,] -0.09986935  0.9590143  0.7455983
```

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

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

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

```
##           [,1]      [,2]
## [1,] -0.47721600 -0.9100745
## [2,] -0.09986935  0.9590143
```

# Relating data to structure

# Example data frames

R has a number of example data frames built-in.

```
data()  
help("ChickWeight")  
head(ChickWeight)
```

You can use these to get an idea of the kind of ways data is structured by R.

(Note here I use the **head()** function to see the first 6 rows of the data frame "ChickWeight")



# Example data frames

```
head(ChickWeight, n = 10)
```

```
## Grouped Data: weight ~ Time | Chick
##      weight Time Chick Diet
## 1      42     0     1     1
## 2      51     2     1     1
## 3      59     4     1     1
## 4      64     6     1     1
## 5      76     8     1     1
## 6      93    10     1     1
## 7     106    12     1     1
## 8     125    14     1     1
## 9     149    16     1     1
## 10     171    18     1     1
```

*ChickWeight* has 578 datapoints from an experiment on effects of diet on early growth of chicks.

Each column is a separate *variable*, with different information.

# Scenario A

You've just started work in a psychology lab. You're asked to help analyse some old data. There is reaction time data from 50 participants. Each participant's data is stored in a separate text file.

- How do you combine the data from each participant together to be able to analyse the data?
- It turns out some of the participants only completed part of the experiment - which ones, and what should you do with their data?
- What steps should you take to select and perform appropriate statistical analysis?

# Let's think about the *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 1) whether they get faster the second time, and 2) whether they faster when the same view is presented both times.

# How the design informs the structure

Variables
Participant ID
Reaction times
Block first/second
Viewpoint same/different

R Data Type
Numeric or character
Numeric
Character/factor
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.

Some possible data frames

# Dependent variable split across columns

```
## # A tibble: 16 x 4
## # Groups:   Participant [8]
##   Participant Viewpoint B1RT B2RT
##   <int> <fct> <dbl> <dbl>
## 1         1 Different 448. 455.
## 2         1 Same      509. 384.
## 3         2 Different 445. 386.
## 4         2 Same      438. 370.
## 5         3 Different 448. 455.
## 6         3 Same      509. 384.
## 7         4 Different 445. 386.
## 8         4 Same      438. 370.
## 9         5 Different 448. 455.
## 10        5 Same      509. 384.
## 11        6 Different 445. 386.
## 12        6 Same      438. 370.
## 13        7 Different 448. 455.
## 14        7 Same      509. 384.
## 15        8 Different 445. 386.
## 16        8 Same      438. 370.
```

# One column for condition, one column for RT

```
## # A tibble: 40 x 3
## # Groups:   Participant [10]
##   Participant exp_condition      RT
##         <int> <fct>          <dbl>
## 1           1 Block1_different 395.
## 2           1 Block1_same      435.
## 3           1 Block2_different 417.
## 4           1 Block2_same      431.
## 5           2 Block1_different 368.
## 6           2 Block1_same      416.
## 7           2 Block2_different 394.
## 8           2 Block2_same      433.
## 9           3 Block1_different 370.
## 10          3 Block1_same      437.
## # ... with 30 more rows
```

# 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         520.         288.         541.         420.
## 2         2         466.         350.         583.         436.
## 3         3         492.         279.         606.         382.
## 4         4         567.         338.         549.         379.
## 5         5         511.         322.         507.         429.
## 6         6         531.         329.         540.         373.
## 7         7         471.         317.         561.         402.
## 8         8         467.         267.         548.         356.
## 9         9         478.         273.         504.         496.
## 10        10         529.         347.         607.         355.
```



# Create a data frame

## Your task:

1. Create a data frame with one column per condition.
2. Each row should be for one participant.
3. Each row should have an identifier for the participant, with the identifiers in one column.

# Create a data frame

## Some helpful functions

- **rnorm()**
  - Use **rnorm()** to generate a normally distributed set of numbers.
  - Type ?rnorm in console for help
  - **rnorm(n, mean = 0, sd = 1)**

```
rnorm(100, 500, 100) # This creates a vector of 100 values  
#with a mean of 500 and a standard deviation of 100
```

- **data.frame()**
  - Create columns in a data frame
  - **data.frame(colname = values)**
  - Separate columns with a comma ","

```
data.frame(col_one = rnorm(...),  
           col_two = rnorm(...))
```

# Create a data frame

## Tips

- Remember to *assign* output to an object using the `<-` operator.
- You can create a sequential vector using the colon (`:`) operator (e.g. `1:5`) or the **`seq()`** function (type `?seq`)
- Remember that objects can *stand in* for their values

```
some_rts <- rnorm(23, 34, 50)
test_df <-
  data.frame(col_one = some_rts,
             col_two = rnorm(...),
             ...)
```

- Once you've created a data frame, try calculating the **`mean()`** and **`sd()`** of the columns

# Your target

```
## # A tibble: 10 x 5
##   Participant Block1_same Block2_same Block1_different Block2_different
##   <int>         <dbl>         <dbl>         <dbl>         <dbl>
## 1           1         497.         296.         561.         361.
## 2           2         499.         275.         566.         367.
## 3           3         558.         302.         573.         328.
## 4           4         544.         289.         580.         396.
## 5           5         481.         308.         599.         424.
## 6           6         488.         325.         509.         384.
## 7           7         474.         287.         531.         394.
## 8           8         463.         334.         551.         460.
## 9           9         482.         291.         557.         338.
## 10          10         481.         301.         579.         376.
```

# A possible solution

```
example_rt_df <-  
  data.frame(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))
```

##	Participant	Block1_same	Block2_same	Block1_different	Block2_different
## 1	1	516.5898	305.1622	498.2227	313.3878
## 2	2	382.0560	386.3059	679.8127	339.2907
## 3	3	514.7835	378.0082	355.0890	442.7510
## 4	4	604.1356	450.9009	616.3194	477.3192
## 5	5	468.6312	211.0952	434.6988	340.4552



# 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 convert or output *tibbles*, which are essentially a more user-friendly version of data frames.



# Tibbles

*Tibbles* directly show what *data type* is stored in each column.

You can convert a data frame to a *tibble* using the **as\_tibble()** function.

```
example_rt_tibble <- as_tibble(example_rt_df)
head(example_rt_tibble)
```

```
## # A tibble: 6 x 5
##   Participant Block1_same Block2_same Block1_different Block2_different
##         <int>      <dbl>      <dbl>          <dbl>          <dbl>
## 1           1        517.        305.          498.          313.
## 2           2        382.        386.          680.          339.
## 3           3        515.        378.          355.          443.
## 4           4        604.        451.          616.          477.
## 5           5        469.        211.          435.          340.
## 6           6        318.        310.          480.          467.
```

# Tibbles

You can create a *tibble* similarly 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 -2.39    Old  
## 2         2 -0.709   Old  
## 3         3  1.07    Old  
## 4         4  0.438   Old  
## 5         5  0.0492  Old  
## 6         6 -0.963   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"  
## [9] "Young" "Young"
```

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

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

# 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.

country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	216766	1280425583

variables

country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	216766	1280425583

observations

country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	216766	1280425583

values

# How many *variables* are there?

##	Participant	Block1_same	Block2_same	Block1_different	Block2_different
## 1	1	516.5898	305.1622	498.2227	313.3878
## 2	2	382.0560	386.3059	679.8127	339.2907
## 3	3	514.7835	378.0082	355.0890	442.7510
## 4	4	604.1356	450.9009	616.3194	477.3192
## 5	5	468.6312	211.0952	434.6988	340.4552
## 6	6	317.7252	309.5307	479.6596	467.2746
## 7	7	451.3933	274.3238	546.2049	297.5012
## 8	8	704.9653	317.5622	594.0583	405.3054
## 9	9	383.3551	385.1461	489.2698	368.8661
## 10	10	668.2327	333.7526	448.7217	596.6026

# How many *variables* are there?

##	Participant	Block1_same	Block2_same	Block1_different	Block2_different
## 1	1	516.5898	305.1622	498.2227	313.3878
## 2	2	382.0560	386.3059	679.8127	339.2907
## 3	3	514.7835	378.0082	355.0890	442.7510
## 4	4	604.1356	450.9009	616.3194	477.3192
## 5	5	468.6312	211.0952	434.6988	340.4552
## 6	6	317.7252	309.5307	479.6596	467.2746
## 7	7	451.3933	274.3238	546.2049	297.5012
## 8	8	704.9653	317.5622	594.0583	405.3054

- Participant
- Block (1 or 2)
- Viewpoint (same or different)
- Reaction time

# 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

country		
Afghanistan	745	2666
Brazil	37737	80488
China	212258	213766

variables

country		
Afghanistan	745	2666
Brazil	37737	80488
China	212258	213766

observations



# 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.

country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20095360
Brazil	1999	3737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	216766	128042583

variables

country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20095360
Brazil	1999	3737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	216766	128042583

observations

country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20095360
Brazil	1999	3737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	216766	128042583

values

# A Tidy Structure

##	Participant	Block	Viewpoint	RT
## 1	1	Block1	same	516.5898
## 2	2	Block1	same	382.0560
## 3	3	Block1	same	514.7835
## 4	4	Block1	same	604.1356
## 5	5	Block1	same	468.6312
## 6	6	Block1	same	317.7252
## 7	7	Block1	same	451.3933
## 8	8	Block1	same	704.9653
## 9	9	Block1	same	383.3551
## 10	10	Block1	same	668.2327
## 11	1	Block2	same	305.1622
## 12	2	Block2	same	386.3059
## 13	3	Block2	same	378.0082
## 14	4	Block2	same	450.9009
## 15	5	Block2	same	211.0952

# Tidyr

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

We'll look now at **gather()** and **separate()**.

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

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

##	Participant	Block1_same	Block2_same	Block1_different	Block2_different
## 1	1	516.5898	305.1622	498.2227	313.3878
## 2	2	382.0560	386.3059	679.8127	339.2907
## 3	3	514.7835	378.0082	355.0890	442.7510
## 4	4	604.1356	450.9009	616.3194	477.3192

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

Look at the help using **?gather**

# Step 1 - gather()

The syntax looks like this:

```
gather(data,  
       key = "key",  
       value = "value",  
       ...)
```

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

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

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

# Step 1 - gather()

```
gather_rt <-  
  gather(example_rt_df,  
         key = "exp_cond",  
         value = "RT")  
head(gather_rt)
```

```
##      exp_cond RT  
## 1 Participant  1  
## 2 Participant  2  
## 3 Participant  3  
## 4 Participant  4  
## 5 Participant  5  
## 6 Participant  6
```

But this isn't right! We need to tell it to leave the *Participant* column alone.

# Step 1 - gather()

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

```
gather_rt <-  
  gather(example_rt_df,  
    key = "exp_cond",  
    value = "RT",  
    2:5)  
head(gather_rt)
```

##	Participant	exp_cond	RT
## 1	1	Block1_same	516.5898
## 2	2	Block1_same	382.0560
## 3	3	Block1_same	514.7835
## 4	4	Block1_same	604.1356
## 5	5	Block1_same	468.6312
## 6	6	Block1_same	317.7252

```
gather_rt <-  
  gather(example_rt_df,  
    key = "exp_cond",  
    value = "RT",  
    Block1_same:Block2_different)  
head(gather_rt)
```

##	Participant	exp_cond	RT
## 1	1	Block1_same	516.5898
## 2	2	Block1_same	382.0560
## 3	3	Block1_same	514.7835
## 4	4	Block1_same	604.1356
## 5	5	Block1_same	468.6312
## 6	6	Block1_same	317.7252

## Step 2 - separate()

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(gather_rt)
```

##	Participant	exp_cond	RT
## 1	1	Block1_same	516.5898
## 2	2	Block1_same	382.0560
## 3	3	Block1_same	514.7835
## 4	4	Block1_same	604.1356
## 5	5	Block1_same	468.6312
## 6	6	Block1_same	317.7252

## Step 2 - separate()

Fortunately, the values in the *exp\_cond* column can be easily split:

```
unique(gather_rt$exp_cond)
```

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

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

We can use the **separate()** command split this into two columns.

Type **?separate()**



## Step 2 - separate()

Let's look at the syntax.

```
separate(data,  
          col,  
          into,  
          sep, ...)
```

*Data* is the data frame you want to modify.

*col* is the name of column you want to separate.

*into* is the names of the new columns you want to create.

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

## Step 2 - separate()

```
gather_rt <-  
  separate(gather_rt,  
           col = "exp_cond",  
           into = c("Block", "Viewpoint"),  
           sep = "_")  
head(gather_rt)
```

##	Participant	Block	Viewpoint	RT
## 1	1	Block1	same	516.5898
## 2	2	Block1	same	382.0560
## 3	3	Block1	same	514.7835
## 4	4	Block1	same	604.1356
## 5	5	Block1	same	468.6312
## 6	6	Block1	same	317.7252

# Your target

##	Participant	Block	Viewpoint	RT
## 1	1	Block1	same	516.5898
## 2	2	Block1	same	382.0560
## 3	3	Block1	same	514.7835
## 4	4	Block1	same	604.1356
## 5	5	Block1	same	468.6312
## 6	6	Block1	same	317.7252
## 7	7	Block1	same	451.3933
## 8	8	Block1	same	704.9653
## 9	9	Block1	same	383.3551
## 10	10	Block1	same	668.2327
## 11	1	Block2	same	305.1622
## 12	2	Block2	same	386.3059
## 13	3	Block2	same	378.0082
## 14	4	Block2	same	450.9009
## 15	5	Block2	same	211.0952

# Your target

##	Participant	Block	Viewpoint	RT
## 1	1	Block1	same	516.5898
## 2	2	Block1	same	382.0560
## 3	3	Block1	same	514.7835
## 4	4	Block1	same	604.1356
## 5	5	Block1	same	468.6312
## 6	6	Block1	same	317.7252
## 7	7	Block1	same	451.3933
## 8	8	Block1	same	704.9653

Step 1 - **gather()** the RTs

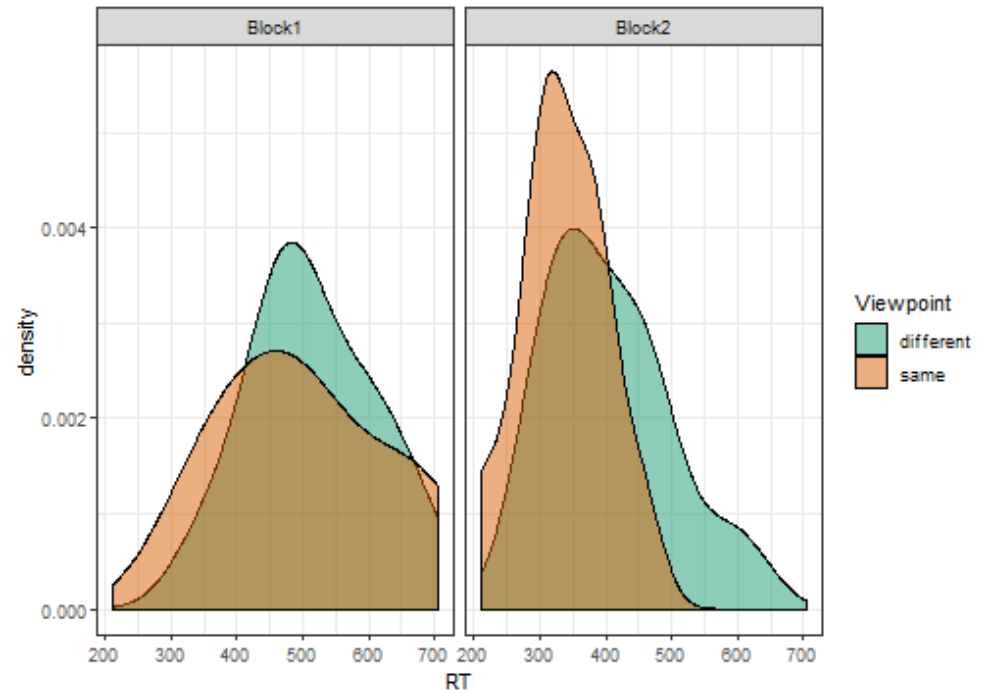
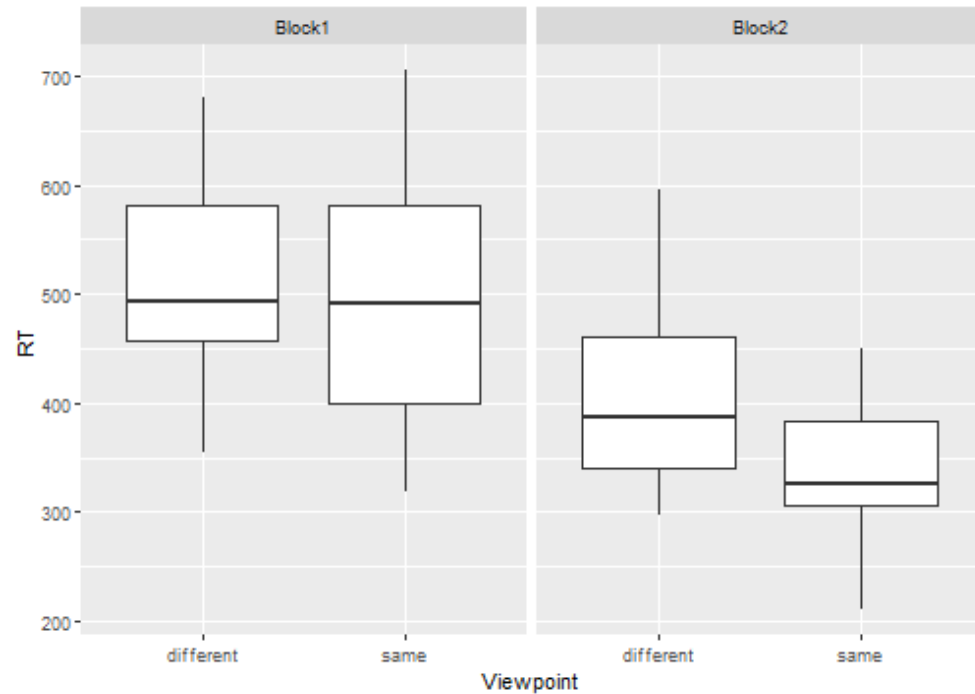
Step 2 - **separate()** the variables

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!)

```
## # A tibble: 4 x 4
## # Groups:   Block [2]
##   Block Viewpoint mean_RT sd_RT
##   <chr>  <chr>      <dbl> <dbl>
## 1 Block1 different    514.  96.2
## 2 Block1 same        501.  127.
## 3 Block2 different    405.  92.5
## 4 Block2 same        335.  67.7
```

# Now that it's tidy...

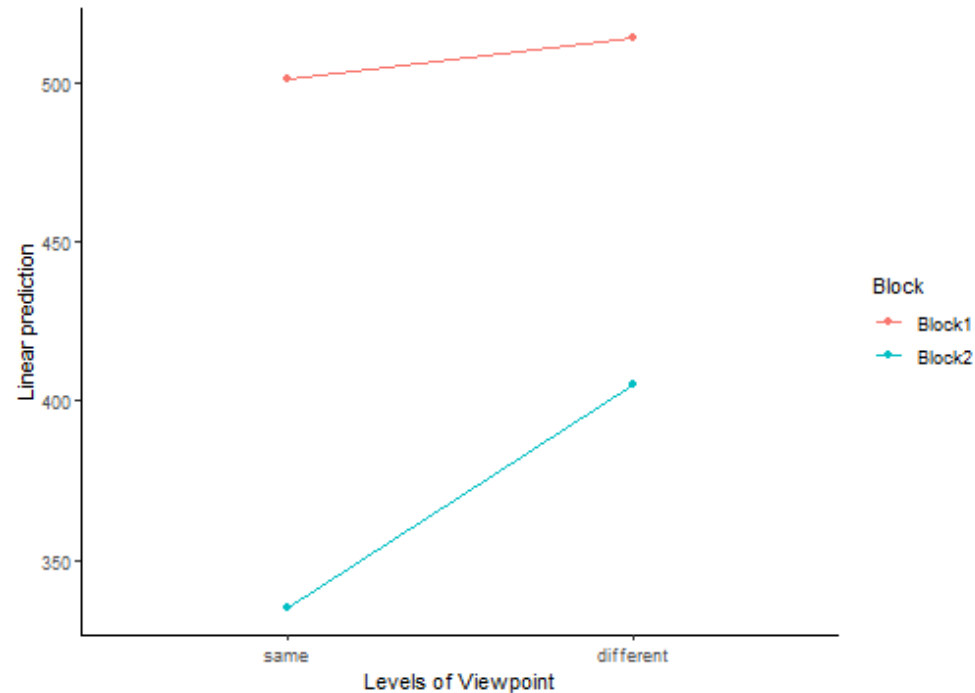
We can run ANOVA with **afex**.

```
## Anova Table (Type 3 tests)
##
## Response: RT
##           Effect    df      MSE      F ges p.value
## 1           Block 1, 9 7947.32 23.85 *** .35   .0009
## 2      Viewpoint 1, 9 3909.24  4.38 + .05   .07
## 3 Block:Viewpoint 1, 9 12691.81  0.63 .02   .45
## ---
## 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    -13.0  40.7  14.1  -0.320  0.754
##
## Block = Block2:
## contrast      estimate    SE    df t.ratio p.val
## same - different    -69.7  40.7  14.1  -1.711  0.109
```

# Next week

- Chapters 3 and 28 of R for Data Science
  - Data Visualization
  - Graphics for communication
- RStudio.cloud Primer
  - Visualize Data
- Datacamp
  - Data Visualization with ggplot2 (Part 1)



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# Splitting columns up

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

**spread()** is the *opposite* of **gather()**.

```
spread_rt <-  
  spread(gather_rt,  
         Block,  
         RT)  
head(spread_rt, 10)
```

##	Participant	Viewpoint	Block1	Block2
## 1	1	different	498.2227	313.3878
## 2	1	same	516.5898	305.1622
## 3	2	different	679.8127	339.2907
## 4	2	same	382.0560	386.3059
## 5	3	different	355.0890	442.7510
## 6	3	same	514.7835	378.0082
## 7	4	different	616.3194	477.3192
## 8	4	same	604.1356	450.9009
## 9	5	different	434.6988	340.4552
## 10	5	same	468.6312	211.0952

# Combining columns into one

We used **separate()** to split up our "exp\_cond" column.

We can use **unite()** to put them back together.

```
united_rt <-  
  unite(gather_rt,  
        exp_cond, # the name of the new column  
        Block,  
        Viewpoint,  
        sep = "_")  
head(united_rt, 8)
```

##	Participant	exp_cond	RT
## 1	1	Block1_same	516.5898
## 2	2	Block1_same	382.0560
## 3	3	Block1_same	514.7835
## 4	4	Block1_same	604.1356
## 5	5	Block1_same	468.6312
## 6	6	Block1_same	317.7252
## 7	7	Block1_same	451.3933
## 8	8	Block1_same	704.9653

# Recreating the original data frame

## Step 1 - **unite()** the columns

```
united_rt <-  
  unite(gather_rt,  
        exp_cond, # the name of the new column  
        Block,  
        Viewpoint,  
        sep = "_")
```

## Step 2 - **spread()** the columns

```
spread_rt <-  
  spread(united_rt,  
        exp_cond,  
        RT)
```

# Recreating the original data frame

```
spread_rt
```

##	Participant	Block1_different	Block1_same	Block2_different	Block2_same
## 1	1	498.2227	516.5898	313.3878	305.1622
## 2	2	679.8127	382.0560	339.2907	386.3059
## 3	3	355.0890	514.7835	442.7510	378.0082
## 4	4	616.3194	604.1356	477.3192	450.9009
## 5	5	434.6988	468.6312	340.4552	211.0952
## 6	6	479.6596	317.7252	467.2746	309.5307
## 7	7	546.2049	451.3933	297.5012	274.3238
## 8	8	594.0583	704.9653	405.3054	317.5622
## 9	9	489.2698	383.3551	368.8661	385.1461
## 10	10	448.7217	668.2327	596.6026	333.7526