## Case Study: effects of exercise on health

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## Setting up

- Connect to GovWifi
- Download files from https://github.com/DSWR1\_pub
- ▶ Create a folder named DSWR with all the downloaded files in Documents
- Open RStudio



- ▶ In R Studio click "File" > "New Project" -> "Existing Directory"
- ► Choose the directory Documents/DSWR
- ► Click "Create project"



# **CASE STUDY.** A study on the effects of exercise on health with data in four flat files

## THE TRUE KEY TO WEIGHT LOSS

- ⇒ EXERCISE 20-30 MINUTES DAILY (THAT'S IT)
- □ GIVE YOURSELF 8 HOURS OF SLEEP EVERY NIGHT
- ⇒ DRINK 1/2 OUNCE OF WATER PER POUND OF YOUR BODYWEIGHT (DAILY)
- ⇒ SUNSHINE VITAMIN D (10 MINS EARLY MORNING, LATE AFTERNOON) ON HANDS OR FACE
- DUMP THE JUNK IN YOUR DIET (NOTHING IN BOXES OR BAGS)
- ➡ LIMIT GRAINS, REFINED SUGARS, AND COMMERCIAL DAIRY
- MORE FRUITS AND VEGETABLES ON EVERY PLATE, EVERY DAY
- ⇒ QUIT SMOKING (YOU CAN DO IT)

Alternative-Doctor.com



- Assess the effectiveness of a new exercise programme which is believed to induce weight loss and improve self-rated health.
- ▶ 5000 people randomized into two groups: 2,500 people to the treatment and another 2,500 to the control group.
- ► Health outcomes, weight and self-rated health, were measured before and after the intervention.



#### The data was provided in 4 files:

- ► EXER\_age\_sex\_race.csv : Subject demographics at baseline: age, sex, and race (we have seen this data when learning how to import comma separated values file)
- ► EXER\_SRH.csv : Self-Rated Health (SRH) on an ordinal scale.
- ► EXER\_weight\_trt.csv : Weight, in pounds, Treatment Group.
- ► EXER\_weight\_con.csv : Weight, in pounds, Control Group.

Import these files using the  $read_{csv}()$  function and explore the variables they contain.



```
data1 <- read_csv("DataFiles/EXER_age_sex_race.csv")
```

```
glimpse(data1)
```

```
## Observations: 5,000
## Variables: 2
## $ subject_ID <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,...
## $ SexAge_Race <chr> "MALE41.2_White", "FEMALE42.9_White", "FEMALE38.5_...
```

- ► There are 5000 subjects in the study.
- ► All the information about each subject is in one column. Separate the information.
- ▶ There are missing values for race.



data2 <- read csv("DataFiles/EXER SRH.csv")</pre>

```
## [1] 1 0
## Levels: 0 1
```

unique(as.factor(data2\$trt))

- This file contains the patient id (note the different column name from the previous file),
- and each participant's self rated health before and after the study.
- trt takes on two values: 0 (individual didn't exercise, control), 1 (individual exercised, treatment).
- data2 has 10035 rows but there should only be 10000 rows.



```
data3 <- read_csv("DataFiles/EXER_weight_trt.csv")
glimpse(data3)</pre>
```

- ▶ Information about the weight of patients who received the exercise plan.
- ▶ Patient id column has different name than in the previous two data sets,
- ▶ Pre- and post-intervention weight.
- ► Many NAs! if pre-intervention weight is recorded, post-intervention weight is an NA, and vice-versa.
- Expect 5000 observations, but there are 5017.



# data4 <- read\_csv("DataFiles/EXER\_weight\_con.csv") glimpse(data4)</pre>

- ▶ Information about the weight of patients who are in the control group.
- Patient id column has different name than in the previous two data sets,
- Pre- and post-intervention weight.
- ► Many NAs! if pre-intervention weight is recorded, post-intervention weight is an NA, and vice-versa.
- Expect 5000 observations, but there are 5012.



#### In this study:

- an observational unit is a patient,
- fixed variables are age, sex and race,
- measured variables are self-rated health and weight at two time points, before and after the intervention.

#### This is messy data:

- ▶ a single observational unit is stored in multiple tables,
- multiple variables are stored in one column,
- there is possibly duplicated information,
- ▶ and more messy features to be discovered!



- ▶ The strategy is to deal with the data sets one by one.
- ▶ Manipulate each of them so that they can be joined.
- ► Have to join by subject id so let us name that column id in all four data frames



## First data set (data1)

```
## Observations: 5,000
## Variables: 2
## $ subject_ID <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,...
## $ SexAge_Race <chr> "MALE41.2_White", "FEMALE42.9_White", "FEMALE38.5_...
# data1_1 will be the modified and tidy version of data1.
data1_1 <- data1
#rename the first column
data1_1 <- rename(data1_1, id = subject_ID)
```





```
glimpse(data1_1)
```

▶ Note Age is of type character. Should be numeric.



```
#make Age a numeric variable
data1_1 <- mutate(data1_1, Age = as.numeric(Age))
glimpse(data1_1)

## Observations: 5,000
## Variables: 4
## $ id <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17...
## $ Sex <chr> "MALE", "FEMALE", "FEMALE
```

## \$ Age <dbl> 41.2, 42.9, 38.5, 35.6, 48.5, 36.9, 28.9, 24.7, 47.1, 37....
## \$ Race <chr> "White", "White", "White", "Hispanic", "White", "NA", "Wh...



- Note that the Race column of data1\_1 has the value "NA", which R reads as a character string and not as a missing value.
- ▶ Need to transform the entries "NA" into NA.



```
#turn "NA" into missing values
data1_1 <- mutate(data1_1, Race = na_if(Race, "NA"))
glimpse(data1_1)

## Observations: 5,000
## Variables: 4</pre>
```

## \$ id <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17...
## \$ Sex <chr> "MALE", "FEMALE", "FEMALE"



#### Summarise the wrangling



```
summary(as.factor(data1 1$Race))
##
     Asian
              Black Hispanic
                               White
                                         NA's
##
       450
                424
                         846
                                2876
                                          404
summary(as.factor(data1 1$Sex))
## FEMALE
           MALE
##
    2556
           2444
summary(data1 1$Age)
##
     Min. 1st Qu. Median
                            Mean 3rd Qu.
                                           Max.
```

38.89

##

18.10

33.40 38.80

44.10

69.30



## Second data set (data2)

```
#remove duplicate rows
data2_1 <- distinct(data2)</pre>
```

```
nrow(data2_1)
```

## [1] 10016

glimpse(data2)

▶ After removing duplicate rows now there are 10,016 rows.



Summaries of columns. Is there anything unusual?

```
summary(as.factor(data2_1$trt))
## 5008 5008
summary(as.factor(data2_1$TIME))
## POST PRE
## 5003 5013
summary(as.factor(data2_1$SRH))
      Excellent
                        Good
                                     Poor Satisfactory Very
                                                                Poor
##
           2947
                        1570
                                     1711
                                                   1411
                                                                  16
```

- ▶ We spotted something unusual! The SRH level Very Poor appears also with a double space between Very and Poor.
- ► This happens for 16 rows.

Very Poor

2361

##



```
data2_1 <- data2_1 %>%
    mutate(SRH = str_replace(SRH, "Very Poor", "Very Poor"))
summary(as.factor(data2_1$SRH))

## Excellent    Good    Poor Satisfactory    Very Poor
##     2947    1570    1711    1411    2377

#remove duplicate rows
data2_1 <- distinct(data2_1)
glimpse(data2_1)

## Observations: 10,000
## Variables: 4</pre>
```

► There are now two rows per patient.



Merge all four data sets into one.

## Observations: 5.000

- ► The first data set has one row per observation. The second data set has two rows per observation.
- Create two new columns, PRE-SRH and POST-SRH, using TIME column.

```
data2_1 <- pivot_wider(data2_1, names_from = TIME, values_from = SRH
glimpse(data2_1)</pre>
```



► Change the names of the 3rd and 4th columns to POST\_SRH and PRE\_SRH and swap their order.

```
data2_1 <- rename(data2_1, POST_SRH = POST, PRE_SRH = PRE)
data2_1 <- select(data2_1, c(1,2,4,3))</pre>
```



```
glimpse(data2_1)
## Observations: 5,000
## Variables: 4
```



### Summary of the wrangling

```
data2_tidy <- read_csv("DataFiles/EXER_SRH.csv") %>%
  mutate(SRH =
    str_replace(SRH, "Very Poor", "Very Poor")) %>%
  distinct() %>%
  pivot_wider(names_from = TIME, values_from = SRH) %>%
  rename(POST_SRH = POST, PRE_SRH = PRE) %>%
  select(c(1,2,4,3))
```



## Third data set (data3)

- Pre- and post-weight of treatment patients.
- ► Change the name of the first column to id.

▶ There should be 5,000 rows in data3 but there are 5,017 rows.



```
#remove duplicate rows
data3_1 <- distinct(data3_1)</pre>
```

```
nrow(data3_1)
```

```
## [1] 5017
```

- There are no exact duplicate rows in data3.
- Let us see if there are more than two records per patient.
- count(), in dplyr, used to count how many instances for each patient id there are.



#### Example

```
#count the instances of each patient id in the first 8 rows
aux1 <- count(data3_1[1:8,],id)
aux1</pre>
```

```
## # A tibble: 4 x 2
## id n
## <dbl> <int>
## 1 1 2
## 2 2 2
## 3 3 2
## 4 4 2
```

► The result has two columns. One is id and the other one is the corresponding count, n.



```
#count the instances of each patient id
aux1 <- count(data3_1,id)
aux2 <- which(aux1$n > 2)
aux3 <- aux1$id[aux2]</pre>
```

```
## [1] 2394 2395 2396 2397 2398 2399 2400 2401 2402
```

aux3

aux3 gives the patient id's with more than two entries. Let us explore the data for those patients.



```
as.data.frame(ff)
        id PRE WEIGHT POST WEIGHT
##
      2394
             137.0663
## 1
                                NA
## 2
      2394
                   NA
                         128.2492
## 3
      2394
                   NA
                         128,2000
## 4
      2395
             164.3000
                                NA
## 5
      2395
             164.3255
                                NA
## 6
      2395
                   NA
                         164.3350
## 7
      2395
                   NA
                         164.3500
## 8
      2396
             160.9983
                               NA
## 9
      2396
             160.9985
                               NA
## 10 2396
                   NA
                         165.7400
## 11 2396
                   NA
                         165.7270
## 12 2397
             147.7983
                               NA
## 13 2397
             147.7990
                               NA
## 14 2397
                   NA
                         137.8439
## 15 2397
                         137.8500
                   NA
## 16 2398
             133.1364
                               NA
## 17 2398
             133.1400
                               NA
## 18 2398
                   NA
                         118.9500
## 19 2398
                   NA
                         118.9398
## 20 2399
             188.8684
                                NA
## 21 2399
             188.9000
                               NA
## 22 2399
                   NA
                         179.1000
## 23 2399
                   NA
                          179.0564
## 24 2400
             166.1632
                                NA
## 25 2400
             166.2000
                               NA
## 26 2400
                   NA
                         150.2311
## 27 2400
                   NA
                         150.2000
## 28 2401
             151.6768
                                NA
## 29 2401
             151.7000
                                NA
## 30 2401
                   NA
                         133.3000
## 31 2401
                         133.2508
                   NA
## 32 2402
             148,7000
                                NA
## 33 2402
             148.7475
                                NA
```

ff <- filter(data3\_1, id %in% aux3)



- ► Truncate the values of weight (pre- and post-). This will hardly affect the results of the study
- ▶ This will create exact row duplicates and then eliminate duplicates.
- ► The function mutate\_all() in the dplyr package is useful to apply a function to each column.
- In this case the function we want to apply is round().



```
#this call truncates all the columns
data3 1 <- mutate_all(data3_1, trunc)</pre>
glimpse(data3_1)
## Observations: 5,017
## Variables: 3
               <dbl> 1, 1, 2, 2, 3, 3, 4, 4, 5, 5, 6, 6, 7, 7, 8, 8, 9,...
## $ id
## $ PRE WEIGHT <dbl> 135, NA, 154, NA, 128, NA, 183, NA, 166, NA, 120, ...
## $ POST WEIGHT <dbl> NA, 125, NA, 153, NA, 115, NA, 177, NA, 163, NA, 1...
```

### Now, remove duplicate rows

```
data3 1 <- distinct(data3 1)</pre>
glimpse(data3 1)
## Observations: 5,000
```

```
## Variables: 3
## $ id
                 <dbl> 1, 1, 2, 2, 3, 3, 4, 4, 5, 5, 6, 6, 7, 7, 8, 8, 9,...
## $ PRE WEIGHT <dbl> 135, NA. 154, NA. 128, NA. 183, NA. 166, NA. 120, ...
## $ POST WEIGHT <dbl> NA. 125, NA. 153, NA. 115, NA. 177, NA. 163, NA. 1...
```

Now we have 5000 rows.



- ▶ Need one row per patient with id, pre- and post-weight.
- ► Strategy: select id and pre-weight, eliminate the rows where pre-weight is NA.
- ► Similarly with id and post-weight.
- Next merge both data frames into one by patient id.



```
#select all columns except POST WEIGHT
temp1 <- select(data3_1, -POST_WEIGHT)</pre>
#filter out the NAs in PRE_WEIGHT
temp1 <- filter(temp1, is.na(PRE_WEIGHT) == "FALSE")</pre>
glimpse(temp1)
## Observations: 2,500
## Variables: 2
```

<dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, ... ## \$ PRE WEIGHT <dbl> 135, 154, 128, 183, 166, 120, 158, 160, 127, 187, 1...

## \$ id



## Alternatively,

```
temp1 <- data3_1 %>%
select(-POST_WEIGHT) %>%
filter(is.na(PRE_WEIGHT) == "FALSE")
```

```
#select all columns except PRE_WEIGHT
temp2 <- select(data3_1, -PRE_WEIGHT)

#filter out the NAs in POST_WEIGHT
temp2 <- filter(temp2, is.na(POST_WEIGHT) == "FALSE")
glimpse(temp2)

## Observations: 2.500</pre>
```

## Variables: 2



```
Alternatively,
```

```
temp2 <- data3_1 %>%
select(-PRE_WEIGHT) %>%
filter(is.na(POST_WEIGHT) == "FALSE")
```



```
#join temp1 and temp2
data3_1 <- inner_join(temp1, temp2)

## Joining, by = "id"
glimpse(data3_1)</pre>
```

<dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,...

## \$ PRE\_WEIGHT <dbl> 135, 154, 128, 183, 166, 120, 158, 160, 127, 187, ...
## \$ POST WEIGHT <dbl> 125, 153, 115, 177, 163, 105, 151, 143, 119, 159, ...

## Observations: 2,500 ## Variables: 3 ## \$ id <dbl>

```
Data Science
Campus
```

```
Summary, using %>%
data3_aux <- read_csv("DataFiles/EXER_weight_trt.csv") %>%
  rename(id = Id) %>%
  mutate all(trunc) %>%
  distinct()
temp1 <- data3_aux %>%
  select(-POST WEIGHT) %>%
  filter(is.na(PRE_WEIGHT) == "FALSE")
temp2 <- data3 aux %>%
  select(-PRE WEIGHT) %>%
  filter(is.na(POST WEIGHT) == "FALSE")
```

## Joining, by = "id"

data3 tidy <- inner join(temp1,temp2)</pre>



# Fourth data set (data4)

- ▶ There are 5,012 rows in this data set when there should be just 5,000.
- ▶ Similar inefficient way of recording information as in previous data set.



▶ Let us first investigate if there are patient with exact duplicate records.

```
data4_1 <- distinct(data4_1)
glimpse(data4_1)</pre>
```

► There aren't any exact duplicate rows.



Let us investigate if any patients have duplicate records.

```
#counts instances of each patient id in the whole data set
aux1 <- count(data4_1,id)
aux2 <- which(aux1$n > 2)
aux3 <- aux1$id[aux2]
aux3</pre>
```

```
## [1] 4980 4981 4982 4983 4984 4985
```

Patients 4980, 4981, 4982, 4983, 4984 and 4985 have more than two records each.



#### ff <- filter(data4\_1, id %in% aux3)

as.data.frame(ff)

```
##
       id PRE WEIGHT POST WEIGHT
## 1
     4980
            151.6736
                               NA
     4980
            151.7000
                               NA
## 2
## 3
     4980
                  NA
                        150.5249
## 4
     4980
                  NΑ
                        150.5300
## 5 4981
            171.0954
                               NA
## 6
    4981
            171.1000
                              NA
## 7 4981
                  NA
                        168.0745
## 8
     4981
                  NA
                        168.0800
## 9 4982
            154.6500
                               NA
## 10 4982
            154.6518
                              NA
## 11 4982
                  NΑ
                       153.5068
## 12 4982
                  NA
                        153.5100
## 13 4983
           141.0200
                               NA
## 14 4983
            141.0217
                               NA
## 15 4983
                  NA
                        140.1000
## 16 4983
                  NA
                        140.1410
## 17 4984
            137.0652
                              NA
## 18 4984
            137.1000
                               NA
## 19 4984
                  NA
                        134.1708
## 20 4984
                  NA
                        134.2000
## 21 4985
            195.0055
                               NA
## 22 4985
            195.0100
                               NA
## 23 4985
                  NA
                       193.3600
## 24 4985
                  NA
                        193.3532
```



As before, truncate the data and eliminate any duplicate rows.

```
#this call rounds all the columns to the nearest integer
data4_1 <- mutate_all(data4_1,trunc)</pre>
```

```
#eliminate duplicate rows
data4_1 <- distinct(data4_1)</pre>
```



```
glimpse(data4_1)
```

▶ We have 5,000 rows now.



▶ We have to create a data frame with one row per patient, as before.

```
temp1 <- select(data4_1, -POST_WEIGHT)

#filter out the NAs in PRE_WEIGHT
temp1 <- filter(temp1, is.na(PRE_WEIGHT) == "FALSE")
glimpse(temp1)</pre>
```

#select all columns except POST WEIGHT



```
temp2 <- select(data4_1, -PRE_WEIGHT)

#filter out the NAs in POST_WEIGHT
temp2 <- filter(temp2, is.na(POST_WEIGHT) == "FALSE")
glimpse(temp2)

## Observations: 2,500</pre>
```

#select all columns except PRE WEIGHT

## \$ id <dbl> 2501, 2502, 2503, 2504, 2505, 2506, 2507, 2508, 25...
## \$ POST WEIGHT <dbl> 158. 174, 179. 175. 137. 159. 155. 164. 160. 177. ...

## Variables: 2



```
data4_1 <- inner_join(temp1,temp2)

## Joining, by = "id"
glimpse(data4_1)</pre>
```



- Next, join the rows of data3\_1 and data4\_1 to create data3\_2 so that all patients are in one data frame.
- ► First, add a column in data3\_1 called trt with all values equal to 1, and a column in data4\_1 called trt as well but with all values equal to zero.

glimpse(data4\_1)





#### A unified data set

Merge data1\_1, data2\_1 and data3\_2.

```
data exer1 <- inner join(data1 1, data2 1)
## Joining, by = "id"
data exer1 <- inner join(data exer1, data3 2)</pre>
## Joining, by = c("id", "trt")
glimpse(data exer1)
## Observations: 5,000
## Variables: 9
## $ id
              <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,...
              <chr> "MALE", "FEMALE", "FEMALE", "FEMALE", "FEMALE", "F...
## $ Sex
## $ Age
              <dbl> 41.2, 42.9, 38.5, 35.6, 48.5, 36.9, 28.9, 24.7, 47...
## $ Race
              <chr> "White", "White", "White", "Hispanic", "White", NA...
              ## $ trt
## $ PRE SRH <chr> "Good", "Poor", "Satisfactory", "Poor", "Poor", "G...
## $ POST SRH
             <chr> "Poor", "Very Poor", "Good", "Good", "Poor", "Exce...
## $ PRE WEIGHT <dbl> 135, 154, 128, 183, 166, 120, 158, 160, 127, 187, ...
```

## \$ POST WEIGHT <dbl> 125, 153, 115, 177, 163, 105, 151, 143, 119, 159, ...



- ► Further narrow the number of variables creating a new variable Time, with values PRE and POST, and two new columns SRH and Weight.
- ► To do that, first create one data frame with all the fixed variables and pre- and post-SRH and another data frame with all the fixed variables and pre- and post-WEIGHT.
- ► Gather the pre- and post- column into Time and SRH or WEIGHT and then we will join both data sets.



```
temp1 <- select(data exer1, 1:7)
temp1 <- pivot longer(temp1, 6:7, names to = "Time", values to = "SR
temp1 <- mutate(temp1,
                    Time = str replace(Time, "PRE SRH", "PRE"))
temp1 <- mutate(temp1,
                    Time = str_replace(Time, "POST SRH", "POST"))
glimpse(temp1)
## Observations: 10,000
## Variables: 7
## $ id <dbl> 1, 1, 2, 2, 3, 3, 4, 4, 5, 5, 6, 6, 7, 7, 8, 8, 9, 9, 10,...
## $ Sex <chr> "MALE", "FEMALE", "FEMALE", "FEMALE", "FEMALE", "...
## $ Age <dbl> 41.2, 41.2, 42.9, 42.9, 38.5, 38.5, 35.6, 35.6, 48.5, 48....
```



```
Using "%>%"

temp1 <- select(data_exer1, 1:7) %>%
  pivot_longer(temp1, 6:7, "Time", "SRH") %>%
  mutate(
    Time = str_replace(Time, "PRE_SRH", "PRE")) %>%
  mutate(
    Time = str_replace(Time, "POST_SRH", "POST"))
```



```
temp2 \leftarrow select(data exer1, c(1:5,8,9))
temp2 <- pivot_longer(temp2, 6:7, "Time", "WEIGHT")</pre>
temp2 <- mutate(</pre>
             temp2, Time = str replace(Time, "PRE WEIGHT", "PRE"))
temp2 <- mutate(
             temp2, Time = str_replace(Time, "POST WEIGHT", "POST"))
glimpse(temp2)
## Observations: 10,000
## Variables: 7
## $ id <dbl> 1, 1, 2, 2, 3, 3, 4, 4, 5, 5, 6, 6, 7, 7, 8, 8, 9, 9, 10...
## $ Sex <chr> "MALE", "MALE", "FEMALE", "FEMA
```



```
Using "%>%"

temp2 <- select(data_exer1, c(1:5, 8, 9)) %>%
  pivot_longer(temp1, 6:7, "Time", "WEIGHT") %>%
  mutate(
    Time = str_replace(Time, "PRE_WEIGHT", "PRE")) %>%
  mutate(
    Time = str_replace(Time, "POST_WEIGHT", "POST"))
```



► Merge temp1 and temp2

```
data_exer2 <- inner_join(temp1, temp2)</pre>
## Joining, by = c("id", "Sex", "Age", "Race", "trt", "Time")
glimpse(data_exer2)
## Observations: 10,000
## Variables: 8
## $ id <dbl> 1, 1, 2, 2, 3, 3, 4, 4, 5, 5, 6, 6, 7, 7, 8, 8, 9, 9, 10...
## $ Sex <chr> "MALE", "MALE", "FEMALE", "FEMALE", "FEMALE", "FEMALE", ...
## $ Age <dbl> 41.2, 41.2, 42.9, 42.9, 38.5, 38.5, 35.6, 35.6, 48.5, 48...
## $ Race <chr> "White", "White", "White", "White", "White", "White", "H...
## $ Time <chr> "PRE", "POST", "PRE", "POST", "PRE", "POST", "PRE", "POS...
        <chr> "Good", "Poor", "Poor", "Very Poor", "Satisfactory", "Go...
## $ SRH
## $ value <dbl> 135, 125, 154, 153, 128, 115, 183, 177, 166, 163, 120, 1...
```



- ▶ Both data\_exer1 and data\_exer2 are tidy, and it is a matter of preference and how the data will be used to choose a format to work with.
- ▶ We will work with both data frames for the purpose of visualising the data.



- ► The variable SRH is an ordinal categorical variable. Let us tell R about the ordinal features of SRH.
- ▶ Also, Time is categorical ordinal. Sex and Race are simply categorical.
- ➤ Treatment, trt, is also a factor and we will let R know and re-label the levels from 0 to Control and 1 to Treatment.
- ▶ We will do this for both data frames data\_exer1 and data\_exer2.



We introduce now a new Tidyverse package called forcats which is designed to deal with factors.



### library(forcats)





```
glimpse(data_exer1)
```

## Observations: 5.000

```
## Variables: 9
                 <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,...
## $ id
## $ Sex
                 <fct> MALE, FEMALE, FEMALE, FEMALE, FEMALE, FEMALE, FEMALE, FEMA...
## $ Age
                 <dbl> 41.2, 42.9, 38.5, 35.6, 48.5, 36.9, 28.9, 24.7, 47...
## $ Race
                 <fct> White, White, White, Hispanic, White, NA, White, H...
## $ trt
                 <fct> Treatment, Treatment, Treatment, Treatment, Treatm...
## $ PRE SRH
                 <fct> Good, Poor, Satisfactory, Poor, Poor, Good, Excell...
## $ POST SRH
                 <fct> Poor, Very Poor, Good, Good, Poor, Excellent, Exce...
## $ PRE WEIGHT
                 <dbl> 135, 154, 128, 183, 166, 120, 158, 160, 127, 187, ...
## $ POST_WEIGHT <dbl> 125, 153, 115, 177, 163, 105, 151, 143, 119, 159, ...
```



#### summary(data\_exer1)

##

Max.

:229.0

```
id
                    Sex
##
                                  Age
                                                 Race
##
   Min. : 1 FEMALE: 2556
                             Min.
                                    :18.10
                                            Asian
                                                   : 450
   1st Qu.:1251 MALE :2444
                                            Black: 424
##
                             1st Qu.:33.40
##
   Median:2500
                             Median :38.80
                                            Hispanic: 846
##
   Mean :2500
                             Mean :38.89
                                           White :2876
##
   3rd Qu.:3750
                             3rd Qu.:44.10
                                           NA's : 404
##
   Max. :5000
                             Max.
                                    :69.30
##
         trt
                         PRE SRH
                                            POST SRH
                                                        PRE WEIGHT
##
   Control :2500
                  Very Poor :1321 Very Poor
                                                :1040
                                                       Min. : 82.0
##
   Treatment: 2500
                  Poor
                             : 959
                                   Poor
                                                : 752
                                                      1st Qu.:145.0
##
                  Satisfactory: 611
                                    Satisfactory: 800
                                                       Median :159.0
##
                  Good: 736 Good
                                                : 834
                                                      Mean :159.4
##
                  Excellent :1373 Excellent :1574
                                                       3rd Qu.:174.0
##
                                                       Max.
                                                             :242.0
##
    POST WEIGHT
##
   Min. : 78.0
   1st Qu.:140.0
##
##
   Median :154.0
##
   Mean :154.5
##
   3rd Qu.:169.0
```



For data\_exer2, we also set the order of the levels of Time to be PRE and POST.



```
glimpse(data_exer2)
```



- Age is continuous in nature.
- ► However, it is not really expected that at each small change in age we would observe changes in treatment effects.
- Also, in case effects change according to age, a change of, say 5 years, at young age will not possibly see the same effect as a change of 5 years at middle or old age.
- Construct age groups.
- Note that we will use Age from data\_exer1 because it contains just one row per observational unit.



```
data_exer1 %>% select(Age) %>% summary()

## Age
## Min. :18.10
## 1st Qu.:33.40
```

##

## ##

##

Median :38.80 Mean :38.89

3rd Qu.:44.10

Max. :69.30



```
aux <- mutate(
  data_exer1, Age = cut(Age, c(18, 20, 30, 40, 50, 60,70)))</pre>
```

```
aux %>% select(Age) %>% summary()
```

```
## (18,20]: 33

## (20,30]: 649

## (30,40]:2133

## (40,50]:1779

## (50,60]: 374

## (60,70]: 32
```

Age

##

- ► Most participants are 30 50 years of age.
- ▶ No participants are younger than 18 years or older than 70 years.
- ▶ Split age into 18-34yrs, 35-40yrs, 41-45yrs, 46-70yrs, so that we don't have an age category over-represented with number of patients.
- ► Create a new column in both data\_exer1 and data\_exer2 called Age\_cat which indicates the age group of the patient.



```
data_exer1 <- data_exer1 %>%
  mutate(Age_cat = cut(Age, c(18, 34, 39, 44, 70)))
data_exer2 <- data_exer2 %>%
  mutate(Age_cat = cut(Age, c(18, 34, 39, 44, 70)))
data_exer1 %>% select(Age_cat) %>% summary()
##
      Age_cat
##
    (18,34]:1345
## (34,39]:1223
## (39,44]:1162
## (44,70]:1270
or in base R
summary(data_exer1$Age_cat)
```

## (18,34] (34,39] (39,44] (44,70] 1223

1345

##

1162

1270



## Let us see how the data looks like now

```
glimpse(data_exer1)
```

```
## Observations: 5,000
## Variables: 10
## $ id
                 <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,...
## $ Sex
                 <fct> MALE, FEMALE, FEMALE, FEMALE, FEMALE, FEMALE, FEMA...
## $ Age
                 <dbl> 41.2, 42.9, 38.5, 35.6, 48.5, 36.9, 28.9, 24.7, 47...
## $ Race
                 <fct> White, White, White, Hispanic, White, NA, White, H...
## $ trt
                 <fct> Treatment, Treatment, Treatment, Treatment, Treatm...
## $ PRE SRH
                 <fct> Good, Poor, Satisfactory, Poor, Poor, Good, Excell...
## $ POST SRH
                 <fct> Poor, Very Poor, Good, Good, Poor, Excellent, Exce...
## $ PRE WEIGHT
                 <dbl> 135, 154, 128, 183, 166, 120, 158, 160, 127, 187, ...
## $ POST_WEIGHT <dbl> 125, 153, 115, 177, 163, 105, 151, 143, 119, 159, ...
## $ Age cat
                 <fct> "(39,44]", "(39,44]", "(34,39]", "(34,39]", "(44,7...
```



```
glimpse(data_exer2)
```

## Observations: 10,000

```
## Variables: 9
            <dbl> 1, 1, 2, 2, 3, 3, 4, 4, 5, 5, 6, 6, 7, 7, 8, 8, 9, 9, ...
## $ id
## $ Sex
            <fct> MALE, MALE, FEMALE, FEMALE, FEMALE, FEMALE, FE...
## $ Age
            <dbl> 41.2, 41.2, 42.9, 42.9, 38.5, 38.5, 35.6, 35.6, 48.5, ...
## $ Race
           <fct> White, White, White, White, White, Hispanic, Hi...
## $ trt
            <fct> Treatment, Treatment, Treatment, Treatment, Treatment,...
## $ Time
            <fct> PRE, POST, PRE, POST, PRE, POST, PRE, POST, PRE, POST,...
## $ SRH
            <fct> Good, Poor, Poor, Very Poor, Satisfactory, Good, Poor,...
## $ value
            <dbl> 135, 125, 154, 153, 128, 115, 183, 177, 166, 163, 120,...
## $ Age cat <fct> "(39.44]", "(39.44]", "(39.44]", "(39.44]", "(34.39]",...
```



Let us shuffle the columns so that Age and Age\_cat are contiguous.

```
data exer1 <- data exer1 \% select(c(1:3,10,4:9))
data exer2 <- data exer2 \% select(c(1:3,9,4:8))
glimpse(data_exer1)
## Observations: 5.000
## Variables: 10
                <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,...
## $ id
                <fct> MALE, FEMALE, FEMALE, FEMALE, FEMALE, FEMALE, FEMAL...
## $ Sex
## $ Age
                <dbl> 41.2, 42.9, 38.5, 35.6, 48.5, 36.9, 28.9, 24.7, 47...
## $ Age_cat
                <fct> "(39,44]", "(39,44]", "(34,39]", "(34,39]", "(44,7...
## $ Race
                <fct> White, White, White, Hispanic, White, NA, White, H...
## $ trt
                <fct> Treatment, Treatment, Treatment, Treatment, Treatm...
                <fct> Good, Poor, Satisfactory, Poor, Poor, Good, Excell...
## $ PRE SRH
## $ POST SRH
                <fct> Poor, Very Poor, Good, Good, Poor, Excellent, Exce...
## $ PRE WEIGHT
                <dbl> 135, 154, 128, 183, 166, 120, 158, 160, 127, 187, ...
## $ POST_WEIGHT <dbl> 125, 153, 115, 177, 163, 105, 151, 143, 119, 159, ...
```



```
glimpse(data exer2)
## Observations: 10,000
## Variables: 9
## $ id
             <dbl> 1, 1, 2, 2, 3, 3, 4, 4, 5, 5, 6, 6, 7, 7, 8, 8, 9, 9, ...
## $ Sex <fct> MALE, MALE, FEMALE, FEMALE, FEMALE, FEMALE, FEMALE, FE...
## $ Age
             <dbl> 41.2, 41.2, 42.9, 42.9, 38.5, 38.5, 35.6, 35.6, 48.5, ...
## $ Age_cat <fct> "(39,44]", "(39,44]", "(39,44]", "(39,44]", "(39,44]", "(34,39]",...
## $ Race
           <fct> White, White, White, White, White, Hispanic, Hi...
           <fct> Treatment, Treatment, Treatment, Treatment, Treatment,...
## $ trt
## $ Time
            <fct> PRE. POST. PRE. POST. PRE. POST. PRE. POST. PRE. POST....
## $ SRH
            <fct> Good, Poor, Poor, Very Poor, Satisfactory, Good, Poor,...
            <dbl> 135, 125, 154, 153, 128, 115, 183, 177, 166, 163, 120,...
## $ value
summary(data_exer2$trt)
```

```
## Control Treatment
## 5000 5000
```



- Let us see a few ways in which we can tabulate some aspects of the data.
- ▶ We can use table(), ftable() (more than two variables) or xtabs().

with(data\_exer2, table(SRH,Time))

```
##
                Time
## SRH
                  PRE POST
    Very Poor 1321 1040
    Poor
                  959
                       752
    Satisfactory 611
                       800
    Good
                  736 834
##
    Excellent
              1373 1574
##
```

- Without considering any other factor, there are less patients in the Poor and Very Poor categories after the intervention.
- ▶ there are more patients in the Satisfactory, Good and Excellent categories after the intervention than before the intervention.



Let us see if the trend stays when we consider also the patient's gender.



```
aux2 <- with(data_exer2, table(SRH, Time, Sex))</pre>
aux2
## , , Sex = FEMALE
##
##
               Time
## SRH
                PRE POST
##
    Very Poor 660 576
##
    Poor
         443 414
##
    Satisfactory 337 367
##
   Good
                391 382
##
   Excellent 725 817
##
## , , Sex = MALE
##
##
               Time
## SRH
               PRE POST
    Very Poor 661 464
##
##
    Poor
                516 338
##
    Satisfactory 274 433
    Good
##
                345 452
```

Excellent 648 757

##



- ► The trend of positive effect of the exercise plan is still present when we consider gender.
- ▶ It seems to be stronger for men than for women.



Visualising SRH using mosaic plots in ggplot2

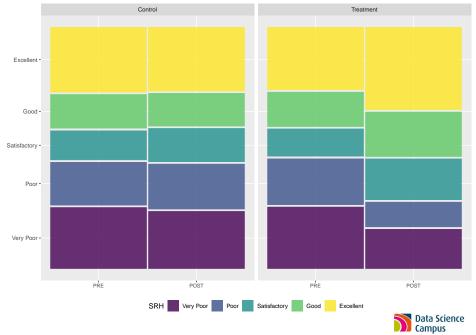


First, we simply consider SRH by gender for the different groups, before and after the treatment.

```
ggplot(data = data_exer2) +
   geom_mosaic(aes( x = product(SRH, Time), fill = SRH), na.rm = TRUE) +
   theme(axis.text.x=element_text(angle = -90, hjust = .1, size = 4)) +
   facet_grid(.~trt, drop = TRUE) +
   theme(axis.text.x = element_text(angle = 0, hjust = .5, size = 8)) +
   theme(axis.title = element_blank()) +
   theme(legend.position = "bottom") +
   ggtitle ('SRH for treatment and control groups')
```



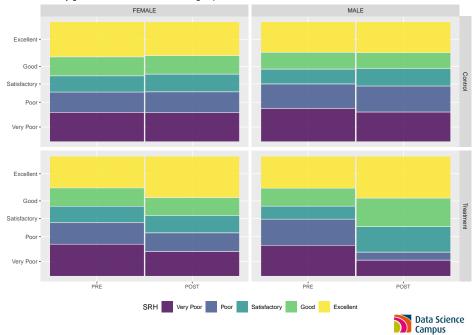
## SRH for treatment and control groups



```
ggplot(data = data_exer2) +
  geom_mosaic(aes( x = product(SRH, Time), fill = SRH), na.rm = TRUE) +
  theme(axis.text.x=element_text(angle = -90, hjust = .1, size = 4)) +
  facet_grid(trt~Sex, drop = TRUE) +
  theme(axis.text.x = element_text(angle = 0, hjust = .5, size = 8)) +
  theme(axis.title = element_blank()) +
  theme(legend.position = "bottom") +
  ggtitle ('SRH by gender for treatment and control groups')
```



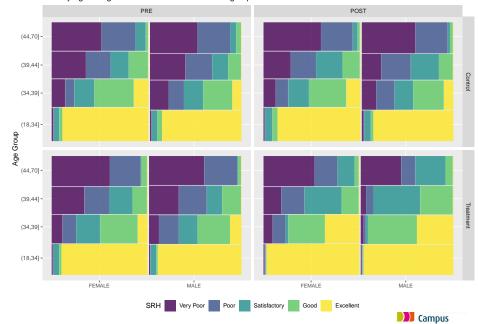
SRH by gender for treatment and control groups



```
ggplot(data = data_exer2) +
  geom_mosaic(aes(x = product(SRH, Age_cat, Sex), fill=SRH), na.rm=TRUE) +
  theme(axis.text.x=element_text(angle = -90, hjust = .1, size = 4)) +
  facet_grid(trt~Time, drop = TRUE) +
  scale_x_productlist(breaks = c(0.25, 0.75), labels = c("FEMALE", "MALE")) +
  labs(y = "Age Group") +
  theme(axis.text.x = element_text(angle = 0, hjust = .5, size = 8)) +
  theme(axis.title.x = element_blank()) +
  theme(legend.position = "bottom") +
  ggtitle ('SRH by age and gender for treatment and control groups')
```



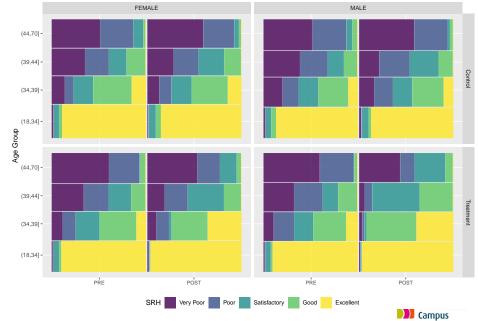
SRH by age and gender for treatment and control groups



```
ggplot(data = data_exer2) +
  geom_mosaic(aes( x = product(SRH, Age_cat, Time), fill=SRH), na.rm=TRUE) +
  theme(axis.text.x=element_text(angle = -90, hjust = .1, size = 4)) +
  facet_grid(trt~Sex, drop = TRUE) +
  scale_x_productlist(breaks = c(0.25, 0.75), labels = c("PRE", "POST")) +
  labs(y = "Age Group") +
  theme(axis.text.x = element_text(angle = 0, hjust = .5, size = 8)) +
  theme(axis.title.x = element_blank()) +
  theme(legend.position = "bottom") +
  ggtitle ('SRH by age and gender for treatment and control groups')
```



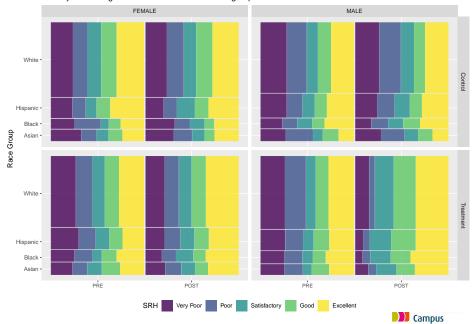
SRH by age and gender for treatment and control groups



```
ggplot(data = subset(data_exer2, is.na(Race) == "FALSE")) +
  geom_mosaic(aes( x = product(SRH, Race, Time), fill = SRH), na.rm=TRUE) +
  theme(axis.text.x = element_text(angle = -90, hjust = .1, size = 4)) +
  facet_grid(trt ~ Sex) +
  scale_x_productlist(breaks = c(0.25, 0.75), labels = c("PRE", "POST")) +
  labs(y = "Race Group") +
  theme(axis.text.x = element_text(angle = 0, hjust = .5, size = 8)) +
  theme(axis.title.x = element_blank()) +
  theme(legend.position = "bottom") +
  ggtitle ('SRH by race and gender for treatment and control groups') +
  theme(legend.position = "bottom")
```

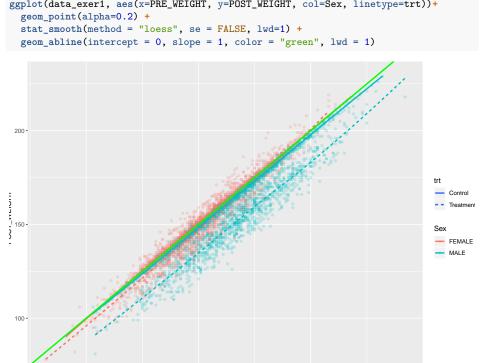


SRH by race and gender for treatment and control groups



- ► Let us visualise now the measured variables that are continuous, namely Weight.
- ▶ Plot POST\_WEIGHT vs PRE\_WEIGHT for males (blue) and females (red), before (solid line) and after (dotted line) the intervention.
- ▶ Add a 45 degree line through zero (symbolising no treatment effect on weight, i.e. weight before is equal to weight after).



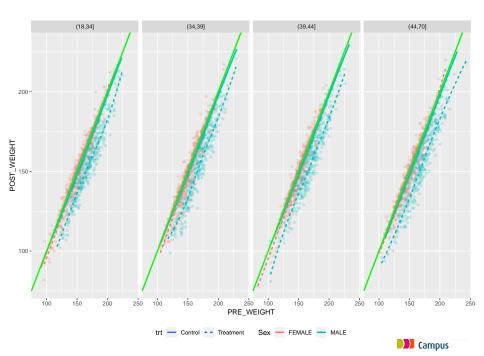


- ► For both sexes the curves of the control patients are nearly overlapping the no-effect green line, as expected.
- ► The treatment curve for women is very near the no-effect green line. There seems to be a very mild positive effect for women whose weights before the intervention were below 150 pounds.
- ► The intervention seems to be effective for weight loss for men who underwent the exercise programme, as the blue dotted curve is clearly below the no-effect green line.



Let us split the data into age categories.





The observations we made before still hold when we split the group by age category. The effect of the exercise programme seems to be more beneficial for men aged 45 or older who weigh over 200 pounds.

