Data Science with R - Introduction

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DATA SCIENCE WITH

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Please, complete the online survey

https://www.smartsurvey.co.uk/s/7C05D/

Download files from

https://github.com/sonjam111/DSWR1_pub

Objectives

- To understand the flow of scientific data analysis.
- To understand how R contributes to each stage of the flow.
- To become acquainted with some Tidyverse packages to import different types of data into R.
- To become acquainted with the process of data tidying and manipulation using R.
- Be able to do basic visualisations of categorical and continuous data in order to explore a data set.

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Plan

- AM: the data analysis flow, importing data into `R`, tidying data sets
- PM: Case studies 1 and 2.

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Why R?

- R was created specifically to support data analysis.
- R is an interactive environment for data analysis, not just a language.
- R allows for **reproducible research**.

The data analysis process

"There are no routine statistical questions, only questionable statistical routines." — Sir David Cox

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Scientific data analysis can be summarised as a process which must contain the following 5 stages:

- Reflection on problem and resources.
- Data collection.
- Data preparation.
- Data analysis.
- Reporting of results.

It is NOT a non-stop, 5-step unidirectional process, where steps are followed in strict sequence.

It is a process with 5 stages, which appear in the order above.

At any point it may be necessary to return to a previous stage and re-start from there.

Reflection

"Far better an approximate answer to the right question, which is often vague, than an exact answer to the wrong question, which can always be made precise." — John Tukey

- What are the questions that need to be answered?
- What resources are needed to answer such questions?
- What resources are available?
- If the data is not yet available, then it is crucial to carefully plan how information will be gathered so that questons of interest can be answered.
- If data is available try to have a glimpse at it and anticipate challenges, tasks to be performed, etc.
- How will the work align with ethical guidelines?

Keep on coming to this stage as needed throughout the data analysis process.

Data collection

- Data can arrive in a myriad of ways.
- How do you transfer the data to your chosen system for analysis?

Data preparation

Once the data has been imported into the system

- Is the format of the data adequate for the system to carry out analyses?
- Data organised adequately, in a standardised format, is **tidy data**.
- Data usually arrives in a "messy" state in terms of the way it is organised.
- Once data is tidy other issues, that must be dealt with, may remain such as errors (mistyped entries), duplication of values, missing values, abnormal values, outliers, etc.

Data preparation is key to meaningful analysis but time consuming

In the New York Times article **For Big-Data scientists, 'Janitor work' is key hurdle to insights** (Aug 17, 2014) we read

> *"Yet far too much handcrafted work — what data scientists call "data wrangling," "data munging" and "data janitor work" — is still required. Data scientists, according to interviews and expert estimates, spend from 50 percent to 80 percent of their time mired in this more mundane labor of collecting and preparing unruly digital data, before it can be explored for useful nuggets. . . . Data experts try to automate as many steps in the process as possible. "But practically, because of the diversity of data, you spend a lot of your time being a data janitor, before you can get to the cool, sexy things that got you into the field in the first place""*

- Time spent in data preparation is well-spent time.
- Data preparation is key for reproducibility and streamlined analyses.
- Adopting common standards for what constitutes a tidy data set is essential for both correctness and reproducibility.

Data analysis

Once our data is readable in the chosen system, has been prepared in the required format and the best effort to clean it has been made, it can be passed on to routines that will analyse the data and quantify the results using adequate paradigms.

Reporting

- The process is reported for checking and dissemination.
- The latest trend in reporting is along the lines of reproducible analysis, using interactive digital platforms which can communicate with the data and software inline.

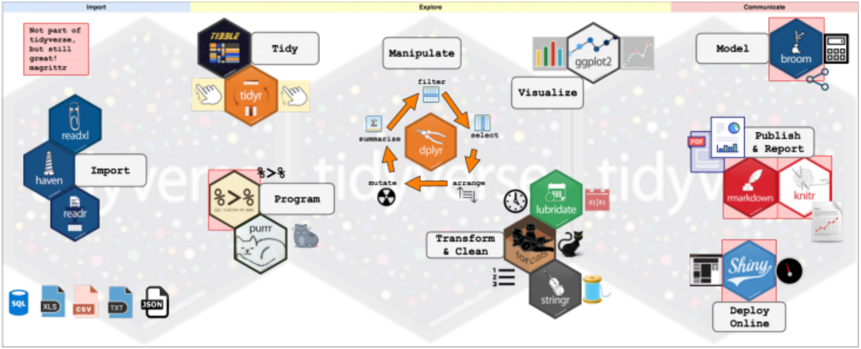
Data science with R course

- In this intermediate course we will focus mainly on the first three steps of the data analysis process using the R software: reflexion, data collection and data preparation.
- We will see ways of importing data in several digital formats into R (excel, SAS, STATA, SPSS, .csv, .tsv, .txt, web data, etc.)
- We will define minimum qualities that a tidy data set must have and the most common features of messy data.
- We will learn how to fix messy data via manipulation of the data arrays and ways to detect common abnormalities via data summaries and simple data visualisation.

R packages for data science

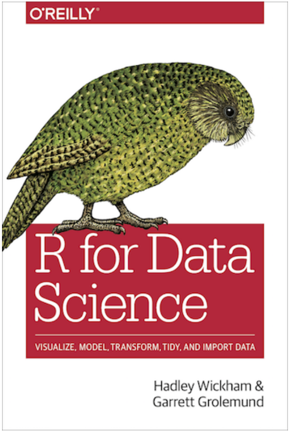
- The basic unit of communication with R is a **function**, writen as a name followed by (), e.g. `summary()`. Inside the brackets we write arguments (options) of the function.
- For example: `summary(mydata)` provides a summary of the data in `mydata`.
- A package is a collection of R functions, bundled together as they have a common purpose.
- For example, `dplyr` is a package useful for data manipulation (wrangling).
- To use a package one must first install it using the function `install.packages()` and then, to use it, it must be invoked or loaded with the function `library()`.
- Installation of a package is done only once. Loading must be done on each new session.
- For example: `install.packages("dplyr")` to install and

The Tidyverse (https://www.Tidyverse.org)



"The Tidyverse is an opinionated collection of R packages designed for data science. All packages share an underlying design philosophy, grammar, and data structures."

Suggested literature:



http://r4ds.had.co.nz

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Cheatsheets

https://www.rstudio.com/resources/cheatsheets/

Working with the teaching laptops

The password is

Datacampus!

Download files (I)

- In the web browser (Chrome) go to

https://github.com/sonjam111/DSWR1_pub

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- Click on the green button "Clone or download".
- Click "Download ZIP"

Dowload files (II)

- Go to your Downloads folder. You should find a folder named "DSWR1_pub-master". Double-click on it.

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- Copy the folder DSWR1_pub-master.

Dowload files (II)

- Go to your Downloads folder. You should find a folder named "DSWR1_pub-master". Double-click on it.
- Copy the folder DSWR1_pub-master.
- Go to the Documents folder and paste it there.

Dowload files (II)

- Go to your Downloads folder. You should find a folder named "DSWR1_pub-master". Double-click on it.
- Copy the folder DSWR1_pub-master.
- Go to the Documents folder and paste it there.
- Check that in the Documents folder you have a new folder called DSWR1_pub-master.

RStudio®

Golden rules for working with RStudio

- Create a folder with a meaningful name for your project. Store all the files for the project in this folder. (Rename the folder DSWR1_pub-master to DSWR)

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- One folder per project.

Golden rules for working with RStudio

- Create a folder with a meaningful name for your project. Store all the files for the project in this folder. (Rename the folder DSWR1_pub-master to DSWR)
- One folder per project.
- The first action after opening RStudio is to set the working directory, i.e. tell R where to find and store all the files needed or generated. (Set the working directory to DSWR)

R code chunks

R code chunks are inserted using

- the keyboard shortcut Ctrl + Alt + I (macOS: Cmd + Option + I),
- or via the Insert menu in the editor toolbar,
- or manually by typing ` ```{r} `. Start typing code in the next line. Finally to close the chunk type ` ``` ` in a separate line.
- One output per chunk.

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- or via the Insert menu in the editor toolbar,
- or manually by typing ```` ```{r} ````. Start typing code in the next line. Finally to close the chunk type ```` ``` ```` in a separate line.
- One output per chunk.
- Execute the chunk and check it does what it's supposed to do before witing a new chunk.

Importing data into R

Data may come in many formats

- text files,
- excel files or workbooks,
- data prepared for SAS, SPSS, Stata, etc.,
- Data from the web.
- Data from a SQL server.

And more!

- R is a versatile software that allows data in almost any format to be imported and analysed.

Importing text files

```r
library(readr)
```

The most common type of file is a "flat file", a text file with a bi-dimensional array of entries or cells. The entries can be separated by either a tab (or blank space), or a comma.

Useful packages to import text files

- `readr` (in the `Tidyverse`, the one we will use)
- `utils` (loads automatically when `R` is started, always useful)
- `data.table` (not in the `Tidyverse`, useful to read large data sets)

utils	readr	use
read.table()	read_delim()	read any flat file with any delimiter
read.csv()	read_csv()	read comma separated values
read.delim()	read_tsv()	read tab delimited files

- Also useful are `read_table()` and `read_table2()`.
- Use to read data which has columns separated by white space.

EXAMPLE.

"EXER_age_sex_race.csv": file containing demographic information about people in a study to assess the health benefits of an exercise plan.

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

```
## Parsed with column specification:
## cols(
##   subject_ID = col_double(),
##   SexAge_Race = col_character()
## )
```

To inspect what type of object `data1` is, we use the command `class()`

```
class(data1)
```

```
## [1] "spec_tbl_df" "tbl_df"      "tbl"         "data.frame"
```

```r
#We can see the top 6 rows of `data1`
head(data1)
```

```
## # A tibble: 6 x 2
##   subject_ID SexAge_Race
##        <dbl> <chr>
## 1          1 MALE41.2_White
## 2          2 FEMALE42.9_White
## 3          3 FEMALE38.5_White
## 4          4 FEMALE35.6_Hispanic
## 5          5 FEMALE48.5_White
## 6          6 FEMALE36.9_NA
```

```r
#and the last 3 rows of `data1`
tail(data1, n = 3)
```

```
## # A tibble: 3 x 2
##   subject_ID SexAge_Race
##        <dbl> <chr>
## 1       4998 FEMALE44.1_Black
## 2       4999 FEMALE46.4_Black
## 3       5000 FEMALE49.9_Black
```

Note:

```r
class(read.csv("DataFiles/EXER_age_sex_race.csv"))
```

```
## [1] "data.frame"
```

and

```r
class(read_csv("DataFiles/EXER_age_sex_race.csv"))
```

```
## Parsed with column specification:
## cols(
##   subject_ID = col_double(),
##   SexAge_Race = col_character()
## )
```

```
## [1] "spec_tbl_df" "tbl_df"      "tbl"         "data.frame"
```

Importing Excel files

- Use the package `readxl` from the `Tidyverse`.
- Use the function `read_excel()`.
- Also useful is `excel_sheets()` : lists different sheets in an excel workbook.

```r
library(readxl)
```

EXAMPLE. Importing an excel file sourced from Gapminder

Let us consider geographical information of countries in the world from https://www.gapminder.org/data/geo/.

- "DataGeographiesGapminder.xlsx": file containing geographical information about countries.
- Workbook with many sheets.
- The second sheet is the one of interest.

```r
#names of sheets in workbook
excel_sheets("DataFiles/DataGeographiesGapminder.xlsx")
```

```
## [1] "ABOUT"                "List of countries" "List of regions"
## [4] "World"
```

```r
# import only the second sheet
continent <-
  read_excel("DataFiles/DataGeographiesGapminder.xlsx", sheet = 2)
```

```r
# first six rows of continent
head(continent)
```

```
## # A tibble: 6 x 11
##   geo   name  four_regions eight_regions six_regions members_oecd_g77
##   <chr> <chr> <chr>        <chr>         <chr>       <chr>
## 1 afg   Afgh~ asia         asia_west     south_asia  g77
## 2 alb   Alba~ europe       europe_east   europe_cen~ others
## 3 dza   Alge~ africa       africa_north  middle_eas~ g77
## 4 and   Ando~ europe       europe_west   europe_cen~ others
## 5 ago   Ango~ africa       africa_sub_s~ sub_sahara~ g77
## 6 atg   Anti~ americas     america_north america     g77
## # ... with 5 more variables: Latitude <dbl>, Longitude <dbl>, `UN member
## #   since` <dttm>, `World bank region` <chr>, `World bank income group
## #   2017` <chr>
```

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Importing data from Statistical software (SAS, SPSS, STATA)

The package `haven`, of the `Tidyverse`, provides easy to use commands to import data from SAS, STATA and SPSS

```r
library(haven)
```

Software	Function
SAS	read_sas()
STATA	read_dta() or read_stata() (identical commands)
SPSS	read_sav() or read_por() (depending on the file type to be imported)

Importing a SAS file

We use the function `read_sas()` in the package `haven` of the `Tidyverse`. We will import the file "tax.sas7bdat" which contains information abot the income and tax paid of 30 US firms in 1988, 1989.

```
tax <- read_sas("DataFiles/tax.sas7bdat")
```

```
glimpse(tax)
```

```
## Observations: 30
## Variables: 4
## $ INC88 <dbl> 9.215, 2.047, 9.989, 8.321, 4.588, 4.736, 3.596, 4.830, ...
## $ TAX88 <dbl> 1.643, 0.413, 1.752, 1.408, 0.838, 0.748, 0.577, 0.752, ...
## $ INC89 <dbl> 9.518, 2.068, 9.992, 8.515, 4.389, 5.015, 3.811, 4.939, ...
## $ TAX89 <dbl> 2.125, 0.565, 2.221, 1.905, 0.943, 1.051, 0.819, 1.015, ...
```

```r
head(tax, n = 5)
```

```
## # A tibble: 5 x 4
##   INC88 TAX88 INC89 TAX89
##   <dbl> <dbl> <dbl> <dbl>
## 1  9.22 1.64   9.52 2.12
## 2  2.05 0.413  2.07 0.565
## 3  9.99 1.75   9.99 2.22
## 4  8.32 1.41   8.52 1.90
## 5  4.59 0.838  4.39 0.943
```

```r
tail(tax, n = 5)
```

```
## # A tibble: 5 x 4
##   INC88 TAX88 INC89 TAX89
##   <dbl> <dbl> <dbl> <dbl>
## 1  7.26 1.14   7.64 1.72
## 2  2.13 0.414  2.17 0.433
## 3  7.53 1.33   7.86 1.46
## 4  9.58 1.66  10.00 2.17
## 5  2.02 0.351  2.26 0.447
```

Importing a SPSS file

- Use the function `read_sav()` (for .sav files)

or

- use `read_por()` (for .por files),
- both in the package `haven`.

EXAMPLE.

- SPSS file "sleep.sav"
- Data concerns the prevalence and impact of sleep problems on people's lives.
- Measured variables are sleep behaviour (e.g. hours slept per night), sleep problems (e.g. difficulty getting to sleep) and the impact that these problems have on aspects of their lives (work, driving, relationships).
- The sample consists of 271 individuals.

```r
sleep <- read_sav("DataFiles/sleep.sav")
```

```r
head(sleep)
```

```
## # A tibble: 6 x 55
##      id     sex   age marital edlevel weight height healthrate fitrate
##   <dbl> <dbl+l> <dbl> <dbl+l> <dbl+l>  <dbl>  <dbl>  <dbl+lbl> <dbl+l>
## 1    83 0 [fem~    42 2 [mar~ 2 [sec~     52    162 10 [very ~       7
## 2   294 0 [fem~    54 2 [mar~ 5 [pos~     65    174  8               7
## 3   425 1 [mal~    NA 2 [mar~ 2 [sec~     89    170  6               5
## 4    64 0 [fem~    41 2 [mar~ 5 [pos~     66    178  9               7
## 5   536 0 [fem~    39 2 [mar~ 5 [pos~     62    160  9               5
## 6    57 0 [fem~    66 2 [mar~ 4 [und~     62    165  8               8
## # ... with 46 more variables: weightrate <dbl+lbl>, smoke <dbl+lbl>,
## #   smokenum <dbl>, alchohol <dbl>, caffeine <dbl>, hourwnit <dbl>,
## #   hourwend <dbl>, hourneed <dbl>, trubslep <dbl+lbl>,
## #   trubstay <dbl+lbl>, wakenite <dbl+lbl>, niteshft <dbl+lbl>,
## #   liteslp <dbl+lbl>, refreshd <dbl+lbl>, satsleep <dbl+lbl>,
## #   qualslp <dbl+lbl>, stressmo <dbl+lbl>, medhelp <dbl+lbl>,
## #   problem <dbl+lbl>, impact1 <dbl+lbl>, impact2 <dbl+lbl>,
## #   impact3 <dbl+lbl>, impact4 <dbl+lbl>, impact5 <dbl+lbl>,
## #   impact6 <dbl+lbl>, impact7 <dbl+lbl>, stopb <dbl+lbl>,
## #   restlss <dbl+lbl>, drvsleep <dbl+lbl>, drvresul <dbl+lbl>, ess <dbl>,
## #   anxiety <dbl>, depress <dbl>, fatigue <dbl>, lethargy <dbl>,
## #   tired <dbl>, sleepy <dbl>, energy <dbl>, stayslprec <dbl+lbl>,
## #   getsleeprec <dbl+lbl>, qualsleeprec <dbl+lbl>, totsas <dbl>,
## #   cigsgp3 <dbl+lbl>, agegp3 <dbl+lbl>, probsleeprec <dbl+lbl>,
## #   drvslprec <dbl+lbl>
```

Factor columns have numeric entries, and each number has a corresponding name or label.

Use this function to get the labels of a factor

```
print_labels(sleep$marital)
```

```
##
## Labels:
##  value             label
##      1            single
##      2 married/defacto
##      3          divorced
##      4           widowed
```

The variable `marital` is a factor with four levels: level 1 corresponds to single people, level 2 to married people, level 3 to divorced and level 4 to widowed people.

Importing a STATA file

"trade.dta": US yearly import and export numbers of sugar, in USD and lbs.

```
sugar <- read_dta("DataFiles/trade.dta")
```

```
glimpse(sugar)
```

```
## Observations: 10
## Variables: 5
## $ Date     <dbl+lbl> 10, 9, 8, 7, 6, 5, 4, 3, 2, 1
## $ Import   <dbl> 37664782, 16316512, 11082246, 35677943, 9879878, 1539...
## $ Weight_I <dbl> 54029106, 21584365, 14526089, 55034932, 14806865, 174...
## $ Export   <dbl> 54505513, 102700010, 37935000, 48515008, 71486545, 12...
## $ Weight_E <dbl> 93350013, 158000010, 88000000, 112000005, 131800000, ...
```

- The values in the column `Date` are labelled and the labels are dates.
- The other four columns contain numerical values.

```r
print_labels(sugar$Date)
```

```
##
## Labels:
##  value      label
##      1 2004-12-31
##      2 2005-12-31
##      3 2006-12-31
##      4 2007-12-31
##      5 2008-12-31
##      6 2009-12-31
##      7 2010-12-31
##      8 2011-12-31
##      9 2012-12-31
##     10 2013-12-31
```

Importing data from the web

- Data from the web can be read directly into `R` if it is a text file (comma or tab separated), sas, stata or spss file.
- Instead of a filename, we specify a url.
- Excel files cannot be retrieved directly from the web. First the file needs to be downloaded using the command `download.file()`.

EXAMPLE. Excel file from Gapminder

- Data: Adults with HIV (estimated prevalence of HIV in percentage, ages 15-49) from Gapminder,
- url: https://docs.google.com/spreadsheet/pub?key=pyj6tScZqmEfbZyl0qjbiRQ&output=xlsx
- The function `read_excel()` cannot download excel files directly from the web.
- First use the function `download.file()` to download the file into a directory,
- then `read_excel()` to read it into R.

```r
url <- "https://docs.google.com/spreadsheet/pub?key=pyj6tScZqmEfbZyl0qjbiRQ&outp
```

```r
download.file(url, "DataFiles/HIV.xlsx")
```

```r
HIV <- read_excel("DataFiles/HIV.xlsx")
```

```r
head(HIV)
```

```
## # A tibble: 6 x 34
##   `Estimated HIV ~ `1979.0` `1980.0` `1981.0` `1982.0` `1983.0` `1984.0`
##   <chr>               <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
## 1 Abkhazia               NA       NA       NA       NA       NA       NA
## 2 Afghanistan            NA       NA       NA       NA       NA       NA
## 3 Akrotiri and Dh~       NA       NA       NA       NA       NA       NA
## 4 Albania                NA       NA       NA       NA       NA       NA
## 5 Algeria                NA       NA       NA       NA       NA       NA
## 6 American Samoa         NA       NA       NA       NA       NA       NA
## # ... with 27 more variables: `1985.0` <dbl>, `1986.0` <dbl>,
## #   `1987.0` <dbl>, `1988.0` <lgl>, `1989.0` <lgl>, `1990.0` <dbl>,
## #   `1991.0` <dbl>, `1992.0` <dbl>, `1993.0` <dbl>, `1994.0` <dbl>,
## #   `1995.0` <dbl>, `1996.0` <dbl>, `1997.0` <dbl>, `1998.0` <dbl>,
## #   `1999.0` <dbl>, `2000.0` <dbl>, `2001.0` <dbl>, `2002.0` <dbl>,
## #   `2003.0` <dbl>, `2004.0` <dbl>, `2005.0` <dbl>, `2006.0` <dbl>,
## #   `2007.0` <dbl>, `2008.0` <dbl>, `2009` <chr>, `2010` <chr>,
## #   `2011` <chr>
```

Tidy data

"Happy families are all alike; every unhappy family is unhappy in its own way." Leo Tolstoy

- Hadley Wikcham in “Tidy Data” defines the three qualities of tidy data which standardise the process of dealing with any data set:

1. Each variable forms a column.
2. Each observation forms a row.
3. Each type of observational unit forms a table.

- These three qualities are what the end product of the data tydying process must possess.
- *Messy data* is data which is not tidy.
- Applying the tidy data criteria standardises the structure of a data set, making exploration and analysis of data easier and less error-prone.

Tidying messy data sets

Common problems with messy data sets are:

1. Column headers are values, not variable names.
2. Multiple variables are stored in one column.
3. Variables are stored in both rows and columns.
4. Multiple types of observational units are stored in the same table.
5. A single observational unit is stored in multiple tables.

The first three features of a messy data set are the most common.

- A tidy data set is not a correct data set.
- Tidy data refers only to the format of data.
- Other problems with data sets are errors, unusual observations, duplicated entries, missing data, and many more.
- These are dealt with once the data is tidy.

Tidying data

```r
library(tidyr); library(dplyr); library(stringr)
```

`tidyr` functions to tidy data

EXAMPLE. Number of text messages that Sue and Peter sent in 2016 and 2017.

Name	2016	2017
Sue	300	500
Peter	400	600

- What are the observational units?
- What are the variables?
- Are there any messy features in this data set?
- If so, what is the structure of the tidy data set?

Name	2016	2017
Sue	300	500
Peter	400	600

- Observational units are Sue and Peter
- Variables are year and number of text messages sent.
- Column headers are values of variable year, not variable names.
- A tidy version of this data set has columns Name, Year, and Number of text messages.

How to transform the messy data

Name	2016	2017
Sue	300	500
Peter	400	600

into tidy data?

Name	Year	NrSMS
Sue	2016	300
Peter	2016	400
Sue	2017	500
Peter	2017	600

First let us create the tibble (enhanced data frame) sms

```r
c1 <- c("Sue", "Peter")
c2 <- c(300, 400)
c3 <- c(500, 600)
sms <- tibble("Name" = c1, "2016" = c2, "2017" = c3)
sms
```

```
## # A tibble: 2 x 3
##   Name  `2016` `2017`
##   <chr>  <dbl>  <dbl>
## 1 Sue      300    500
## 2 Peter    400    600
```

Use the function ‘gather()‘, in ‘tidyr‘, to create a column with column names values.

Tidy the data by gathering column names under a new variable and creating a column with the corresponding values.

```
#"Year":  the "key", new column with the column names being gathered
#"NrSMS": the "value", new column that will have the values which used
#         to be under 2016 and 2017
#the -1 stands for don't gather the first column
```

```
sms_tidy <- gather(sms, key = "Year", value = "NrSMS", -1)
```

```
sms_tidy
```

```
## # A tibble: 4 x 3
##   Name  Year  NrSMS
##   <chr> <chr> <dbl>
## 1 Sue   2016    300
## 2 Peter 2016    400
## 3 Sue   2017    500
## 4 Peter 2017    600
```

EXAMPLE

Number of text messages and tweets Alice, Ann and John made in 2016.

Name	Number	Type
Alice	100	sms
Alice	200	twt
Ann	300	sms
Ann	400	twt
John	500	sms
John	600	twt

- What are the observational units?
- What are the variables?
- Are there any messy features in this data set?
- If so, what is the structure of the tidy data set?

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Name	Number	Type
Alice	100	sms
Alice	200	twt
Ann	300	sms
Ann	400	twt
John	500	sms
John	600	twt

- Observational units are Alice, Ann and John
- Variables measured are number of sms sent and number of tweets made.
- `Type` is not a measured variable. It stores the names of two variables: sms and tweet.

Messy data: variables are stored in both rows and columns.

How to transform the messy data

Name	Number	Type
Alice	100	sms
Alice	200	twt
Ann	300	sms
Ann	400	twt
John	500	sms
John	600	twt

into tidy data?

Name	sms	twt
Alice	100	200
Ann	300	400
John	500	600

To do this in `R` let us first create the tibble `smstwt`

```
Name <- c("Alice", "Alice",  "Ann", "Ann", "John", "John")
Number <- c(100, 200, 300, 400, 500, 600)
Type <- c("sms", "twt", "sms","twt", "sms", "twt")
```

```
smstwt <- tibble(Name, Number, Type)
smstwt
```

```
## # A tibble: 6 x 3
##   Name  Number Type
##   <chr>  <dbl> <chr>
## 1 Alice    100 sms
## 2 Alice    200 twt
## 3 Ann      300 sms
## 4 Ann      400 twt
## 5 John     500 sms
## 6 John     600 twt
```

Use the function ‘spread()‘, in ‘tidyr‘, to create new columns from the values of another column.

In order to tidy the data set we must “spread” the values of `Type` into two new columns, “sms” an “twt”, and distribute the values in `Number` accordingly.

```
#Type   "key"  : create new columns with names from values of Type.
#Number "value": the values to spread under the new columns.
#
```

```
smstwt_tidy <- spread(smstwt, key = Type, value = Number)
```

```
smstwt_tidy
```

```
## # A tibble: 3 x 3
##   Name    sms   twt
##   <chr> <dbl> <dbl>
## 1 Alice   100   200
## 2 Ann     300   400
## 3 John    500   600
```

EXAMPLE. Extra data about the number of sms sent and tweets made by Alice, Ann and John in 2017.

Name	sms_2016	twt_2016	sms_2017	twt_2017
Alice	100	200	10	20
Ann	300	400	30	40
John	500	600	50	60

- The data without the last two columns was tidy; this data set is messy.
- Observational units are Alice, Ann and John and measured variables are year, number of tweets and number of sms.

Let us create a tibble, smstwt2, with the data.

```
Name <- c("Alice", "Ann", "John")
sms_2016 <- c(100, 300, 500)
twt_2016 <- c(200, 400, 600)
sms_2017 <- c(10, 30, 50)
twt_2017 <- c(20, 40, 60)
```

```
smstwt2 <- tibble(Name, sms_2016, twt_2016, sms_2017, twt_2017)
```

```
smstwt2
```

```
## # A tibble: 3 x 5
##   Name  sms_2016 twt_2016 sms_2017 twt_2017
##   <chr>    <dbl>    <dbl>    <dbl>    <dbl>
## 1 Alice      100      200       10       20
## 2 Ann        300      400       30       40
## 3 John       500      600       50       60
```

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- Names of columns, except `Name`, are values of variables.
- Gather column names into one new column named "year-type" and put the corresponding values in the new column "Number".

```
smstwt2_g <- gather(smstwt2, "type_year", "Number", -1)
```

```
head(smstwt2_g)
```

```
## # A tibble: 6 x 3
##   Name  type_year Number
##   <chr> <chr>      <dbl>
## 1 Alice sms_2016     100
## 2 Ann   sms_2016     300
## 3 John  sms_2016     500
## 4 Alice twt_2016     200
## 5 Ann   twt_2016     400
## 6 John  twt_2016     600
```

- Not tidy: multiple variables are stored in column `type_year`.

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- Separate column `type_year` into two new columns: "type" and "year".

> The function ‘separate()‘ from ‘tidyr‘ separates one column into several.

```
smstwt2_gs <-
 separate(smstwt2_g, "type_year", c("type", "year"), sep = "_")
```

```
head(smstwt2_gs)
```

```
## # A tibble: 6 x 4
##   Name  type  year  Number
##   <chr> <chr> <chr>  <dbl>
## 1 Alice sms   2016     100
## 2 Ann   sms   2016     300
## 3 John  sms   2016     500
## 4 Alice twt   2016     200
## 5 Ann   twt   2016     400
## 6 John  twt   2016     600
```

- Not tidy: variables are stored in both rows and columns.

- "spread" the values of `type` into "sms" and "twt", with the corresponding values of `Number`.

```
smstwt2_tidy <- spread(smstwt2_gs, type, Number)
```

```
smstwt2_tidy
```

```
## # A tibble: 6 x 4
##   Name  year    sms   twt
##   <chr> <chr> <dbl> <dbl>
## 1 Alice 2016    100   200
## 2 Alice 2017     10    20
## 3 Ann   2016    300   400
## 4 Ann   2017     30    40
## 5 John  2016    500   600
## 6 John  2017     50    60
```

From messy data

Name	sms_2016	twt_2016	sms_2017	twt_2017
Alice	100	200	10	20
Ann	300	400	30	40
John	500	600	50	60

to tidy data

Name	year	sms	twt
Alice	2016	100	200
Alice	2017	10	20
Ann	2016	300	400
Ann	2017	30	40
John	2016	500	600
John	2017	50	60

We can use the pipe, %>%, to do the entire tidying in one go without creating the intermediate objects.

```
smstwt2_tidy <- smstwt2 %>%
  gather("type_year", "Number",-1) %>%
  separate("type_year", c("type", "year"), sep = "_") %>%
  mutate(year = as.numeric(year)) %>%
  spread(type, Number)
```

```
smstwt2_tidy
```

```
## # A tibble: 6 x 4
##   Name   year   sms   twt
##   <chr> <dbl> <dbl> <dbl>
## 1 Alice  2016   100   200
## 2 Alice  2017    10    20
## 3 Ann    2016   300   400
## 4 Ann    2017    30    40
## 5 John   2016   500   600
## 6 John   2017    50    60
```

The function mutate() of the dplyr package is used to transform an existing column of a tibble or to create a new column in the tibble. The syntax is
'mutate(tibb, new_col = definition)'
or, using the pipe,
'tibb %>% mutate(new_col = definition)'

EXAMPLE. Add information on the ages of Alice, Ann, John, Peter and Sue

Name	Age
Alice	15
Ann	25
John	35
Peter	45
Sue	55

Now, we have feature 5 of messy data sets: a single observational unit is stored in multiple tables.

Let us enter the new information into R.

```
dem1 <- c("Alice", "Ann", "John", "Peter", "Sue")
dem2 <- c(15, 25, 35, 45, 55)
```

```
dem <- tibble("Name" = dem1, "Age" = dem2)
```

```
dem
```

```
## # A tibble: 5 x 2
##   Name    Age
##   <chr> <dbl>
## 1 Alice    15
## 2 Ann      25
## 3 John     35
## 4 Peter    45
## 5 Sue      55
```

- Add this information to our data sets sms_tidy and smstwt2_tidy.

The function ‘inner_join()‘ of the ‘dplyr‘ package will join data sets by matching only the entries of all common columns, or by a specific column, in both data sets.

```
inner_join(sms_tidy,dem)
```

```
## Joining, by = "Name"
```

```
## # A tibble: 4 x 4
##   Name  Year  NrSMS   Age
##   <chr> <chr> <dbl> <dbl>
## 1 Sue   2016    300    55
## 2 Peter 2016    400    45
## 3 Sue   2017    500    55
## 4 Peter 2017    600    45
```

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```r
inner_join(smstwt2_tidy,dem)
```

```
## Joining, by = "Name"

## # A tibble: 6 x 5
##   Name   year   sms   twt   Age
##   <chr> <dbl> <dbl> <dbl> <dbl>
## 1 Alice  2016   100   200    15
## 2 Alice  2017    10    20    15
## 3 Ann    2016   300   400    25
## 4 Ann    2017    30    40    25
## 5 John   2016   500   600    35
## 6 John   2017    50    60    35
```

- Age is added twice for each observational unit.
- May need to keep, for example, demographic informaton about observational units in a separate data sets,
- or may need to merge both data sets into one for the purpose of analysis.

- Messy data is not necessarily incorrect data.
- Messy features are introduced when data for presentations is confused with data for analysis.
- Elegantly presented data may constitute a very messy data set and a tidy data set is usually unsuitable for presentation.