Getting and cleaning data

ADS2 week 7

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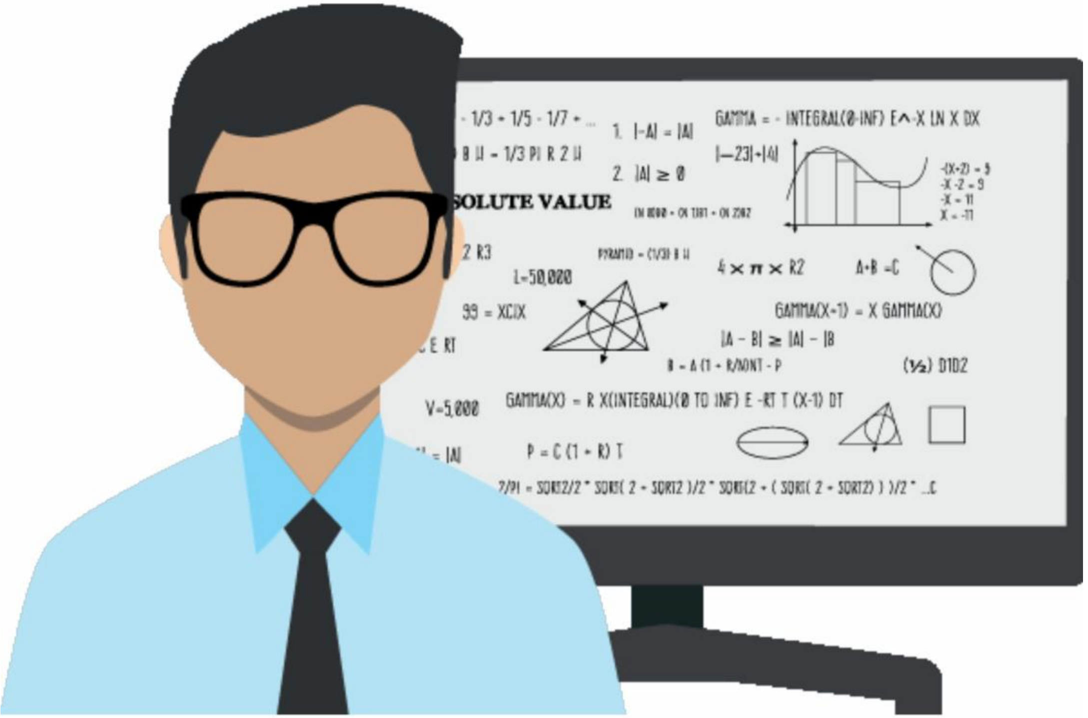
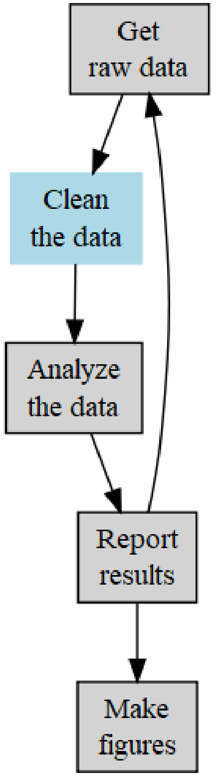
Why do we care about cleaning data?

What you imagine a data scientists do:



What data scientists really do:

Data analysis workflow



Before you analyze your data, answer these questions:

- Is your data ready to be analyzed?
- Is your data ready to be modelled?
- Is your data ready to be plotted?

What does it mean – raw data?

Raw data are “raw” if:

- No software processed it;
- No values are modified;
- No data are removed;
- No summary available.

Examples:

- RNA- and RNA-sequencing data;
- Data from flow cytometry;
- Data from image analysis;
- HTML data after data mining;
- Data from observations;
- etc.

Why do we need to clean raw data?

I want to make use of my flow cytometry data. But there are a few issues:

1. The data are not summarized;
2. From the current output, you get no valuable information;
3. You need to process it to get anything valuable.

	FSC.H	SSC.H	FITC.H	APC.H	Other data
1	370669	40987	309	102564	...
2	4007789	289260	3751	29742	...
3	1827661	613884	5290	3685276	...
4	7669807	727412	9280	52017	...
5	1228843	229826	3162	705259	...
6	1315640	289438	6748	1313375	...
7	1799229	99692	1558	2105	...
8	12735706	1892834	17371	339346	...
9	4009833	400802	2410	17196	...
10	...	...	...	...	...

Can these data be analyzed?

```
head(weather, 9) %>% select(2:14)
  year month           measure X1 X2  X3 X4 X5  X6 X7 X8  X9 X10 Other data
1 2014    12  Max.TemperatureF 64 42  51 43 42  45 38 29  49  48        ...
2 2014    12 Mean.TemperatureF 52 38  44 37 34  42 30 24  39  43        ...
3 2014    12  Min.TemperatureF 39 33  37 30 26  38 21 18  29  38        ...
4 2014    12    Max.Dew.PointF 46 40  49 24 37  45 36 28  49  45        ...
5 2014    12    MeanDew.PointF 40 27  42 21 25  40 20 16  41  39        ...
6 2014    12     Min.DewpointF 26 17  24 13 12  36 -3  3  28  37        ...
7 2014    12      Max.Humidity 74 92 100 69 85 100 92 92 100 100        ...
8 2014    12     Mean.Humidity 63 72  79 54 66  93 61 70  93  95        ...
9 2014    12      Min.Humidity 52 51  57 39 47  85 29 47  86  89        ...
```

“Dirty” data is a problem

The data may not be analyzed easily due to:

- Special characters where not needed;
- Use of the wrong data structures;
- Duplicated rows;
- Misspelling;
- White spaces;
- Missing data;
- Zeroes instead of `NULL` or `NA` values;
- Other inaccuracies;
- Poor structure.

```
weather %>% head(9) %>% select(2:8)
  year month            measure X1 X2  X3 X4
1 2014    12  Max.TemperatureF 64 42  51 43
2 2014    12 Mean.TemperatureF 52 38  44 37
3 2014    12  Min.TemperatureF 39 33  37 30
4 2014    12    Max.Dew.PointF 46 40  49 24
5 2014    12    MeanDew.PointF 40 27  42 21
6 2014    12     Min.DewpointF 26 17  24 13
7 2014    12      Max.Humidity 74 92 100 69
8 2014    12     Mean.Humidity 63 72  79 54
9 2014    12      Min.Humidity 52 51  57 39
```

What data scientists really do:

They take these dirty and messy data:

- Special characters where not needed;
- Use of the wrong data structures;
- Duplicated rows;
- Misspelling;
- White spaces;
- Missing data;
- Zeroes instead of `NULL` or `NA` values;
- Other inaccuracies;
- Poor structure.

And make it clean and tidy:

- Free of duplicate rows/values
- Error-free (e.g. free of misspellings)
- Relevant (e.g. free of special characters)
- The **appropriate data type** for analysis
- Free of outliers (or only contain outliers that have been identified/understood)
- Follows a "**tidy data**" structure.

Learning objectives

1. Describe features of **tidy** data and explain advantages of tidy datasets
2. Explain the process of cleaning data
3. Describe ways of handling different data types and data structures in R
4. Introduce the key data cleaning tools: `tidyverse` package and its elements

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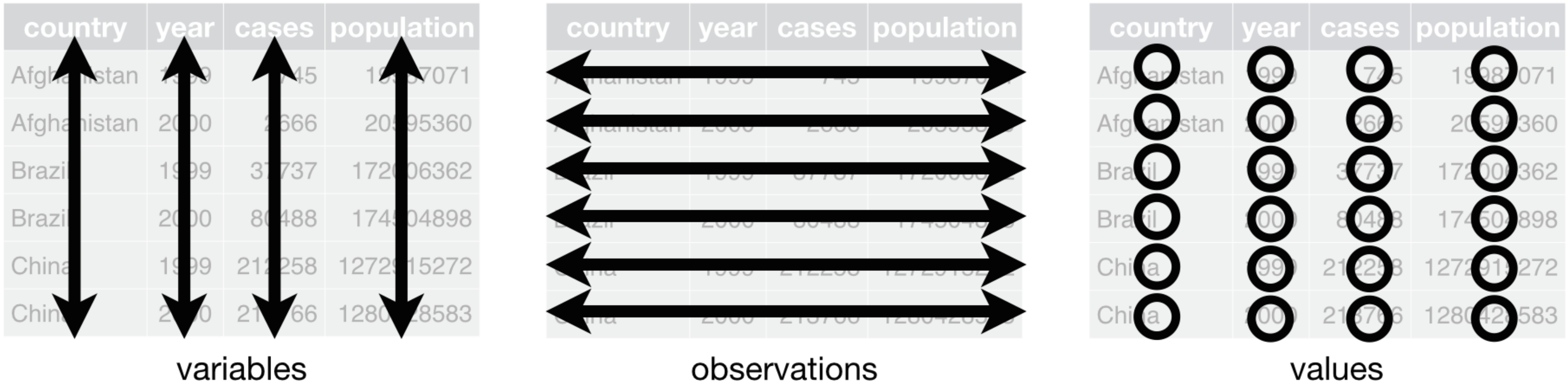
TIDY DATA, ITS FEATURES AND ADVANTAGES

Tidy data: main features



Tidy data: advantages

```
head(weather, 9) %>% select(2:15)
  year month           measure X1 X2  X3 X4 X5  X6 X7 X8  X9 X10 X11 Other data
1 2014    12  Max.TemperatureF 64 42  51 43 42  45 38 29  49  48  39        ...
2 2014    12 Mean.TemperatureF 52 38  44 37 34  42 30 24  39  43  36        ...
3 2014    12  Min.TemperatureF 39 33  37 30 26  38 21 18  29  38  32        ...
4 2014    12    Max.Dew.PointF 46 40  49 24 37  45 36 28  49  45  37        ...
5 2014    12    MeanDew.PointF 40 27  42 21 25  40 20 16  41  39  31        ...
6 2014    12     Min.DewpointF 26 17  24 13 12  36 -3  3  28  37  27        ...
7 2014    12      Max.Humidity 74 92 100 69 85 100 92 92 100 100  92        ...
8 2014    12     Mean.Humidity 63 72  79 54 66  93 61 70  93  95  87        ...
9 2014    12      Min.Humidity 52 51  57 39 47  85 29 47  86  89  82        ...
```

Tidy data: advantages

```
head(tidyWeather, 10) %>% select(1:6)
   year month       Date CloudCover    Events Max.Dew.PointF Other data
1  2014    12 2014-12-01          6      Rain             46        ...
2  2014    12 2014-12-02          7 Rain-Snow             40        ...
3  2014    12 2014-12-03          8      Rain             49        ...
4  2014    12 2014-12-04          3                       24        ...
5  2014    12 2014-12-05          5      Rain             37        ...
6  2014    12 2014-12-06          8      Rain             45        ...
7  2014    12 2014-12-07          6      Rain             36        ...
8  2014    12 2014-12-08          8      Snow             28        ...
9  2014    12 2014-12-09          8      Rain             49        ...
10 2014    12 2014-12-10          8      Rain             45        ...
```

Wide data format

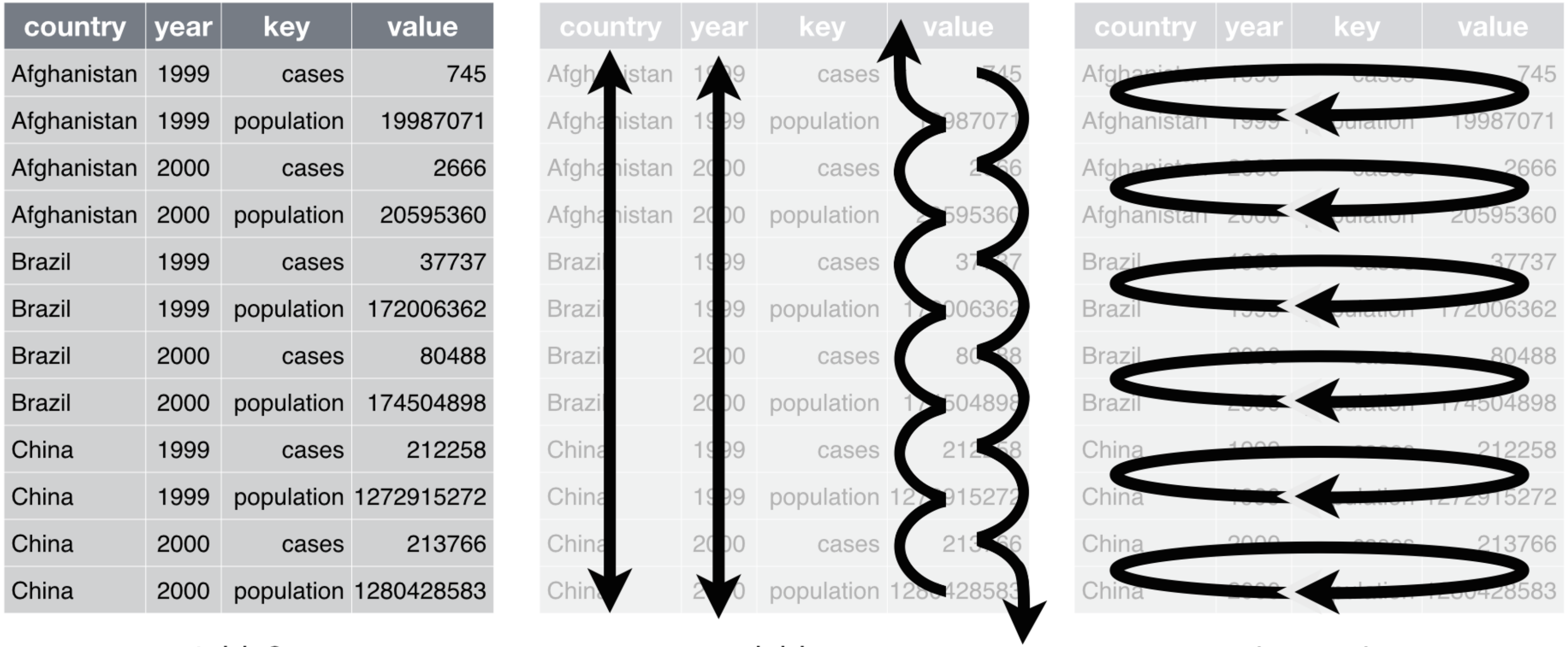
country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	213766	1280428583

table1

variables

observations

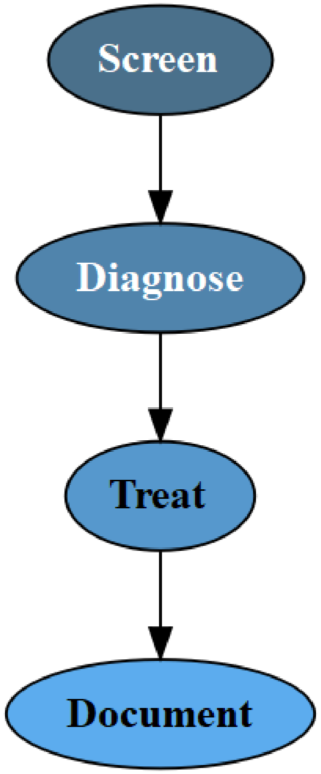
Long data format



country	year	key	value
Afghanistan	1999	cases	745
Afghanistan	1999	population	19987071
Afghanistan	2000	cases	2666
Afghanistan	2000	population	20595360
Brazil	1999	cases	37737
Brazil	1999	population	172006362
Brazil	2000	cases	80488
Brazil	2000	population	174504898
China	1999	cases	212258
China	1999	population	1272915272
China	2000	cases	213766
China	2000	population	1280428583

DATA CLEANING

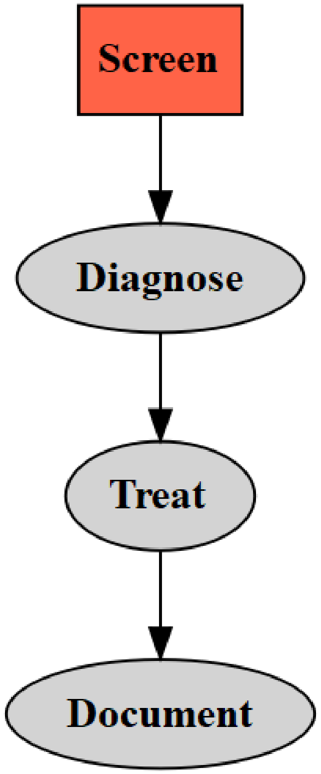
The key steps of data cleaning



The key steps of the data cleaning:

- **Screen**: Check the data set systematically
- **Diagnose**: Find out the nature of the problem.
- **Treat**: Delete, edit, or leave the data as it is.
- **Document**: Comment on each step to make sure you will not forget the reason of the action and the original state.

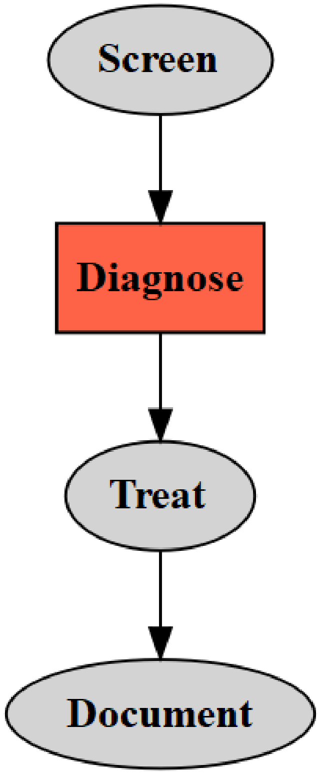
The key steps of data cleaning: Screening



Possible signs of the *bad* data:

- **Lack of data**: Some columns/rows have fewer values. Why?
- **Excess of data**: Some rows are duplicated or include more values than it should be. Were some rows duplicated? Were there some additional values added?
- **Outliers**: Some values are far beyond the limits of the data. An error is possible.
- **Strange patterns of data or results**: The results look quite weird. Was there an error or falsification?

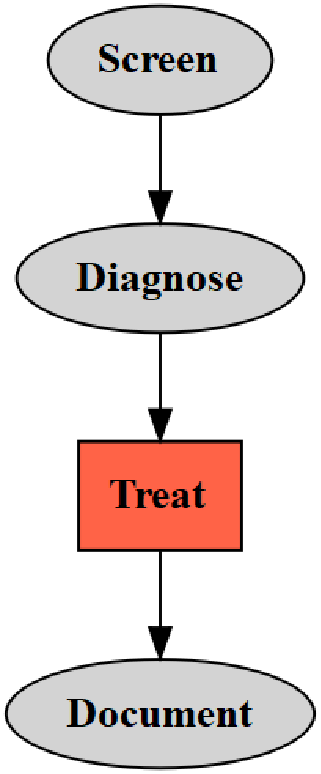
The key steps of data cleaning: Diagnosis



Possible reasons of the *bad* data:

- **Missing data**: Some answers were not recorded or test subjects were lost for the follow-up (dropped out from the study).
- **Errors or typos**: Errors can always take place.
- **No error**: The value is strange, but is actually valid. The researcher has to accept it.

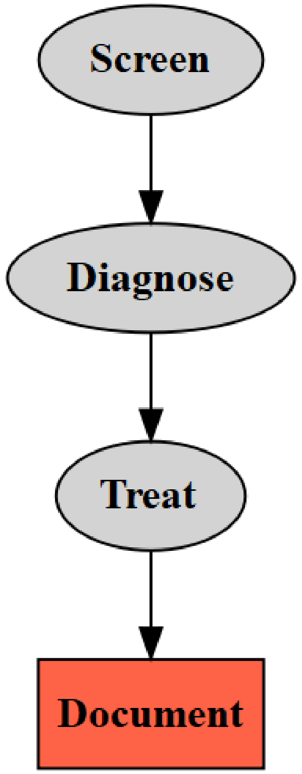
The key steps of data cleaning: Treatment



Possible actions to take:

- **Leave as it is**: Consider not changing anything. The larger the sample size is, the less influencing the suspect observation is.
- **Correct it**: You may change the value if you have figured out the source of the problem (for example, clear typos).
- **Delete it**: It may be reasonable to get rid of the suspect values. But which one to discard? And is there a really good reason for it? Avoid **cherry picking**!
- **Repeat the measurement**.

The key steps of data cleaning: Documenting



Important principles of documenting your data cleaning:

- **Clearly document the data cleaning process**.
- **Keep track of all changes**. Create some sort of a change log with all the relecant information about where changes were introduced:
  - Table;
  - Column, row;
  - Date changed -> Changed by;
  - Old value -> New value;
  - Comments.
- **Document which procedures were done, by whom, why, and how many responses were affected.**
- **This information must be accessible by you and by those with whom you share your data.**

HANDLING DATA IN R

Data types and structures in R

The main classes of data:

- Character
- Numeric
- Integer
- Logical
- Complex

Data structures:

- Vectors
- Factors
- Lists
- Matrices and arrays
- Data frames
- …

Check properties of the object

There is a set of commands that allow you to check the properties of the studied object

```
class(), mode(), typeof()
is.<DATA_CLASS/TYPE>(), as.<DATA_CLASS/TYPE>()

str(), summary()

attributes(), names()
dimnames(), colnames(), rownames()
dim(), length()

...
```

Subsetting and rearranging data in R

Subset or rearrange 1D data structures

```
vec.num <- c(1, 2.8, 3, 4.4)
vec.num[2]
[1] 2.8
vec.num[c(1, 4)]
[1] 1.0 4.4
vec.num_2 <- vec.num[c(2, 4, 3, 1)]

someList <- list(first_vec = vec.num,
second_vec = vec.num_2)

someList[[2]]
[1] 2.8 4.4 3.0 1.0
```

Subset or rearrange 2D data structures

```
matrix.num <- matrix(data = c(vec.num,
sqrt(vec.num_2)), nrow = 2, byrow = T)

matrix.num
        [,1]     [,2]     [,3] [,4]
[1,] 1.00000 2.800000 3.000000  4.4
[2,] 1.67332 2.097618 1.732051  1.0

dim(matrix.num)
[1] 2 4

matrix.num[1, c(4, 1)]
[1] 4.4 1.0
```

Working with data frames in R

```r
head(diamonds, 10) %>% as.data.frame()
   carat       cut color clarity depth table price    x    y    z
1   0.23     Ideal     E     SI2  61.5    55   326 3.95 3.98 2.43
2   0.21   Premium     E     SI1  59.8    61   326 3.89 3.84 2.31
3   0.23      Good     E     VS1  56.9    65   327 4.05 4.07 2.31
4   0.29   Premium     I     VS2  62.4    58   334 4.20 4.23 2.63
5   0.31      Good     J     SI2  63.3    58   335 4.34 4.35 2.75
6   0.24 Very Good     J    VVS2  62.8    57   336 3.94 3.96 2.48
7   0.24 Very Good     I    VVS1  62.3    57   336 3.95 3.98 2.47
8   0.26 Very Good     H     SI1  61.9    55   337 4.07 4.11 2.53
9   0.22      Fair     E     VS2  65.1    61   337 3.87 3.78 2.49
10  0.23 Very Good     H     VS1  59.4    61   338 4.00 4.05 2.39
```

Working with data frames in R

```
head(diamonds[diamonds$cut == "Ideal", ], 3)
   carat   cut color clarity depth table price    x    y    z
1   0.23 Ideal     E     SI2  61.5    55   326 3.95 3.98 2.43
12  0.23 Ideal     J     VS1  62.8    56   340 3.93 3.90 2.46
14  0.31 Ideal     J     SI2  62.2    54   344 4.35 4.37 2.71

diamonds[diamonds$cut == "Ideal" & diamonds$clarity == "VS1", ][1:3,]
   carat   cut color clarity depth table price    x    y    z
12  0.23 Ideal     J     VS1  62.8    56   340 3.93 3.90 2.46
52  0.23 Ideal     G     VS1  61.9    54   404 3.93 3.95 2.44
61  0.35 Ideal     I     VS1  60.9    57   552 4.54 4.59 2.78
```

CLEANING DATA IN R: `tidyverse` and related packages

`tidyverse` and friends

```
library(tidyverse)
── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
✔ dplyr     1.1.2     ✔ readr     2.1.4
✔ forcats   1.0.0     ✔ stringr   1.5.0
✔ ggplot2   3.4.3     ✔ tibble    3.2.1
✔ lubridate 1.9.2     ✔ tidyr     1.3.0
✔ purrr     1.0.2
── Conflicts ──────────────────────────────────────────── tidyverse_conflicts() ──
✖ dplyr::filter() masks stats::filter()
✖ dplyr::lag()    masks stats::lag()
ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all
conflicts to become errors
```

Cleaning data in R: `dplyr`

Subsetting tables in R

`tibble(), as_tibble()`

`select(dataframe, variables)`

`relocate(dataframe, variables)`

`rename(dataframe, variables)`

`filter(dataframe, variable == value)`

`slice(dataframe, rows)`

Modifying tables in R

`mutate(dataframe, new_variable = your_code)`

`transmute()`

`arrange(dataframe, variable_to_arrange)`

`group_by(dataframe, grouping_variable)`

`summarise(dataframe, summary_stat = your_code)`

`Pipe operator (%>%)`

Cleaning data in R: chaining operations with the `%>%` operator

ADS2, week 1, R refresher

```
1. Create a vector consisting of 5
numbers: 5, 6, 4, 5, 10.

2. Add "1" to all elements of the
vector.

3. Extract the first element of the
vector and add 3 to it.

4. Add the resultant number as the
sixth element of the vector.

5. Take the square root from the
resultant vector and assign it as a new
vector.

6. Convert it to a matrix with 3
columns
```

Regular way of solving the task

```
vec <- c(5, 6, 4, 5, 10)
vec <- vec + 1
vec[6] <- vec[1] + 3


vec

[1]  6  7  5  6 11  9

vec_new <- sqrt(vec)
vec_new <- matrix(data = vec_new, ncol
= 3, byrow = T)


vec_new

        [,1]     [,2]     [,3]

[1,] 2.44949 2.645751 2.236068

[2,] 2.44949 3.316625 3.000000
```

Cleaning data in R: chaining operations with the %>% operator

ADS2, week 1, R refresher

```
1. Create a vector consisting of 5
numbers: 5, 6, 4, 5, 10.

2. Add "1" to all elements of the
vector.

3. Extract the first element of the
vector and add 3 to it.

4. Add the resultant number as the
sixth element of the vector.

5. Take the square root from the
resultant vector and assign it as a new
vector.

6. Convert it into a matrix with 3
columns
```

Solving the task with chaining

```
vec <- c(5, 6, 4, 5, 10)

vec_new <- vec %>%
  + 1 %>%
  c(., .[1]+3) %>%
  sqrt(.) %>%
  matrix(nrow = 2, byrow = T)

vec_new
        [,1]     [,2]     [,3]
[1,] 2.44949 2.645751 2.236068
[2,] 2.44949 3.316625 3.000000
```

Cleaning data in R: chaining operations with the %>% operator

```
head(case1_col_desc, 4)

     Var_name Difference pooledSD Description Measure_unit p_value
1 splenocytes       5.63     5.05 splenocytes  10^6^ cells   0.117
2  CD8T_cells       0.59     0.97 CD8 T-cells            %   0.381
3  CD4T_cells       0.10     3.06 CD4 T-cells            %   0.958
4     B_cells       0.78     1.51     B-cells            %   0.440

dim(case1_col_desc)
[1] 16  6
```

Cleaning data in R: chaining operations with the %>% operator

```
case1_differ <- case1_col_desc %>%
  filter(p_value < 0.05) %>%
  mutate(Cohen_d = (Difference/pooledSD) %>%
           round(2)) %>%
  select(4,2,7) %>%
  arrange(desc(Cohen_d)) %>%
  rename(`Absolute difference, %` = Difference,
         `Variable` = Description)

head(case1_differ, 3)
```

```
                       Variable Absolute difference, % Cohen_d
1 memory phenotype CD8 T-cells                   10.21    9.20
2                IgM^+^ B-cells                   6.16    3.08
3       follicular CD4 T-cells                    1.58    3.04
```

Reshaping data in R: `tidyr`

```
tuberculosisAlgria <- who2

head(tuberculosisAlgria, 9) %>%
select(1:4)
```

```
  country year sp_m_014 sp_m_1524 Others
1 Algeria 2000       59       927    ...
2 Algeria 2001       41      1345    ...
3 Algeria 2002       39      1364    ...
4 Algeria 2003       40      1316    ...
5 Algeria 2004       63      1326    ...
6 Algeria 2005       53      1309    ...
7 Algeria 2006       41      1173    ...
8 Algeria 2007       95      1388    ...
9 Algeria 2008       99      1505    ...
```

```
gather(data = tuberculosisAlgria, key =
"Group", value = "Cases",
3:ncol(tuberculosisAlgria)) %>% head(9)
```

```
  country year    Group Cases
1 Algeria 2000 sp_m_014    59
2 Algeria 2001 sp_m_014    41
3 Algeria 2002 sp_m_014    39
4 Algeria 2003 sp_m_014    40
5 Algeria 2004 sp_m_014    63
6 Algeria 2005 sp_m_014    53
7 Algeria 2006 sp_m_014    41
8 Algeria 2007 sp_m_014    95
9 Algeria 2008 sp_m_014    99
```

Reshaping data in R: `tidyr`

Separate one column into several

```
separate(data = tub_AlgeriaGather, col =
"Group", into = c("Form", "Gender",
"Age"), sep = "_") %>% head(9)
  country year Form Gender Age Cases
1 Algeria 2000   sp      m 014    59
2 Algeria 2001   sp      m 014    41
3 Algeria 2002   sp      m 014    39
4 Algeria 2003   sp      m 014    40
5 Algeria 2004   sp      m 014    63
6 Algeria 2005   sp      m 014    53
7 Algeria 2006   sp      m 014    41
8 Algeria 2007   sp      m 014    95
9 Algeria 2008   sp      m 014    99
```

Spread the dataset

```
tub_AlgeriaSample <- tub_AlgeriaGather %>%

  separate(col = "Group", into = c("Form",
"Gender", "Age"), sep = "_") %>%

  filter(Form == "sp", Age == "2534") %>%

  select(1,2,4,6)

spread(tub_AlgeriaSample, key = "year",
value = "Cases") %>% select(1:5)

  country Gender 2000 2001 2002 Other data
1 Algeria      f 1293  782  730        ...
2 Algeria      m 1516 1614 1580        ...
```

Conclusions

By now, you should

1. Know the criteria of the **tidy** data.
2. Know how to clean data.
3. Be aware of different ways how to handle data in R.
4. Got introduced to the `tidyverse` package.

Further reading

- `library(swirl)   # An R package for self-learning Exploratory data analysis course`

- Wickham H. Tidy data. J Stat Softw [Internet]. 2014;59(10). Available from: http://dx.doi.org/10.18637/jss.v059.i10

- Wickham H. Ggplot2: Elegant graphics for data analysis. 2nd ed. Cham, Switzerland: Springer International Publishing; 2016.

- `library(data.table)   # A useful R package for data cleaning`

THANK YOU FOR ATTENTION