# Tidy data

#### PS239T

## Spring 2019

- I adapted the following content from Wickham's R data science book (2017) chapter: https://r4ds. had.co.nz/tidy-data.html and his earlier paper (2014) published in Journal of Statistical Software: http://www.jstatsoft.org/v59/i10/paper.
- Wickham created so many essential packages used in R for data science. For more information, please see the following website: http://hadley.nz/

## 1. What's tidy principles

- 1. The dataset: strucure (physical layout) + semantics (meaning)
- 1.1. Data structure
  - rows and columns

#### 1.2. Data semantics

- variables > values (numbers or strings)
- 2. Tidy tada: "provide a standard way to organize data values within a dataset"
- 2.1 Tidy principles

table1

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

```
# load library
library(tidyverse)
## -- Attaching packages ------ tidyverse 1.2.1 --
## v ggplot2 3.1.0
                    v purrr
                            0.2.5
## v tibble 1.4.2
                    v dplyr
                            0.7.8
                   v stringr 1.3.1
## v tidyr
           0.8.2
                    v forcats 0.3.0
## v readr
           1.2.1
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                  masks stats::lag()
# tidy data example
```

```
## # A tibble: 6 x 4
##
     country
                 year cases population
##
     <chr>>
                 <int>
                        <int>
## 1 Afghanistan 1999
                         745
                                19987071
## 2 Afghanistan
                 2000
                         2666
                                20595360
## 3 Brazil
                  1999
                       37737 172006362
## 4 Brazil
                  2000 80488 174504898
## 5 China
                  1999 212258 1272915272
## 6 China
                  2000 213766 1280428583
```

Practically, this approach is good because you're going to have consistency in the format of data across all the projects you're working on. Also, tidy data works well with key packages (e.g., dplyr, ggplot2) in R.

Computationally, this approach is good for vectorized programming because "different variables from the same observation are always paired".

#### 3. Messay datasets

#### 3.1. Signs of messay datasets

- 1. Column headers are values, not variable names.
- 2. Multiple variables are not 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.

## 4. Tody tools

Either input or output or both of them can be messy. Tidy tools can fix these problems.

## 4.1. Manipulation

- Filter
- Transform
- Aggregate
- Sort

#### 4.1.1. Gather (from wide to long)

#### table4a

```
## # A tibble: 3 x 3
##
                 `1999` `2000`
    country
## * <chr>
                  <int>
                        <int>
## 1 Afghanistan
                   745
                          2666
## 2 Brazil
                  37737 80488
## 3 China
                 212258 213766
# from long to wide
table4a %>%
  gather('1999', '2000', key = "year", value = "population")
```

```
## # A tibble: 6 x 3
##
     country year population
##
     <chr>
                <chr>
## 1 Afghanistan 1999
                             745
## 2 Brazil 1999
                           37737
## 3 China
              1999
                          212258
## 4 Afghanistan 2000
                            2666
## 5 Brazil
                2000
                           80488
## 6 China
                 2000
                           213766
# save the file
table4a_wide <- table4a %>%
  gather('1999', '2000', key = "year", value = "population")
4.1.2. Spread (from wide to long)
table4a wide %>%
  spread(key = "year", value = "population")
## # A tibble: 3 x 3
     country `1999` `2000`
##
##
     <chr>
                 <int> <int>
## 1 Afghanistan
                 745 2666
## 2 Brazil
                 37737 80488
## 3 China
                212258 213766
4.1.3. Separate (split one into many columns)
table3
## # A tibble: 6 x 3
## country year rate
## * <chr>
                 <int> <chr>
## 1 Afghanistan 1999 745/19987071
## 2 Afghanistan 2000 2666/20595360
## 3 Brazil 1999 37737/172006362
              2000 80488/174504898
1999 212258/1272915272
## 4 Brazil
## 5 China
## 6 China
                 2000 213766/1280428583
table3 %>%
  separate(rate, into = c("cases" , "population"))
## # A tibble: 6 x 4
## country year cases population
## * <chr>
                <int> <chr> <chr>
## 1 Afghanistan 1999 745
                              19987071
## 2 Afghanistan 2000 2666
                             20595360
## 3 Brazil 1999 37737 172006362
             2000 80488 174504898
1999 212258 1272915272
2000 213766 1280428522
## 4 Brazil
## 5 China
## 6 China
                 2000 213766 1280428583
```

#### 4.1.4. Unite

# 4.2. Visualization

Will be covered in the future session.

# 4.3. Modeling

Will not be extensively covered in this course.