

R MIEF Skills Workshop

Session 2

January 14, 2026

Today

- Practice visualizations
- Learn how to:
 - Filter, mutate, group, and summarize data using Tidyverse functions
 - Reshape data using Tidyverse functions
- Be introduced to:
 - The concept of a "tidy" dataset
- Practice the above!

Practical Visualization Exercise

Using the World Values Survey Dataset

World Values Survey

Background

"The survey, which started in 1981, seeks to use the most rigorous, high-quality research designs in each country. The WVS consists of nationally representative surveys conducted in almost 100 countries which contain almost 90 percent of the world's population, using a common questionnaire. [...] WVS seeks to help scientists and policy makers understand changes in the beliefs, values and motivations of people throughout the world."

Survey Contents

- Social values, attitudes & stereotypes
- Societal well-being
- Social capital, trust and organizational membership
- Economic values
- Corruption
- Migration
- Post-materialist index
- Science & technology
- Religious values
- Security
- Ethical values & norms
- Political interest and political participation
- Political culture and political regimes
- Demography

Today's practical component

1. Successfully run the code in the `session_2_pt1.R` script
2. Attempt the challenges at the bottom of the script!

BREAK

Data 'Wrangling'

Tidyverse Introduction

Base R Layout

Tidyverse Layout

```
names(iris)
```

```
## [1] "Sepal.Length" "Sepal.Width"   "Petal.Length"  "Petal.Width"   "Species"
```

```
str_replace(str_to_lower(names(iris)), "\\.", "_")
```

```
## [1] "sepal_length" "sepal_width"   "petal_length"  "petal_width"   "species"
```

Tidyverse Introduction

Base R Layout

Tidyverse Layout

Tidyverse functions introduce a 'cleaner' method to write code out, using what is called the 'pipe operator': `%>%`. It's almost like writing a recipe, step by step.

```
names(iris)
```

```
## [1] "Sepal.Length" "Sepal.Width"    "Petal.Length"  "Petal.Width"   "Species"
```

```
iris %>%
  names() %>%
  str_to_lower() %>%
  str_replace("\.", "_")
```

```
## [1] "sepal_length" "sepal_width"   "petal_length" "petal_width"  "species"
```

Basic Wrangling Functions

filter() select() mutate()

filter() is used to **extract** rows (a.k.a. observations) from a dataset. It does so using a logical condition.

```
filter_example <- mtcars %>%  
  filter(wt > 3)
```

```
filter_example %>% head()
```

```
##          mpg cyl  disp  hp drat    wt  qsec vs am gear carb  
## Hornet 4 Drive 21.4   6 258.0 110 3.08 3.215 19.44  1  0    3    1  
## Hornet Sportabout 18.7   8 360.0 175 3.15 3.440 17.02  0  0    3    2  
## Valiant        18.1   6 225.0 105 2.76 3.460 20.22  1  0    3    1  
## Duster 360      14.3   8 360.0 245 3.21 3.570 15.84  0  0    3    4  
## Merc 240D       24.4   4 146.7  62 3.69 3.190 20.00  1  0    4    2  
## Merc 230        22.8   4 140.8  95 3.92 3.150 22.90  1  0    4    2
```

Basic Wrangling Functions

filter() **select()** mutate()

select() is used to **extract** columns (a.k.a variables) from a dataset. It does so using the variable(s)'s name.

```
select_example <- mtcars %>%
  select(
    mpg, carb
  )
select_example %>% head()
```

```
##                                     mpg carb
## Mazda RX4           21.0     4
## Mazda RX4 Wag      21.0     4
## Datsun 710          22.8     1
## Hornet 4 Drive      21.4     1
## Hornet Sportabout   18.7     2
## Valiant              18.1     1
```

Basic Wrangling Functions

filter() select() mutate()

mutate() can be used to either **create** a new column (a.k.a. variable) or to **modify** an existing column (a.k.a. variable).

```
mutate_example <- mtcars %>%
  mutate(
    heavy = case_when(
      wt > 3 ~ "Yes",
      TRUE ~ "No"
    )
  )
mutate_example %>% select(wt, heavy) %>% head()
```

```
##                               wt  heavy
## Mazda RX4           2.620   No
## Mazda RX4 Wag       2.875   No
## Datsun 710          2.320   No
## Hornet 4 Drive     3.215 Yes
## Hornet Sportabout  3.440 Yes
## Valiant            3.460 Yes
```

Basic Wrangling Functions

group_by() and summarize()

pivot_longer()

pivot_longer() result

pivot_wider()

pivot_wider() result

group_by() and summarize() are used to **aggregate** data, i.e. to summarize information to a different level of observation.

```
group_by_summarize_example <- mtcars %>%
  group_by(cyl) %>%
  summarize(
    mpg = mean(mpg, na.rm = TRUE)
  )
```

```
group_by_summarize_example
```

```
## # A tibble: 3 × 2
##       cyl   mpg
##   <dbl> <dbl>
## 1     4  26.7
## 2     6  19.7
## 3     8  15.1
```

Basic Wrangling Functions

group_by() and summarize()

pivot_longer()

pivot_longer() result

pivot_wider() pivot_wider() result

```
relig_income[1:6] %>% head(n = 2)
```

```
## # A tibble: 2 × 6
##   religion `<$10k` `'$10-20k` `'$20-30k` `'$30-40k` `'$40-50k`
##   <chr>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>
## 1 Agnostic     27       34       60       81       76
## 2 Atheist      12       27       37       52       35
```

```
relig_income_long ← relig_income %>%
  pivot_longer(
    cols      = !religion, # Everything but religion
    names_to = "levels",
    values_to = "num"
  )
```

Basic Wrangling Functions

group_by() and summarize()

pivot_longer()

pivot_longer() result

pivot_wider()

pivot_wider() result

```
relig_income[1:6] %>% head(n = 2)
```

```
## # A tibble: 2 × 6
##   religion `<$10k` `'$10-20k` `'$20-30k` `'$30-40k` `'$40-50k`
##   <chr>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>
## 1 Agnostic     27       34       60       81       76
## 2 Atheist      12       27       37       52       35
```

```
relig_income_long %>% head(n = 4)
```

```
## # A tibble: 4 × 3
##   religion levels    num
##   <chr>     <chr>    <dbl>
## 1 Agnostic <$10k      27
## 2 Agnostic $10-20k    34
## 3 Agnostic $20-30k    60
## 4 Agnostic $30-40k    81
```

Basic Wrangling Functions

group_by() and summarize() pivot_longer() pivot_longer() result

pivot_wider() pivot_wider() result

```
fish_encounters %>% head(n = 4)
```

```
## # A tibble: 4 × 3
##   fish station  seen
##   <fct> <fct>   <int>
## 1 4842  Release    1
## 2 4842  I80_1     1
## 3 4842  Lisbon     1
## 4 4842  Rstr       1
```

```
fish_encounters_wide ← fish_encounters %>%
  pivot_wider(
    names_from = station,
    values_from = seen
  )
```

Basic Wrangling Functions

group_by() and summarize() pivot_longer() pivot_longer() result

pivot_wider() pivot_wider() result

```
fish_encounters %>% head(n = 4)
```

```
## # A tibble: 4 × 3
##   fish station  seen
##   <fct> <fct>   <int>
## 1 4842  Release    1
## 2 4842  I80_1     1
## 3 4842  Lisbon     1
## 4 4842  Rstr       1
```

```
fish_encounters_wide[1:6] %>% head(n = 2)
```

```
## # A tibble: 2 × 6
##   fish  Release I80_1  Lisbon  Rstr Base_TD
##   <fct>   <int> <int>   <int> <int>   <int>
## 1 4842        1      1       1      1       1
## 2 4843        1      1       1      1       1
```

Working with 'Tidy' Datasets

```
table1
#> # A tibble: 6 x 4
#>   country     year   cases population
#>   <chr>     <int>   <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
```

```
table2
#> # A tibble: 12 x 4
#>   country     year   type     count
#>   <chr>     <int> <chr>     <int>
#> 1 Afghanistan 1999  cases      745
#> 2 Afghanistan 1999  population 19987071
#> 3 Afghanistan 2000  cases      2666
#> 4 Afghanistan 2000  population 20595360
#> 5 Brazil       1999  cases      37737
#> 6 Brazil       1999  population 172006362
#> # ... with 6 more rows
```

```
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
#> 4 Brazil       2000  80488/174504898
#> 5 China        1999  212258/1272915272
#> 6 China        2000  213766/1280428583

# Spread across two tibbles
table4a # cases
#> # A tibble: 3 x 3
#>   country     `1999` `2000`
#> * <chr>       <int>  <int>
#> 1 Afghanistan    745    2666
#> 2 Brazil         37737   80488
#> 3 China          212258  213766
table4b # population
#> # A tibble: 3 x 3
#>   country     `1999`     `2000`
#> * <chr>       <int>     <int>
#> 1 Afghanistan  19987071  20595360
#> 2 Brazil       172006362  174504898
#> 3 China        1272915272 1280428583
```

These are all useable versions of the same data. Only one of them, however, is 'tidy'.

What makes a dataset 'tidy'? From Hadley Wickham, Mine Çetinkaya-Rundel, and Garrett Grolemund, *R for Data Science (2e)* Chapter 5 – Tidy Tidying:

1. Each **variable** must have **its own column**.
2. Each **observation** must have **its own row**.
3. Each **value** must have **its own cell**.

Easier to think about when these conditions are *not* met:

- When one variable is spread across multiple columns.
- When one observation is scattered across multiple rows.

`table1` is the tidy version of this dataset. How can we convert the other versions to be tidy?

table2 table3 table4 table4 results

```
table2 %>% head(n = 2)

## # A tibble: 2 × 4
##   country     year type      count
##   <chr>       <dbl> <chr>      <dbl>
## 1 Afghanistan 1999 cases      745
## 2 Afghanistan 1999 population 19987071
```

```
table2 %>%
  pivot_wider(
    names_from = type,
    values_from = count
  ) %>% head(n = 4)

## # A tibble: 4 × 4
##   country     year cases population
##   <chr>       <dbl> <dbl>      <dbl>
## 1 Afghanistan 1999    745     19987071
## 2 Afghanistan 2000   2666     20595360
## 3 Brazil       1999  37737    172006362
## 4 Brazil       2000  80488    174504898
```

table2

table3

table4

table4 results

```
table3 %>% head(n = 2)
```

```
## # A tibble: 2 × 3
##   country     year    rate
##   <chr>       <dbl>  <chr>
## 1 Afghanistan 1999 745/19987071
## 2 Afghanistan 2000 2666/20595360
```

```
table3 %>%
  mutate(
    cases      = as.numeric(str_extract(rate, ".*(?=\\/))),
    population = as.numeric(str_extract(rate, "(?=<\\/).*"))
  ) %>% select(-rate) %>% head(n = 4)
```

```
## # A tibble: 4 × 4
##   country     year  cases population
##   <chr>       <dbl> <dbl>      <dbl>
## 1 Afghanistan 1999    745  19987071
## 2 Afghanistan 2000   2666  20595360
## 3 Brazil        1999  37737 172006362
## 4 Brazil        2000  80488 174504898
```

table2

table3

table4

table4 results

```
table4a %>% head(n = 2)
```

```
## # A tibble: 2 × 3
##   country     `1999` `2000`
##   <chr>        <dbl>   <dbl>
## 1 Afghanistan    745    2666
## 2 Brazil         37737  80488
```

```
table4b %>% head(n = 2)
```

```
## # A tibble: 2 × 3
##   country     `1999`     `2000`
##   <chr>        <dbl>      <dbl>
## 1 Afghanistan 19987071  20595360
## 2 Brazil       172006362 174504898
```

```
table4a %>%  
  pivot_longer(  
    cols      = c(`1999`, `2000`),  
    names_to  = "year",  
    values_to = "cases"  
  ) %>%  
  left_join(  
    table4b %>%  
      pivot_longer(  
        cols      = c(`1999`, `2000`),  
        names_to  = "year",  
        values_to = "population"  
      )  
  ) %>% head(n = 4)
```

```
## Joining with `by = join_by(country, year)`  
  
## # A tibble: 4 × 4  
##   country     year   cases population  
##   <chr>       <chr> <dbl>      <dbl>  
## 1 Afghanistan 1999     745  19987071  
## 2 Afghanistan 2000    2666  20595360  
## 3 Brazil       1999  37737  172006362  
## 4 Brazil       2000  80488  174504898
```

BREAK

Practical Exercise

Using the World Values Survey Dataset

World Values Survey

Background

"The survey, which started in 1981, seeks to use the most rigorous, high-quality research designs in each country. The WVS consists of nationally representative surveys conducted in almost 100 countries which contain almost 90 percent of the world's population, using a common questionnaire. [...] WVS seeks to help scientists and policy makers understand changes in the beliefs, values and motivations of people throughout the world."

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- Social values, attitudes & stereotypes
- Societal well-being
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- Religious values
- Security
- Ethical values & norms
- Political interest and political participation
- Political culture and political regimes
- Demography

Today's practical component

1. Successfully run the code in the `session_2_pt2.R` script
2. Create your own script and do the following:
 - Find mean values for 'importance in life' variables (Q1-6) for countries in another region than Europe
 - Calculate average 'enthusiasm' for these life subjects in countries in another region than Europe
 - Perform the same analysis, either on European countries or other countries, for another group of indicators in the dataset:
 - Important child qualities: Q7-18
 - Neighbors: Q19-26
 - Statements to agree with: Q27-41
 - Save one dataset for each of the tasks above.

NOTE — You should refer to documentation for the dataset, which can be found on [the course's landing page](#), for details on the variables and their given values.

Links

Dominic Royé, “[A very short introduction to Tidyverse](#)”

tidyr, “[Pivoting](#)”

Hadley Wickham, Mine Çetinkaya-Rundel & Garrett Grolemund, [R for Data Science, 2e](#)

RStudio, [RStudio Cheatsheets](#)