

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
```

table2

table3

table4

table4 results

```
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."

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_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: Q7-17
 - Neighbors: Q18-26
 - 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](#)