Session 3: Data Processing

R for Stata Users

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Goals of this session

- To organize data in a way that it will be easier to analyze it and communicate it.
- We'll use a set of packages that are bundled into something called the `tidyverse`.

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Goals of this session

- To organize data in a way that it will be easier to analyze it and communicate it.
- We'll use a set of packages that are bundled into something called the `tidyverse`.

Things to keep in mind

- We'll take you through the same steps we've taken when we were preparing the datasets.
- In most cases, your datasets won't be `tidy`.

> **Tidy data**: A dataset is said to be tidy if it satisfies the following conditions:
>
> 1. observations are in rows
> 2. variables are in columns
> 3. contained in a single dataset.

Takeaway: long format > wide format

Introduction

- In this session, you'll be introduced to some basic conceptos of data cleaning in R. We will cover:

1. Exploring a dataset;
2. Creating new variables;
3. Filtering and subsetting datasets;
4. Merging datasets;
5. Dealing with factor variables;
6. Saving data.

Introduction

- In this session, you'll be introduced to some basic conceptos of data cleaning in R. We will cover:

1. Exploring a dataset;
2. Creating new variables;
3. Filtering and subsetting datasets;
4. Merging datasets;
5. Dealing with factor variables;
6. Saving data.

> There are many other tasks that we usually perform as part of data cleaning that are beyond the scope of this session.

Introduction

- Before we start, let's makue sure we are all set:

1. Start a fresh session.
2. Load the tidyverse package.
3. Set your file paths.

Tidyverse packages

Let's load the tidyverse meta-package:

```
# If you haven't installed the package uncomment the next line
# install.package("tidyverse", dependencies = TRUE)

# Load packages
library(tidyverse)
library(janitor)
```

> Remember that you should always load your packages before your start coding.

File paths

For this session, my file paths are as follows. We will use them to load and export datasets.

```
# Example of my filepaths for this presentation
project           ← "D:/Documents/RA Jobs/DIME/trainings/dime-r-training"
dataWorkFolder    ← file.path(projectFolder,"DataWork")
Data              ← file.path(dataWorkFolder,"DataSets")
finalData         ← file.path(Data,"Final")
rawData           ← file.path(Data,"Raw")
rawOutput         ← file.path(dataWorkFolder,"Output","Raw")
```

Just in case: Check your R and RStudio versions

☑ R version:

```
version$version.string
```

```
## [1] "R version 4.0.3 (2020-10-10)"
```

☑ RStudio version:

```
# Use the following function to get the version: RStudio.Version()$version
# [1] '1.3.1073'
```

☑ Packages:

```
update.packages(ask = FALSE, checkBuilt = TRUE)
```

Loading a dataset in R

Before we start wrangling our data, let's read ourdataset. In R, we can use the `read.csv` function from Base R, or `read_csv` from the `readr` package if we want to load a CSV file. For this exercise, we are going to use the World Happiness Report (2015-2018)

Exercise 1: Load Data.

Use either of the functions mentioned above and load the three WHR datasets from the `DataWork/DataSets/Raw` folder. Use the following notation for each dataset: `whrYY`.

- Remember to sue `file.path()` to simplify the folder path.

Loading a dataset in R

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Exercise 1: Load Data.

Use either of the functions mentioned above and load the three WHR datasets from the `DataWork/DataSets/Raw` folder. Use the following notation for each dataset: `whrYY`.

- Remember to sue `file.path()` to simplify the folder path.

How to do it?

```
whr15 ← read_csv(file.path(rawData, "Un WHR" , "WHR2015.csv")) %>% clean_names()
whr16 ← read_csv(file.path(rawData, "Un WHR" , "WHR2016.csv")) %>% clean_names()
whr17 ← read_csv(file.path(rawData, "Un WHR" , "WHR2017.csv")) %>% clean_names()
```

> Notice the `clean_names()` function.

Load and show a dataset

We can just show our dataset using the name of the object; in this case, `census`.

```
whr15
```

```
## # A tibble: 158 x 12
##    country region happiness_rank happiness_score standard_error economy_gdp_per~
##    <chr>   <chr>           <dbl>           <dbl>          <dbl>             <dbl>
##  1 Switze~ Weste~              1            7.59         0.0341              1.40
##  2 Iceland Weste~              2            7.56         0.0488              1.30
##  3 Denmark Weste~              3            7.53         0.0333              1.33
##  4 Norway  Weste~              4            7.52         0.0388              1.46
##  5 Canada  North~              5            7.43         0.0355              1.33
##  6 Finland Weste~              6            7.41         0.0314              1.29
##  7 Nether~ Weste~              7            7.38         0.0280              1.33
##  8 Sweden  Weste~              8            7.36         0.0316              1.33
##  9 New Ze~ Austr~              9            7.29         0.0337              1.25
## 10 Austra~ Austr~             10            7.28         0.0408              1.33
## # ... with 148 more rows, and 6 more variables: family <dbl>,
## #   health_life_expectancy <dbl>, freedom <dbl>,
## #   trust_government_corruption <dbl>, generosity <dbl>,
## #   dystopia_residual <dbl>
```

Exploring your data

Exploring a data set

Some useful functions from base R:

- `View()`: open the data set
- `class()`: reports object type of type of data stored.
- `dim()`: reports the size of each one of an object's dimension.
- `names()`: returns the variable names of a dataset.
- `str()`: general information on an R object.
- `summary()`: summary information about the variables in a data frame.
- `head()`: shows the first few observations in the dataset.
- `tail()`: shows the last few observations in the dataset.

Some other useful functions from the tidyverse:

- `glimpse()`: get a glimpse of your data

Glimpse your data

This functions give your information about your variables (e.g., type, row, columns,)

```
whr15 %>%
  glimpse()
```

```
## Rows: 158
## Columns: 12
## $ country                    <chr> "Switzerland", "Iceland", "Denmark", "N ...
## $ region                     <chr> "Western Europe", "Western Europe", "We ...
## $ happiness_rank             <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,  ...
## $ happiness_score            <dbl> 7.587, 7.561, 7.527, 7.522, 7.427, 7.40 ...
## $ standard_error             <dbl> 0.03411, 0.04884, 0.03328, 0.03880, 0.0 ...
## $ economy_gdp_per_capita     <dbl> 1.39651, 1.30232, 1.32548, 1.45900, 1.3 ...
## $ family                     <dbl> 1.34951, 1.40223, 1.36058, 1.33095, 1.3 ...
## $ health_life_expectancy     <dbl> 0.94143, 0.94784, 0.87464, 0.88521, 0.9 ...
## $ freedom                    <dbl> 0.66557, 0.62877, 0.64938, 0.66973, 0.6 ...
## $ trust_government_corruption <dbl> 0.41978, 0.14145, 0.48357, 0.36503, 0.3 ...
## $ generosity                 <dbl> 0.29678, 0.43630, 0.34139, 0.34699, 0.4 ...
## $ dystopia_residual          <dbl> 2.51738, 2.70201, 2.49204, 2.46531, 2.4 ...
```

ID variables

ID variables

Desired properties of an ID variable: uniquely and fully identifying.

- An ID variable cannot have duplicates
- An ID variable may never be missing
- The ID variable must be constant across a project
- The ID variable must be anonymous

ID variables

Let's see first:

- **Dimensions of your data**:

```
dim(whr15)
```

```
## [1] 158  12
```

```
dim_desc(whr15)
```

```
## [1] "[158 x 12]"
```

- **The number of distinct values of a particular variable**:

```
n_distinct(DATASET$variable, na.rm = TRUE)
```

ID variables

In the last example, we used `n_distinct`. This allows us to count the number of unique values of a variablelength of a vector. We included `na.rm = TRUE`, so we don't count missing values.

ID variables

In the last example, we used `n_distinct`. This allows us to count the number of unique values of a variablelength of a vector. We included `na.rm = TRUE`, so we don't count missing values.

Exercise 2: Identify the ID.

Using the `n_distinct` function, can you tell if the following variables are IDs of the whr15 data set?

1. Region
2. Country

ID variables

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Exercise 2: Identify the ID.

Using the `n_distinct` function, can you tell if the following variables are IDs of the whr15 data set?

1. Region
2. Country

How to do it?

```
n_distinct(whr15$country, na.rm = TRUE)
```

```
## [1] 158
```

```
n_distinct(whr15$region, na.rm = TRUE)
```

```
## [1] 10
```

ID variables

We can also test whether the number of rows is equal to the number of distinct values in a specific variable as follows:

```
nrow(whr15)
```

```
## [1] 158
```

```
n_distinct(whr15$country, na.rm = TRUE) == nrow(whr15)
```

```
## [1] TRUE
```

```
n_distinct(whr16$country, na.rm = TRUE) == nrow(whr16)
```

```
## [1] TRUE
```

```
n_distinct(whr17$country, na.rm = TRUE) == nrow(whr17)
```

```
## [1] TRUE
```

Comparing two dataframes

setdiff(): Prints all the elements of the first object that are not in the second object (ignores duplicates).

We can use this function to see which countries are coming in and out of the WHR dataset set between 2015 and 2016. This function takes two arguments `setdiff(df1, df2)`:

Comparing two dataframes

Exercise 3: Compare vectors.

Use the setdiff() function to see which countries are coming in and out of the WHR data set between 2015 and 2016

Comparing two dataframes

Exercise 3: Compare vectors.

Use the setdiff() function to see which countries are coming in and out of the WHR data set between 2015 and 2016

How to do it

```
# Any countries in 2015 that are not in 2016?
setdiff(whr15$country, whr16$country)
```

```
## [1] "Oman"                  "Somaliland region"     "Mozambique"
## [4] "Lesotho"               "Swaziland"             "Djibouti"
## [7] "Central African Republic"
```

```
# And vice-versa
setdiff(whr16$country, whr15$country)
```

```
## [1] "Puerto Rico"       "Belize"            "Somalia"           "Somaliland Region" "Namibia"
## [6] "South Sudan"
```

Comparing two dataframes

Replacing values

You might notice in the last slide, that *Somaliland region* and *Somaliland Region* are not considered the same. We can fix this as follows using base R:

```
whr15$country[whr15$country == "Somaliland region"] <- "Somaliland Region"
```

Now, if run again `setdiff` again, we get:

```
# Any countries in 2015 that are not in 2016?
setdiff(whr15$country, whr16$country)
```

```
## [1] "Oman"                  "Mozambique"            "Lesotho"
## [4] "Swaziland"             "Djibouti"              "Central African Republic"
```

```
# And vice-versa
setdiff(whr16$country, whr15$country)
```

```
## [1] "Puerto Rico" "Belize"      "Somalia"     "Namibia"     "South Sudan"
```

Wrangling your data

dplyr::filter

Filter or subsetting a dataset.

```
whr15 %>%
  filter(region == "Western Europe",
         happiness_rank <= 10)
```

```
## # A tibble: 7 x 12
##   country region happiness_rank happiness_score standard_error economy_gdp_per~
##   <chr>   <chr>           <dbl>           <dbl>          <dbl>             <dbl>
## 1 Switze~ Weste~              1            7.59         0.0341              1.40
## 2 Iceland Weste~              2            7.56         0.0488              1.30
## 3 Denmark Weste~              3            7.53         0.0333              1.33
## 4 Norway  Weste~              4            7.52         0.0388              1.46
## 5 Finland Weste~              6            7.41         0.0314              1.29
## 6 Nether~ Weste~              7            7.38         0.0280              1.33
## 7 Sweden  Weste~              8            7.36         0.0316              1.33
## # ... with 6 more variables: family <dbl>, health_life_expectancy <dbl>,
## #   freedom <dbl>, trust_government_corruption <dbl>, generosity <dbl>,
## #   dystopia_residual <dbl>
```

dplyr::filter

Exercise 4: Filter the dataset.

- Use `filter()`
- Filter only for the regions: (1) Eastern Asia and (2) North America.

This would be the normal way to do it:

```
whr15 %>%
  filter(region == "Eastern Asia" | region == "North America")
```

dplyr::filter

Exercise 4: Filter the dataset.

- Use `filter()`
- Filter only for the regions: (1) Eastern Asia and (2) North America.

This would be the normal way to do it:

```
whr15 %>%
  filter(region == "Eastern Asia" | region == "North America")
```

A more elegant approach would be:

```
whr15 %>%
  filter(region %in% c("Eastern Asia", "North America"))
```

dplyr::filter regular expressions

One advantage of the filter command over Stata is that you can also integrate regular expressions in quite a better way. Let's say that we want to subset all regions' divisions that have `East` in their names. We can use the following:

```
whr15 %>%
  filter(grepl("America", region)) %>%
  head(5)
```

```
## # A tibble: 5 x 12
##   country region happiness_rank happiness_score standard_error economy_gdp_per~
##   <chr>   <chr>           <dbl>           <dbl>          <dbl>            <dbl>
## 1 Canada  North~              5            7.43         0.0355            1.33
## 2 Costa ~ Latin~             12            7.23         0.0445            0.956
## 3 Mexico  Latin~             14            7.19         0.0418            1.02
## 4 United~ North~             15            7.12         0.0384            1.39
## 5 Brazil  Latin~             16            6.98         0.0408            0.981
## # ... with 6 more variables: family <dbl>, health_life_expectancy <dbl>,
## #   freedom <dbl>, trust_government_corruption <dbl>, generosity <dbl>,
## #   dystopia_residual <dbl>
```

> Notice that I have used `head()` to show just the first 8 observations of the subset. If you want to save this subset you can assign it to an objet. For example `whr15_east <- + the code above`.

dplyr::filter missing cases

If case you want to remove the missing cases for a specif variable, you can use `!is.na()`. Now we have a dataset that contains information per region and division without missing values.

```
whr15 %>%
  filter(!is.na(region)) %>%
  head(5)
```

```
## # A tibble: 5 x 12
##   country region happiness_rank happiness_score standard_error economy_gdp_per~
##   <chr>   <chr>           <dbl>           <dbl>          <dbl>             <dbl>
## 1 Switze~ Weste~              1            7.59         0.0341              1.40
## 2 Iceland Weste~              2            7.56         0.0488              1.30
## 3 Denmark Weste~              3            7.53         0.0333              1.33
## 4 Norway  Weste~              4            7.52         0.0388              1.46
## 5 Canada  North~              5            7.43         0.0355              1.33
## # ... with 6 more variables: family <dbl>, health_life_expectancy <dbl>,
## #   freedom <dbl>, trust_government_corruption <dbl>, generosity <dbl>,
## #   dystopia_residual <dbl>
```

> Notice that we are negating a function, i.e., !
> In case we want to keep the observations that contains missing information we will only use `is.na()`.

Other relevant functions: slice, subset, select

Arrange | Slice | Select | Combining functions

`Arrange`: allows you to order by a specific column.

```
whr15 %>%
  arrange(region, country) %>%
  head(5)
```

```
## # A tibble: 5 x 12
##   country region happiness_rank happiness_score standard_error economy_gdp_per~
##   <chr>   <chr>           <dbl>           <dbl>          <dbl>             <dbl>
## 1 Austra~ Austr~             10            7.28         0.0408             1.33
## 2 New Ze~ Austr~              9            7.29         0.0337             1.25
## 3 Albania Centr~             95            4.96         0.0501             0.879
## 4 Armenia Centr~            127            4.35         0.0476             0.768
## 5 Azerba~ Centr~             80            5.21         0.0336             1.02
## # ... with 6 more variables: family <dbl>, health_life_expectancy <dbl>,
## #   freedom <dbl>, trust_government_corruption <dbl>, generosity <dbl>,
## #   dystopia_residual <dbl>
```

Creating new variables

Creating new variables

In the tidyverse, we refer to creating variables as mutating

So, instead of **gen**erate, we use `mutate()`. Let's say we want to have interactions:

```
whr15 %>%
  arrange(region, country, -happiness_rank) %>%
  mutate(
    hap_hle = happiness_score * health_life_expectancy,
  ) %>%
  select(country:happiness_score, health_life_expectancy, hap_hle) %>%
  head(5)
```

```
## # A tibble: 5 x 6
##   country   region      happiness_rank happiness_score health_life_expe~ hap_hle
##   <chr>     <chr>                <dbl>           <dbl>              <dbl>   <dbl>
## 1 Australia Australia ~             10            7.28              0.932    6.79
## 2 New Zeal~ Australia ~              9            7.29              0.908    6.62
## 3 Albania   Central an~             95            4.96              0.813    4.03
## 4 Armenia   Central an~            127            4.35              0.730    3.18
## 5 Azerbaij~ Central an~             80            5.21              0.640    3.34
```

Creating new variables: Dummy variables

```
whr15 %>%
  mutate(
    happiness_score_6 = (happiness_score > 6)
  )
```

Q Well, what do you think is happening to this variable?

Creating new variables: Dummy variables

```
whr15 %>%
  mutate(
    happiness_score_6 = (happiness_score > 6)
  )
```

Q Well, what do you think is happening to this variable?

A The variable we created contains either TRUE or FALSE.
If we want to have it as a numeric (1 or 0), we could include `as.numeric()`

Creating new variables: Dummy variables

```
whr15 %>%
  mutate(
    happiness_score_6 = (happiness_score > 6)
  )
```

Q Well, what do you think is happening to this variable?

A The variable we created contains either TRUE or FALSE.
If we want to have it as a numeric (1 or 0), we could include `as.numeric()`

```
whr15 %>%
  mutate(
    happiness_score_6 = as.numeric((happiness_score > 6))
  )
```

Creating new variables: Dummy variables

```
whr15 %>%
  mutate(
    happiness_score_6 = (happiness_score > 6)
  )
```

Q Well, what do you think is happening to this variable?

A The variable we created contains either TRUE or FALSE.
If we want to have it as a numeric (1 or 0), we could include `as.numeric()`

```
whr15 %>%
  mutate(
    happiness_score_6 = as.numeric((happiness_score > 6))
  )
```

Finally, instead of using a random number such as 6, we can do the following:

```
whr15 %>%
  mutate(
    happiness_high_mean = as.numeric((happiness_score > mean(happiness_score)))
  )
```

Using ifelse when creating a variable

We can also create a dummy variable with `ifelse` as follows:

```
whr15 %>%
  mutate(
    latin_america_car = ifelse(region == "Latin America and Caribbean", 1, 0)
  ) %>%
  arrange(-latin_america_car) %>%
  head(5)
```

```
## # A tibble: 5 x 13
##   country region happiness_rank happiness_score standard_error economy_gdp_per~ family health_life_exp~
##   <chr>   <chr>           <dbl>           <dbl>          <dbl>            <dbl>  <dbl>            <dbl>
## 1 Costa ~ Latin~             12            7.23         0.0445            0.956  1.24             0.860
## 2 Mexico  Latin~             14            7.19         0.0418            1.02   0.915            0.814
## 3 Brazil  Latin~             16            6.98         0.0408            0.981  1.23             0.697
## 4 Venezu~ Latin~             23            6.81         0.0648            1.04   1.26             0.721
## 5 Panama  Latin~             25            6.79         0.0491            1.06   1.20             0.797
## # ... with 5 more variables: freedom <dbl>, trust_government_corruption <dbl>, generosity <dbl>,
## #   dystopia_residual <dbl>, latin_america_car <dbl>
```

The way we use this function is as: `ifelse(test, yes, no)`. We can also use the `case_when()` function.

Some notes: mutate() vs transmute()

`mutate()` *vs* `transmute()`

Similar in nature but:

1. `mutate()` returns original and new columns (variables).
2. `transmute()` returns only the new columns (variables).

Creating variables by groups

Let's imagine now that we want to create a variable at the region level -- recal `bys gen` in Stata. In R, we can `group_by()` before we mutate. For example:

```
whr15 %>%
  arrange(country, region, happiness_score) %>%
  group_by(region) %>%
  mutate(
    mean_hap = mean(happiness_score)
  ) %>%
  select(country:happiness_score, mean_hap) %>%
  head(5)
```

```
## # A tibble: 5 x 5
## # Groups:   region [5]
##   country     region                          happiness_rank happiness_score mean_hap
##   <chr>       <chr>                                    <dbl>           <dbl>    <dbl>
## 1 Afghanistan Southern Asia                              153            3.58     4.58
## 2 Albania     Central and Eastern Europe                  95            4.96     5.33
## 3 Algeria     Middle East and Northern Africa             68            5.60     5.41
## 4 Angola      Sub-Saharan Africa                         137            4.03     4.20
## 5 Argentina   Latin America and Caribbean                 30            6.57     6.14
```

Creating multiple variables at the same type

With the new version of `dplyr`, we now can create multiple variables in an easier way. So, let's imagine that we want to estimate the mean value for the variables: white, black, black_free, black_slaves.

Across | Output

```
vars ← c("happiness_score", "health_life_expectancy", "trust_government_corruption")

whr15 %>%
  group_by(region) %>%
  summarize(
    across(all_of(vars), mean)
  )
```

Creating variables

Exercise 5: Create a variable called year that equals to the year of each dataframe .

- Use `mutate()`
- Remember to assign it to the same dataframe.

Creating variables

Exercise 5: Create a variable called year that equals to the year of each dataframe .

- Use `mutate()`
- Remember to assign it to the same dataframe.

How to do it?

```
whr15 ← whr15 %>%
  mutate(
    year = 2015
  )

whr16 ← whr16 %>%
  mutate(
    year = 2016
  )

whr17 ← whr17 %>%
  mutate(
    year = 2017
  )
```

Appending and merging data sets

Appending and merging data sets

Now that we can identify the observations, we can combine the data set. Here are tweo functions to append objects by row

```
rbind( ... )

bind_rows( ... )
```

Exercise 6: Append data sets.

- Use either functions to append the three WHR datasets:

How to do it?

```
bind_rows(whr15, whr16, whr17)
```

Appending and merging data sets

Now that we can identify the observations, we can combine the data set. Here are tweo functions to append objects by row

```
rbind( ... )

bind_rows( ... )
```

Exercise 6: Append data sets.

- Use either functions to append the three WHR datasets:

How to do it?

```
bind_rows(whr15, whr16, whr17)
```

> ***Notes***: One of the problems with binding rows like this is that, sometimes, columns compatibility is quite junky.

Appending and merging data sets

To be honest, the most important variable that we will need to include in the 2017 dataset is the region variable.

Exercise 7: Fixing our variables and appending the dfs correctly.

Exercise 7a:

- Create a region data frame from the `whr2015` that includes only the vars: country and region.

Appending and merging data sets

To be honest, the most important variable that we will need to include in the 2017 dataset is the region variable.

Exercise 7: Fixing our variables and appending the dfs correctly.

Exercise 7a:

- Create a region data frame from the `whr2015` that includes only the vars: country and region.

```
regions ← whr15 %>%
  select(country, region)
```

Appending and merging data sets

We can use the `left_join()` function merge two dataframes. We could either use pipes or just `left_join(df1, df2)`.

Appending and merging data sets

We can use the `left_join()` function merge two dataframes. We could either use pipes or just `left_join(df1, df2)`.

Exercise 7b:

- Now, we join the `regions` dataframe with the `whr17` dataframe.

Appending and merging data sets

We can use the `left_join()` function merge two dataframes. We could either use pipes or just `left_join(df1, df2)`.

Exercise 7b:

- Now, we join the `regions` dataframe with the `whr17` dataframe.

```
whr17 ← whr17 %>%
  left_join(regions) %>%
  select(country, region, everything())
```

```
## Joining, by = "country"
```

> ***Notes***: Look at the everything() function. It takes all the variables.

Appending and merging data sets

But unfortunately, some countries were not in the whr15 data.

```
whr17 %>%
  filter(is.na(region))
```

```
## # A tibble: 0 x 14
## # ... with 14 variables: country <chr>, region <chr>, happiness_rank <dbl>,
## #   happiness_score <dbl>, whisker_high <dbl>, whisker_low <dbl>,
## #   economy_gdp_per_capita <dbl>, family <dbl>, health_life_expectancy <dbl>,
## #   freedom <dbl>, generosity <dbl>, trust_government_corruption <dbl>,
## #   dystopia_residual <dbl>, year <dbl>
```

Appending and merging data sets

Let's fix these six countries.

Appending and merging data sets

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- Taiwan and Hong Kong have different names. Let's use `case_when`:

```
whr17 ← whr17 %>%
  mutate(
    country = case_when(country == "Hong Kong S.A.R., China" ~ "Hong Kong",
                        country == "Taiwan Province of China" ~ "Taiwan",
                        TRUE ~ country)
  )
```

Appending and merging data sets

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- Taiwan and Hong Kong have different names. Let's use `case_when`:

```
whr17 ← whr17 %>%
  mutate(
    country = case_when(country == "Hong Kong S.A.R., China" ~ "Hong Kong",
                        country == "Taiwan Province of China" ~ "Taiwan",
                        TRUE ~ country)
  )
```

- Now, let's joing again the regions dataframe.

```
whr17 ← whr17 %>%
  select(-region) %>%
  left_join(regions) %>%
  select(country, region, everything())
```

```
## Joining, by = "country"
```

Appending and merging data sets

Exercise 7c:

Check if there is any other country without region info:

- Only use pipes %>%
- And `filter()`

Appending and merging data sets

Exercise 7c:

Check if there is any other country without region info:

- Only use pipes %>%
- And `filter()`

```
whr17 %>%
  filter(is.na(region))
```

```
## # A tibble: 4 x 14
##   country region happiness_rank happiness_score whisker_high whisker_low economy_gdp_per~ family
##   <chr>   <chr>           <dbl>           <dbl>        <dbl>       <dbl>            <dbl>  <dbl>
## 1 Belize  <NA>               50            5.96         6.20        5.71            0.908   1.08
## 2 Somalia <NA>               93            5.15         5.24        5.06            0.0226  0.721
## 3 Namibia <NA>              111            4.57         4.77        4.38            0.964   1.10
## 4 South ~ <NA>              147            3.59         3.73        3.46            0.397   0.601
## # ... with 6 more variables: health_life_expectancy <dbl>, freedom <dbl>, generosity <dbl>,
## #   trust_government_corruption <dbl>, dystopia_residual <dbl>, year <dbl>
```

Appending and merging data sets

We can get their info from the `whr16` dataset as follows

```
whr17 ← whr17 %>%
  left_join(
    whr16 %>%
      select(country, new_region = region),
    by = "country"
  ) %>%
  mutate(
    region = ifelse(is.na(region), as.character(new_region), region)
  ) %>%
  select(-new_region)
```

Appending and merging data sets

We can get their info from the `whr16` dataset as follows

```
whr17 ← whr17 %>%
  left_join(
    whr16 %>%
      select(country, new_region = region),
    by = "country"
  ) %>%
  mutate(
    region = ifelse(is.na(region), as.character(new_region), region)
  ) %>%
  select(-new_region)
```

Let's look at each of the parts of this pipe:

- `left_join()` and region is now called `new_region`.
- `mutate()` with the condition that if region is missing we assign the values from new region, if not we keep the og values.
- `select()` to eliminate new_region.

Appending and merging data sets

Any other country that still doesn't have region information?

Appending and merging data sets

Any other country that still doesn't have region information?

```
whr17 %>%
  filter(is.na(region))
```

```
## # A tibble: 0 x 14
## # ... with 14 variables: country <chr>, region <chr>, happiness_rank <dbl>, happiness_score <dbl>,
## #   whisker_high <dbl>, whisker_low <dbl>, economy_gdp_per_capita <dbl>, family <dbl>,
## #   health_life_expectancy <dbl>, freedom <dbl>, generosity <dbl>, trust_government_corruption <dbl>,
## #   dystopia_residual <dbl>, year <dbl>
```

Appending and merging data sets

Finally, let's keep those relevant variables first and bind those baby rows.

Exercise 8: Bind all rows and create a panel called: `whr_panel`.

- Use `rbind()`
- Select the variables: country, region, year, happiness_rank, happiness_score, economy_gdp_per_capita, health_life_expectancy, freedom for each df, i.e., 15,16,16.

```
keepvars ← c("country", "region", "year", "happiness_rank",
             "happiness_score", "economy_gdp_per_capita",
             "health_life_expectancy", "freedom")

whr15 ← select(whr15, all_of(keepvars))
whr16 ← select(whr16, all_of(keepvars))
whr17 ← select(whr17, all_of(keepvars))

whr_panel ← rbind(whr15, whr16, whr17)    # or bind_rows
```

Saving a dataset

Saving a dataset

- The data set you have now is the same data set we've been using for earlier sessions, so we can save it now
- As mentioned before, R data sets are often save as csv.
- To save a dataset we can use the `write_csv` function from the tidyverse, or `write.csv` from base R.

The function takes the following structure:

`write.csv(x, file, row.names = TRUE)`:

- `x:` the object (usually a data frame) you want to export to CSV
- `file:` the file path to where you want to save it, including the file name and the format (".csv")
- `row.names:` by default, R adds a column to the CSV file with the names (or numbers) of the rows in the data frame. Set it to `FALSE` if you don't want that column to be exported.

Saving a dataset

Exercise 9: Save the dataset.

- Use `write.csv()`
- Use `file.path()`

```
# Save the whr data set

write.csv(whr_panel,
          file.path(finalData,"whr_panel.csv"),
          row.names = FALSE)
```

Saving a dataset

Exercise 9: Save the dataset.

- Use `write.csv()`
- Use `file.path()`

```
# Save the whr data set

write.csv(whr_panel,
          file.path(finalData,"whr_panel.csv"),
          row.names = FALSE)
```

- The problem with CSVs is that they cannot differentiate between `strings` and `factors`
- They also don't save factor orders
- Data attributes (which are beyong the scope of this training, but also useful to document data sets) are also lost in csv data

Saving a dataset

The R equivalent of a `.dta` file is a `.Rds` file. It can be saved and loaded using the following commands:

- `saveRDS(object, file = "")`: Writes a single R object to a file.
- `readRDS(file)`: Load a single R object from a file.

```
# Save the data set

saveRDS(whr_panel, file = file.path(finalData, "whr_panel.Rds"))
```

Factor variables

Factor variables

- When we imported this data set, we told R explicitly to not read strings as factor.
- We did that because we knew that we'd have to fix the country names.
- The region variable, however, should be a factor.

```
str(whr_panel$region)
```

```
##  chr [1:470] "Western Europe" "Western Europe" "Western Europe" "Western Europe" "North America" ...
```

Factor variables

To create a factor variable, we use the `factor()` function (or `as_factor()` from the `forcats` package).

- `factor(x, levels, labels)` : turns numeric or string vector `x` into a factor vector.
- `levels`: a vector containing the possible values of `x`.
- `labels`: a vector of strings containing the labels you want to apply to your factor variable
- `ordered`: logical flag to determine if the levels should be regarded as ordered (in the order given).

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- `ordered`: logical flag to determine if the levels should be regarded as ordered (in the order given).

If your categorical variable does not need to be ordered, and your string variable already has the label you want, making the conversion is quite easy.

Factor variables

Exercise 10: Turn a string variable into a factor.

- Use the mutate function to create a variable called region_cat containing a categorical version of the region variable.
- TIP: to do this, you only need the first argument of the factor function.

Factor variables

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How to do it?

```
whr_panel ← mutate(whr_panel, region_cat = factor(region))
```

Factor variables

Exercise 10: Turn a string variable into a factor.

- Use the mutate function to create a variable called region_cat containing a categorical version of the region variable.
- TIP: to do this, you only need the first argument of the factor function.

How to do it?

```
whr_panel ← mutate(whr_panel, region_cat = factor(region))
```

And now we can check the class of our variable.

```
class(whr_panel$region_cat)
```

```
## [1] "factor"
```

Reshaping a dataset

Reshaping a dataset

Finally, let's try to reshape our dataset using the tidyverse functions. No more `reshape` from Stata. We can use `pivot_wider` or `pivot_longer`

Long to Wide | Wide to Long

```
whr_panel %>%
  select(country, region, year, happiness_score) %>%
  pivot_wider(
    names_from = year,
    values_from = happiness_score
  ) %>%
  head(5)
```

```
## # A tibble: 5 x 5
##   country     region         `2015` `2016` `2017`
##   <chr>       <chr>           <dbl>  <dbl>  <dbl>
## 1 Switzerland Western Europe   7.59   7.51   7.49
## 2 Iceland     Western Europe   7.56   7.50   7.50
## 3 Denmark     Western Europe   7.53   7.53   7.52
## 4 Norway      Western Europe   7.52   7.50   7.54
## 5 Canada      North America    7.43   7.40   7.32
```

Thank you~~