# Practice R

## Tutorial 05: Prepare Data

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### Prepare categorical variables

Welcome to the data preparation tutorial of the Practice R book (Treischl 2023). Practice R is a text book for the social sciences which provides several tutorials supporting students to learn R. Feel free to inspect the tutorials even if you are not familiar with the book, but keep in mind these tutorials are supposed to complement the Practice R book.

Chapter 5 was dedicated to support you to prepare data. We learned how to import, clean, and combine data. In addition, we got in touch with the `naniar` package which offers many functions to inspect missing values (Tierney et al. 2021); and I introduced the `forcats` package to prepare categorical variables for the analysis (Wickham 2022).

What preparation steps you need to apply is dependent on the data at hand and the analysis intended, which is why Chapter 5 provided a detailed overview of what happens under the hood when we import data. Keep in mind that RStudio has many cool features (e.g., data preview) to import data and packages such as `readr` helps us with this task:

```
# Import a csv file
library(readr)
my_data <- read_csv("path_to_the_file/data.csv")
```

Since I have no idea what your data looks, this tutorial will not focus on how to import and clean data. Instead, let's focus systematically on the `forcats` package. Suppose we started to analyze whether participant's income has an effect on their happiness, but we need to control for participant's educational background, religious beliefs, and if other categorical variables affect our estimation results. I already introduced several functions of the `forcats` package, but this tutorial systematically focuses on the main tasks of the package, as is outlined in its cheat sheet (click on the hex sticker to download the cheat sheet from the website).

Thus, we repeat and systematize our forcats skills: (1) We inspect factors; (2) change the order of levels; (3) change the value of levels; (4) and we add or drop levels. For this purpose, we use the `gss2016` data and I assigned a smaller subset as `df` with several categorical variables.

```
# Packages for Tutorial Nr. 5
library(naniar)
library(dplyr)
library(tidyr)
library(forcats)
library(PracticeR)

# The gss2016 data
df <- PracticeR::gss2016 |>
  select(id, degree, relig, income16, happy, marital)
head(df)
```

```
#> # A tibble: 6 x 6
#>      id degree         relig    income16         happy         marital
#>   <dbl> <fct>          <fct>    <fct>            <fct>         <fct>
#> 1     1 Bachelor       None     $170000 or over  Pretty Happy  Married
#> 2     2 High School    None     $50000 to 59999  Pretty Happy  Never Married
#> 3     3 Bachelor       Catholic $75000 to $89999 Very Happy    Married
#> 4     4 High School    Catholic $170000 or over  Pretty Happy  Married
#> 5     5 Graduate       None     $170000 or over  Very Happy    Married
#> 6     6 Junior College None     $60000 to 74999  Very Happy    Married
```

Finally, we transform and combine data once more given that such steps are often necessary before we can start to prepare data. However, this time we examine how built-in data sets from the `tidyr` and the `dplyr` package make the first move a bit easier.

## Inspect factors

Suppose we need to prepare several categorical variables, such as religion (`relig`) or marital status (`marital`), for an analysis. To inspect factors, count them with `fct_count()`.

```
# Count factor variable
fct_count(df$marital)
```

```
#> # A tibble: 6 x 2
#>   f                 n
#>   <fct>         <int>
```

```
#> 1 Married        1212
#> 2 Widowed         251
#> 3 Divorced        495
#> 4 Separated       102
#> 5 Never Married   806
#> 6 <NA>              1
```

Or examine the unique levels of a variable with the `fct_unique()` function:

```
# How many unique levels do we observe
fct_unique(df$marital)
```

```
#> [1] Married       Widowed       Divorced      Separated     Never Married
#> [6] <NA>
#> Levels: Married Widowed Divorced Separated Never Married
```

### Change the order of levels

The variable religion (`relig`) has 13 different levels. Let's assume we want to control for the largest religious groups only in the analysis. Use the `fct_infreq()` function to identify how often each level appears.

```
# fct_infreq: Reorder factor levels by frequency
f <- fct_infreq(df$relig)
fct_count(f)
```

```
#> # A tibble: 14 x 2
#>    f                           n
#>    <fct>                   <int>
#>  1 Protestant               1371
#>  2 Catholic                  649
#>  3 None                      619
#>  4 Jewish                     51
#>  5 Other                      44
#>  6 Christian                  40
#>  7 Buddhism                   21
#>  8 Moslem/Islam               19
#>  9 Hinduism                   13
#> 10 Orthodox-Christian          7
#> 11 Inter-Nondenominational     7
```

```
#> 12 Other Eastern                4
#> 13 Native American              4
#> 14 <NA>                        18
```

The `fct_infreq()` sorts them in order of their frequency, but note we can also order the levels by first appearance (`fct_inorder`) or in a numeric order (`fct_inseq`). As the next console illustrates, R sorts levels alphabetically, which is clearly not always a desirable default behavior. Use the `fct_inorder()` to sort them by appearance.

```r
# Example factor
f <- factor(c("b", "a", "c"))
levels(f)
```

```
#> [1] "a" "b" "c"
```

```r
# fct_inorder: Reorder factor levels by first appearance
fct_inorder(f)
```

```
#> [1] b a c
#> Levels: b a c
```

Can you still remember how to manually relevel? Use the `fct_relevel()` and sort the level `Never Married` at the second position. You can provide a vector with level names or use the `after` option to change the position of the level.

```r
# Relevel manually
# f <- fct_relevel(df$marital, c("Married", "Never Married"))
f <- fct_relevel(df$marital, "Never Married", after = 1)
fct_count(f)
```

```
#> # A tibble: 6 x 2
#>   f                 n
#>   <fct>         <int>
#> 1 Married        1212
#> 2 Never Married   806
#> 3 Widowed         251
#> 4 Divorced        495
#> 5 Separated       102
#> 6 <NA>              1
```

Sometimes we need to turn the order around. Reverse the order of the levels with `fct_rev()`.

```
# fct_rev: Reverse order of factor levels
f <- fct_rev(df$marital)
fct_count(f)
```

```
#> # A tibble: 6 x 2
#>   f                 n
#>   <fct>         <int>
#> 1 Never Married   806
#> 2 Separated       102
#> 3 Divorced        495
#> 4 Widowed         251
#> 5 Married        1212
#> 6 <NA>              1
```

### Change the value of levels

The `relig` variable has many levels and even has a category named `other`, since there are so many religious groups. The same logic applies the `fct_other()` function which collapses all levels but the one we actually need. Create a variable that includes the five largest groups only. Use the `fct_other()` function and tell R which variables to `keep`.

```
# Create a variable with the five largest, rest are others
df$relig5 <- fct_other(df$relig,
  keep = c("Protestant", "Catholic", "None", "Jewish")
)

fct_count(df$relig5)
```

```
#> # A tibble: 6 x 2
#>   f              n
#>   <fct>      <int>
#> 1 Protestant  1371
#> 2 Catholic     649
#> 3 Jewish        51
#> 4 None         619
#> 5 Other        159
#> 6 <NA>          18
```

The `fct_other()` function includes in the code the used levels. If we are unconcerned about this information, you can use one of the `fct_lump()` functions. The function picks between different methods to lump together factor levels. Nowadays the authors recommend to use one of the specific `fct_lump_*` functions (`fct_lump_min`, `fct_lump_prop`, `fct_lump_lowfreq`) as outlined in the help file. In our case, use the `fct_lump_n()` function to lump together the most frequent (`n`) ones.

```
# Lump uncommon factor together levels into "other"
f <- fct_lump_n(df$relig, n = 5, other_level = "Further groups")
fct_count(f)
```

```
#> # A tibble: 7 x 2
#>   f                  n
#>   <fct>          <int>
#> 1 Protestant      1371
#> 2 Catholic         649
#> 3 Jewish            51
#> 4 None             619
#> 5 Other             44
#> 6 Further groups   115
#> 7 <NA>              18
```

Next, we are going to prepare the educational background. The variable `degree` includes several levels, as the console shows.

```
# Count degrees
fct_count(df$degree)
```

```
#> # A tibble: 6 x 2
#>   f                  n
#>   <fct>          <int>
#> 1 Lt High School   328
#> 2 High School     1461
#> 3 Junior College   216
#> 4 Bachelor         536
#> 5 Graduate         318
#> 6 <NA>               8
```

We already used the `fct_recode()` function to change factor levels by hand. The lowest category of `degree` is called *less than high school* but the text label is confusing. Recode the variable, insert the new label in back ticks to replace the old label (`Lt High School`).

```r
# fct_recode: Change factor levels by hand
f <- fct_recode(df$degree, `Less than high school` = "Lt High School")
fct_count(f)
```

```
#> # A tibble: 6 x 2
#>   f                         n
#>   <fct>                 <int>
#> 1 Less than high school   328
#> 2 High School            1461
#> 3 Junior College          216
#> 4 Bachelor                536
#> 5 Graduate                318
#> 6 <NA>                      8
```

Suppose we want to control only if participants have a high educational background. Use the `fct_collapse()` function to create a binary dummy variable. The variable should indicate if a person's educational background is low (`Lt High School`; `High School`, and `Junior College`) or high (`Bachelor` and `Graduate`).

```r
# Collapse factor variable
df$edu_dummy <- fct_collapse(df$degree,
  low = c(
    "Lt High School",
    "High School",
    "Junior College"
  ),
  high = c("Bachelor", "Graduate")
)

fct_count(df$edu_dummy)
```

```
#> # A tibble: 3 x 2
#>   f         n
#>   <fct> <int>
#> 1 low    2005
#> 2 high    854
#> 3 <NA>      8
```

### Add or drop levels

As always, the `forcats` package has more to offer than I can outline. For example, suppose we observed the following `religion` variable.

```
# New religion variable
religion <- factor(
  x = c("Protestant", "Jewish", NA, NA),
  levels = c("Protestant", "Jewish", "Catholic")
)

religion
```

```
#> [1] Protestant Jewish     <NA>       <NA>
#> Levels: Protestant Jewish Catholic
```

Did you notice that the variable has a level for `Catholic` even though we do not observe it. The `fct_expand()` can be used to expand levels, while the `fct_drop()` function helps us to get rid of unused levels.

```
# Drop unused levels
fct_drop(religion)
```

```
#> [1] Protestant Jewish     <NA>       <NA>
#> Levels: Protestant Jewish
```

Furthermore, I included missing values on purpose and the latter may have an impact on our analysis. We can make them explicit and include them as a level with `fct_na_value_to_level()`.

```
# Make NAs explicit
fct_na_value_to_level(religion, level = "Missing")
```

```
#> [1] Protestant Jewish     Missing    Missing
#> Levels: Protestant Jewish Catholic Missing
```

### Further steps

Chapter 5 discussed many steps to prepare data, but of course this was not an all-encompassing list. I introduced data formats and we learned how to combine data given that many official data sets are split into several files. Unfortunately, transforming and combining data can be tricky and we may introduce mistakes if we neglected to prepare and clean the data properly. Thus, it is up to you to assure that the data can be transformed (combined) and further cleaning steps might be necessary.

Instead of re-running these steps with the `gss2016` data, let us explore how the `tidyr` package can help with the task (Wickham and Girlich 2022). As other packages, `tidyr` has a cheat sheet and provides a tiny data set that lets us repeat how the functions work. For example, the `table4a` data is a wide data set with observations of three countries and two years.

```
# Example wide table
head(table4a)
```

```
#> # A tibble: 3 x 3
#>   country     `1999` `2000`
#>   <chr>        <dbl>  <dbl>
#> 1 Afghanistan    745   2666
#> 2 Brazil       37737  80488
#> 3 China       212258 213766
```

Use the `pivot_longer()` function to transform the data. The long data should have a new variable for the `year` (via `names_to`) and you can give the values (`values_to`) to a variable named `cases`.

```
# Make em longer
pivot_longer(table4a,
  cols = 2:3, names_to = "year",
  values_to = "cases"
)
```

```
#> # A tibble: 6 x 3
#>   country     year   cases
#>   <chr>       <chr>  <dbl>
#> 1 Afghanistan 1999     745
#> 2 Afghanistan 2000    2666
#> 3 Brazil      1999   37737
#> 4 Brazil      2000   80488
#> 5 China       1999  212258
#> 6 China       2000  213766
```

Or consider the `table2` data, the variable `type` has two outcome types (`cases` and `population`) which underline why we should transform the data into the wide format.

```
# Example long table
head(table2)
```

```
#> # A tibble: 6 x 4
#>   country      year type            count
#>   <chr>       <dbl> <chr>           <dbl>
#> 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
```

Keep in mind that we need to provide *where* the names (`names_from`) and the values (`values_from`) are coming from to transform the data.

```
# Make it wider
pivot_wider(table2,
  names_from = type,
  values_from = count
)
```

```
#> # A tibble: 6 x 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
#> 5 China        1999 212258 1272915272
#> 6 China        2000 213766 1280428583
```

I introduced these data sets because `tidyr` offers such simple examples in the cheat sheet that demonstrates how we can transform data. In addition, the `copycat` package has the code snippets from the `tidyverse` cheat sheets included. As the animation shows, it only takes a few seconds to insert these examples via the add-in. Start with such a simple example if you do not transform and combine data on a regular basis. After you made sure that the code works, adjust it for your purpose, but be careful how the data is transformed.

The same applies if you need to combine data. The `dplyr` also offers a small data set to practice mutating joins (Wickham et al. 2022). The `band_members` data includes `names` from members of two different music bands; and the `band_instruments` data includes their instruments.

```
# Small data to recapture the join_* functions
band_members
```

```
#> # A tibble: 3 x 2
#>   name  band
#>   <chr> <chr>
#> 1 Mick  Stones
#> 2 John  Beatles
#> 3 Paul  Beatles
```

```
band_instruments
```

```
#> # A tibble: 3 x 2
#>   name  plays
#>   <chr> <chr>
#> 1 John  guitar
#> 2 Paul  bass
#> 3 Keith guitar
```

Use one of the `join` function (e.g., `inner_join`, `full_join`) to combine the data.

```
# Mutating joins
band_members |> inner_join(band_instruments, by = "name")
```

```
#> # A tibble: 2 x 3
#>   name  band    plays
#>   <chr> <chr>   <chr>
#> 1 John  Beatles guitar
#> 2 Paul  Beatles bass
```

```
band_members |> full_join(band_instruments, by = "name")
```

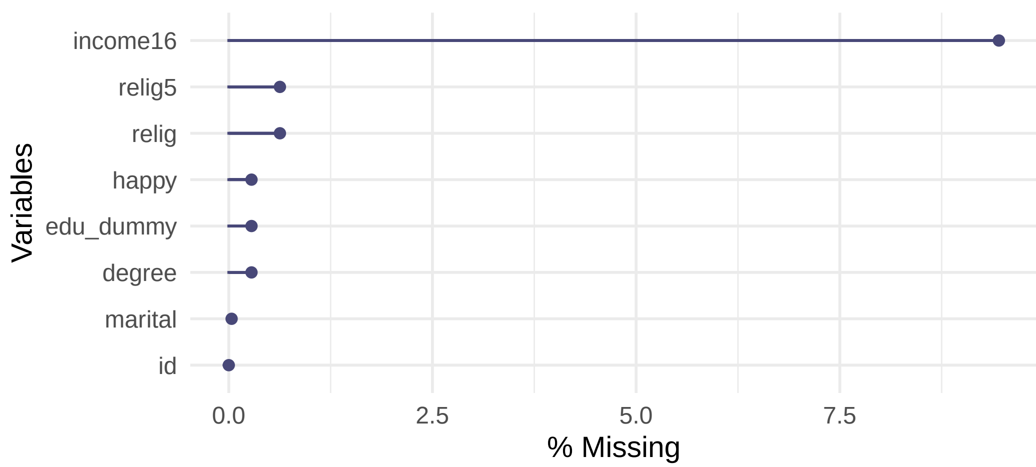
```
#> # A tibble: 4 x 3
#>   name  band    plays
#>   <chr> <chr>   <chr>
```

```
#> 1 Mick  Stones  <NA>
#> 2 John  Beatles guitar
#> 3 Paul  Beatles bass
#> 4 Keith <NA>    guitar

# Further joins:
# band_members |> left_join(band_instruments)
# band_members |> right_join(band_instruments)
```

Finally, one last word about missing values: make sure you explore the data before you run an analysis, but don't neglect to inspect missing and implausible values as well. The `naniar` package has a lot to offer for this task and of course I did not introduce everything it is capable of in Chapter 5. For example, we used the `vis_miss()` function to visualize missing values, but not the amount of missing values. Give the `gg_miss_var()` function a try. It returns a lollipop chart to visualize the amount of missing values. To display percentages, set the `show_pct` option to `TRUE`.

```
# Visualize the amount of missing values
library(naniar)
gg_miss_var(df, show_pct = TRUE)
```




## Summary

In addition to the discussed content, keep the following R functions and packages in mind:

- Import data with different packages. For example:

  - CSV with the `readr` package (Wickham, Hester, and Bryan 2022)
  - Excel with the `readxl` package (Wickham and Bryan 2022)
  - SPSS or Stata with the `haven` package (Wickham, Miller, and Smith 2022)

- Convert objects into numeric (character) vectors (`as.numeric, as.character`)
- Rename columns (`dplyr::rename`)
- Cleans names of an object (`janitor::clean_names`: Firke 2021)
- Combine data:

  - Pivot data from long to wide (`tidyr::pivot_wider`)
  - Pivot data from wide to long (`tidyr::pivot_longer`)
  - Mutating joins (`dplyr::inner_join, left_join, right_join, full_join`)
  - Filtering joins (`dplyr::semi_join, anti_join`)
  - Set pperations (`base::union, intersect, setdiff, setequal`)

- Missing (and implausible) values:

  - The `naniar` package and its function to explore missing values (e.g., `n_miss, n_complete, vis_miss`)
  - Check if something is not available (e.g., `base::is.na`)
  - Convert values to NA (`dplyr::na_if`)
  - Drop rows containing missing values (`tidyr::drop_na`)
  - Replace NAs with specified values (`tidyr::replace_na`)

## References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