Data Wrangling with dplyr and tidyr

Overview

Teaching: 50 min
Exercises: 30 min
Questions

- How can I select specific rows and/or columns from a dataframe?
- How can I combine multiple commands into a single command?
- How can I create new columns or remove existing columns from a dataframe?
- How can I reformat a dataframe to meet my needs?

Objectives

- Describe the purpose of an R package and the **`dplyr`** and **`tidyr`** packages.
- Select certain columns in a dataframe with the **`dplyr`** function `select`.
- Select certain rows in a dataframe according to filtering conditions with the **`dplyr`** function `filter`.
- Link the output of one **`dplyr`** function to the input of another function with the 'pipe' operator `%>%`.
- Add new columns to a dataframe that are functions of existing columns with `mutate`.
- Use the split-apply-combine concept for data analysis.
- Use `summarize`, `group_by`, and `count` to split a dataframe into groups of observations, apply a summary statistics for each group, and then combine the results.
- Describe the concept of a wide and a long table format and for which purpose those formats are useful.
- Describe the roles of variable names and their associated values when a table is reshaped.
- Reshape a dataframe from long to wide format and back with the `pivot_wider` and `pivot_longer` commands from the **`tidyr`** package.
- Export a dataframe to a csv file.

`dplyr` is a package for making tabular data wrangling easier by using a limited set of functions that can be combined to extract and summarize insights from your data. It pairs nicely with **`tidyr`** which enables you to swiftly convert between different data formats (long vs. wide) for plotting and analysis.

Similarly to **`readr`**, **`dplyr`** and **`tidyr`** are also part of the tidyverse. These packages were loaded in R's memory when we called `library(tidyverse)` earlier.

Note

The packages in the tidyverse, namely **`dplyr`**, **`tidyr`** and **`ggplot2`** accept both the British (e.g. *summarise*) and American (e.g. *summarize*) spelling variants of different function and option names. For this lesson, we utilize the American spellings of different functions; however, feel free to use the regional variant for where you are teaching.

What is an R package?

The package **`dplyr`** provides easy tools for the most common data wrangling tasks. It is built to work directly with dataframes, with many common tasks optimized by being written in a compiled language (C++) (not all R packages are written in R!).

The package **`tidyr`** addresses the common problem of wanting to reshape your data for plotting and use by different R functions. Sometimes we want data sets where we have one row per measurement. Sometimes we want a dataframe where each measurement type has its own column, and rows are instead more aggregated groups. Moving back and forth between these formats is nontrivial, and **`tidyr`** gives you tools for this and more sophisticated data wrangling.

But there are also packages available for a wide range of tasks including building plots (**`ggplot2`**, which we'll see later), downloading data from the NCBI database, or performing statistical analysis on your data set. Many packages such as these are housed on, and downloadable from, the **C**omprehensive **R** **A**rchive **N**etwork (CRAN) using `install.packages`. This function makes the package accessible by your R installation with the command `library()`, as you did with `tidyverse` earlier.

To easily access the documentation for a package within R or RStudio, use `help(package = "package_name")`.

To learn more about **`dplyr`** and **`tidyr`** after the workshop, you may want to check out this handy data transformation with **`dplyr`** cheatsheet (https://raw.githubusercontent.com/rstudio/cheatsheets/main/data-transformation.pdf) and this one about **`tidyr`** (https://raw.githubusercontent.com/rstudio/cheatsheets/main/tidyr.pdf).

Learning `dplyr` and `tidyr`

To make sure everyone will use the same dataset for this lesson, we'll read again the SAFI dataset that we downloaded earlier.

R

```r
## load the tidyverse
library(tidyverse)
library(here)

interviews <- read_csv(here("data", "SAFI_clean.csv"), na = "NULL")

## inspect the data
interviews

## preview the data
# view(interviews)
```

We're going to learn some of the most common **`dplyr`** functions:

- `select()` : subset columns
- `filter()` : subset rows on conditions
- `mutate()` : create new columns by using information from other columns
- `group_by()` and `summarize()` : create summary statistics on grouped data
- `arrange()` : sort results
- `count()` : count discrete values

Selecting columns and filtering rows

To select columns of a dataframe, use `select()` . The first argument to this function is the dataframe (`interviews`), and the subsequent arguments are the columns to keep, separated by commas. Alternatively, if you are selecting columns adjacent to each other, you can use a `:` to select a range of columns, read as "select columns from ___ *to* ___." You may have done something similar in the past using subsetting. `select()` is essentially doing the same thing as subsetting, using a package (`dplyr`) instead of R's base functions.

R

```r
# to select columns throughout the dataframe
select(interviews, village, no_membrs, months_lack_food)
# to do the same thing with subsetting
interviews[c("village","no_membrs","months_lack_food")]
# to select a series of connected columns
select(interviews, village:respondent_wall_type)
```

To choose rows based on specific criteria, we can use the `filter()` function. The argument after the dataframe is the condition we want our final dataframe to adhere to (e.g. village name is Chirodzo):

R

```r
# filters observations where village name is "Chirodzo"
filter(interviews, village == "Chirodzo")
```

Output

```
# A tibble: 39 × 14
   key_ID village interview_date      no_membrs years_liv respondent_wall… rooms
    <dbl> <chr>   <dttm>                  <dbl>     <dbl> <chr>            <dbl>
 1      8 Chirod… 2016-11-16 00:00:00        12        70 burntbricks          3
 2      9 Chirod… 2016-11-16 00:00:00         8         6 burntbricks          1
 3     10 Chirod… 2016-12-16 00:00:00        12        23 burntbricks          5
 4     34 Chirod… 2016-11-17 00:00:00         8        18 burntbricks          3
 5     35 Chirod… 2016-11-17 00:00:00         5        45 muddaub              1
 6     36 Chirod… 2016-11-17 00:00:00         6        23 sunbricks            1
 7     37 Chirod… 2016-11-17 00:00:00         3         8 burntbricks          1
 8     43 Chirod… 2016-11-17 00:00:00         7        29 muddaub              1
 9     44 Chirod… 2016-11-17 00:00:00         2         6 muddaub              1
10     45 Chirod… 2016-11-17 00:00:00         9         7 muddaub              1
# … with 29 more rows, and 7 more variables: memb_assoc <chr>,
#   affect_conflicts <chr>, liv_count <dbl>, items_owned <chr>, no_meals <dbl>,
#   months_lack_food <chr>, instanceID <chr>
```

We can also specify multiple conditions within the `filter()` function. We can combine conditions using either "and" or "or" statements. In an "and" statement, an observation (row) must meet **every** criteria to be included in the resulting dataframe. To form "and" statements within dplyr, we can pass our desired conditions as arguments in the `filter()` function, separated by commas:

R

```
# filters observations with "and" operator (comma)
# output dataframe satisfies ALL specified conditions
filter(interviews, village == "Chirodzo",
                   rooms > 1,
                   no_meals > 2)
```

Output

```
# A tibble: 10 × 14
   key_ID village interview_date      no_membrs years_liv respondent_wall… rooms
    <dbl> <chr>   <dttm>                  <dbl>     <dbl> <chr>            <dbl>
 1     10 Chirod… 2016-12-16 00:00:00        12        23 burntbricks          5
 2     49 Chirod… 2016-11-16 00:00:00         6        26 burntbricks          2
 3     52 Chirod… 2016-11-16 00:00:00        11        15 burntbricks          3
 4     56 Chirod… 2016-11-16 00:00:00        12        23 burntbricks          2
 5     65 Chirod… 2016-11-16 00:00:00         8        20 burntbricks          3
 6     66 Chirod… 2016-11-16 00:00:00        10        37 burntbricks          3
 7     67 Chirod… 2016-11-16 00:00:00         5        31 burntbricks          2
 8     68 Chirod… 2016-11-16 00:00:00         8        52 burntbricks          3
 9    199 Chirod… 2017-06-04 00:00:00         7        17 burntbricks          2
10    200 Chirod… 2017-06-04 00:00:00         8        20 burntbricks          2
# … with 7 more variables: memb_assoc <chr>, affect_conflicts <chr>,
#   liv_count <dbl>, items_owned <chr>, no_meals <dbl>, months_lack_food <chr>,
#   instanceID <chr>
```

We can also form "and" statements with the `&` operator instead of commas:

R

```
# filters observations with "&" logical operator
# output dataframe satisfies ALL specified conditions
filter(interviews, village == "Chirodzo" &
                   rooms > 1 &
                   no_meals > 2)
```

Output

```
# A tibble: 10 × 14
   key_ID village interview_date      no_membrs years_liv respondent_wall… rooms
    <dbl> <chr>   <dttm>                  <dbl>     <dbl> <chr>            <dbl>
 1     10 Chirod… 2016-12-16 00:00:00        12        23 burntbricks          5
 2     49 Chirod… 2016-11-16 00:00:00         6        26 burntbricks          2
 3     52 Chirod… 2016-11-16 00:00:00        11        15 burntbricks          3
 4     56 Chirod… 2016-11-16 00:00:00        12        23 burntbricks          2
 5     65 Chirod… 2016-11-16 00:00:00         8        20 burntbricks          3
 6     66 Chirod… 2016-11-16 00:00:00        10        37 burntbricks          3
 7     67 Chirod… 2016-11-16 00:00:00         5        31 burntbricks          2
 8     68 Chirod… 2016-11-16 00:00:00         8        52 burntbricks          3
 9    199 Chirod… 2017-06-04 00:00:00         7        17 burntbricks          2
10    200 Chirod… 2017-06-04 00:00:00         8        20 burntbricks          2
# … with 7 more variables: memb_assoc <chr>, affect_conflicts <chr>,
#   liv_count <dbl>, items_owned <chr>, no_meals <dbl>, months_lack_food <chr>,
#   instanceID <chr>
```

In an "or" statement, observations must meet *at least one* of the specified conditions. To form "or" statements we use the logical operator for "or," which is the vertical bar (|):

R

```
# filters observations with "|" logical operator
# output dataframe satisfies AT LEAST ONE of the specified conditions
filter(interviews, village == "Chirodzo" | village == "Ruaca")
```

Output

```
# A tibble: 88 × 14
   key_ID village interview_date      no_membrs years_liv respondent_wall… rooms
    <dbl> <chr>   <dttm>                  <dbl>     <dbl> <chr>            <dbl>
 1      8 Chirod… 2016-11-16 00:00:00        12        70 burntbricks          3
 2      9 Chirod… 2016-11-16 00:00:00         8         6 burntbricks          1
 3     10 Chirod… 2016-12-16 00:00:00        12        23 burntbricks          5
 4     23 Ruaca   2016-11-21 00:00:00        10        20 burntbricks          4
 5     24 Ruaca   2016-11-21 00:00:00         6         4 burntbricks          2
 6     25 Ruaca   2016-11-21 00:00:00        11         6 burntbricks          3
 7     26 Ruaca   2016-11-21 00:00:00         3        20 burntbricks          2
 8     27 Ruaca   2016-11-21 00:00:00         7        36 burntbricks          2
 9     28 Ruaca   2016-11-21 00:00:00         2         2 muddaub              1
10     29 Ruaca   2016-11-21 00:00:00         7        10 burntbricks          2
# … with 78 more rows, and 7 more variables: memb_assoc <chr>,
#   affect_conflicts <chr>, liv_count <dbl>, items_owned <chr>, no_meals <dbl>,
#   months_lack_food <chr>, instanceID <chr>
```

Pipes

What if you want to select and filter at the same time? There are three ways to do this: use intermediate steps, nested functions, or pipes.

With intermediate steps, you create a temporary dataframe and use that as input to the next function, like this:

R

```
interviews2 <- filter(interviews, village == "Chirodzo")
interviews_ch <- select(interviews2, village:respondent_wall_type)
```

This is readable, but can clutter up your workspace with lots of objects that you have to name individually. With multiple steps, that can be hard to keep track of.

You can also nest functions (i.e. one function inside of another), like this:

R

```
interviews_ch <- select(filter(interviews, village == "Chirodzo"),
                         village:respondent_wall_type)
```

This is handy, but can be difficult to read if too many functions are nested, as R evaluates the expression from the inside out (in this case, filtering, then selecting).

The last option, *pipes*, are a recent addition to R. Pipes let you take the output of one function and send it directly to the next, which is useful when you need to do many things to the same dataset. Pipes in R look like `%>%` and are made available via the **`magrittr`** package, installed automatically with **`dplyr`**. If you use RStudio, you can type the pipe with:

- Ctrl + Shift + M if you have a PC or Cmd + Shift + M if you have a Mac.

R

```
interviews %>%
    filter(village == "Chirodzo") %>%
    select(village:respondent_wall_type)
```

Output

```
# A tibble: 39 × 5
   village  interview_date      no_membrs years_liv respondent_wall_type
   <chr>    <dttm>                  <dbl>     <dbl> <chr>
 1 Chirodzo 2016-11-16 00:00:00        12        70 burntbricks
 2 Chirodzo 2016-11-16 00:00:00         8         6 burntbricks
 3 Chirodzo 2016-12-16 00:00:00        12        23 burntbricks
 4 Chirodzo 2016-11-17 00:00:00         8        18 burntbricks
 5 Chirodzo 2016-11-17 00:00:00         5        45 muddaub
 6 Chirodzo 2016-11-17 00:00:00         6        23 sunbricks
 7 Chirodzo 2016-11-17 00:00:00         3         8 burntbricks
 8 Chirodzo 2016-11-17 00:00:00         7        29 muddaub
 9 Chirodzo 2016-11-17 00:00:00         2         6 muddaub
10 Chirodzo 2016-11-17 00:00:00         9         7 muddaub
# … with 29 more rows
```

In the above code, we use the pipe to send the `interviews` dataset first through `filter()` to keep rows where `village` is “Chirodzo”, then through `select()` to keep only the `no_membrs` and `years_liv` columns. Since `%>%` takes the object on its left and passes it as the first argument to the function on its right, we don’t need to explicitly include the dataframe as an argument to the `filter()` and `select()` functions any more.

Some may find it helpful to read the pipe like the word “then”. For instance, in the above example, we take the dataframe `interviews`, *then* we `filter` for rows with `village == "Chirodzo"`, *then* we `select` columns `no_membrs` and `years_liv`. The **`dplyr`** functions by themselves are somewhat simple, but by combining them into linear workflows with the pipe, we can accomplish more complex data wrangling operations.

If we want to create a new object with this smaller version of the data, we can assign it a new name:

R

```
interviews_ch <- interviews %>%
    filter(village == "Chirodzo") %>%
    select(village:respondent_wall_type)

interviews_ch
```

Output

```
# A tibble: 39 × 5
   village  interview_date      no_membrs years_liv respondent_wall_type
   <chr>    <dttm>                  <dbl>     <dbl> <chr>
 1 Chirodzo 2016-11-16 00:00:00        12        70 burntbricks
 2 Chirodzo 2016-11-16 00:00:00         8         6 burntbricks
 3 Chirodzo 2016-12-16 00:00:00        12        23 burntbricks
 4 Chirodzo 2016-11-17 00:00:00         8        18 burntbricks
 5 Chirodzo 2016-11-17 00:00:00         5        45 muddaub
 6 Chirodzo 2016-11-17 00:00:00         6        23 sunbricks
 7 Chirodzo 2016-11-17 00:00:00         3         8 burntbricks
 8 Chirodzo 2016-11-17 00:00:00         7        29 muddaub
 9 Chirodzo 2016-11-17 00:00:00         2         6 muddaub
10 Chirodzo 2016-11-17 00:00:00         9         7 muddaub
# … with 29 more rows
```

Note that the final dataframe (`interviews_ch`) is the leftmost part of this expression.

Exercise

Using pipes, subset the `interviews` data to include interviews where respondents were members of an irrigation association (`memb_assoc`) and retain only the columns `affect_conflicts` , `liv_count` , and `no_meals` .

Solution

R

```
interviews %>%
    filter(memb_assoc == "yes") %>%
    select(affect_conflicts, liv_count, no_meals)
```

Output

```
# A tibble: 33 × 3
   affect_conflicts liv_count no_meals
   <chr>                <dbl>    <dbl>
 1 once                     3        2
 2 never                    2        2
 3 never                    2        3
 4 once                     3        2
 5 frequently               1        3
 6 more_once                5        2
 7 more_once                3        2
 8 more_once                2        3
 9 once                     3        3
10 never                    3        3
# … with 23 more rows
```

Mutate

Frequently you'll want to create new columns based on the values in existing columns, for example to do unit conversions, or to find the ratio of values in two columns. For this we'll use `mutate()` .

We might be interested in the ratio of number of household members to rooms used for sleeping (i.e. avg number of people per room):

R

```
interviews %>%
    mutate(people_per_room = no_membrs / rooms)
```

Output

```
# A tibble: 131 × 15
   key_ID village interview_date      no_membrs years_liv respondent_wall… rooms
    <dbl> <chr>   <dttm>                  <dbl>     <dbl> <chr>            <dbl>
 1      1 God     2016-11-17 00:00:00         3         4 muddaub              1
 2      1 God     2016-11-17 00:00:00         7         9 muddaub              1
 3      3 God     2016-11-17 00:00:00        10        15 burntbricks          1
 4      4 God     2016-11-17 00:00:00         7         6 burntbricks          1
 5      5 God     2016-11-17 00:00:00         7        40 burntbricks          1
 6      6 God     2016-11-17 00:00:00         3         3 muddaub              1
 7      7 God     2016-11-17 00:00:00         6        38 muddaub              1
 8      8 Chirod… 2016-11-16 00:00:00        12        70 burntbricks          3
 9      9 Chirod… 2016-11-16 00:00:00         8         6 burntbricks          1
10     10 Chirod… 2016-12-16 00:00:00        12        23 burntbricks          5
# … with 121 more rows, and 8 more variables: memb_assoc <chr>,
#   affect_conflicts <chr>, liv_count <dbl>, items_owned <chr>, no_meals <dbl>,
#   months_lack_food <chr>, instanceID <chr>, people_per_room <dbl>
```

We may be interested in investigating whether being a member of an irrigation association had any effect on the ratio of household members to rooms. To look at this relationship, we will first remove data from our dataset where the respondent didn't answer the question of whether they were a member of an irrigation association. These cases are recorded as "NULL" in the dataset.

To remove these cases, we could insert a `filter()` in the chain:

R

```
interviews %>%
    filter(!is.na(memb_assoc)) %>%
    mutate(people_per_room = no_membrs / rooms)
```

Output

```
# A tibble: 92 × 15
   key_ID village interview_date      no_membrs years_liv respondent_wall… rooms
    <dbl> <chr>   <dttm>                  <dbl>     <dbl> <chr>            <dbl>
 1      1 God     2016-11-17 00:00:00         7         9 muddaub              1
 2      7 God     2016-11-17 00:00:00         6        38 muddaub              1
 3      8 Chirod… 2016-11-16 00:00:00        12        70 burntbricks          3
 4      9 Chirod… 2016-11-16 00:00:00         8         6 burntbricks          1
 5     10 Chirod… 2016-12-16 00:00:00        12        23 burntbricks          5
 6     12 God     2016-11-21 00:00:00         7        20 burntbricks          3
 7     13 God     2016-11-21 00:00:00         6         8 burntbricks          1
 8     15 God     2016-11-21 00:00:00         5        30 sunbricks            2
 9     21 God     2016-11-21 00:00:00         8        20 burntbricks          1
10     24 Ruaca   2016-11-21 00:00:00         6         4 burntbricks          2
# … with 82 more rows, and 8 more variables: memb_assoc <chr>,
#   affect_conflicts <chr>, liv_count <dbl>, items_owned <chr>, no_meals <dbl>,
#   months_lack_food <chr>, instanceID <chr>, people_per_room <dbl>
```

The `!` symbol negates the result of the `is.na()` function. Thus, if `is.na()` returns a value of `TRUE` (because the `memb_assoc` is missing), the `!` symbol negates this and says we only want values of `FALSE`, where `memb_assoc` **is not** missing.

Exercise

Create a new dataframe from the `interviews` data that meets the following criteria: contains only the `village` column and a new column called `total_meals` containing a value that is equal to the total number of meals served in the household per day on average (`no_membrs` times `no_meals`). Only the rows where `total_meals` is greater than 20 should be shown in the final dataframe.

Hint: think about how the commands should be ordered to produce this data frame!

Solution

R

```
interviews_total_meals <- interviews %>%
    mutate(total_meals = no_membrs * no_meals) %>%
    filter(total_meals > 20) %>%
    select(village, total_meals)
```

Split-apply-combine data analysis and the summarize() function

Many data analysis tasks can be approached using the *split-apply-combine* paradigm: split the data into groups, apply some analysis to each group, and then combine the results. **`dplyr`** makes this very easy through the use of the `group_by()` function.

The `summarize()` function

`group_by()` is often used together with `summarize()`, which collapses each group into a single-row summary of that group. `group_by()` takes as arguments the column names that contain the **categorical** variables for which you want to calculate the summary statistics. So to compute the average household size by village:

R

```
interviews %>%
    group_by(village) %>%
    summarize(mean_no_membrs = mean(no_membrs))
```

Output

```
# A tibble: 3 × 2
  village  mean_no_membrs
  <chr>             <dbl>
1 Chirodzo           7.08
2 God                6.86
3 Ruaca              7.57
```

You may also have noticed that the output from these calls doesn't run off the screen anymore. It's one of the advantages of `tbl_df` over dataframe.

You can also group by multiple columns:

R

```
interviews %>%
    group_by(village, memb_assoc) %>%
    summarize(mean_no_membrs = mean(no_membrs))
```

Output

```
`summarise()` has grouped output by 'village'. You can override using the `.groups` argument.
```

Output

```
# A tibble: 9 × 3
# Groups:   village [3]
  village  memb_assoc mean_no_membrs
  <chr>    <chr>               <dbl>
1 Chirodzo no                   8.06
2 Chirodzo yes                  7.82
3 Chirodzo <NA>                 5.08
4 God      no                   7.13
5 God      yes                  8
6 God      <NA>                 6
7 Ruaca    no                   7.18
8 Ruaca    yes                  9.5
9 Ruaca    <NA>                 6.22
```

Note that the output is a grouped tibble. To obtain an ungrouped tibble, use the `ungroup` function:

R

```
interviews %>%
    group_by(village, memb_assoc) %>%
    summarize(mean_no_membrs = mean(no_membrs)) %>%
    ungroup()
```

Output

```
`summarise()` has grouped output by 'village'. You can override using the `.groups` argument.
```

Output

```
# A tibble: 9 × 3
  village  memb_assoc mean_no_membrs
  <chr>    <chr>               <dbl>
1 Chirodzo no                   8.06
2 Chirodzo yes                  7.82
3 Chirodzo <NA>                 5.08
4 God      no                   7.13
5 God      yes                  8
6 God      <NA>                 6
7 Ruaca    no                   7.18
8 Ruaca    yes                  9.5
9 Ruaca    <NA>                 6.22
```

When grouping both by `village` and `membr_assoc` , we see rows in our table for respondents who did not specify whether they were a member of an irrigation association. We can exclude those data from our table using a filter step.

R

```
interviews %>%
    filter(!is.na(memb_assoc)) %>%
    group_by(village, memb_assoc) %>%
    summarize(mean_no_membrs = mean(no_membrs))
```

Output

```
`summarise()` has grouped output by 'village'. You can override using the `.groups` argument.
```

Output

```
# A tibble: 6 × 3
# Groups:   village [3]
  village  memb_assoc mean_no_membrs
  <chr>    <chr>               <dbl>
1 Chirodzo no                   8.06
2 Chirodzo yes                  7.82
3 God      no                   7.13
4 God      yes                  8
5 Ruaca    no                   7.18
6 Ruaca    yes                  9.5
```

Once the data are grouped, you can also summarize multiple variables at the same time (and not necessarily on the same variable). For instance, we could add a column indicating the minimum household size for each village for each group (members of an irrigation association vs not):

R

```
interviews %>%
    filter(!is.na(memb_assoc)) %>%
    group_by(village, memb_assoc) %>%
    summarize(mean_no_membrs = mean(no_membrs),
              min_membrs = min(no_membrs))
```

Output

```
`summarise()` has grouped output by 'village'. You can override using the `.groups` argument.
```

Output

```
# A tibble: 6 × 4
# Groups:   village [3]
  village  memb_assoc mean_no_membrs min_membrs
  <chr>    <chr>               <dbl>      <dbl>
1 Chirodzo no                   8.06          4
2 Chirodzo yes                  7.82          2
3 God      no                   7.13          3
4 God      yes                  8             5
5 Ruaca    no                   7.18          2
6 Ruaca    yes                  9.5           5
```

It is sometimes useful to rearrange the result of a query to inspect the values. For instance, we can sort on `min_membrs` to put the group with the smallest household first:

R

```r
interviews %>%
    filter(!is.na(memb_assoc)) %>%
    group_by(village, memb_assoc) %>%
    summarize(mean_no_membrs = mean(no_membrs),
              min_membrs = min(no_membrs)) %>%
    arrange(min_membrs)
```

Output

```
`summarise()` has grouped output by 'village'. You can override using the `.groups` argument.
```

Output

```
# A tibble: 6 × 4
# Groups:   village [3]
  village  memb_assoc mean_no_membrs min_membrs
  <chr>    <chr>               <dbl>      <dbl>
1 Chirodzo yes                  7.82          2
2 Ruaca    no                   7.18          2
3 God      no                   7.13          3
4 Chirodzo no                   8.06          4
5 God      yes                  8             5
6 Ruaca    yes                  9.5           5
```

To sort in descending order, we need to add the `desc()` function. If we want to sort the results by decreasing order of minimum household size:

R

```r
interviews %>%
    filter(!is.na(memb_assoc)) %>%
    group_by(village, memb_assoc) %>%
    summarize(mean_no_membrs = mean(no_membrs),
              min_membrs = min(no_membrs)) %>%
    arrange(desc(min_membrs))
```

Output

```
`summarise()` has grouped output by 'village'. You can override using the `.groups` argument.
```

Output

```
# A tibble: 6 × 4
# Groups:   village [3]
  village  memb_assoc mean_no_membrs min_membrs
  <chr>    <chr>               <dbl>      <dbl>
1 God      yes                  8             5
2 Ruaca    yes                  9.5           5
3 Chirodzo no                   8.06          4
4 God      no                   7.13          3
5 Chirodzo yes                  7.82          2
6 Ruaca    no                   7.18          2
```

Counting

When working with data, we often want to know the number of observations found for each factor or combination of factors. For this task, **`dplyr`** provides `count()`. For example, if we wanted to count the number of rows of data for each village, we would do:

R

```r
interviews %>%
    count(village)
```

Output

```
# A tibble: 3 × 2
  village      n
  <chr>    <int>
1 Chirodzo    39
2 God         43
3 Ruaca       49
```

For convenience, `count()` provides the `sort` argument to get results in decreasing order:

R

```r
interviews %>%
    count(village, sort = TRUE)
```

Output

```
# A tibble: 3 × 2
  village      n
  <chr>    <int>
1 Ruaca       49
2 God         43
3 Chirodzo    39
```

Exercise

How many households in the survey have an average of two meals per day? Three meals per day? Are there any other numbers of meals represented?

Solution

R

```
interviews %>%
   count(no_meals)
```

Output

```
# A tibble: 2 × 2
  no_meals     n
     <dbl> <int>
1        2    52
2        3    79
```

Use `group_by()` and `summarize()` to find the mean, min, and max number of household members for each village. Also add the number of observations (hint: see `?n`).

Solution

R

```
interviews %>%
  group_by(village) %>%
  summarize(
      mean_no_membrs = mean(no_membrs),
      min_no_membrs = min(no_membrs),
      max_no_membrs = max(no_membrs),
      n = n()
  )
```

Output

```
# A tibble: 3 × 5
  village  mean_no_membrs min_no_membrs max_no_membrs     n
  <chr>             <dbl>         <dbl>         <dbl> <int>
1 Chirodzo           7.08             2            12    39
2 God                6.86             3            15    43
3 Ruaca              7.57             2            19    49
```

What was the largest household interviewed in each month?

Solution

R

```r
# if not already included, add month, year, and day columns
library(lubridate) # load lubridate if not already loaded
```

Output

```
Attaching package: 'lubridate'
```

Output

```
The following objects are masked from 'package:base':

    date, intersect, setdiff, union
```

R

```r
interviews %>%
    mutate(month = month(interview_date),
           day = day(interview_date),
           year = year(interview_date)) %>%
    group_by(year, month) %>%
    summarize(max_no_membrs = max(no_membrs))
```

Output

```
`summarise()` has grouped output by 'year'. You can override using the `.groups` argument.
```

Output

```
# A tibble: 5 × 3
# Groups:   year [2]
   year month max_no_membrs
  <dbl> <dbl>         <dbl>
1  2016    11            19
2  2016    12            12
3  2017     4            17
4  2017     5            15
5  2017     6            15
```

Reshaping with pivot_wider() and pivot_longer()

There are essentially three rules that define a "tidy" dataset:

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

In this section we will explore how these rules are linked to the different data formats researchers are often interested in: "wide" and "long". This tutorial will help you efficiently transform your data shape regardless of original format. First we will explore qualities of the `interviews` data and how they relate to these different types of data formats.

Long and wide data formats

In the `interviews` data, each row contains the values of variables associated with each record collected (each interview in the villages), where it is stated that the `key_ID` was "added to provide a unique Id for each observation" and the `instance_ID` "does this as well but it is not as convenient to use."

However, with some inspection, we notice that there are more than one row in the dataset with the same `key_ID` (as seen below). However, the `instanceID` s associated with these duplicate `key_ID` s are not the same. Thus, we should think of `instanceID` as the unique identifier for observations!

R

```r
interviews %>%
  select(key_ID, village, interview_date, instanceID)
```

Output

```
# A tibble: 131 × 4
   key_ID village  interview_date      instanceID
    <dbl> <chr>    <dttm>              <chr>
 1      1 God      2016-11-17 00:00:00 uuid:ec241f2c-0609-46ed-b5e8-fe575f6cefef
 2      1 God      2016-11-17 00:00:00 uuid:099de9c9-3e5e-427b-8452-26250e840d6e
 3      3 God      2016-11-17 00:00:00 uuid:193d7daf-9582-409b-bf09-027dd36f9007
 4      4 God      2016-11-17 00:00:00 uuid:148d1105-778a-4755-aa71-281eadd4a973
 5      5 God      2016-11-17 00:00:00 uuid:2c867811-9696-4966-9866-f35c3e97d02d
 6      6 God      2016-11-17 00:00:00 uuid:daa56c91-c8e3-44c3-a663-af6a49a2ca70
 7      7 God      2016-11-17 00:00:00 uuid:ae20a58d-56f4-43d7-bafa-e7963d850844
 8      8 Chirodzo 2016-11-16 00:00:00 uuid:d6cee930-7be1-4fd9-88c0-82a08f90fb5a
 9      9 Chirodzo 2016-11-16 00:00:00 uuid:846103d2-b1db-4055-b502-9cd510bb7b37
10     10 Chirodzo 2016-12-16 00:00:00 uuid:8f4e49bc-da81-4356-ae34-e0d794a23721
# … with 121 more rows
```

As seen in the code below, for each interview date in each village no `instanceID` s are the same. Thus, this format is what is called a “long” data format, where each observation occupies only one row in the dataframe.

R

```r
interviews %>%
  filter(village == "Chirodzo") %>%
  select(key_ID, village, interview_date, instanceID) %>%
  sample_n(size = 10)
```

Output

```
# A tibble: 10 × 4
   key_ID village  interview_date      instanceID
    <dbl> <chr>    <dttm>              <chr>
 1     61 Chirodzo 2016-11-16 00:00:00 uuid:2401cf50-8859-44d9-bd14-1bf9128766f2
 2     44 Chirodzo 2016-11-17 00:00:00 uuid:f9fadf44-d040-4fca-86c1-2835f79c4952
 3     47 Chirodzo 2016-11-17 00:00:00 uuid:2d0b1936-4f82-4ec3-a3b5-7c3c8cd6cc2b
 4     56 Chirodzo 2016-11-16 00:00:00 uuid:973c4ac6-f887-48e7-aeaf-4476f2cfab76
 5     57 Chirodzo 2016-11-16 00:00:00 uuid:a7184e55-0615-492d-9835-8f44f3b03a71
 6     70 Chirodzo 2016-11-16 00:00:00 uuid:1feb0108-4599-4bf9-8a07-1f5e66a50a0a
 7     34 Chirodzo 2016-11-17 00:00:00 uuid:14c78c45-a7cc-4b2a-b765-17c82b43feb4
 8     63 Chirodzo 2016-11-16 00:00:00 uuid:86ed4328-7688-462f-aac7-d6518414526a
 9     35 Chirodzo 2016-11-17 00:00:00 uuid:ff7496e7-984a-47d3-a8a1-13618b5683ce
10     51 Chirodzo 2016-11-16 00:00:00 uuid:18ac8e77-bdaf-47ab-85a2-e4c947c9d3ce
```

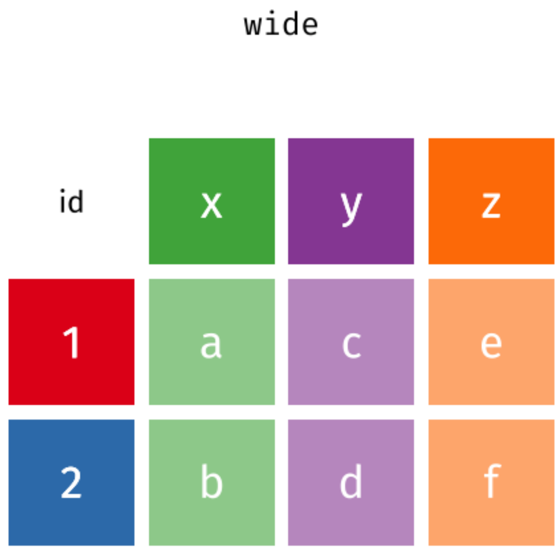
We notice that the layout or format of the `interviews` data is in a format that adheres to rules 1-3, where

- each column is a variable
- each row is an observation
- each value has its own cell

This is called a “long” data format. But, we notice that each column represents a different variable. In the “longest” data format there would only be three columns, one for the id variable, one for the observed variable, and one for the observed value (of that variable). This data format is quite unsightly and difficult to work with, so you will rarely see it in use.

Alternatively, in a “wide” data format we see modifications to rule 1, where each column no longer represents a single variable. Instead, columns can represent different levels/values of a variable. For instance, in some data you encounter the researchers may have chosen for every survey date to be a different column.

These may sound like dramatically different data layouts, but there are some tools that make transitions between these layouts much simpler than you might think! The gif below shows how these two formats relate to each other, and gives you an idea of how we can use R to shift from one format to the other.



Long and wide dataframe layouts mainly affect readability. You may find that visually you may prefer the “wide” format, since you can see more of the data on the screen. However, all of the R functions we have used thus far expect for your data to be in a “long” data format. This is because the long format is more machine readable and is closer to the formatting of databases.

Questions which warrant different data formats

In interviews, each row contains the values of variables associated with each record (the unit), values such as the village of the respondent, the number of household members, or the type of wall their house had. This format allows for us to make comparisons across individual surveys, but what if we wanted to look at differences in households grouped by different types of housing construction materials?

To facilitate this comparison we would need to create a new table where each row (the unit) was comprised of values of variables associated with housing material (e.g. the `respondent_wall_type`). In practical terms this means the values of the wall construction materials in `respondent_wall_type` (e.g. muddaub, burntbricks, cement, sunbricks) would become the names of column variables and the cells would contain values of `TRUE` or `FALSE` , for whether that house had a wall made of that material.

Once we we’ve created this new table, we can explore the relationship within and between villages. The key point here is that we are still following a tidy data structure, but we have **reshaped** the data according to the observations of interest.

Alternatively, if the interview dates were spread across multiple columns, and we were interested in visualizing, within each village, how irrigation conflicts have changed over time. This would require for the interview date to be included in a single column rather than spread across multiple columns. Thus, we would need to transform the column names into values of a variable.

We can do both these of transformations with two `tidyr` functions, `pivot_wider()` and `pivot_longer()` .

Pivoting wider

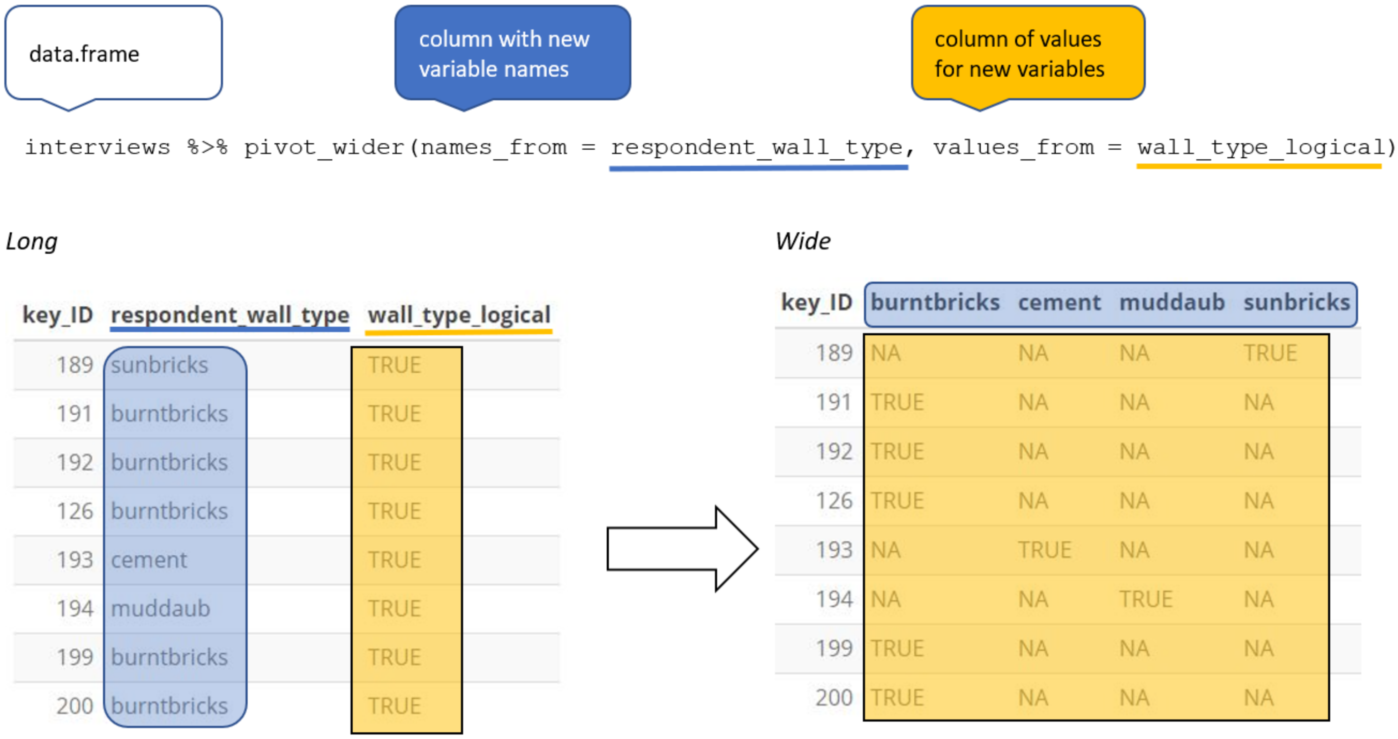
`pivot_wider()` takes three principal arguments:

1. the data
2. the *names_from* column variable whose values will become new column names.
3. the *values_from* column variable whose values will fill the new column variables.

Further arguments include `values_fill` which, if set, fills in missing values with the value provided.

Let’s use `pivot_wider()` to transform interviews to create new columns for each type of wall construction material. We will make use of the pipe operator as have done before. Because both the `names_from` and `values_from` parameters must come from column values, we will create a dummy column (we’ll name it `wall_type_logical`) to hold the value `TRUE` , which we will then place into the appropriate column that corresponds to the wall construction material for that respondent. When using `mutate()` if you give a single value, it will be used for all observations in the dataset.

For each row in our newly pivoted table, only one of the newly created wall type columns will have a value of `TRUE` , since each house can only be made of one wall type. The default value that `pivot_wider` uses to fill the other wall types is `NA` .



Long

key_ID	respondent_wall_type	wall_type_logical
189	sunbricks	TRUE
191	burntbricks	TRUE
192	burntbricks	TRUE
126	burntbricks	TRUE
193	cement	TRUE
194	muddaub	TRUE
199	burntbricks	TRUE
200	burntbricks	TRUE

Wide

key_ID	burntbricks	cement	muddaub	sunbricks
189	NA	NA	NA	TRUE
191	TRUE	NA	NA	NA
192	TRUE	NA	NA	NA
126	TRUE	NA	NA	NA
193	NA	TRUE	NA	NA
194	NA	NA	TRUE	NA
199	TRUE	NA	NA	NA
200	TRUE	NA	NA	NA

If instead of the default value being `NA`, we wanted these values to be `FALSE`, we can insert a default value into the `values_fill` argument. By including `values_fill = list(wall_type_logical = FALSE)` inside `pivot_wider()`, we can fill the remainder of the wall type columns for that row with the value `FALSE`.

R

```
interviews_wide <- interviews %>%
    mutate(wall_type_logical = TRUE) %>%
    pivot_wider(names_from = respondent_wall_type,
                values_from = wall_type_logical,
                values_fill = list(wall_type_logical = FALSE))
```

View the `interviews_wide` dataframe and notice that there is no longer a column titled `respondent_wall_type`. This is because there is a default parameter in `pivot_wider()` that drops the original column. The values that were in that column have now become columns named `muddaub`, `burntbricks`, `sunbricks`, and `cement`. You can use `dim(interviews)` and `dim(interviews_wide)` to see how the number of columns has changed between the two datasets.

Pivoting longer

The opposing situation could occur if we had been provided with data in the form of `interviews_wide`, where the building materials are column names, but we wish to treat them as values of a `respondent_wall_type` variable instead.

In this situation we are gathering these columns turning them into a pair of new variables. One variable includes the column names as values, and the other variable contains the values in each cell previously associated with the column names. We will do this in two steps to make this process a bit clearer.

`pivot_longer()` takes four principal arguments:

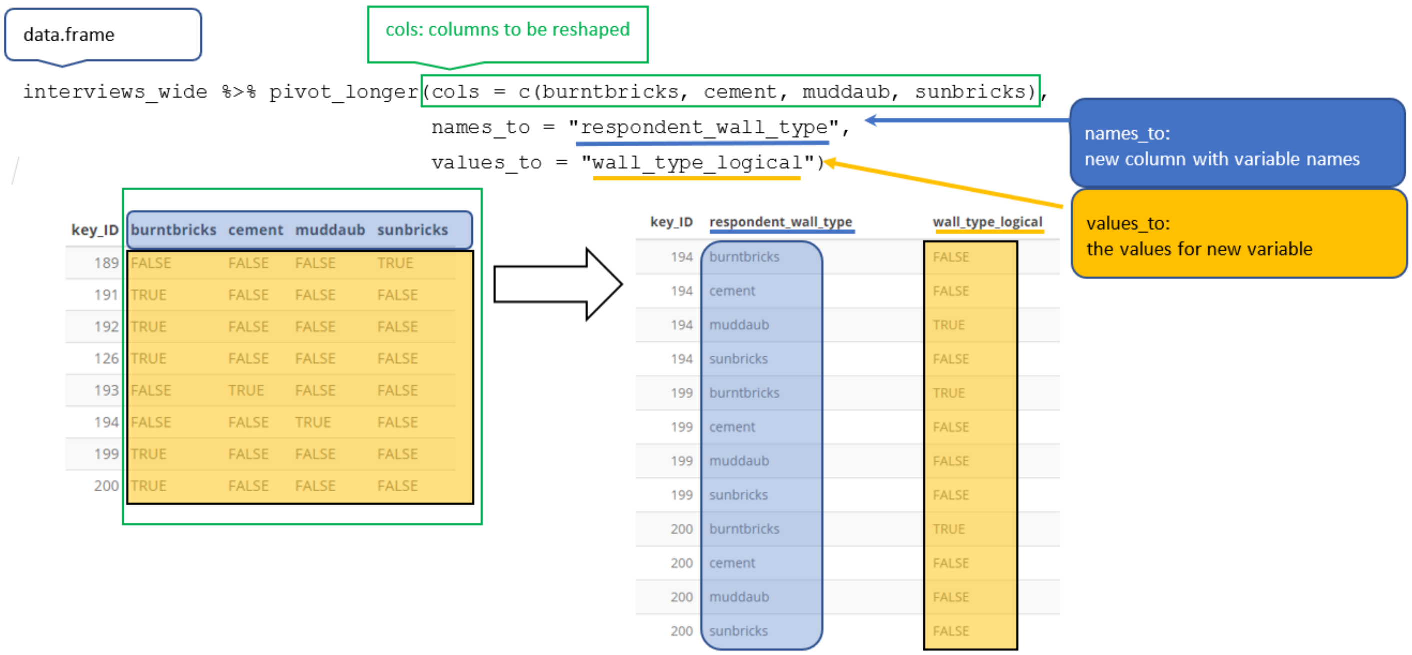
1. the data
2. *cols* are the names of the columns we use to fill the a new values variable (or to drop).
3. the *names_to* column variable we wish to create from the *cols* provided.
4. the *values_to* column variable we wish to create and fill with values associated with the *cols* provided.

To recreate our original dataframe, we will use the following:

1. the data - `interviews_wide`
2. a list of *cols* (columns) that are to be reshaped; these can be specified using a `:` if the columns to be reshaped are in one area of the dataframe, or with a vector (`c()`) command if the columns are spread throughout the dataframe.
3. the *names_to* column will be a character string of the name the column these columns will be collapsed into (“respondent_wall_type”).
4. the *values_to* column will be a character string of the name of the column the values of the collapsed columns will be inserted into (“wall_type_logical”). This column will be populated with values of `TRUE` or `FALSE`.

R

```
interviews_long <- interviews_wide %>%
    pivot_longer(cols = burntbricks:sunbricks,
                 names_to = "respondent_wall_type",
                 values_to = "wall_type_logical")
```



This creates a dataframe with 262 rows (4 rows per interview respondent). The four rows for each respondent differ only in the value of the “respondent_wall_type” and “wall_type_logical” columns. View the data to see what this looks like.

Only one row for each interview respondent is informative–we know that if the house walls are made of “sunbrick” they aren’t made of any other the other materials. Therefore, it would make sense to filter our dataset to only keep values where `wall_type_logical` is `TRUE` . Because `wall_type_logical` is already either `TRUE` or `FALSE` , when passing the column name to `filter()` , it will automatically already only keep rows where this column has the value `TRUE` . We can then remove the `wall_type_logical` column.

We do all of these steps together in the next chunk of code:

R

```
interviews_long <- interviews_wide %>%
    pivot_longer(cols = c(burntbricks, cement, muddaub, sunbricks),
                 names_to = "respondent_wall_type",
                 values_to = "wall_type_logical") %>%
    filter(wall_type_logical) %>%
    select(-wall_type_logical)
```

View both `interviews_long` and `interviews_wide` and compare their structure.

Applying `pivot_wider()` to clean our data

Now that we’ve learned about `pivot_longer()` and `pivot_wider()` we’re going to put these functions to use to fix a problem with the way that our data is structured. In the spreadsheets lesson, we learned that it’s best practice to have only a single piece of information in each cell of your spreadsheet. In this dataset, we have several columns which contain multiple pieces of information. For example, the `items_owned` column contains information about whether our respondents owned a fridge, a television, etc. To make this data easier to analyze, we will split this column and create a new column for each item. Each cell in that column will either be `TRUE` or `FALSE` and will indicate whether that interview respondent owned that item (similar to what we did previously with `wall_type`).

R

```
interviews_items_owned <- interviews %>%
  separate_rows(items_owned, sep = ";") %>%
  replace_na(list(items_owned = "no_listed_items")) %>%
  mutate(items_owned_logical = TRUE) %>%
    pivot_wider(names_from = items_owned,
                values_from = items_owned_logical,
                values_fill = list(items_owned_logical = FALSE))

nrow(interviews_items_owned)
```

Output

```
[1] 131
```

There are a couple of new concepts in this code chunk, so let’s walk through it line by line. First we create a new object (`interviews_items_owned`) based on the `interviews` dataframe.

R

```
interviews_items_owned <- interviews %>%
```

Then we use the new function `separate_rows()` from the **`tidyr`** package to separate the values of `items_owned` based on the presence of semi-colons (`;`). The values of this variable were multiple items separated by semi-colons, so this action creates a row for each item listed in a household's possession. Thus, we end up with a long format version of the dataset, with multiple rows for each respondent. For example, if a respondent has a television and a solar panel, that respondent will now have two rows, one with "television" and the other with "solar panel" in the `items_owned` column.

R

```
separate_rows(items_owned, sep = ";") %>%
```

You may notice that one of the columns is called `´NA´`. This is because some of the respondents did not own any of the items that was in the interviewer's list. We can use the `replace_na()` function to change these `NA` values to something more meaningful. The `replace_na()` function expects for you to give it a `list()` of columns that you would like to replace the `NA` values in, and the value that you would like to replace the `NA` s. This ends up looking like this:

R

```
replace_na(list(items_owned = "no_listed_items")) %>%
```

Next, we create a new variable named `items_owned_logical`, which has one value (`TRUE`) for every row. This makes sense, since each item in every row was owned by that household. We are constructing this variable so that when spread the `items_owned` across multiple columns, we can fill the values of those columns with logical values describing whether the household did (`TRUE`) or didn't (`FALSE`) own that particular item.

R

```
mutate(items_owned_logical = TRUE) %>%
```

Lastly, we use `pivot_wider()` to switch from long format to wide format. This creates a new column for each of the unique values in the `items_owned` column, and fills those columns with the values of `items_owned_logical`. We also declare that for items that are missing, we want to fill those cells with the value of `FALSE` instead of `NA`.

R

```
pivot_wider(names_from = items_owned,
            values_from = items_owned_logical,
            values_fill = list(items_owned_logical = FALSE))
```

View the `interviews_items_owned` dataframe. It should have 131 rows (the same number of rows you had originally), but extra columns for each item. How many columns were added?

This format of the data allows us to do interesting things, like make a table showing the number of respondents in each village who owned a particular item:

R

```
interviews_items_owned %>%
  filter(bicycle) %>%
  group_by(village) %>%
  count(bicycle)
```

Output

```
# A tibble: 3 × 3
# Groups:   village [3]
  village  bicycle     n
  <chr>    <lgl>   <int>
1 Chirodzo TRUE       17
2 God      TRUE       23
3 Ruaca    TRUE       20
```

Or below we calculate the average number of items from the list owned by respondents in each village. This code uses the `rowSums()` function to count the number of `TRUE` values in the `bicycle` to `car` columns for each row, hence its name. We then group the data by villages and calculate the mean number of items, so each average is grouped by village.

R

```
interviews_items_owned %>%
    mutate(number_items = rowSums(select(., bicycle:car))) %>%
    group_by(village) %>%
    summarize(mean_items = mean(number_items))
```

Output

```
# A tibble: 3 × 2
  village  mean_items
  <chr>         <dbl>
1 Chirodzo       4.62
2 God            4.07
3 Ruaca          5.63
```

Exercise

1. Create a new dataframe (named `interviews_months_lack_food`) that has one column for each month and records `TRUE` or `FALSE` for whether each interview respondent was lacking food in that month.

Solution

R

```r
interviews_months_lack_food <- interviews %>%
  separate_rows(months_lack_food, sep = ";") %>%
  mutate(months_lack_food_logical  = TRUE) %>%
  pivot_wider(names_from = months_lack_food,
              values_from = months_lack_food_logical,
              values_fill = list(months_lack_food_logical = FALSE))
```

1. How many months (on average) were respondents without food if they did belong to an irrigation association? What about if they didn't?

Solution

R

```r
interviews_months_lack_food %>%
  mutate(number_months = rowSums(select(., Jan:May))) %>%
  group_by(memb_assoc) %>%
  summarize(mean_months = mean(number_months))
```

Output

```
# A tibble: 3 × 2
  memb_assoc mean_months
  <chr>            <dbl>
1 no                2
2 yes               2.30
3 <NA>              2.82
```

Exporting data

Now that you have learned how to use **`dplyr`** to extract information from or summarize your raw data, you may want to export these new data sets to share them with your collaborators or for archival.

Similar to the `read_csv()` function used for reading CSV files into R, there is a `write_csv()` function that generates CSV files from dataframes.

Before using `write_csv()`, we are going to create a new folder, `data_output`, in our working directory that will store this generated dataset. We don't want to write generated datasets in the same directory as our raw data. It's good practice to keep them separate. The `data` folder should only contain the raw, unaltered data, and should be left alone to make sure we don't delete or modify it. In contrast, our script will generate the contents of the `data_output` directory, so even if the files it contains are deleted, we can always re-generate them.

In preparation for our next lesson on plotting, we are going to create a version of the dataset where each of the columns includes only one data value. To do this, we will use `pivot_wider` to expand the `months_lack_food` and `items_owned` columns. We will also create a couple of summary columns.

R

```
interviews_plotting <- interviews %>%
  ## pivot wider by items_owned
  separate_rows(items_owned, sep = ";") %>%
  ## if there were no items listed, changing NA to no_listed_items
  replace_na(list(items_owned = "no_listed_items")) %>%
  mutate(items_owned_logical = TRUE) %>%
  pivot_wider(names_from = items_owned,
              values_from = items_owned_logical,
              values_fill = list(items_owned_logical = FALSE)) %>%
  ## pivot wider by months_lack_food
  separate_rows(months_lack_food, sep = ";") %>%
  mutate(months_lack_food_logical = TRUE) %>%
  pivot_wider(names_from = months_lack_food,
              values_from = months_lack_food_logical,
              values_fill = list(months_lack_food_logical = FALSE)) %>%
  ## add some summary columns
  mutate(number_months_lack_food = rowSums(select(., Jan:May))) %>%
  mutate(number_items = rowSums(select(., bicycle:car)))
```

Now we can save this dataframe to our `data_output` directory.

R

```
write_csv (interviews_plotting, file = "data_output/interviews_plotting.csv")
```

Key Points

- Use the `dplyr` package to manipulate dataframes.
- Use `select()` to choose variables from a dataframe.
- Use `filter()` to choose data based on values.
- Use `group_by()` and `summarize()` to work with subsets of data.
- Use `mutate()` to create new variables.
- Use the `tidyr` package to change the layout of dataframes.
- Use `pivot_wider()` to go from long to wide format.
- Use `pivot_longer()` to go from wide to long format.

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