
Grouping and summarizing

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Introduction

You currently know how to keep your data entries of interest, how keep relevant variables and how to modify them or create new ones.

Now, we will take your data wrangling skills one step further by understanding how to easily extract summary statistics, through the verb `summarize()`, such as calculating the mean of a variable.

Moreover, we will begin exploring a crucial verb, `group_by()`, capable of grouping your variables together to perform grouped operations on your data set.

Let's go !

Learning objectives

1. You can use `dplyr::summarize()` to extract summary statistics from datasets.
2. You can use `dplyr::group_by()` to group data by one or more variables before performing operations on them.
3. You understand why and how to ungroup grouped data frames.
4. You can use `dplyr::n()` together with `group_by()`-`summarize()` to count rows per group.
5. You can use `sum()` together with `group_by()`-`summarize()` to count rows that meet a condition.
6. You can use `dplyr::count()` as a handy function to count rows per group.

The Yaounde COVID-19 dataset

In this lesson, we will again use data from the COVID-19 serological survey conducted in Yaounde, Cameroon.

```
yaounde <- read_csv(here::here('data/yaounde_data.csv'))

# A smaller subset of variables
yao <- yaounde %>% select(
  age, age_category_3, sex, weight_kg, height_cm,
  neighborhood, is_smoker, is_pregnant, occupation,
  treatment_combinations, symptoms, n_days_miss_work, n_bedridden_days,
  highest_education, igg_result)

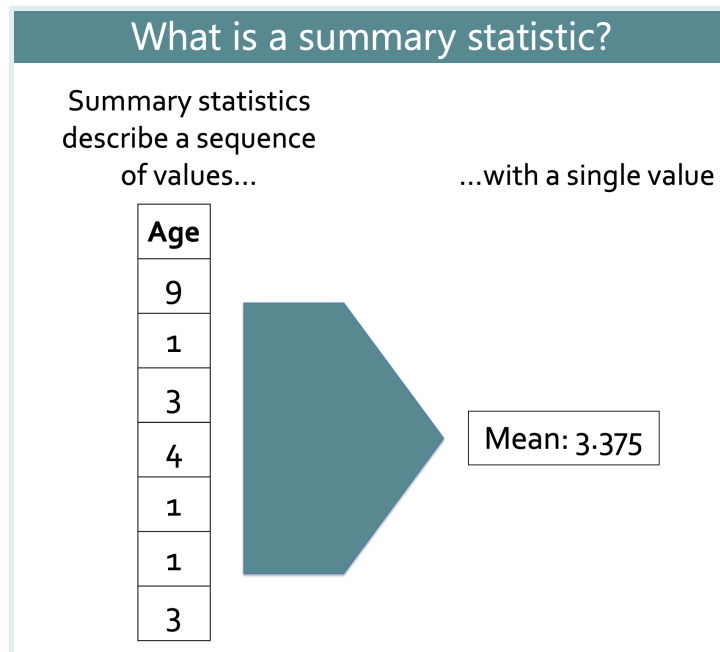
yao
```

```
## # A tibble: 971 × 15
##   age age_category_3 sex   weight_kg height_cm
##   <dbl> <chr>         <chr>     <dbl>     <dbl>
## 1    45 Adult      Female      95      169
## 2    55 Adult      Male       96      185
## 3    23 Adult      Male       74      180
## 4    20 Adult      Female     70      164
## 5    55 Adult      Female     67      147
## 6    17 Child      Female     65      162
## 7    13 Child      Female     65      150
## 8    28 Adult      Male       62      173
## 9    30 Adult      Male       73      170
## 10   13 Child      Female     56      153
## # ... with 961 more rows, and 10 more variables:
## #   neighborhood <chr>, is_smoker <chr>, ...
```

See the first lesson in this chapter for more information about this dataset.

What are summary statistics?

A summary statistic is a single value (such as a mean or median) that describes a sequence of values (typically a column in your dataset).



Summary statistics can describe the center, spread or range of a variable, or the counts and positions of values within that variable. Some common summary statistics are shown in the diagram below:

Examples of summary statistics

```
age <- (9, 1, 4, 2, 2, 2)
```

Summary statistic	R code	Output
Counts		
No. of elements	<code>dplyr::n(age)</code>	6
No. of distinct elements	<code>dplyr::n_distinct(age)</code>	4
Position		
First element	<code>dplyr::first(age)</code>	9
Last element	<code>dplyr::last(age)</code>	2
3rd element	<code>dplyr::nth(age, 3)</code>	4
Center		
Mean	<code>mean(age)</code>	3.3
Median	<code>median(age)</code>	2
Spread		
Standard deviation	<code>sd(age)</code>	2.9
Interquartile range	<code>IQR(age)</code>	1.5
Range		
Minimum	<code>min(age)</code>	1
Maximum	<code>max(age)</code>	9
25th quantile	<code>quantile(age, 0.25)</code>	2

Computing summary statistics is a very common operation in most data analysis workflows, so it will be important to become fluent in extracting them from your datasets. And for this task, there is no better tool than the `{dplyr}` function `summarize()`! So let's see how to use this powerful function.

Introducing `dplyr::summarize()`

To get started, it is best to first consider how to get simple summary statistics *without* using `summarize()`, then we will consider why you *should* actually use `summarize()`.

Imagine you were asked to find the mean age of respondents in the `yao` data frame. How might you do this in base R?

First, recall that the dollar sign function, `$`, allows you to extract a data frame column to a vector:

```
yao$age # extract the `age` column from `yao`
```

To obtain the mean, you simply pass this `yao$age` vector into the `mean()` function:

```
mean(yao$age)
```

```
## [1] 29.01751
```

And that's it! You now have a simple summary statistic. Extremely easy, right?

So why do we need `summarize()` to get summary statistics if the process is already so simple without it? We'll come back to the *why* question soon. First let's see *how* to obtain summary statistics with `summarize()`.

Going back to the previous example, the correct syntax to get the mean age with `summarize()` would be:

```
yao %>%  
  summarize(mean_age = mean(age))
```

```
## # A tibble: 1 × 1  
##   mean_age  
##   <dbl>  
## 1      29.0
```

The anatomy of this syntax is shown below. You simply need to input name of the new column (e.g. `mean_age`), the summary function (e.g. `mean()`), and the column to summarize (e.g. `age`).

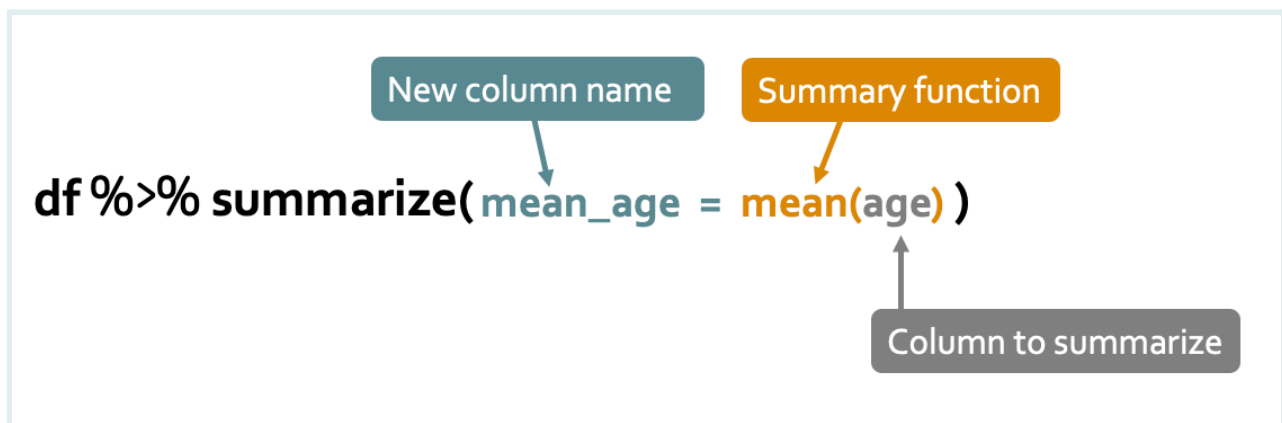


Fig. Basic syntax for the `summarize()` function.

You can also compute multiple summary statistics in a single `summarize()` statement. For example, if you wanted both the mean and the median age, you could run:

```
yao %>%  
  summarize(mean_age = mean(age),  
            median_age = median(age))
```

```
## # A tibble: 1 × 2
##   mean_age median_age
##   <dbl>      <dbl>
## 1     29.0         26
```

Nice!

Now, you should be wondering why `summarize()` puts the summary statistics into a data frame, with each statistic in a different column.

The main benefit of this data frame structure is to make it easy to produce *grouped* summaries (and creating such grouped summaries will be the primary benefit of using `summarize()`).

We will look at these grouped summaries in the next section. For now, attempt the practice questions below.

Use `summarize()` and the relevant summary functions to obtain the mean, median and standard deviation of respondent weights from the `weight_kg` variable of the `yao` data frame.



Your output should be a data frame with three columns named as shown below:

mean_weight_kg	median_weight_kg	sd_weight_kg
----------------	------------------	--------------

```
Q_weight_summary <-
yao %>%
```

Use `summarize()` and the relevant summary functions to obtain the minimum and maximum respondent heights from the `height_cm` variable of the `yao` data frame.



Your output should be a data frame with two columns named as shown below:

min_height_cm	max_height_cm
---------------	---------------

```
Q_height_summary <-
yao %>%
```


PRACTICE



(in RMD)

```
.CHECK_Q_height_summary()  
.HINT_Q_height_summary()
```

Grouped summaries with `dplyr::group_by()`

As its name suggests, `dplyr::group_by()` lets you group a data frame by the values in a variable (e.g. male vs female sex). You can then perform operations that are split according to these groups.

What effect does `group_by()` have on a data frame? Let's try to group the `yao` data frame by sex and observe the effect:

```
yao %>%  
  group_by(sex)
```

```
## # A tibble: 971 × 15  
## # Groups:   sex [2]  
##   age age_category_3 sex   weight_kg height_cm  
##   <dbl> <chr>         <chr>     <dbl>     <dbl>  
## 1    45 Adult        Female      95      169  
## 2    55 Adult        Male       96      185  
## 3    23 Adult        Male       74      180  
## 4    20 Adult        Female      70      164  
## 5    55 Adult        Female      67      147  
## 6    17 Child        Female      65      162  
## 7    13 Child        Female      65      150  
## 8    28 Adult        Male       62      173  
## 9    30 Adult        Male       73      170  
## 10   13 Child        Female      56      153  
## # ... with 961 more rows, and 10 more variables:  
## #   neighborhood <chr>, is_smoker <chr>, ...
```

Hmm. Apparently nothing happened. The one thing you *might* notice is a new section in the header that tells you the grouped-by variable—sex—and the number of groups—2:

```
# A tibble: 971 × 10  
👉 # Groups:   sex [2] 👉
```

Apart from this header however, the data frame appears unchanged.

But watch what happens when we chain the `group_by()` with the `summarize()` call we used in the previous section:

```
yao %>%
  group_by(sex) %>%
  summarize(mean_age = mean(age))
```

```
## # A tibble: 2 × 2
##   sex      mean_age
##   <chr>      <dbl>
## 1 Female    29.5
## 2 Male     28.4
```

You get a different summary statistic for each group! The statistics for women are in one row and those for men are in another. (From this output data frame, you can tell that, for example, the mean age for female respondents is 29.5, while that for male respondents is 28.4)

As was mentioned earlier, this kind of grouped summary is the primary reason the `summarize()` function is so useful!

Let's see another example of a simple `group_by()` + `summarize()` operation.

Suppose you were asked to obtain the maximum and minimum weights for individuals in different neighborhoods in the `yao` data frame. First you would `group_by()` the `neighbourhood` variable, then call the `max()` and `min()` functions inside `summarize()`:

```
yao %>%
  group_by(neighborhood) %>%
  summarize(max_weight = max(weight_kg),
            min_weight = min(weight_kg))
```

```
## # A tibble: 9 × 3
##   neighborhood max_weight min_weight
##   <chr>      <dbl>      <dbl>
## 1 Briqueterie    128         20
## 2 Carriere      129         14
## 3 Cité Verte    118         16
## 4 Ekoudou       135         15
## 5 Messa         96         19
## 6 Mokolo       162         16
## 7 Nkomkana      161         15
## 8 Tsinga       105         15
## 9 Tsinga Oliga  100         17
```

Great! With just a few code lines you are able to extract quite a lot of information.

Let's see one more example for good measure. The variable `n_days_miss_work` tells us the number of days that respondents missed work due to COVID-like symptoms. Individuals who reported no COVID-like symptoms have an `NA` for this variable:

```
yao %>%
  select(n_days_miss_work)
```

```
## # A tibble: 971 × 1
##   n_days_miss_work
##   <dbl>
## 1             0
## 2            NA
## 3            NA
## 4             7
## 5            NA
## 6             7
## 7             0
## 8             0
## 9             0
## 10            NA
## # ... with 961 more rows
```

To count the total number of work days missed for each sex group, you could try to run the `sum()` function on the `n_days_miss_work` variable:

```
yao %>%
  group_by(sex) %>%
  summarise(total_days_missed = sum(n_days_miss_work))
```

```
## # A tibble: 2 × 2
##   sex      total_days_missed
##   <chr>          <dbl>
## 1 Female            NA
## 2 Male              NA
```

Hmmm. This gives you NA results because some rows in the `n_days_miss_work` column have NAs in them, and R cannot find the sum of values containing an NA. To solve this, the argument `na.rm = TRUE` is needed:

```
yao %>%
  group_by(sex) %>%
  summarise(total_days_missed = sum(n_days_miss_work, na.rm = TRUE))
```

```
## # A tibble: 2 × 2
##   sex      total_days_missed
##   <chr>          <dbl>
## 1 Female            256
## 2 Male              272
```

The output tells us that across all women in the sample, 256 work days were missed due to COVID-like symptoms, and across all men, 272 days.

So hopefully now you see why `summarize()` is so powerful. In combination with `group_by()`, it lets you obtain highly informative grouped summaries of your datasets with very few lines of code.

Producing such summaries is a very important part of most data analysis workflows, so this skill is likely to come in handy soon!



`summarize()` produces “Pivot Tables”

The summary data frames created by `summarize()` are often called Pivot Tables in the context of spreadsheet software like Microsoft Excel.

Use `group_by()` and `summarize()` to obtain the mean weight (kg) by smoking status in the `yao` data frame. Name the average weight column `weight_mean`

The output data frame should look like this:



(in RMD)

is_smoker	weight_mean
Ex-smoker	
Non-smoker	
Smoker	
NA	

```
Q_weight_by_smoking_status <-  
yao %>%
```

```
_____
```

```
_____
```

Use `group_by()`, `summarize()`, and the relevant summary functions to obtain the minimum and maximum heights for each sex in the `yao` data frame.



(in RMD)

Your output should be a data frame with three columns named as shown below:

sex	min_height_cm	max_height_cm
Female		
Male		

PRACTICE



(in RMD)

```
Q_min_max_height_by_sex <-  
yao %>%  
_____  
_____
```

Use `group_by()`, `summarize()`, and the `sum()` function to calculate the total number of bedridden days (from the `n_bedridden_days` variable) reported by respondents of each sex.

Your output should be a data frame with two columns named as shown below:

PRACTICE



(in RMD)

neighborhood	total_bedridden_days
--------------	----------------------

Female	
--------	--

Male	
------	--

```
Q_sum_bedridden_days <-  
yao %>%  
_____  
_____
```

Grouping by multiple variables (nested grouping)

It is possible to group a data frame by more than one variable. This is sometimes called “nested” grouping.

Let’s see an example. Suppose you want to know the mean age of men and women *in each neighbourhood* (rather than the mean age of *all* women), you could put both `sex` and `neighborhood` in the `group_by()` statement:

```
yao %>%  
  group_by(sex, neighborhood) %>%  
  summarize(mean_age = mean(age))
```

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

```
## # A tibble: 18 × 3  
## # Groups:   sex [2]
```

```
## 1 Female Briqueterie      31.6
## 2 Female Carriere        28.2
## 3 Female Cité Verte      31.8
## 4 Female Ekoudou         29.3
## 5 Female Messa           30.2
## 6 Female Mokolo          28.0
## 7 Female Nkomkana        33.0
## 8 Female Tsinga          30.6
## 9 Female Tsinga Oliga    24.3
## 10 Male Briqueterie      33.7
## 11 Male Carriere         30.0
## 12 Male Cité Verte       27.0
## 13 Male Ekoudou          25.2
## 14 Male Messa            23.9
## 15 Male Mokolo           30.5
## 16 Male Nkomkana         29.8
## 17 Male Tsinga           28.8
## 18 Male Tsinga Oliga     24.3
```

From this output data frame you can tell that, for example, women from Briqueterie have a mean age of 31.6 years, while men from Briqueterie have a mean age of 33.7 years.

The order of the columns listed in `group_by()` is interchangeable. So if you run `group_by(neighborhood, sex)` instead of `group_by(sex, neighborhood)`, you'll get the same result, although it will be ordered differently:

```
yao %>%
  group_by(neighborhood, sex) %>%
  summarize(mean_age = mean(age))
```

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

```
## # A tibble: 18 × 3
## # Groups:   neighborhood [9]
##   neighborhood sex    mean_age
##   <chr>         <chr>    <dbl>
## 1 Briqueterie Female    31.6
## 2 Briqueterie Male      33.7
## 3 Carriere     Female    28.2
## 4 Carriere     Male      30.0
## 5 Cité Verte   Female    31.8
## 6 Cité Verte   Male      27.0
## 7 Ekoudou      Female    29.3
## 8 Ekoudou      Male      25.2
## 9 Messa        Female    30.2
## 10 Messa       Male      23.9
## 11 Mokolo      Female    28.0
## 12 Mokolo      Male      30.5
## 13 Nkomkana    Female    33.0
## 14 Nkomkana    Male      29.8
```

```
## 15 Tsinga      Female      30.6
## 16 Tsinga      Male        28.8
## 17 Tsinga Oliga Female      24.3
## 18 Tsinga Oliga Male        24.3
```

Now the column order is different: `neighborhood` is the first column, and `sex` is the second. And the row order is also different: rows are first ordered by `neighborhood`, then ordered by `sex` within each neighborhood.

But the actual summary statistics are the same. For example, you can again see that women from Briqueterie have a mean age of 31.6 years, while men from Briqueterie have a mean age of 33.7 years.

Using the `yao` data frame, group your data by gender (`sex`) and treatments (`treatment_combinations`) using `group_by`. Then, using `summarize()` and the relevant summary function, calculate the mean weight (`weight_kg`) for each group.

Your output should be a data frame with three columns named as shown below:

sex	treatment_combinations	mean_weight_kg
-----	------------------------	----------------

```
Q_weight_by_sex_treatments <-
yao %>%
```

PRACTICE



(in RMD)

Using the `yao` data frame, group your data by age category (`age_category_3`), gender (`sex`), and IgG results (`igg_result`) using `group_by`. Then, using `summarize()` and the relevant summary function, calculate the mean number of bedridden days (`n_bedridden_days`) for each group.

Your output should be a data frame with four columns named as shown below:

age_category_3	sex	igg_result	mean_n_bedridden_days
----------------	-----	------------	-----------------------

```
Q_bedridden_by_age_sex_iggresult <-
yao %>%
```

Ungrouping with `dplyr::ungroup()` (why and how)

When you `group_by()` more than one variable before using `summarize()`, the output data frame is still grouped. This persistent grouping can have unwanted downstream effects, so you will sometimes need to use `dplyr::ungroup()` to ungroup the data before doing further analysis.

To understand *why* you should `ungroup()` data, first consider the following example, where we group by only one variable before summarizing:

```
yao %>%
  group_by(sex) %>%
  summarize(mean_age = mean(age))
```

```
## # A tibble: 2 × 2
##   sex      mean_age
##   <chr>      <dbl>
## 1 Female      29.5
## 2 Male       28.4
```

The data comes out like a normal data frame; it is not grouped. You can tell this because there is no information about groups in the header.

But now consider when you group by two variables before summarizing:

```
yao %>%
  group_by(sex, neighborhood) %>%
  summarize(mean_age = mean(age))
```

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

```
## # A tibble: 18 × 3
## # Groups:   sex [2]
##   sex      neighborhood mean_age
##   <chr> <chr>          <dbl>
## 1 Female Briqueterie      31.6
## 2 Female Carriere        28.2
## 3 Female Cité Verte      31.8
## 4 Female Ekoudou         29.3
## 5 Female Messa           30.2
## 6 Female Mokolo          28.0
## 7 Female Nkomkana        33.0
## 8 Female Tsinga          30.6
## 9 Female Tsinga Oliga    24.3
## 10 Male  Briqueterie      33.7
```



```
## 11 Male    Carriere      30.0
## 12 Male    Cité Verte    27.0
## 13 Male    Ekoudou       25.2
## 14 Male    Messa         23.9
## 15 Male    Mokolo        30.5
## 16 Male    Nkomkana      29.8
## 17 Male    Tsinga        28.8
## 18 Male    Tsinga Oliga  24.3
```

Now the header tells you that the data is still grouped by the first variable in `group_by()`, `sex`:

```
# A tibble: 18 × 3
# Groups:   sex [2]
```

What is the implication of this persistent grouping in the data frame? It means that the data frame may exhibit what seems like weird behavior when you try to apply some `{dplyr}` functions on it.

For example, if you try to `select()` a single variable, perhaps the `mean_age` variable, you should normally be able to just use `select(mean_age)`:

```
yao %>%
  group_by(sex, neighborhood) %>%
  summarize(mean_age = mean(age)) %>%
  select(mean_age) # doesn't work as expected
```

```
## `summarise()` has grouped output by 'sex'. You can override using the
## `.groups` argument.
## Adding missing grouping variables: `sex`
```

```
## # A tibble: 18 × 2
## # Groups:   sex [2]
##   sex    mean_age
##   <chr>    <dbl>
## 1 Female    31.6
## 2 Female    28.2
## 3 Female    31.8
## 4 Female    29.3
## 5 Female    30.2
## 6 Female    28.0
## 7 Female    33.0
## 8 Female    30.6
## 9 Female    24.3
## 10 Male     33.7
## 11 Male     30.0
## 12 Male     27.0
## 13 Male     25.2
## 14 Male     23.9
```

```
## 15 Male      30.5
## 16 Male      29.8
## 17 Male      28.8
## 18 Male      24.3
```

But as you can see, the grouped-by variable, `sex`, is *still* selected, even though we only asked for `mean_age` in the `select()` statement.

This is one of the many examples of unique behaviors of grouped data frames. Other dplyr verbs like `filter()`, `mutate()` and `arrange()` also act in special ways on grouped data. We will address this in detail in a future lesson.

So you now know *why* you should ungroup data when you no longer need it grouped. Let's now see *how* to ungroup data. It's quite simple: just add the `ungroup()` function to your pipe chain. For example:

```
yao %>%
  group_by(sex, neighborhood) %>%
  summarize(mean_age = mean(age)) %>%
  ungroup()
```

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

```
## # A tibble: 18 × 3
##   sex      neighborhood mean_age
##   <chr>   <chr>          <dbl>
## 1 Female Briqueterie      31.6
## 2 Female Carriere        28.2
## 3 Female Cité Verte      31.8
## 4 Female Ekoudou         29.3
## 5 Female Messa           30.2
## 6 Female Mokolo          28.0
## 7 Female Nkomkana        33.0
## 8 Female Tsinga          30.6
## 9 Female Tsinga Oliga    24.3
## 10 Male   Briqueterie      33.7
## 11 Male   Carriere        30.0
## 12 Male   Cité Verte      27.0
## 13 Male   Ekoudou         25.2
## 14 Male   Messa           23.9
## 15 Male   Mokolo          30.5
## 16 Male   Nkomkana        29.8
## 17 Male   Tsinga          28.8
## 18 Male   Tsinga Oliga    24.3
```

Now that the data frame is ungrouped, it will behave like a normal data frame again. For example, you can `select()` any column(s) you want; you won't have some unwanted columns tagging along:

```
yao %>%
  group_by(sex, neighborhood) %>%
  summarize(mean_age = mean(age)) %>%
  ungroup() %>%
  select(mean_age)
```

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

```
## # A tibble: 18 × 1
##   mean_age
##   <dbl>
## 1     31.6
## 2     28.2
## 3     31.8
## 4     29.3
## 5     30.2
## 6     28.0
## 7     33.0
## 8     30.6
## 9     24.3
## 10     33.7
## 11     30.0
## 12     27.0
## 13     25.2
## 14     23.9
## 15     30.5
## 16     29.8
## 17     28.8
## 18     24.3
```

Counting rows

You can do a lot of data science by just *counting* and occasionally *dividing*. -
Hadley Wickham, Chief Scientist at RStudio

A common data summarization task is counting how many observations (rows) there are for each group. You can achieve this with the special `n()` function from {dplyr}, which is specifically designed to be used within `summarise()`.

For example, if you want to count how many individuals are in each neighborhood group, you would run:

```
yao %>%
  group_by(neighborhood) %>%
  summarize(count = n())
```

```
## # A tibble: 9 × 2
##   neighborhood count
##   <chr>          <int>
## 1 Briqueterie    106
## 2 Carriere       236
## 3 Cité Verte     72
## 4 Ekoudou        190
## 5 Messa          48
## 6 Mokolo         96
## 7 Nkomkana       75
## 8 Tsinga         81
## 9 Tsinga Oliga   67
```

As you can see, the `n()` function does not require any arguments. It just “knows its job” in the data frame!

Of course, you can include other summary statistics in the same `summarize()` call. For example, below we also calculate the mean age per neighborhood.

```
yao %>%
  group_by(neighborhood) %>%
  summarize(count = n(),
            mean_age = mean(age))
```

```
## # A tibble: 9 × 3
##   neighborhood count mean_age
##   <chr>          <int>   <dbl>
## 1 Briqueterie    106     32.5
## 2 Carriere       236     28.9
## 3 Cité Verte     72      29.9
## 4 Ekoudou        190     27.6
## 5 Messa          48      27.3
## 6 Mokolo         96      29.1
## 7 Nkomkana       75      31.7
## 8 Tsinga         81      29.7
## 9 Tsinga Oliga   67      24.3
```

PRACTICE



(in RMD)

Group your `yao` data frame by the respondents' occupation (`occupation`) and use `summarize()` to create columns that show:

- how many individuals there are with each occupation (think of the `n()` function)
- the mean number of work days missed (`n_days_miss_work`) by those in that occupation

PRACTICE



(in RMD)

Your output should be a data frame with three columns named as shown below:

occupation	count	mean_n_days_miss_work
------------	-------	-----------------------

```
Q_occupation_summary <-  
yao %>%  
_____
```

Counting rows that meet a condition

Rather than counting *all* rows as above, it is sometimes more useful to count just the rows that meet specific conditions. This can be done easily by placing the required conditions within the `sum()` function.

For example, to count the number of people under 18 in each neighborhood, you place the condition `age < 18` inside `sum()`:

```
yao %>%  
  group_by(neighborhood) %>%  
  summarize(count_under_18 = sum(age < 18))
```

```
## # A tibble: 9 × 2  
##   neighborhood count_under_18  
##   <chr>          <int>  
## 1 Briqueterie      28  
## 2 Carriere        58  
## 3 Cité Verte      19  
## 4 Ekoudou         66  
## 5 Messa           18  
## 6 Mokolo          32  
## 7 Nkomkana        22  
## 8 Tsinga          23  
## 9 Tsinga Oliga    25
```

Similarly, to count the number of people with doctorate degrees in each neighborhood, you place the condition `highest_education == "Doctorate"` inside `sum()`:

```
yao %>%  
  group_by(neighborhood) %>%  
  summarize(count_with_doctorates = sum(highest_education == "Doctorate"))
```

```
## # A tibble: 9 × 2  
##   neighborhood count_with_doctorates  
##   <chr>          <int>  
## 1 Briqueterie      2  
## 2 Carriere         1
```

```
## 3 Cité Verte 1
## 4 Ekoudou 1
## 5 Messa 2
## 6 Mokolo 0
## 7 Nkomkana 4
## 8 Tsinga 3
## 9 Tsinga Oliga 3
```

Under the hood: counting with conditions

Why are you able to use `sum()` which is meant to add numbers, on a condition like `highest_education == "Doctorate"`?

Using `sum()` on a condition works because the condition evaluates to the Boolean values `TRUE` and `FALSE`. And these Boolean values are treated as numbers (where `TRUE` equals 1 and `FALSE` equals 0), and numbers can, of course, be summed.

The code below demonstrates what is going on under the hood in a step-by-step way. Run through it and see if you can follow.

CHALLENGE



```
demo_of_condition_sums <- yao %>%
  select(highest_education) %>%
  mutate(with_doctorate = highest_education == "Doctorate") %>%
  mutate(numeric_with_doctorate = as.numeric(with_doctorate))

demo_of_condition_sums
```

```
## # A tibble: 971 × 3
##   highest_education with_doctorate numeric_with_doctorate
##   <chr>              <lgl>              <dbl>
## 1 Secondary          FALSE              0
## 2 University          FALSE              0
## 3 University          FALSE              0
## 4 Secondary          FALSE              0
## 5 Primary            FALSE              0
## 6 Secondary          FALSE              0
## 7 Secondary          FALSE              0
## 8 Doctorate          TRUE               1
## 9 Secondary          FALSE              0
## 10 Secondary         FALSE              0
## # ... with 961 more rows
```

The numeric values can then be added to produce a count of rows fulfilling the condition `highest_education == "Doctorate"`:

CHALLENGE



```
demo_of_condition_sums %>%
  summarize(count_with_doctorate = sum(numeric_with_doctorate))
```

```
## # A tibble: 1 × 1
##   count_with_doctorate
##                   <dbl>
## 1                   17
```

For a final illustration of counting with conditions, consider the `treatment_combinations` variable, which lists the treatments received by people with COVID-like symptoms. People who received no treatments have an `NA` value:

```
yao %>%
  select(treatment_combinations)
```

```
## # A tibble: 971 × 1
##   treatment_combinations
##   <chr>
## 1 Paracetamol
## 2 <NA>
## 3 <NA>
## 4 Antibiotics
## 5 <NA>
## 6 Paracetamol--Antibiotics
## 7 Traditional meds.
## 8 Paracetamol
## 9 Paracetamol--Traditional meds.
## 10 <NA>
## # ... with 961 more rows
```

If you want to count the number of people who received *no treatment*, you would sum up those who meet the `is.na(treatment_combinations)` condition:

```
yao %>%
  group_by(neighborhood) %>%
  summarize(unknown_treatments = sum(is.na(treatment_combinations)))
```

```
## # A tibble: 9 × 2
##   neighborhood unknown_treatments
##   <chr>           <int>
## 1 Briqueterie      82
## 2 Carriere        192
## 3 Cité Verte       46
## 4 Ekoudou         133
## 5 Messa           35
## 6 Mokolo          65
```

```
## 7 Nkomkana 53
## 8 Tsinga 56
## 9 Tsinga Oliga 47
```

These are the people with NA values for the `treatment_combinations` column.

To count the people who *did* receive some treatment, you can simply negate the `is.na()` function with `!`:

```
yao %>%
  group_by(neighborhood) %>%
  summarize(known_treatments = sum(!is.na(treatment_combinations)))
```

```
## # A tibble: 9 × 2
##   neighborhood known_treatments
##   <chr>          <int>
## 1 Briqueterie    24
## 2 Carriere      44
## 3 Cité Verte    26
## 4 Ekoudou       57
## 5 Messa         13
## 6 Mokolo        31
## 7 Nkomkana      22
## 8 Tsinga        25
## 9 Tsinga Oliga  20
```

Group your `yao` data frame by the respondents' symptoms (`symptoms`) and use the `sum()` function to count how many adults have each symptom combination.



Your output should be a data frame with two columns named as shown below:

symptoms	sum_adults
----------	------------

```
Q_symptoms_adults <-
  yao %>%
  group_by(GROUPED VARIABLE HERE) %>%
  summarise(sum_adults = sum(HERE, INPUT A CONDITION TO MATCH
    ADULTS))
```

`dplyr::count()`

The `dplyr::count()` function wraps a bunch of things into one beautiful friendly line of code to help you find counts of observations by group.

Let's use `dplyr::count()` on our occupation variable:

```
yao %>%  
  count(occupation)
```

```
## # A tibble: 28 × 2  
##   occupation      n  
##   <chr>      <int>  
## 1 Farmer      5  
## 2 Farmer--Other 1  
## 3 Home-maker  65  
## 4 Home-maker--Farmer 2  
## 5 Home-maker--Informal worker 3  
## 6 Home-maker--Informal worker--Farmer 1  
## 7 Home-maker--Trader 3  
## 8 Informal worker 189  
## 9 Informal worker--Other 2  
## 10 Informal worker--Trader 4  
## # ... with 18 more rows
```

Note that this is the same output as:

```
yao %>%  
  group_by(occupation) %>%  
  summarize(n = n())
```

```
## # A tibble: 28 × 2  
##   occupation      n  
##   <chr>      <int>  
## 1 Farmer      5  
## 2 Farmer--Other 1  
## 3 Home-maker  65  
## 4 Home-maker--Farmer 2  
## 5 Home-maker--Informal worker 3  
## 6 Home-maker--Informal worker--Farmer 1  
## 7 Home-maker--Trader 3  
## 8 Informal worker 189  
## 9 Informal worker--Other 2  
## 10 Informal worker--Trader 4  
## # ... with 18 more rows
```

You can also apply `dplyr::count()` in a nested fashion:

```
yao %>%  
  count(sex, occupation)
```

```
## # A tibble: 40 × 3  
##   sex      occupation      n  
##   <chr>   <chr>      <int>
```

```
## 1 Female Farmer 3
## 2 Female Home-maker 65
## 3 Female Home-maker--Farmer 2
## 4 Female Home-maker--Informal worker 3
## 5 Female Home-maker--Informal worker--Farmer 1
## 6 Female Home-maker--Trader 3
## 7 Female Informal worker 77
## 8 Female Informal worker--Trader 1
## 9 Female No response 8
## 10 Female Other 6
## # ... with 30 more rows
```

The `count()` verb gives you key information about your dataset in a very quick manner. Let's look at our IgG results stratified by age category and sex in one line of code.

Using the `yao` data frame, count the different combinations of gender (`sex`), age categories (`age_category_3`) and IgG results (`igg_result`).

Your output should be a data frame with four columns named as shown below:

sex	age_category_3	igg_result	n
-----	----------------	------------	---



```
Q_count_iggresults_stratified_by_sex_agecategories <-
yao %>%
  _____
```

Using the `yao` data frame, count the different combinations of age categories (`age_category_3`) and number of bedridden days (`n_bedridden_days`).

Your output should be a data frame with three columns named as shown below:

age_category_3	n_bedridden_days	n
----------------	------------------	---

```
Q_count_bedridden_age_categories <-
yao %>%
  _____
```

The downside of `count()` is that it can only give you a single summary statistic in the data frame. When you use `summarize()` and `n()` you can include multiple summary statistics. For example:

```
yao %>%
  group_by(sex, neighborhood) %>%
  summarize(count = n(),
            median_age = median(age))
```

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

```
## # A tibble: 18 × 4
## # Groups:   sex [2]
##   sex    neighborhood count median_age
##   <chr> <chr>          <int>      <dbl>
## 1 Female Briqueterie     61        28
## 2 Female Carriere       140       25.5
## 3 Female Cité Verte     44        28
## 4 Female Ekoudou       110       26.5
## 5 Female Messa          26       27.5
## 6 Female Mokolo         53        23
## 7 Female Nkomkana       43        28
## 8 Female Tsinga         42        29
## 9 Female Tsinga Oliga   30       23.5
## 10 Male   Briqueterie     45        28
## 11 Male   Carriere       96        27
## 12 Male   Cité Verte     28       22.5
## 13 Male   Ekoudou       80       21.5
## 14 Male   Messa          22       24.5
## 15 Male   Mokolo         43        32
## 16 Male   Nkomkana       32        27
## 17 Male   Tsinga         39        27
## 18 Male   Tsinga Oliga    37        21
```

But `count()` can only yield counts:

```
yao %>%
  group_by(sex, neighborhood) %>%
  count()
```

```
## # A tibble: 18 × 3
## # Groups:   sex, neighborhood [18]
##   sex    neighborhood     n
##   <chr> <chr>          <int>
## 1 Female Briqueterie     61
## 2 Female Carriere       140
## 3 Female Cité Verte     44
## 4 Female Ekoudou       110
## 5 Female Messa          26
## 6 Female Mokolo         53
## 7 Female Nkomkana       43
## 8 Female Tsinga         42
## 9 Female Tsinga Oliga   30
```

```
## 10 Male Briqueterie 45
## 11 Male Carriere 96
## 12 Male Cité Verte 28
## 13 Male Ekoudou 80
## 14 Male Messa 22
## 15 Male Mokolo 43
## 16 Male Nkomkana 32
## 17 Male Tsinga 39
## 18 Male Tsinga Oliga 37
```

Including missing combinations in summaries

When you use `group_by()` and `summarize()` on multiple variables, you obtain a summary statistic for every unique combination of the grouped variables. For instance, consider the code and output below, which counts the number of individuals in each age-sex group:

```
yao %>%
  group_by(sex, age_category_3) %>%
  summarise(number_of_individuals = n())
```

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

```
## # A tibble: 6 × 3
## # Groups:   sex [2]
##   sex   age_category_3 number_of_individuals
##   <chr> <chr>                <int>
## 1 Female Adult                368
## 2 Female Child                155
## 3 Female Senior                26
## 4 Male Adult                267
## 5 Male Child                136
## 6 Male Senior                19
```

In the output data frame, there is one row for each combination of sex and age group (Female–Adult, Female–Child and so on).

But what happens if one of these combinations is not present in the data?

Let's create an artificial example to observe this. With the code below, we artificially drop all male children from the `yao` data frame:

```
yao_no_male_children <-
  yao %>%
  filter(!(sex == "Male" & age_category_3 == "Child"))
```

Now if you run the same `group_by()` and `summarize()` call on `yao_no_male_children`, you'll notice the missing combination:

```
yao_no_male_children %>%
  group_by(sex, age_category_3) %>%
  summarise(number_of_individuals = n())
```

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

```
## # A tibble: 5 × 3
## # Groups:   sex [2]
##   sex      age_category_3 number_of_individuals
##   <chr>   <chr>                <int>
## 1 Female Adult                368
## 2 Female Child                155
## 3 Female Senior                26
## 4 Male    Adult                267
## 5 Male    Senior                19
```

Indeed, there is no row for male children.

But sometimes it is useful to include such missing combinations in the output data frame, with an NA or 0 value for the summary statistic.

To do this, you can run the following code instead:

```
yao_no_male_children %>%
  # convert variables to factors
  mutate(sex = as.factor(sex),
         age_category_3 = as.factor(age_category_3)) %>%
  # Note the the .drop = FALSE argument
  group_by(sex, age_category_3, .drop = FALSE) %>%
  summarise(number_of_individuals = n())
```

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

```
## # A tibble: 6 × 3
## # Groups:   sex [2]
##   sex      age_category_3 number_of_individuals
##   <fct>   <fct>                <int>
## 1 Female Adult                368
## 2 Female Child                155
## 3 Female Senior                26
## 4 Male    Adult                267
```

```
## 5 Male    Child    0
## 6 Male    Senior   19
```

What does the code do?

- First it converts the grouping variables to factors with `as.factor()` (inside a `mutate()` call)
- Then it uses the argument `.drop = FALSE` in the `group_by()` function to avoid dropping the missing combinations.

Now you have a clear 0 count for the number of male children!

Let's see one more example, this time without artificially modifying our data.

The code below calculates the average age by sex and education group:

```
yao %>%
  group_by(sex, highest_education) %>%
  summarise(mean_age = mean(age))
```

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

```
## # A tibble: 13 × 3
## # Groups:   sex [2]
##   sex    highest_education    mean_age
##   <chr>   <chr>                <dbl>
## 1 Female  Doctorate                28
## 2 Female  No formal instruction    45.6
## 3 Female  No response              35
## 4 Female  Primary                  26.8
## 5 Female  Secondary                28.8
## 6 Female  University               31.5
## 7 Male    Doctorate                42.2
## 8 Male    No formal instruction    37.9
## 9 Male    No response              22
## 10 Male   Other                    5.5
## 11 Male   Primary                 22.9
## 12 Male   Secondary                29.4
## 13 Male   University               31.9
```

Notice that in the output data frame, there are 7 rows for men but only 6 rows for women, because no woman answered “Other” to the question on highest education level.

If you nonetheless want to include the “Female–Other” row in the output data frame, you would run:

```
yao %>%
  mutate(sex = as.factor(sex),
         highest_education = as.factor(highest_education)) %>%
  group_by(sex, highest_education, .drop = FALSE) %>%
  summarise(mean_age = mean(age))
```

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

```
## # A tibble: 14 × 3
## # Groups:   sex [2]
##   sex    highest_education    mean_age
##   <fct> <fct>                <dbl>
## 1 Female Doctorate                28
## 2 Female No formal instruction    45.6
## 3 Female No response              35
## 4 Female Other                    NaN
## 5 Female Primary                 26.8
## 6 Female Secondary               28.8
## 7 Female University              31.5
## 8 Male   Doctorate                42.2
## 9 Male   No formal instruction    37.9
## 10 Male  No response              22
## 11 Male  Other                    5.5
## 12 Male  Primary                 22.9
## 13 Male  Secondary               29.4
## 14 Male  University              31.9
```

Using the `yao` data frame, let's calculate the median age when grouping by neighborhood, age_category, and gender

Note, we want all possible combinations of these three variables (not just those present in our data).

PRACTICE



(in RMD)

Pay attention to two data wrangling imperatives!

- convert your grouping variables to factors beforehand using `mutate()`
- calculate your statistic, the median, while removing any NA values.

Your output should be a data frame with four columns named as shown below:

neighborhood	age_category_3	sex	median_age
--------------	----------------	-----	------------

PRACTICE



```
Q_median_age_by_neighborhood_agecategory_sex <-  
yao %>%  
_____
```

Why include missing combinations?

Above, we mentioned that including missing combinations is often useful in the data analysis workflow. Let's see one use case: plotting with {ggplot}. If you have not yet learned {ggplot}, that is okay, just focus on the plot outputs.

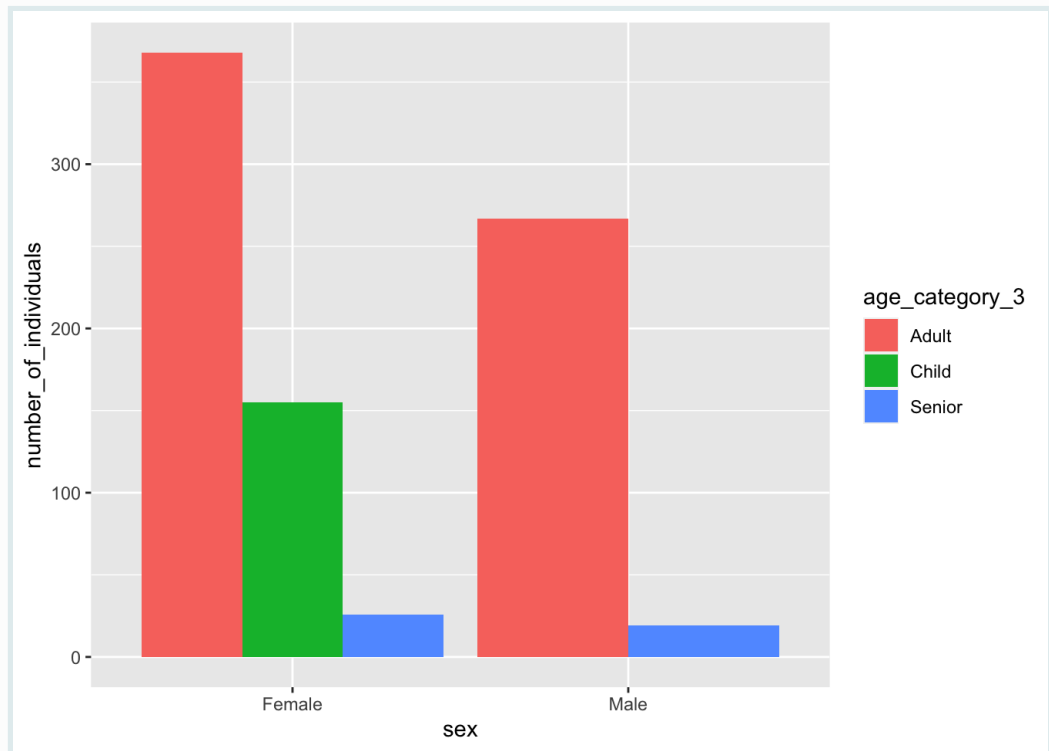
To make a dodged bar chart with the age-sex counts of `yao_no_male_children`, you could run:

SIDE NOTE



```
yao_no_male_children %>%  
  group_by(sex, age_category_3) %>%  
  summarise(number_of_individuals = n()) %>%  
  ungroup() %>%  
  
  # pass the output to ggplot  
  ggplot() +  
  geom_col(aes(x = sex, y = number_of_individuals, fill =  
               age_category_3),  
           position = "dodge")
```

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



SIDE NOTE



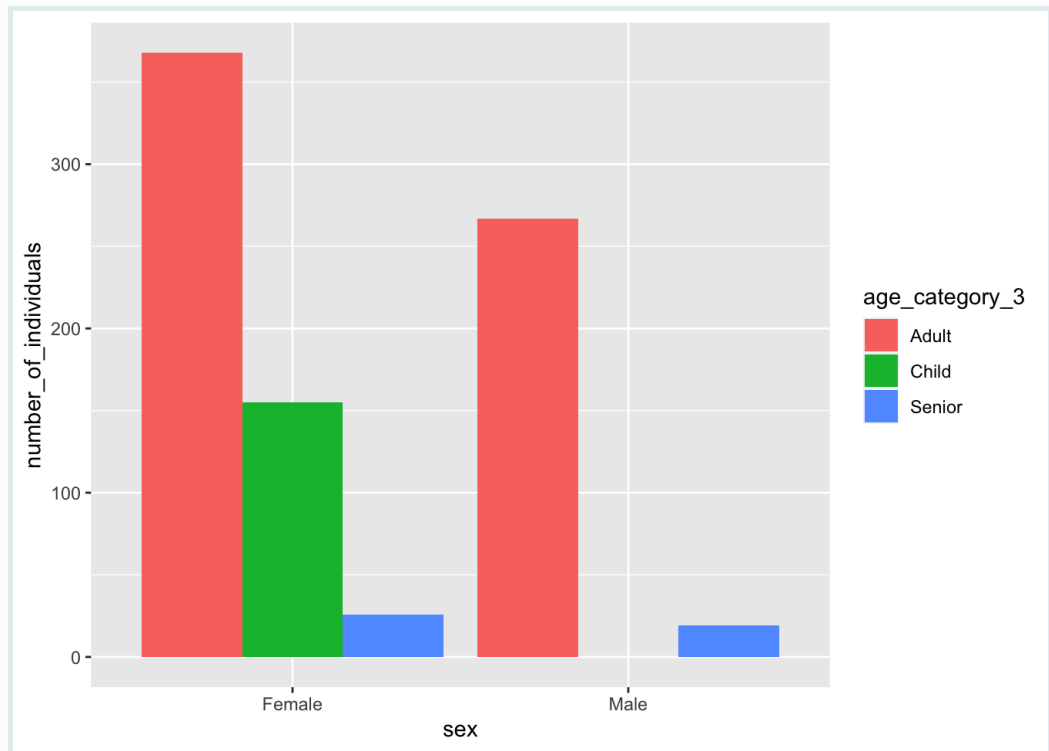
Not very elegant! Ideally there should be an empty space indicating 0 for the number of male children.

If you instead implement the procedure to include missing combinations, you get a more natural dodged bar plot, with an empty space for male children:

```
yao_no_male_children %>%
  mutate(sex = as.factor(sex),
         age_category_3 = as.factor(age_category_3)) %>%
  group_by(sex, age_category_3, .drop = FALSE) %>%
  summarise(number_of_individuals = n()) %>%
  ungroup() %>%

  # pass the output to ggplot
  ggplot() +
  geom_col(aes(x = sex, y = number_of_individuals, fill =
              age_category_3,
              position = "dodge"))
```

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



SIDE NOTE



Much better!

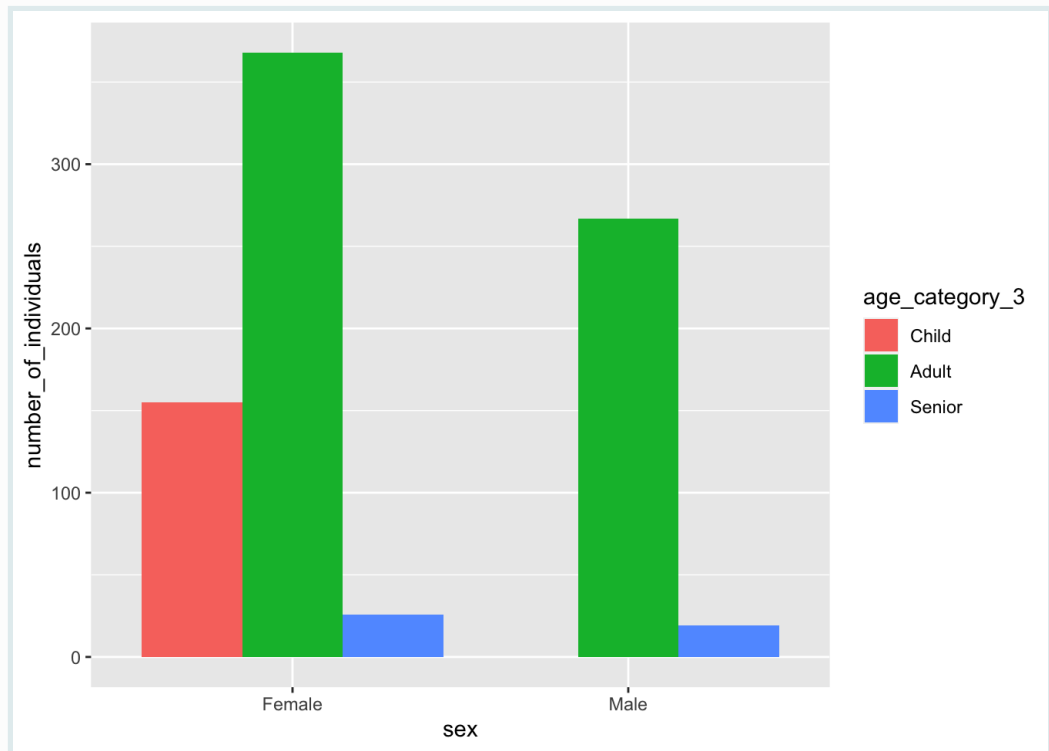
By the way, this output can be improved slightly by setting the factor levels for age to their proper ascending order: first "Child", then "Adult" then "Senior":

```
yao_no_male_children %>%
  mutate(sex = as.factor(sex),
         age_category_3 = factor(age_category_3,
                                levels = c("Child",
                                             "Adult",
                                             "Senior"))) %>%
  group_by(sex, age_category_3, .drop = FALSE) %>%
  summarise(number_of_individuals = n()) %>%
  ungroup() %>%

# pass the output to ggplot
ggplot() +
  geom_col(aes(x = sex, y = number_of_individuals, fill =
              age_category_3),
           position = "dodge")
```

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

SIDE NOTE



Wrap-up

You have now seen how to obtain quick summary statistics from your data, either for exploratory data or for further data presentation or plotting.

Additionally, you have discovered one of the marvels of {dplyr}, the possibility to group your data using `group_by()`.

`group_by()` combined with `summarize()` is a one of the most common grouping manipulations.

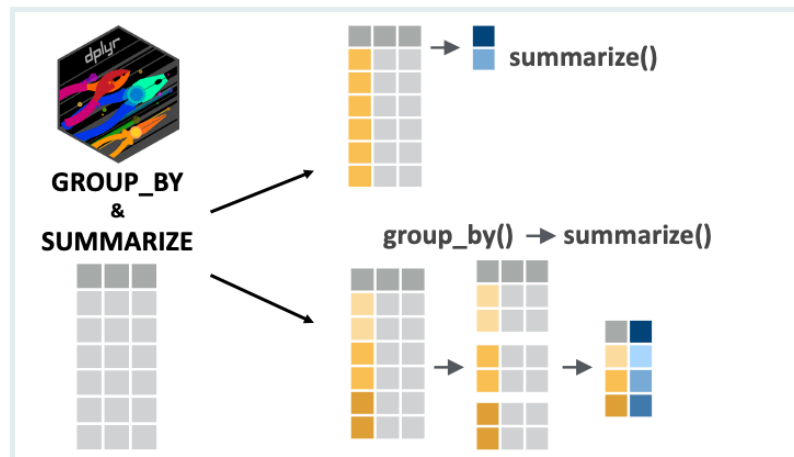


Fig: summarize() and group_by()

However, you can also combine `group_by()` with many of the other {dplyr} verbs: this is what we will cover in our next lesson. See you soon !

Contributors

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Thank you to [Alice Osmaston](#) and [Saifeldin Shehata](#) for their comments and review.

References

Some material in this lesson was adapted from the following sources:

- Horst, A. (2022). *Dplyr-learnr*. <https://github.com/allisonhorst/dplyr-learnr> (Original work published 2020)
- *Group by one or more variables*. (n.d.). Retrieved 21 February 2022, from https://dplyr.tidyverse.org/reference/group_by.html
- *Summarise each group to fewer rows*. (n.d.). Retrieved 21 February 2022, from <https://dplyr.tidyverse.org/reference/summarize.html>
- The Carpentries. (n.d.). *Grouped operations using 'dplyr'*. Grouped operations using 'dplyr' - Introduction to R/tidyverse for Exploratory Data Analysis. Retrieved July 28, 2022, from https://tavareshugo.github.io/r-intro-tidyverse-gapminder/06-grouped_operations_dplyr/index.html

Artwork was adapted from:

- Horst, A. (2022). *R & stats illustrations by Allison Horst*. <https://github.com/allisonhorst/stats-illustrations> (Original work published 2018)