

Introduction to R for Disease Surveillance and Outbreak Forecasting: Day 3

Designing data tables

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1 Introduction

Today you will get an introduction to creating and manipulating data. We begin to more fully explore two more of packages of the tidyverse: `tibble`, `dplyr`. The `tibble` package makes creating and viewing data frames easier, while the `dplyr` packages provides powerful functions for manipulating data frames. You will master those concepts to the point where you can work effectively with almost any dataset. You will learn some useful new tools for working with single tables, including summarizing data by groups, organizing data so that it is *tidy*, and dealing with both explicit and implicit missing values. Next, you will learn to combine datasets using functions that work no two or more tables.

2 Data transformations

You now have a solid background in plotting data with ggplot. But what happens when your data is not already in the correct format for plotting? Or what if you want to plot only a subset of your data?

In this part of the demonstration, you will learn the basic commands for manipulating data frames (and tibbles). Such manipulations can be accomplished in a variety of ways, but the most intuitive and efficient way is by using the functions provided in the **dplyr** package.

dplyr is a member of the tidyverse which focuses exclusively on manipulating data frames.

Start by loading dplyr.

```
library(dplyr)

##
## Attaching package: 'dplyr'
##
## The following objects are masked from 'package:stats':
##
##   filter, lag
##
## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union

library(readr)
```

The dplyr package has some excellent vignettes, including an Introduction to dplyr which can be accessed by running `vignette("dplyr")`

2.1 Single table verbs

Each data transformation has a corresponding dplyr function that accomplishes it. These functions take the form of verbs that describe the action. Some dplyr verbs operate on a single data frame or tibble, while others operate on two or more tables. Here is a list of the main dplyr verbs for single tables:

- `filter()` selects observations (rows) based on their values.
- `arrange()` reorders observations.
- `select()` and `rename()` select variables (columns) based on their names.
- `mutate()` and `transmute()` add new variables that are functions of existing variables.

2.1.1 Filter

```
mecha <- read_csv("data_mecha.csv")

## Parsed with column specification:
## cols(
##   WID = col_double(),
##   worda_name = col_character(),
##   obs_date = col_date(format = ""),
##   test_pf_tot = col_double(),
##   test_pv_only = col_double(),
##   pop_at_risk = col_double(),
##   mal_case = col_double(),
##   iso_year = col_double(),
##   iso_week = col_double(),
##   data_source = col_character()
## )
```

```
mecha
```

```
## # A tibble: 156 x 10
##   WID woreda_name obs_date test_pf_tot test_pv_only pop_at_risk
##   <dbl> <chr>      <date>      <dbl>      <dbl>      <dbl>
## 1  106 Mecha      2016-01-10         6         15      377232.
## 2  106 Mecha      2016-01-17         8         12      377232.
## 3  106 Mecha      2016-01-24         9         11      377232.
## 4  106 Mecha      2016-01-31         9         11      377232.
## 5  106 Mecha      2016-02-07        11         11      377232.
## 6  106 Mecha      2016-02-14        11         10      377232.
## 7  106 Mecha      2016-02-21        10         10      377232.
## 8  106 Mecha      2016-02-28         9         8       377232.
## 9  106 Mecha      2016-03-06         9         6       377232.
## 10 106 Mecha      2016-03-13         8         6       377232.
## # ... with 146 more rows, and 4 more variables: mal_case <dbl>,
## #   iso_year <dbl>, iso_week <dbl>, data_source <chr>
```

```
filter(mecha, iso_week == 1)
```

```
## # A tibble: 3 x 10
##   WID woreda_name obs_date test_pf_tot test_pv_only pop_at_risk
##   <dbl> <chr>      <date>      <dbl>      <dbl>      <dbl>
## 1  106 Mecha      2016-01-10         6         15      377232.
## 2  106 Mecha      2017-01-08         2         8      384022.
## 3  106 Mecha      2018-01-07         5         4      390935.
## # ... with 4 more variables: mal_case <dbl>, iso_year <dbl>,
## #   iso_week <dbl>, data_source <chr>
```

```
filter(mecha, iso_year %in% 2015:2016)
```

```
## # A tibble: 52 x 10
##   WID woreda_name obs_date test_pf_tot test_pv_only pop_at_risk
##   <dbl> <chr>      <date>      <dbl>      <dbl>      <dbl>
## 1  106 Mecha      2016-01-10         6         15      377232.
## 2  106 Mecha      2016-01-17         8         12      377232.
## 3  106 Mecha      2016-01-24         9         11      377232.
## 4  106 Mecha      2016-01-31         9         11      377232.
## 5  106 Mecha      2016-02-07        11         11      377232.
## 6  106 Mecha      2016-02-14        11         10      377232.
## 7  106 Mecha      2016-02-21        10         10      377232.
## 8  106 Mecha      2016-02-28         9         8       377232.
## 9  106 Mecha      2016-03-06         9         6       377232.
## 10 106 Mecha      2016-03-13         8         6       377232.
## # ... with 42 more rows, and 4 more variables: mal_case <dbl>,
## #   iso_year <dbl>, iso_week <dbl>, data_source <chr>
```

```
filter(mecha, mal_case > 200, iso_year != 2016)
```

```
## # A tibble: 0 x 10
## # ... with 10 variables: WID <dbl>, woreda_name <chr>, obs_date <date>,
## #   test_pf_tot <dbl>, test_pv_only <dbl>, pop_at_risk <dbl>,
## #   mal_case <dbl>, iso_year <dbl>, iso_week <dbl>, data_source <chr>
```

2.1.2 Arrange

```
arrange(mecha, iso_week)
```

```
## # A tibble: 156 x 10
##   WID worda_name obs_date test_pf_tot test_pv_only pop_at_risk
##   <dbl> <chr>      <date>      <dbl>      <dbl>      <dbl>
## 1  106 Mecha      2016-01-10         6         15      377232.
## 2  106 Mecha      2017-01-08         2          8      384022.
## 3  106 Mecha      2018-01-07         5          4      390935.
## 4  106 Mecha      2016-01-17         8         12      377232.
## 5  106 Mecha      2017-01-15         3          7      384022.
## 6  106 Mecha      2018-01-14         3          4      390935.
## 7  106 Mecha      2016-01-24         9         11      377232.
## 8  106 Mecha      2017-01-22         2          7      384022.
## 9  106 Mecha      2018-01-21         3          5      390935.
## 10 106 Mecha      2016-01-31         9         11      377232.
## # ... with 146 more rows, and 4 more variables: mal_case <dbl>,
## #   iso_year <dbl>, iso_week <dbl>, data_source <chr>
```

Use `desc()` to order a column in descending rather than ascending order.

```
arrange(mecha, desc(mal_case))
```

```
## # A tibble: 156 x 10
##   WID worda_name obs_date test_pf_tot test_pv_only pop_at_risk
##   <dbl> <chr>      <date>      <dbl>      <dbl>      <dbl>
## 1  106 Mecha      2016-05-22        36         20      377232.
## 2  106 Mecha      2016-05-29        35         21      377232.
## 3  106 Mecha      2016-05-15        35         20      377232.
## 4  106 Mecha      2016-06-05        33         22      377232.
## 5  106 Mecha      2016-06-12        29         22      377232.
## 6  106 Mecha      2016-11-13        34         15      384022.
## 7  106 Mecha      2016-05-08        31         17      377232.
## 8  106 Mecha      2016-11-06        33         15      384022.
## 9  106 Mecha      2016-05-01        28         18      377232.
## 10 106 Mecha      2016-10-30        31         14      384022.
## # ... with 146 more rows, and 4 more variables: mal_case <dbl>,
## #   iso_year <dbl>, iso_week <dbl>, data_source <chr>
```

2.1.3 Select and Rename

Select columns to keep by name. Other columns are removed from the data frame.

```
select(mecha, worda_name, iso_year, iso_week, mal_case)
```

```
## # A tibble: 156 x 4
##   worda_name iso_year iso_week mal_case
##   <chr>      <dbl>      <dbl>      <dbl>
## 1 Mecha      2016         1         21
## 2 Mecha      2016         2         20
## 3 Mecha      2016         3         20
## 4 Mecha      2016         4         20
## 5 Mecha      2016         5         22
## 6 Mecha      2016         6         21
## 7 Mecha      2016         7         20
```

```
## 8 Mecha      2016      8      17
## 9 Mecha      2016      9      15
## 10 Mecha     2016     10      14
## # ... with 146 more rows
```

Use the `:` operator to select a continuous series of columns. The helper functions `starts_with()`, `ends_with()`, and `contains()` can be used to find multiple columns by matching part of the column name.

```
select(mecha,
       woreda_name:mal_case)
```

```
## # A tibble: 156 x 6
##   woreda_name obs_date test_pf_tot test_pv_only pop_at_risk mal_case
##   <chr>      <date>      <dbl>      <dbl>      <dbl>      <dbl>
## 1 Mecha     2016-01-10         6         15    377232.        21
## 2 Mecha     2016-01-17         8         12    377232.        20
## 3 Mecha     2016-01-24         9         11    377232.        20
## 4 Mecha     2016-01-31         9         11    377232.        20
## 5 Mecha     2016-02-07        11         11    377232.        22
## 6 Mecha     2016-02-14        11         10    377232.        21
## 7 Mecha     2016-02-21        10         10    377232.        20
## 8 Mecha     2016-02-28         9          8    377232.        17
## 9 Mecha     2016-03-06         9          6    377232.        15
## 10 Mecha    2016-03-13         8          6    377232.        14
## # ... with 146 more rows
```

```
select(mecha,
       starts_with("test"))
```

```
## # A tibble: 156 x 2
##   test_pf_tot test_pv_only
##   <dbl>      <dbl>
## 1         6         15
## 2         8         12
## 3         9         11
## 4         9         11
## 5        11         11
## 6        11         10
## 7        10         10
## 8          9          8
## 9          9          6
## 10         8          6
## # ... with 146 more rows
```

Remove columns by prefixing their names with a `-`. Other columns will be kept.

```
select(mecha,
       -test_pf_tot,
       -test_pv_only)
```

```
## # A tibble: 156 x 8
##   WID woreda_name obs_date pop_at_risk mal_case iso_year iso_week
##   <dbl> <chr>      <date>      <dbl>      <dbl>      <dbl>      <dbl>
## 1  106 Mecha     2016-01-10    377232.        21    2016         1
## 2  106 Mecha     2016-01-17    377232.        20    2016         2
## 3  106 Mecha     2016-01-24    377232.        20    2016         3
```

```
## 4 106 Mecha 2016-01-31 377232. 20 2016 4
## 5 106 Mecha 2016-02-07 377232. 22 2016 5
## 6 106 Mecha 2016-02-14 377232. 21 2016 6
## 7 106 Mecha 2016-02-21 377232. 20 2016 7
## 8 106 Mecha 2016-02-28 377232. 17 2016 8
## 9 106 Mecha 2016-03-06 377232. 15 2016 9
## 10 106 Mecha 2016-03-13 377232. 14 2016 10
## # ... with 146 more rows, and 1 more variable: data_source <chr>
```

Rename columns using the = operator, placing the new name first and the old name second.

```
rename(mecha, district = woreda_name,
       malaria_case = mal_case)
```

```
## # A tibble: 156 x 10
##   WID district obs_date test_pf_tot test_pv_only pop_at_risk
##   <dbl> <chr>   <date>         <dbl>         <dbl>         <dbl>
## 1 106 Mecha 2016-01-10         6          15      377232.
## 2 106 Mecha 2016-01-17         8          12      377232.
## 3 106 Mecha 2016-01-24         9          11      377232.
## 4 106 Mecha 2016-01-31         9          11      377232.
## 5 106 Mecha 2016-02-07        11          11      377232.
## 6 106 Mecha 2016-02-14        11          10      377232.
## 7 106 Mecha 2016-02-21        10          10      377232.
## 8 106 Mecha 2016-02-28         9           8      377232.
## 9 106 Mecha 2016-03-06         9           6      377232.
## 10 106 Mecha 2016-03-13         8           6      377232.
## # ... with 146 more rows, and 4 more variables: malaria_case <dbl>,
## #   iso_year <dbl>, iso_week <dbl>, data_source <chr>
```

2.1.4 Mutate and Transmute

Add new variables using `mutate()`. You can create multiple new variables at a time, and you can refer to ones you've just created.

```
mutate(mecha,
       inc = mal_case / pop_at_risk,
       inc_per_1000 = inc * 1000)
```

```
## # A tibble: 156 x 12
##   WID woreda_name obs_date test_pf_tot test_pv_only pop_at_risk
##   <dbl> <chr>   <date>         <dbl>         <dbl>         <dbl>
## 1 106 Mecha 2016-01-10         6          15      377232.
## 2 106 Mecha 2016-01-17         8          12      377232.
## 3 106 Mecha 2016-01-24         9          11      377232.
## 4 106 Mecha 2016-01-31         9          11      377232.
## 5 106 Mecha 2016-02-07        11          11      377232.
## 6 106 Mecha 2016-02-14        11          10      377232.
## 7 106 Mecha 2016-02-21        10          10      377232.
## 8 106 Mecha 2016-02-28         9           8      377232.
## 9 106 Mecha 2016-03-06         9           6      377232.
## 10 106 Mecha 2016-03-13         8           6      377232.
## # ... with 146 more rows, and 6 more variables: mal_case <dbl>,
## #   iso_year <dbl>, iso_week <dbl>, data_source <chr>, inc <dbl>,
## #   inc_per_1000 <dbl>
```

If you only want to keep the new variables, use `transmute()`.

```
transmute(mecha,
  inc = mal_case / pop_at_risk,
  inc_per_1000 = inc * 1000)
```

```
## # A tibble: 156 x 2
##       inc inc_per_1000
##   <dbl>   <dbl>
## 1 0.0000557 0.0557
## 2 0.0000530 0.0530
## 3 0.0000530 0.0530
## 4 0.0000530 0.0530
## 5 0.0000583 0.0583
## 6 0.0000557 0.0557
## 7 0.0000530 0.0530
## 8 0.0000451 0.0451
## 9 0.0000398 0.0398
## 10 0.0000371 0.0371
## # ... with 146 more rows
```

For the next few exercises, you will use the `data_day3` dataset. Let's begin by loading the dataset again using `read_csv()`.

```
library(readr)
data <- read_csv("data_day3_subset.csv")
```

3 Grouped summaries with `summarize()`

The only main dplyr verb we did not cover yesterday was `summarize()`, which collapses a data frame into a single row:

```
library(dplyr)

summarize(data, n_cases = sum(mal_case, na.rm = TRUE))
```

```
## # A tibble: 1 x 1
##   n_cases
##   <dbl>
## 1 268421
```

Don't worry about the `na.rm` argument for now. We will cover that below.

`summarize()` becomes particularly useful when we pair it with another dplyr function, `group_by()`, which groups rows of data together to produce a “grouped data frame”. When a grouped data frame is summarized, the summaries are for individual groups rather than the entire dataset, and the result is a data frame with one row per group.

```
by_woreda_year <- group_by(data, woreda_name, iso_year)
summarized_cases <- summarize(by_woreda_year, n_cases = sum(mal_case, na.rm = TRUE))
summarized_cases
```

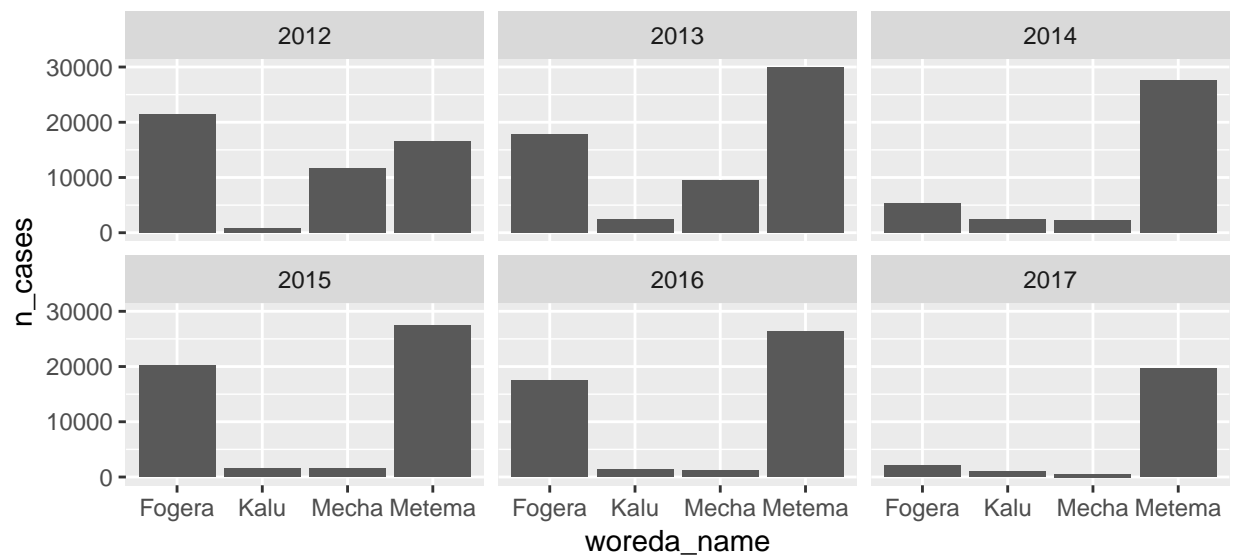
```
## # A tibble: 24 x 3
## # Groups:   woreda_name [?]
##   woreda_name iso_year n_cases
##   <chr>       <dbl>   <dbl>
## 1 Fogera     2012    21521
## 2 Fogera     2013    17781
## 3 Fogera     2014     5298
```

```
## 4 Fogera          2015    20231
## 5 Fogera          2016    17415
## 6 Fogera          2017     2011
## 7 Kalu            2012      739
## 8 Kalu            2013     2410
## 9 Kalu            2014     2527
## 10 Kalu           2015     1473
## # ... with 14 more rows
```

In this example, we calculated the total number of cases observed in each woreda in each year. In this case, we grouped by two variables, but you can group any number of variables you want.

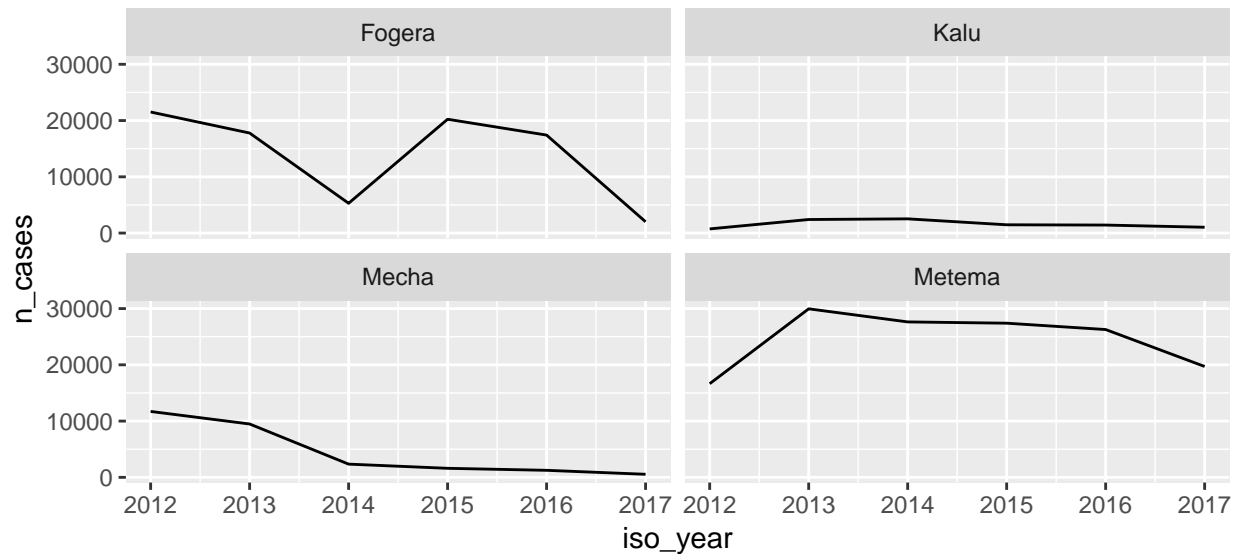
We can also visualize the summaries with a column plot:

```
library(ggplot2)
ggplot(summarized_cases) +
  geom_col(aes(x = woreda_name, y = n_cases)) +
  facet_wrap(~ iso_year)
```



Or with as a time series plot:

```
ggplot(summarized_cases) +
  geom_line(aes(x = iso_year, y = n_cases)) +
  facet_wrap(~ woreda_name)
```

Grouped summaries are a powerful tool for data exploration or for transforming data into group summaries for further analysis or visualization.

3.1 Missing data

In the previous section, you saw the argument `na.rm = TRUE`. That argument told R to remove the missing values, identified by NAs, from the data before summarizing.

If you set `na.rm = FALSE`, which is the default value, then NAs are not removed. Any vector that includes an NA value will yield an NA value when summarized. The logic is that if you are missing some elements in a set of values, you can't accurately summarize the set. Thus we see the following behaviors:

```
sum(c(1, 2, 3))
```

```
## [1] 6
```

```
sum(c(1, 2, 3, NA))
```

```
## [1] NA
```

```
sum(c(1, 2, 3, NA), na.rm = TRUE)
```

```
## [1] 6
```

3.2 Counts

When summarizing, it is often useful to count the number of values used. This can be done with the `dplyr` function `n()`, which will include NA values, or `sum(!is.na(x))` which will exclude them. It's often a good idea to count when summarizing to make sure your summaries are not based on a very small sample size.

```
summarize(by_woreda_year,
  n_cases = sum(test_pv_only, na.rm = TRUE),
  n_weeks = n())
```

```
## # A tibble: 24 x 4
## # Groups:   woreda_name [?]
##   woreda_name iso_year n_cases n_weeks
##   <chr>         <dbl>   <dbl>   <int>
## 1 Fogera       2012     3300     20
```

```
## 2 Fogera      2013    3214    36
## 3 Fogera      2014    1409    33
## 4 Fogera      2015    6156    41
## 5 Fogera      2016    8634    35
## 6 Fogera      2017     803    39
## 7 Kalu        2012     393    13
## 8 Kalu        2013    1282    36
## 9 Kalu        2014    1733    36
## 10 Kalu       2015    1084    37
## # ... with 14 more rows
```

If the only summary you want to perform is counting, you can also use the dplyr function `count()`. This is basically a shortcut to perform a grouped summarize.

```
count(by_woreda_year, woreda_name, iso_year)
```

```
## # A tibble: 24 x 3
## # Groups:   woreda_name, iso_year [24]
##   woreda_name iso_year     n
##   <chr>      <dbl> <int>
## 1 Fogera      2012     20
## 2 Fogera      2013     36
## 3 Fogera      2014     33
## 4 Fogera      2015     41
## 5 Fogera      2016     35
## 6 Fogera      2017     39
## 7 Kalu        2012     13
## 8 Kalu        2013     36
## 9 Kalu        2014     36
## 10 Kalu       2015     37
## # ... with 14 more rows
```

3.3 Useful summary functions

Up to this point, you've only seen two summary functions: `sum()` and `n()`. Other useful summary functions include:

- Measures of location: `mean(x)` and `median(x)`. The mean is the sum divided by the length; the median is a value where 50% of `x` is above it, and 50% is below it.
- Measures of spread: `sd(x)`, `IQR(x)`, `mad(x)`. The mean squared deviation, or standard deviation or `sd` for short, is the standard measure of spread. The interquartile range `IQR()` and median absolute deviation `mad(x)` are robust equivalents that may be more useful if you have outliers.
- Measures of rank: `min(x)`, `quantile(x, 0.25)`, `max(x)`. Quantiles are a generalisation of the median. For example, `quantile(x, 0.25)` will find a value of `x` that is greater than 25% of the values, and less than the remaining 75%.
- Measures of position: `first(x)`, `nth(x, 2)`, `last(x)`. These work similarly to `x[1]`, `x[2]`, and `x[length(x)]` but let you set a default value if that position does not exist (i.e. you're trying to get the 3rd element from a group that only has two elements).
- Counts: You've seen `n()`, which takes no arguments, and returns the size of the current group. To count the number of non-missing values, use `sum(!is.na(x))`. To count the number of distinct (unique) values, use `n_distinct(x)`.

4 Working with epidemiological weeks (WHO ISO 8601)

Up until this point we have been working with epidemiological datasets organized by epidemiological week number (or iso week) and epidemiological year (or iso year). We will use a trimmed down version of our full (without missing rows) dataset earlier in the day as an example.

```
day3 <- read_csv("data_day3.csv")

## Parsed with column specification:
## cols(
##   WID = col_double(),
##   woreda_name = col_character(),
##   obs_date = col_date(format = ""),
##   test_pf_tot = col_double(),
##   test_pv_only = col_double(),
##   pop_at_risk = col_double(),
##   mal_case = col_double(),
##   iso_year = col_double(),
##   iso_week = col_double(),
##   pfm_inc = col_double(),
##   pv_inc = col_double(),
##   data_source = col_character()
## )

incid <- select(day3, woreda_name, iso_year, iso_week, pfm_inc, pv_inc)
incid

## # A tibble: 1,144 x 5
##   woreda_name iso_year iso_week pfm_inc pv_inc
##   <chr>      <dbl>    <dbl>  <dbl> <dbl>
## 1 Fogera      2012      28    3.32  0.563
## 2 Fogera      2012      29    3.13  0.582
## 3 Fogera      2012      30    2.63  0.511
## 4 Fogera      2012      31    2.35  0.506
## 5 Fogera      2012      32    2.05  0.506
## 6 Fogera      2012      33    1.93  0.511
## 7 Fogera      2012      34    1.83  0.530
## 8 Fogera      2012      35    1.88  0.558
## 9 Fogera      2012      36    1.96  0.587
## 10 Fogera     2012      37    2.24  0.644
## # ... with 1,134 more rows

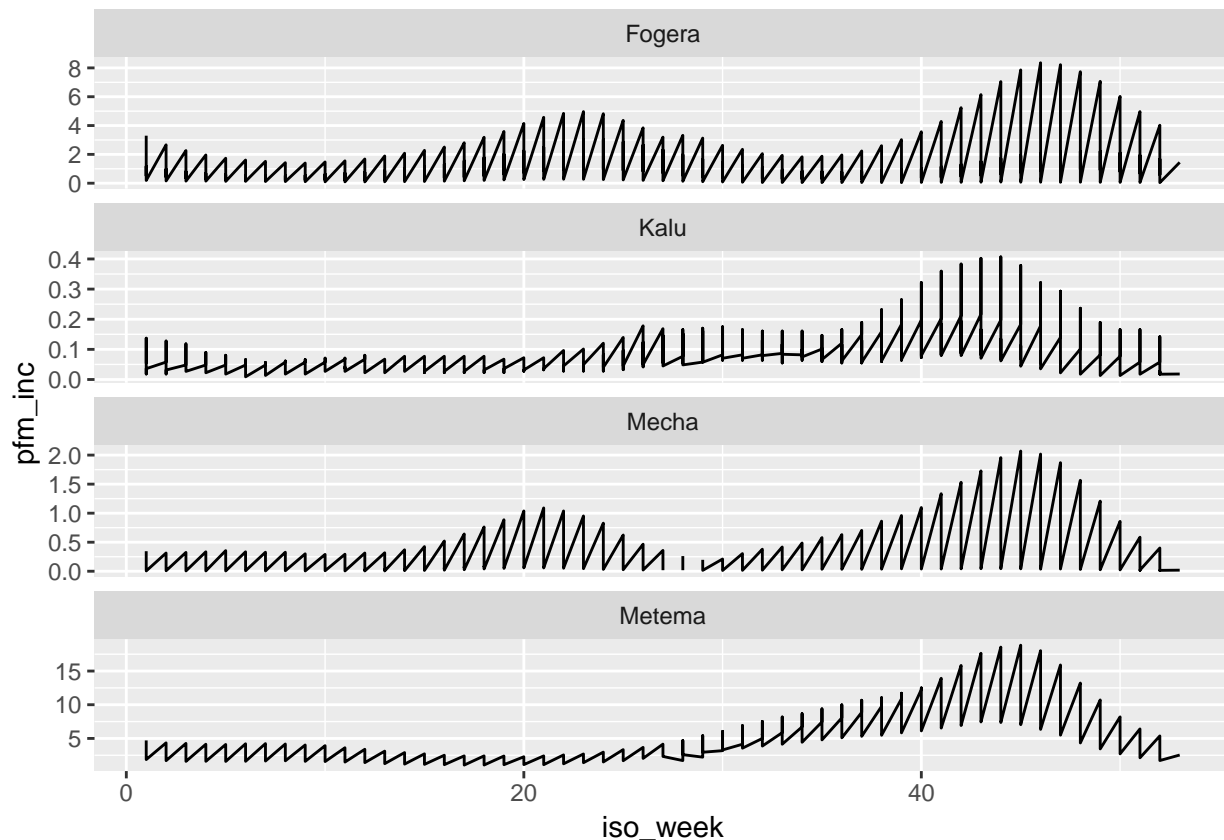
count(incid, woreda_name)

## # A tibble: 4 x 2
##   woreda_name    n
##   <chr>    <int>
## 1 Fogera    286
## 2 Kalu     286
## 3 Mecha    286
## 4 Metema    286
```

We can see that we have n weeks of data for each woreda. If we wanted to plot this data as a single time series of n weeks, we might do something like this:

```
ggplot(incid) +
  geom_line(aes(x = iso_week, y = pfm_inc)) +
```

```
facet_wrap(~ worda_name, ncol = 1, scales = "free_y")
```



The problem is that ggplot does not know that we have data from different years, so for each week it plots all years on top of each other and tries to connect them with a line. Unfortunately, the aesthetic mappings in ggplot plot must be 1 to 1, meaning you can't map two columns in the data frame (iso_year and iso_week) as the x axis values.

In this situation we need to add a new column to our dataset that contains properly ordered values to use as the x-axis variable. But what values do we use? We could simply number the rows as 1 to n for each worda, but then we lose the date-related information on the x axis when we plot it. The solution is to convert from epi weeks to dates, i.e. the Date class you learned about on day 1. Dates contain all the necessary information to be ordered correctly, and they fit in a single column.

Although the lubridate package in R contains many useful functions for working with dates in general, it does not yet include a function to convert from iso weeks and iso years to calendar dates. For that we will need to use a custom function, which we will load (or "source") from another R file.

```
library(lubridate)
```

```
##
## Attaching package: 'lubridate'
## The following object is masked from 'package:base':
##
##      date
source("date_functions.R")
```

If you look at the Environment tab in RStudio you will see that it now includes a function named

`make_date_yw()`. This function takes vectors of iso years, week numbers (1–53), and weekdays (1–7) and returns a vector of Dates. For example:

```
make_date_yw(year = 2017, week = 1, weekday = 1) # first day of 2017 week 1
```

```
## [1] "2017-01-02"
```

```
make_date_yw(2017, 1, 2) # second day of that week
```

```
## [1] "2017-01-03"
```

```
make_date_yw(2017, 1) # weekday defaults to 1
```

```
## [1] "2017-01-02"
```

```
make_date_yw(2015:2017, 1:3) # arguments can be vectors
```

```
## [1] "2014-12-29" "2016-01-11" "2017-01-16"
```

```
make_date_yw(2017, 1:3) # arguments are "recycled"
```

```
## [1] "2017-01-02" "2017-01-09" "2017-01-16"
```

Other very useful functions exist in the `lubridate` package.

```
isoweek(Sys.Date()) # today's ISO week number
```

```
## [1] 16
```

```
isoyear(Sys.Date()) # today's ISO year
```

```
## [1] 2019
```

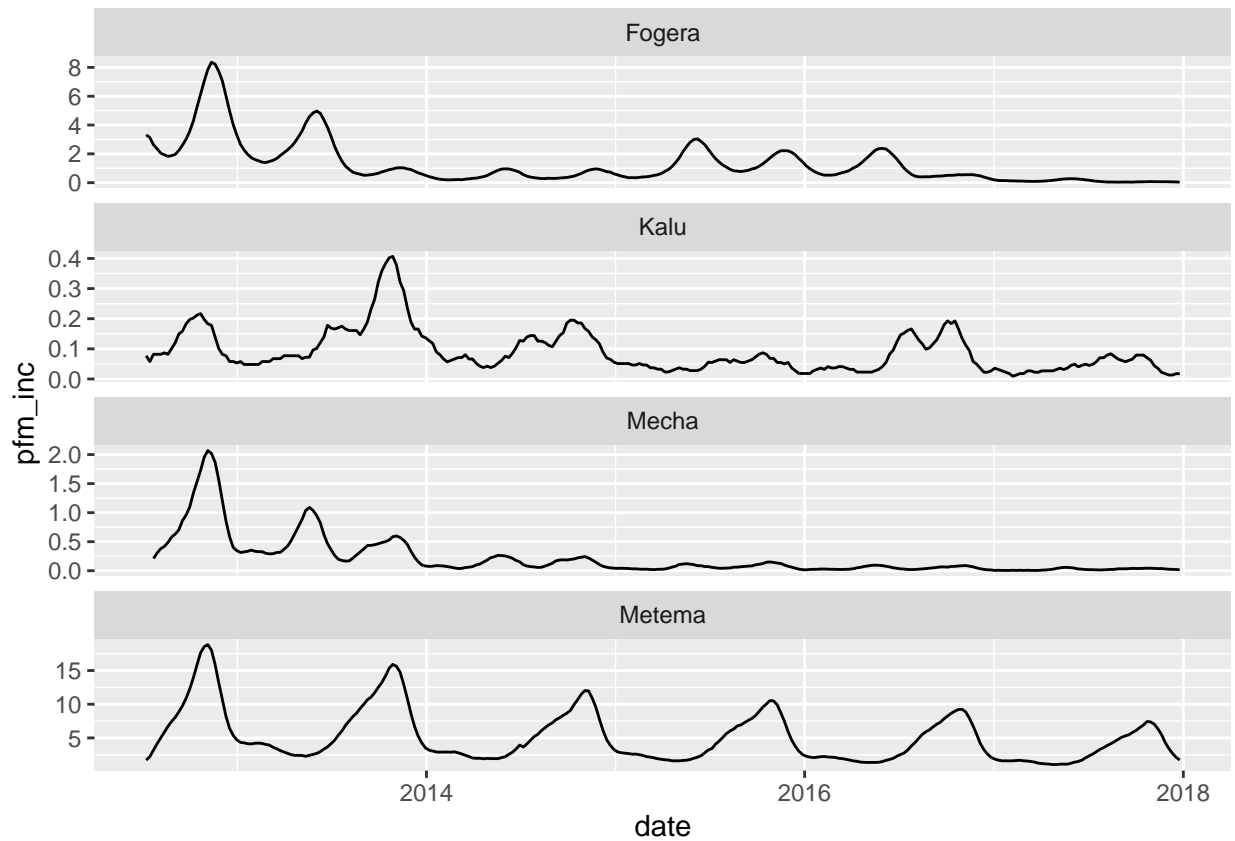
Because `make_date_yw()` accepts vectors as arguments, we can use it with `mutate()`.

```
incid_date <- mutate(incid, date = make_date_yw(iso_year, iso_week))
incid_date <- select(incid_date, woreda_name, iso_year, iso_week,
                    date, pfm_inc, pv_inc) # put the new column after date
incid_date
```

```
## # A tibble: 1,144 x 6
##   woreda_name iso_year iso_week date      pfm_inc pv_inc
##   <chr>      <dbl>    <dbl> <date>    <dbl>  <dbl>
## 1 Fogera      2012      28 2012-07-09    3.32  0.563
## 2 Fogera      2012      29 2012-07-16    3.13  0.582
## 3 Fogera      2012      30 2012-07-23    2.63  0.511
## 4 Fogera      2012      31 2012-07-30    2.35  0.506
## 5 Fogera      2012      32 2012-08-06    2.05  0.506
## 6 Fogera      2012      33 2012-08-13    1.93  0.511
## 7 Fogera      2012      34 2012-08-20    1.83  0.530
## 8 Fogera      2012      35 2012-08-27    1.88  0.558
## 9 Fogera      2012      36 2012-09-03    1.96  0.587
## 10 Fogera     2012      37 2012-09-10    2.24  0.644
## # ... with 1,134 more rows
```

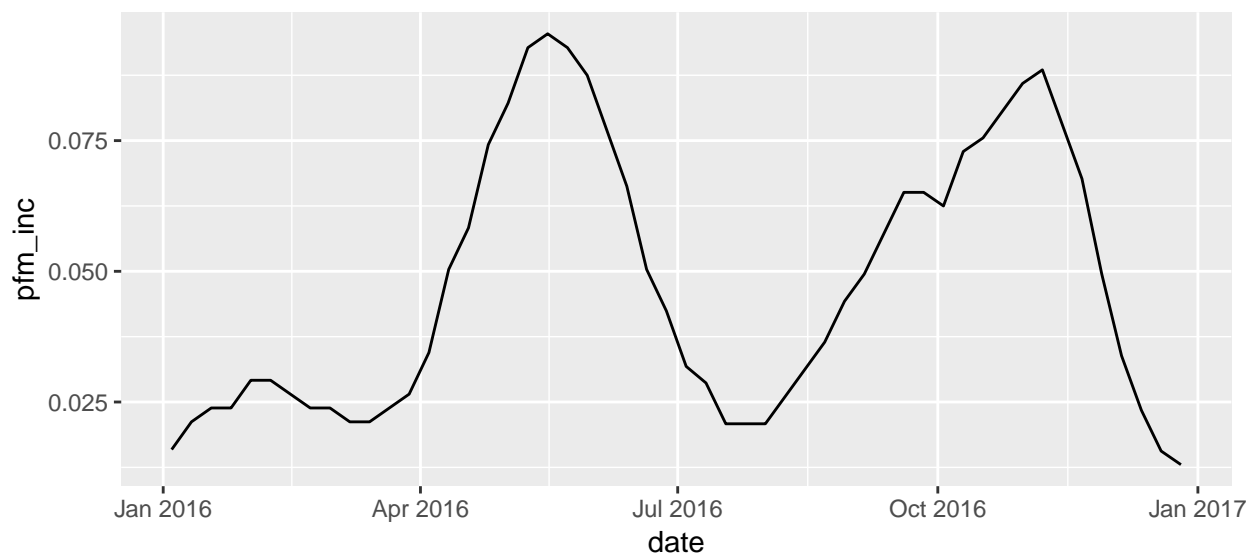
Now when we plot, we can map the x axis value to the date column `date`:

```
ggplot(incid_date) +
  geom_line(aes(x = date, y = pfm_inc)) +
  facet_wrap(~ woreda_name, ncol = 1, scales = "free_y")
```

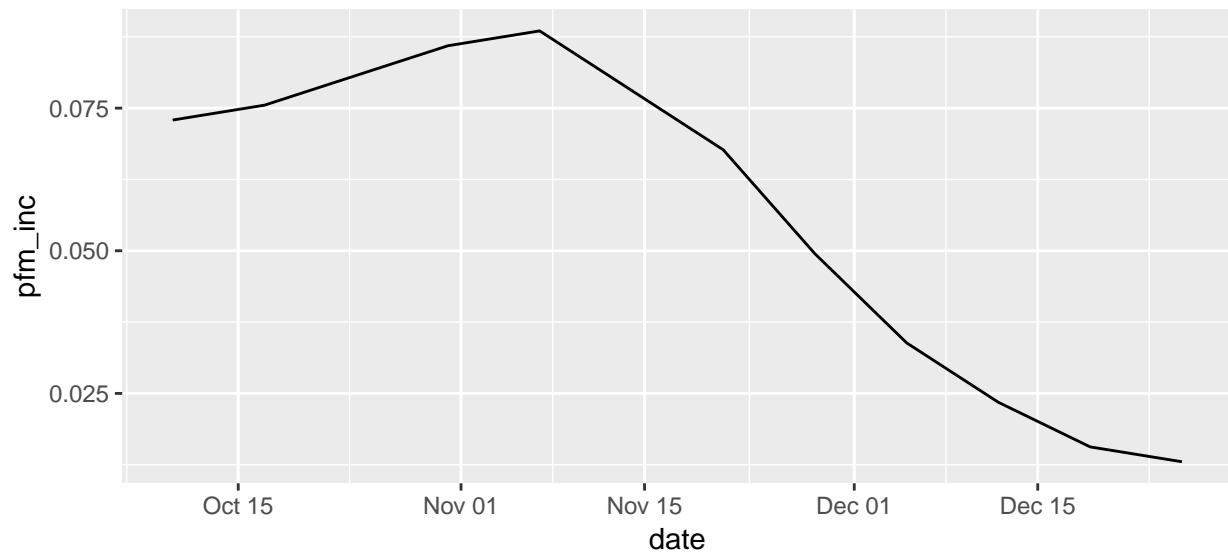


R automatically adjusts the x-axis labels based on the range of dates. In this case, the major axis lines and labels are on January 1 of each year and the minor axis lines are on June 1. Notice how the labels change when a smaller set of data is used:

```
# plot a single year of Mecha incidence
ggplot(filter(incid_date, woreda_name == "Mecha", iso_year == 2016)) +
  geom_line(aes(x = date, y = pfm_inc))
```

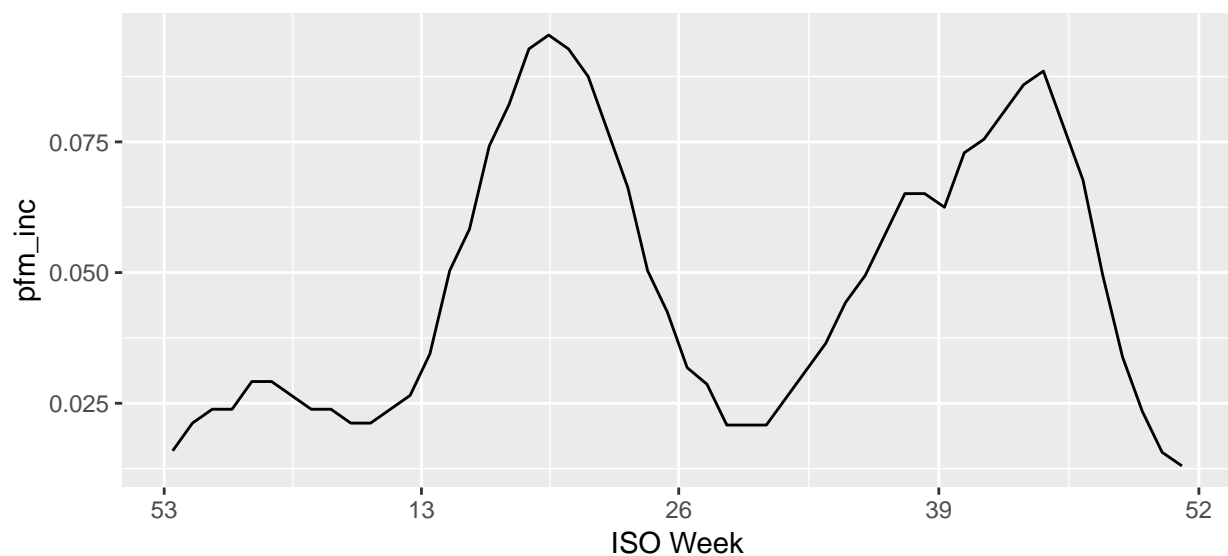


```
# plot a few months of Mecha incidence
ggplot(filter(incid_date, woreda_name == "Mecha", iso_year == 2016, iso_week > 40)) +
  geom_line(aes(x = date, y = pfm_inc))
```



For epidemiological data, of course, it might be more useful to label the weeks by iso week number rather than date. In this case, we can use a new function `scale_x_date()` to modify how the x axis labels appear. `scale_x_date()` takes an argument named `labels`, which can be defined in several ways (see the help page), but importantly for our purposes it can be given the name of a function which converts Dates to character or numeric values to use as labels. We have just such a function in `isoweek()`!

```
# plot a single year with iso week labels
ggplot(filter(incid_date, woreda_name == "Mecha", iso_year == 2016)) +
  geom_line(aes(x = date, y = pfm_inc)) +
  scale_x_date(labels = isoweek) +
  labs(x = "ISO Week") # dont forget to change the axis label to match
```



5 Tidying data with the tidyr package

The concept of **tidy** data has become increasingly popular among R users over the past few years thanks to the tidyr package, and more recently the tidyverse family of packages. Tidy data refers to data tables in which each row is an **observation**, each column is a **variable**, and each cell is a **value**.

Tidy data has three main advantages: it is consistent and therefore easily replicated and easily taught, R's emphasis on vectors works well when variables are organized into columns, and an increasing number of R packages are designed to work on tidy data, e.g. those in the tidyverse, but also dozens of others and more every month.

Unfortunately data is not always stored in tidy format. For example, data is often stored in a format that facilitates data entry. The functions in the tidyr package help you tidy your data so that it may be used for further visualization and analysis.

5.1 Spreading and gathering

Two common problems with un-tidy datasets are when one variable is spread across multiple columns or one observation is spread across multiple rows. In these cases, you can use the two tidyr functions `gather()` and `spread()`.

As an example, let us look at our `incid_data` data again.

```
incid_data

## # A tibble: 1,144 x 6
##   woreda_name iso_year iso_week date      pfm_inc pv_inc
##   <chr>         <dbl>   <dbl> <date>    <dbl>  <dbl>
## 1 Fogera      2012     28 2012-07-09  3.32  0.563
## 2 Fogera      2012     29 2012-07-16  3.13  0.582
## 3 Fogera      2012     30 2012-07-23  2.63  0.511
## 4 Fogera      2012     31 2012-07-30  2.35  0.506
## 5 Fogera      2012     32 2012-08-06  2.05  0.506
## 6 Fogera      2012     33 2012-08-13  1.93  0.511
## 7 Fogera      2012     34 2012-08-20  1.83  0.530
## 8 Fogera      2012     35 2012-08-27  1.88  0.558
## 9 Fogera      2012     36 2012-09-03  1.96  0.587
## 10 Fogera     2012     37 2012-09-10  2.24  0.644
## # ... with 1,134 more rows
```

Both `pfm_inc` and `pv_inc` are values of incidence, the first for *P. falciparum* and mixed infection malaria, the second for *P. vivax* malaria. In that sense, *falciparum* and *vivax* are not variables, but rather values identifying the malaria-causing agent. Both columns contain incidence values, and each row represents two observations, not one.

To tidy a dataset like this we need to **gather** those columns into two new variables, one that holds the name of the malaria agent and the other that holds the incidence.

The names of the columns will become values in a new variable called the **key**, which we will call “agent”. The values of the two columns will become a single new *value* variable, which we will call “inc”.

```
library(tidyr)
incid_tidy <- gather(incid_data, key = agent, value = inc,
                    pfm_inc, pv_inc) # these are the columns to gather
incid_tidy
```

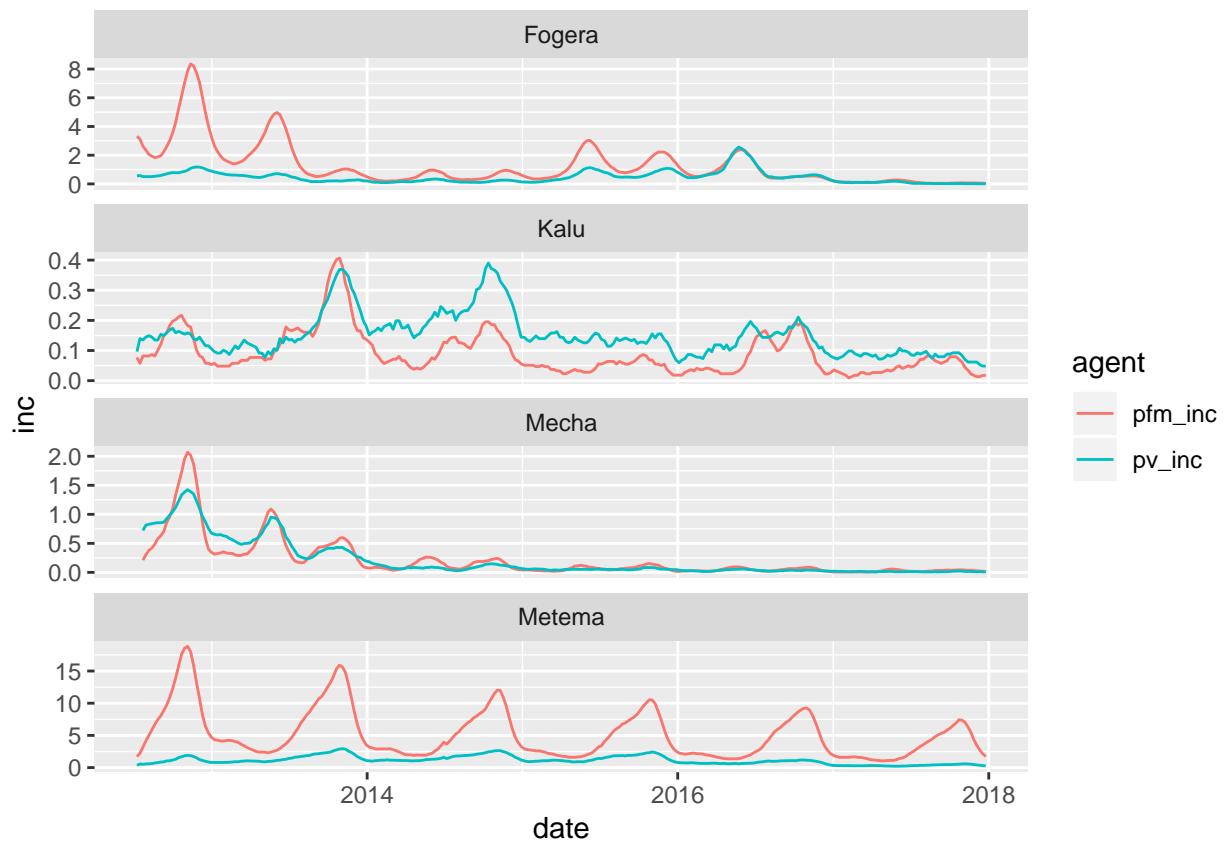
```
## # A tibble: 2,288 x 6
##   woreda_name iso_year iso_week date      agent      inc
##   <chr>         <dbl>   <dbl> <date>    <chr>    <dbl>
```



```
## 1 Fogera      2012      28 2012-07-09 pfm_inc  3.32
## 2 Fogera      2012      29 2012-07-16 pfm_inc  3.13
## 3 Fogera      2012      30 2012-07-23 pfm_inc  2.63
## 4 Fogera      2012      31 2012-07-30 pfm_inc  2.35
## 5 Fogera      2012      32 2012-08-06 pfm_inc  2.05
## 6 Fogera      2012      33 2012-08-13 pfm_inc  1.93
## 7 Fogera      2012      34 2012-08-20 pfm_inc  1.83
## 8 Fogera      2012      35 2012-08-27 pfm_inc  1.88
## 9 Fogera      2012      36 2012-09-03 pfm_inc  1.96
## 10 Fogera     2012      37 2012-09-10 pfm_inc  2.24
## # ... with 2,278 more rows
```

Now that we have the dataset in tidy format, we can plot it and “map” the new agent variable to the color aesthetic in the plot.

```
ggplot(incid_tidy) +
  geom_line(aes(date, inc, color = agent)) +
  facet_wrap(~ woreda_name, ncol = 1, scales = "free_y")
```



When observations are scattered across multiple rows, we need to **spread** the data into multiple columns. The `incid_tidy` dataset is already in tidy format, but we can use it as an example for how to use `spread()`:

```
library(tidyr)
spread(incid_tidy, key = agent, value = inc)
```

```
## # A tibble: 1,144 x 6
##   woreda_name iso_year iso_week date      pfm_inc pv_inc
##   <chr>         <dbl>   <dbl> <date>     <dbl>  <dbl>
```

```
## 1 Fogera      2012      28 2012-07-09    3.32 0.563
## 2 Fogera      2012      29 2012-07-16    3.13 0.582
## 3 Fogera      2012      30 2012-07-23    2.63 0.511
## 4 Fogera      2012      31 2012-07-30    2.35 0.506
## 5 Fogera      2012      32 2012-08-06    2.05 0.506
## 6 Fogera      2012      33 2012-08-13    1.93 0.511
## 7 Fogera      2012      34 2012-08-20    1.83 0.530
## 8 Fogera      2012      35 2012-08-27    1.88 0.558
## 9 Fogera      2012      36 2012-09-03    1.96 0.587
## 10 Fogera     2012      37 2012-09-10    2.24 0.644
## # ... with 1,134 more rows
```

5.2 Separating and uniting

Sometimes you may find that a single column contains multiple values. In that case, you need to **separate** the two values into multiple columns.

Imagine we have a dataset where the iso week is provided in year-week format, e.g. “2017-W01”.

```
yw_example <- tibble(yw = c("2016-W01", "2016-W02", "2016-W03"),
                     mal_case = c(2565, 2042, 1803))
yw_example
```

```
## # A tibble: 3 x 2
##   yw      mal_case
##   <chr>      <dbl>
## 1 2016-W01    2565
## 2 2016-W02    2042
## 3 2016-W03    1803
```

In this case, 2017 is the year and 1 is the week number. You can use `separate()` to put them into their own columns. Here, `col` is the column to separate, `into` is a character vector of the names of the new columns, `sep` is the character string separating the two values, and `convert = TRUE` causes the new columns to be converted from character to numeric format if possible.

```
yw_sep <- separate(yw_example, col = yw,
                  into = c("iso_year", "iso_week"),
                  sep = "-W", convert = TRUE)
yw_sep
```

```
## # A tibble: 3 x 3
##   iso_year iso_week mal_case
##   <int>    <int>    <dbl>
## 1   2016        1    2565
## 2   2016        2    2042
## 3   2016        3    1803
```

The complement of `separate()` is `unite()`, which can be used to **unite** multiple columns into one.

```
unite(yw_sep, col = "yw", iso_year, iso_week, sep = "-W")
```

```
## # A tibble: 3 x 2
##   yw      mal_case
##   <chr>      <dbl>
## 1 2016-W1    2565
## 2 2016-W2    2042
## 3 2016-W3    1803
```

5.3 Dealing with missing rows

An important distinction can be made with regards to missing values. Missing values can be missing in one of two ways: **explicitly**, as with NA values, or **implicitly**, as when they are simply not present in the data.

To illustrate this point, we will modify our `incid` data created above by removing some of the rows to create implicitly missing values.

To begin with, `incid` has `n` weeks of data for each `woreda`.

```
count(incid, woreda_name)
```

```
## # A tibble: 4 x 2
##   woreda_name      n
##   <chr>         <int>
## 1 Fogera        286
## 2 Kalu          286
## 3 Mecha         286
## 4 Metema        286
```

Now let us exclude some of the rows using the `dplyr` function `sample_frac()`, which selects a random fraction of rows to keep and discards the rest. First we will `set.seed()` so that the R's random number generator will yield the same results for everybody.

```
set.seed(1)
incid_incompl <- sample_frac(incid, 0.9)
count(incid_incompl, woreda_name)
```

```
## # A tibble: 4 x 2
##   woreda_name      n
##   <chr>         <int>
## 1 Fogera        255
## 2 Kalu          261
## 3 Mecha         259
## 4 Metema        255
```

As you can see, each `woreda` is missing some weeks of data. To convert these missing weeks from implicitly missing to explicitly missing, we can use the `dplyr` function `complete()`.

```
complete(incid_incompl, woreda_name, iso_year, iso_week)
```

```
## # A tibble: 1,272 x 5
##   woreda_name iso_year iso_week pfm_inc pv_inc
##   <chr>         <dbl>   <dbl>   <dbl>   <dbl>
## 1 Fogera        2012     1     NA     NA
## 2 Fogera        2012     2     NA     NA
## 3 Fogera        2012     3     NA     NA
## 4 Fogera        2012     4     NA     NA
## 5 Fogera        2012     5     NA     NA
## 6 Fogera        2012     6     NA     NA
## 7 Fogera        2012     7     NA     NA
## 8 Fogera        2012     8     NA     NA
## 9 Fogera        2012     9     NA     NA
## 10 Fogera       2012    10     NA     NA
## # ... with 1,262 more rows
```

New rows have been added and NAs have been inserted for each variable not named in `complete`, in this case `pfm_inc` and `pv_inc`.

But wait! We can see that at least some of the weeks that were added were never in `incid` to begin with. The original dataset before being “completed” began on 2012 week 28. Now it begins on week 1. That’s because `complete()` created new rows for every distinct combination of `iso_year` and `iso_week`.

What if we only wanted combinations of year and week that were already in the data, i.e. we want the completed dataset to start on 2012 week 28? The answer is to use the dplyr helper function `nesting()`, which causes `complete()` to only add existing combinations of two or more variables, in this case `iso_year` and `iso_week`.

```
complete(incid_incompl, woreda_name, nesting(iso_year, iso_week))
```

```
## # A tibble: 1,144 x 5
##   woreda_name iso_year iso_week pfm_inc pv_inc
##   <chr>      <dbl>   <dbl>   <dbl> <dbl>
## 1 Fogera      2012     28    3.32  0.563
## 2 Fogera      2012     29    3.13  0.582
## 3 Fogera      2012     30    2.63  0.511
## 4 Fogera      2012     31    2.35  0.506
## 5 Fogera      2012     32    2.05  0.506
## 6 Fogera      2012     33    1.93  0.511
## 7 Fogera      2012     34    1.83  0.530
## 8 Fogera      2012     35    NA     NA
## 9 Fogera      2012     36    1.96  0.587
## 10 Fogera     2012     37    2.24  0.644
## # ... with 1,134 more rows
```

Now we’re back to starting on week 28 and having `n` rows, the same number we had before we randomly removed rows. And we now have a dataset “complete” with explicitly missing values.

5.4 Combining datasets with dplyr

A common need when working with multiple data files is to combine the data into a single dataset. There are two conceptual ways to do this: **binding** and **joining**.

Binding two tables together matches rows or columns by position. The datasets to be bound need to have the same variables or the rows need to be aligned for binding to work.

Joining two tables together matches rows by value rather than position. The datasets need to have some variable in common between them for joining to work.

5.4.1 Binding tables

If data have the same columns, you can use `bind_rows()` to “stack” them one on top of the other in a new data frame.

```
mecha <- read_csv("data_mecha.csv")
fogera <- read_csv("data_fogera.csv")
mf_bind <- bind_rows(mecha, fogera)
mecha
```

```
## # A tibble: 156 x 10
##   WID woreda_name obs_date test_pf_tot test_pv_only pop_at_risk
##   <dbl> <chr>      <date>      <dbl>      <dbl>      <dbl>
## 1  106 Mecha    2016-01-10         6         15    377232.
## 2  106 Mecha    2016-01-17         8         12    377232.
## 3  106 Mecha    2016-01-24         9         11    377232.
## 4  106 Mecha    2016-01-31         9         11    377232.
## 5  106 Mecha    2016-02-07        11         11    377232.
```

```
## 6 106 Mecha 2016-02-14 11 10 377232.
## 7 106 Mecha 2016-02-21 10 10 377232.
## 8 106 Mecha 2016-02-28 9 8 377232.
## 9 106 Mecha 2016-03-06 9 6 377232.
## 10 106 Mecha 2016-03-13 8 6 377232.
```

```
## # ... with 146 more rows, and 4 more variables: mal_case <dbl>,
## # iso_year <dbl>, iso_week <dbl>, data_source <chr>
```

```
count(mf_bind, woreda_name, iso_year)
```

```
## # A tibble: 4 x 3
##   woreda_name iso_year    n
##   <chr>      <dbl> <int>
## 1 Fogera    2018    52
## 2 Mecha     2016    52
## 3 Mecha     2017    52
## 4 Mecha     2018    52
```

If data contain different variables that belong to the same observation, you can combine them by row position using `bind_cols()`. For this to work, the two data frames must have the same number of rows, and the same rows in each dataset must belong to the same observation.

```
mecha_mal_case <- select(mecha, woreda_name, iso_year, iso_week, mal_case)
mecha_pf_pv <- select(mecha, c("test_pf_tot", "test_pv_only"))
bind_cols(mecha_mal_case, mecha_pf_pv)
```

5.5 Joining tables

Table joins are a concept shared across many data science disciplines and are implemented in relational database management systems such as MySQL.

With a join, two tables are connected to each other conceptually through variables called **keys**, which are variables found in both tables. For the datasets you've seen so far, possible key columns include `woreda`, `iso_year`, or `iso_week`.

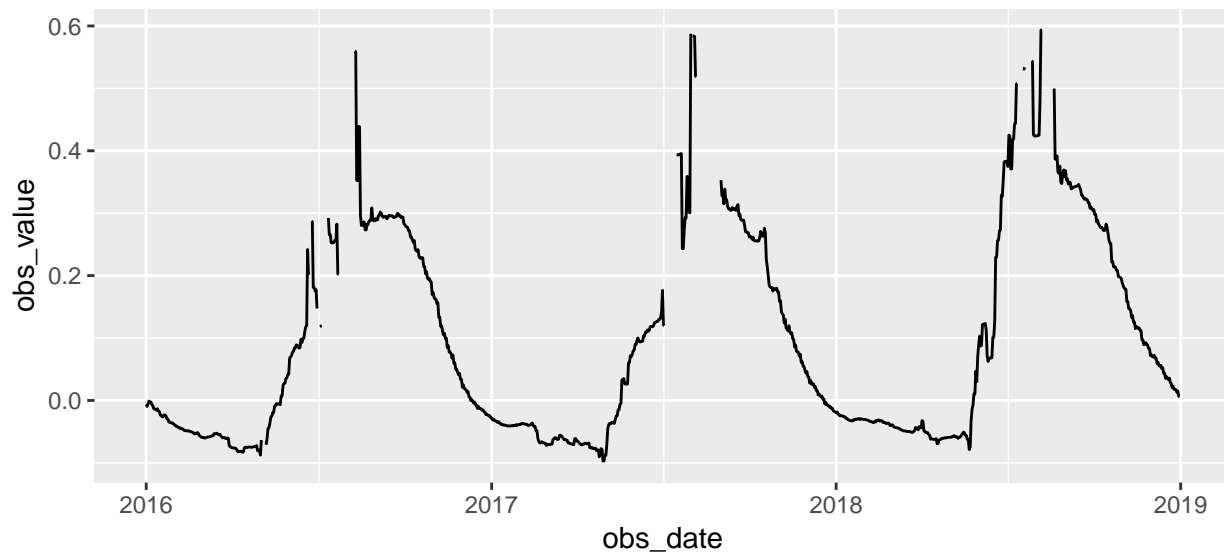
For the following exercises, we will use a new dataset found in `data_ndwi.csv`. This dataset contains satellite-derived values of NDWI, normalized difference water index, an index of vegetation water content (VWC). VWC is related to the abundance of suitable mosquito breeding habitat and is therefore useful when predicting future malaria outbreaks. This dataset is a subset containing years 2016, 2017, and 2018.

The problem is that the NDWI data is daily, while our epidemiological data is weekly. If we want to connect one to the other, we will need to perform two main tasks: summarize the daily data by epi week, and join the new weekly environmental data to the weekly epidemiological data.

```
ndwi <- read_csv("data_ndwi.csv")
glimpse(ndwi) # like str() but but simpler output
```

```
## Observations: 51,512
## Variables: 5
## $ WID <dbl> 121, 121, 121, 121, 121, 121, 121, 121, 121, ...
## $ woreda_name <chr> "Abargelie", "Abargelie", "Abargelie", "Abarg...
## $ environ_var_code <chr> "ndwi6", "ndwi6", "ndwi6", "ndwi6", "ndwi6", ...
## $ obs_date <date> 2016-01-01, 2016-01-02, 2016-01-03, 2016-01-...
## $ obs_value <dbl> -0.08590598, -0.08791568, -0.08760408, -0.087...
```

```
ggplot(filter(ndwi, woreda_name=="Mecha")) +
  geom_line(aes(x = obs_date, y = obs_value))
```



The next step is to the daily data by iso week. Unfortunately, we do not have columns for `iso_year` and `iso_week`.

```
# convert date to epi year and epi week
ndwi <- mutate(ndwi,
               iso_year = isoyear(obs_date),
               iso_week = isoweek(obs_date))
ndwi
```

```
## # A tibble: 51,512 x 7
##       WID worda_name environ_var_code obs_date  obs_value iso_year
##   <dbl> <chr>         <chr>         <date>      <dbl>    <dbl>
## 1   121 Abargelie    ndwi6      2016-01-01  -0.0859    2015
## 2   121 Abargelie    ndwi6      2016-01-02  -0.0879    2015
## 3   121 Abargelie    ndwi6      2016-01-03  -0.0876    2015
## 4   121 Abargelie    ndwi6      2016-01-04  -0.0878    2016
## 5   121 Abargelie    ndwi6      2016-01-05  -0.0888    2016
## 6   121 Abargelie    ndwi6      2016-01-06  -0.0879    2016
## 7   121 Abargelie    ndwi6      2016-01-07  -0.0885    2016
## 8   121 Abargelie    ndwi6      2016-01-08  -0.0887    2016
## 9   121 Abargelie    ndwi6      2016-01-09  -0.0906    2016
## 10  121 Abargelie    ndwi6      2016-01-10  -0.0912    2016
## # ... with 51,502 more rows, and 1 more variable: iso_week <dbl>
```

Note that the calendar year in our `obs_date` column is not always the same as `iso_year`:

```
filter(ndwi, year(ndwi$obs_date) != iso_year, worda_name == "Mecha")
```

```
## # A tibble: 5 x 7
##       WID worda_name environ_var_code obs_date  obs_value iso_year iso_week
##   <dbl> <chr>         <chr>         <date>      <dbl>    <dbl>    <dbl>
## 1   106 Mecha      ndwi6      2016-01-01  -0.00634    2015      53
## 2   106 Mecha      ndwi6      2016-01-02  -0.00964    2015      53
## 3   106 Mecha      ndwi6      2016-01-03  -0.00472    2015      53
## 4   106 Mecha      ndwi6      2017-01-01  -0.0279     2016      52
## 5   106 Mecha      ndwi6      2018-12-31   0.00632     2019       1
```

This is exactly why we must calculate `iso_year` rather than using calendar year. If we used calendar year,

some values would not be grouped correctly when we summarize.

Now we can summarize by epi week.

```
ndwi_wk <- group_by(ndwi, woreda_name, iso_year, iso_week)
ndwi_wk <- summarize(ndwi_wk,
                      ndwi = mean(obs_value, na.rm = TRUE),
                      n = sum(!is.na(obs_value)))
ndwi_wk
```

```
## # A tibble: 7,426 x 5
## # Groups:   woreda_name, iso_year [?]
##   woreda_name iso_year iso_week   ndwi     n
##   <chr>       <dbl>   <dbl>   <dbl> <int>
## 1 Abargelie   2015     53 -0.0871     3
## 2 Abargelie   2016      1 -0.0891     7
## 3 Abargelie   2016      2 -0.0923     7
## 4 Abargelie   2016      3 -0.0933     7
## 5 Abargelie   2016      4 -0.0915     7
## 6 Abargelie   2016      5 -0.0917     7
## 7 Abargelie   2016      6 -0.0923     7
## 8 Abargelie   2016      7 -0.0915     7
## 9 Abargelie   2016      8 -0.0949     7
##10 Abargelie   2016      9 -0.0955     7
## # ... with 7,416 more rows
```

However, many of those mean values were estimated using fewer than half the days in the week, and may therefore be poor approximations of the true mean. To be safe, we will exclude summaries calculated from fewer than 6 days of the week.

```
ndwi_wk <- filter(ndwi_wk, n >= 6)
ndwi_wk
```

```
## # A tibble: 6,300 x 5
## # Groups:   woreda_name, iso_year [141]
##   woreda_name iso_year iso_week   ndwi     n
##   <chr>       <dbl>   <dbl>   <dbl> <int>
## 1 Abargelie   2016      1 -0.0891     7
## 2 Abargelie   2016      2 -0.0923     7
## 3 Abargelie   2016      3 -0.0933     7
## 4 Abargelie   2016      4 -0.0915     7
## 5 Abargelie   2016      5 -0.0917     7
## 6 Abargelie   2016      6 -0.0923     7
## 7 Abargelie   2016      7 -0.0915     7
## 8 Abargelie   2016      8 -0.0949     7
## 9 Abargelie   2016      9 -0.0955     7
##10 Abargelie   2016     10 -0.0948     7
## # ... with 6,290 more rows
```

At this point, we are ready to join the NDWI data with the epidemiological data.

5.5.1 Inner join

The first type of join we will perform is called an **inner join**. With this type of join, rows are included in the output only if there are matching key values in both tables.

We will start with our `mecha` dataset and join the `ndwi_wk` dataset using `inner_join()`. Before we do that, let's remove some columns from `mecha` so we can more easily see what is happening when we join.

```
mecha_mal_case <- select(mecha, woreda_name, iso_year, iso_week, mal_case)
```

Because our datasets have three columns in common (woreda, iso_year, iso_week) and it takes all three columns to uniquely identify an observation in one dataset or the other, all three columns will serve as our keys.

```
inner_join(mecha_mal_case, ndwi_wk, by = c("woreda_name", "iso_year", "iso_week"))
```

```
## # A tibble: 139 x 6
##   woreda_name iso_year iso_week mal_case    ndwi      n
##   <chr>      <dbl>    <dbl>    <dbl>    <dbl> <int>
## 1 Mecha      2016        1      21 -0.00697    7
## 2 Mecha      2016        2      20 -0.0181     7
## 3 Mecha      2016        3      20 -0.0261     7
## 4 Mecha      2016        4      20 -0.0362     7
## 5 Mecha      2016        5      22 -0.0429     7
## 6 Mecha      2016        6      21 -0.0476     7
## 7 Mecha      2016        7      20 -0.0507     7
## 8 Mecha      2016        8      17 -0.0545     7
## 9 Mecha      2016        9      15 -0.0595     7
## 10 Mecha     2016       10      14 -0.0569     7
## # ... with 129 more rows
```

Looking at the resulting table, we can see that the columns in `mecha` are all present in the output, in the same order, followed by the non-key columns from `ndwi_wk`.

We can also see that the resulting dataset has only `n` rows. `mecha` had `n` rows, so some rows must not have had a key match between the two tables. Examining more closely and we can see that YYYY week W was not present in `ndwi_wk` and is also not present in the joined tables.

5.5.2 Outer joins

It may be perfectly fine to have rows with non-matching keys removed by an inner join. It depends on your goal. However for our demonstration let's assume we want to keep all rows from `mecha`. This is possible using a **left join**. With this type of join, all rows from the table on the “left” side of the join are kept, and missing values are inserted where there is no matching row in the table on the “right” side.

We can perform a left join using `left_join()`, where the first argument is the left table and the second argument is the right table.

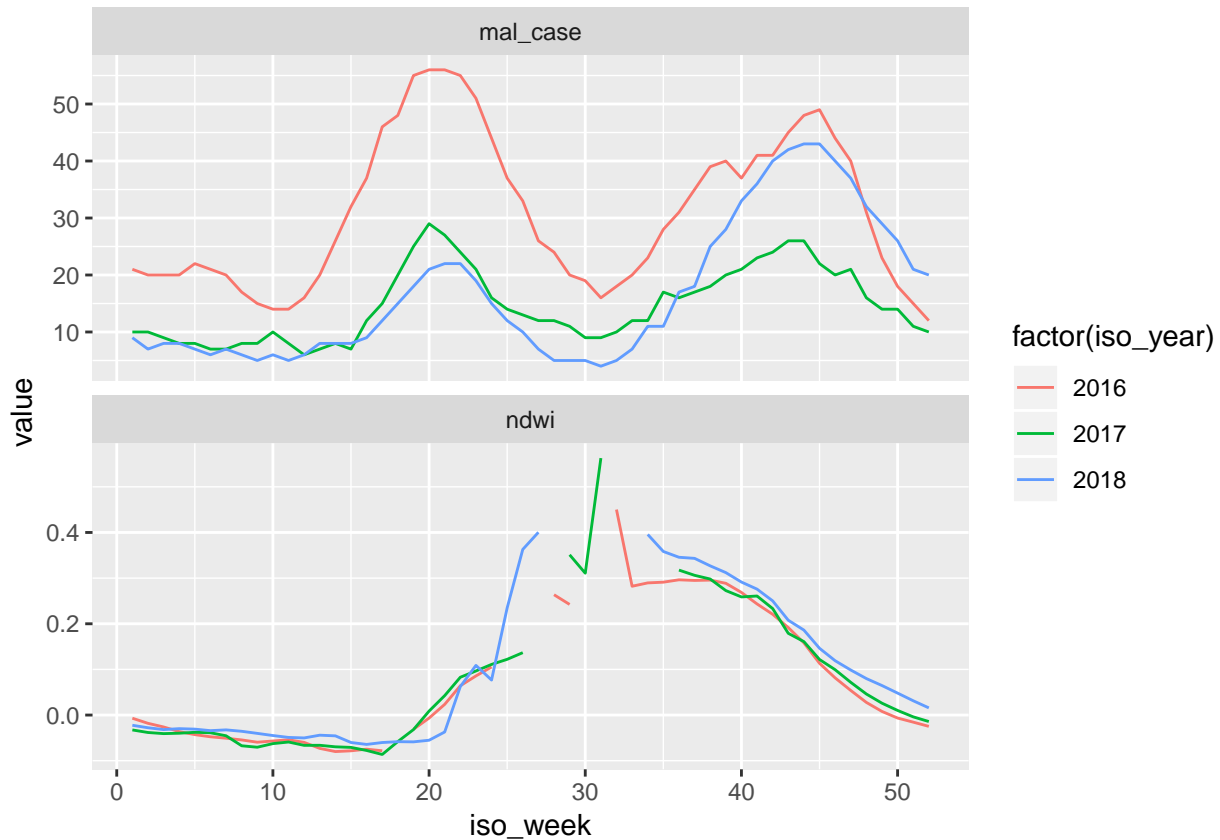
```
lj <- left_join(mecha_mal_case, ndwi_wk, by = c("woreda_name", "iso_year", "iso_week"))
lj
```

```
## # A tibble: 156 x 6
##   woreda_name iso_year iso_week mal_case    ndwi      n
##   <chr>      <dbl>    <dbl>    <dbl>    <dbl> <int>
## 1 Mecha      2016        1      21 -0.00697    7
## 2 Mecha      2016        2      20 -0.0181     7
## 3 Mecha      2016        3      20 -0.0261     7
## 4 Mecha      2016        4      20 -0.0362     7
## 5 Mecha      2016        5      22 -0.0429     7
## 6 Mecha      2016        6      21 -0.0476     7
## 7 Mecha      2016        7      20 -0.0507     7
## 8 Mecha      2016        8      17 -0.0545     7
## 9 Mecha      2016        9      15 -0.0595     7
## 10 Mecha     2016       10      14 -0.0569     7
## # ... with 146 more rows
```


You can see that the resulting table still has `n` rows. The first row, for YYYY week W, was missing after the left join. Here it is present, with missing values for the variables `ndwi` and `n`, the two that came from the table on the right.

Using `gather()` we can easily plot the joined dataset.

```
ggplot(gather(lj, key, value, mal_case, ndwi)) +
  geom_line(aes(iso_week, value, color = factor(iso_year))) +
  facet_wrap(~ key, ncol = 1, scales = "free_y")
```



6 Day 3 exercises

1. Read the `data_2016_2018.csv` dataset.
2. Summarize the data. Calculate the min, max, and mean values of `mal_case` for each `woreda`.
3. Now summarize the data by `woreda` *and* year.
4. Starting with the `data_mecha.csv` data, create a tidy data frame with columns for `iso_year`, `iso_week`, and malaria agent (*P. falciparum* vs. *P. vivax*). Unnecessary columns can be removed.
5. Plot this tidy data frame using colors for malaria agent and facets for years.
6. Create a data frame that contains both the daily *and* weekly NDWI data for a `woreda` and year (2016 - 2018) of your choice. Plot the values on the same plot, with Date on the x axis and NDWI on the y axis. Use either point or line geoms and choose aesthetics to help differentiate the daily and weekly data.
7. Create a data frame that contains both the daily and weekly NDWI data for a `woreda` and year of your choice. Plot the values on the same plot, with Date on the x axis and NDWI on the y axis. Use either point or line geoms and choose aesthetics to help differentiate the daily and weekly data.