Data transformation with dplyr

Introduction to R - Day 2

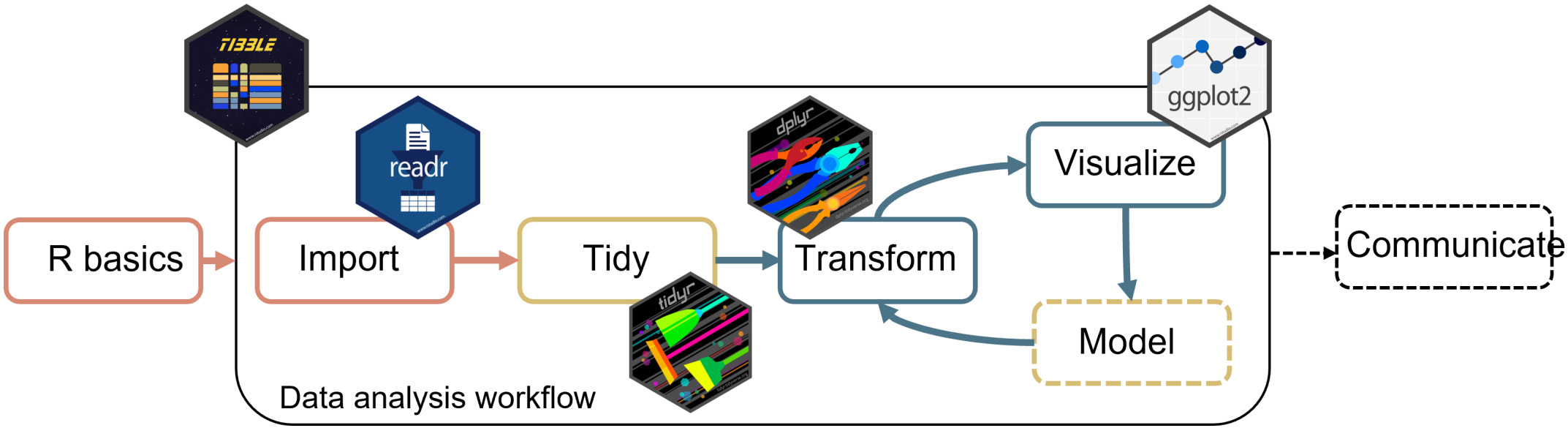
Instructor: Selina Baldauf

Freie Universität Berlin - Theoretical Ecology

2021-06-15 (updated: 2023-02-26)

Data transformation

Data transformation is an important step in **understanding** the data and **preparing** it for further analysis.



We can use the tidyverse package `dplyr` for this.

Data transformation

With `dplyr` we can (among other things)

- **Filter** data to analyse only a part of it
- **Create** new variables
- **Summarize** data
- **Combine** multiple tables
- **Rename** variables
- **Reorder** observations or variables

To get started load the package `dplyr`:

```
library(dplyr)
# or
library(tidyverse)
```

Dplyr basic vocuabulary

`dplyr` provides basic vocabulary for data manipulation:

- `filter()` picks observations (rows) based on their values
- `select()` picks variables (columns) based on their names
- `mutate()` adds new variables based on existing ones
- `summarize()` combines multiple values into a single summary value

Perform any of these operations by group with `group_by()`

from dplyr package description

Dplyr basic vocabulary

All of the `dplyr` functions work similarly:

- **First argument** is the data (a tibble)
- **Other arguments** specify what to do exactly
- **Return** a tibble

Example data

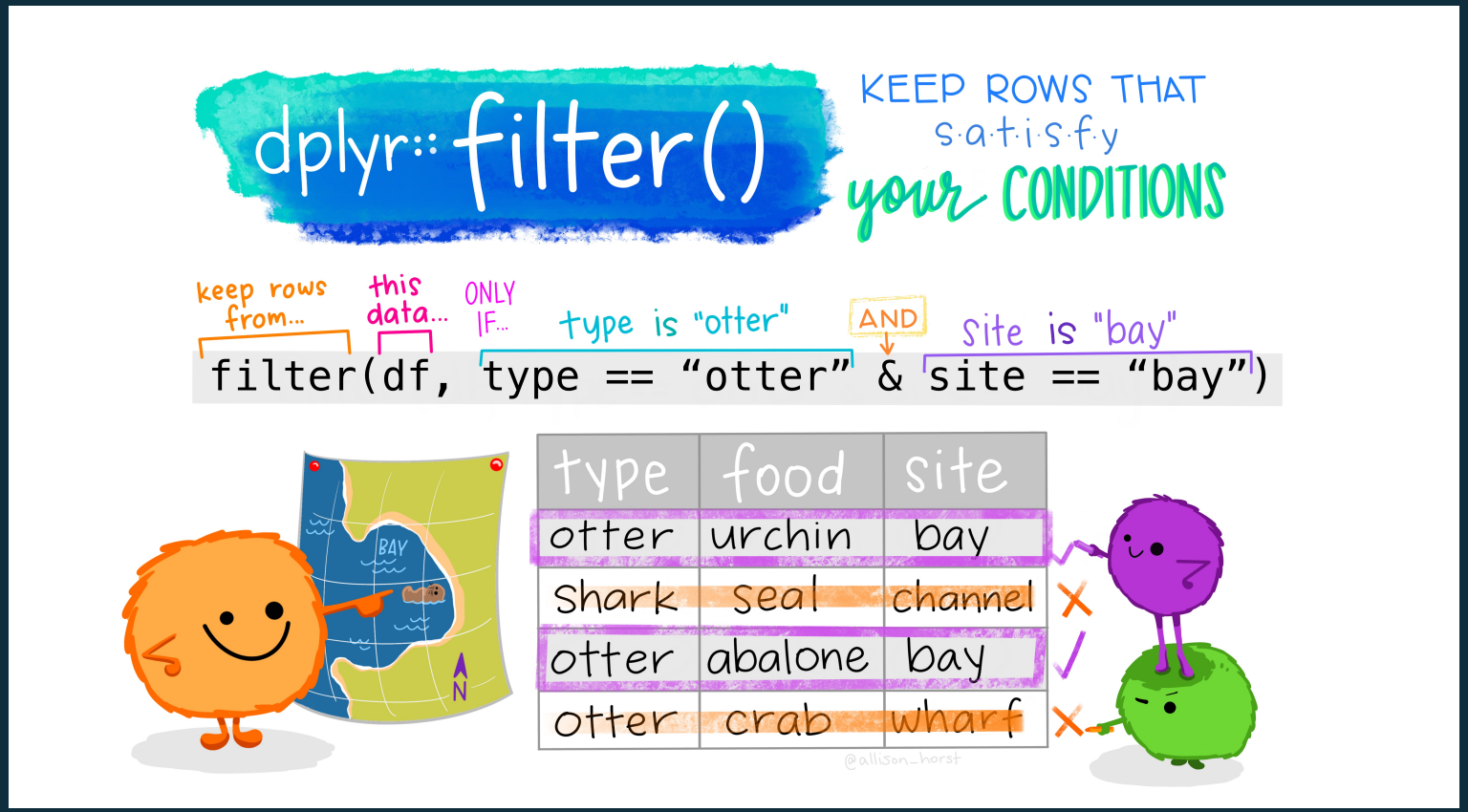
Soybean production for different use by year and country.

```
soybean_use
```

```
## # A tibble: 9,897 × 6
##   entity code   year human_food animal_feed processed
##   <chr>  <chr> <dbl>      <dbl>       <dbl>     <dbl>
## 1 Africa <NA>   1961      33000        6000     14000
## 2 Africa <NA>   1962      43000        7000     17000
## 3 Africa <NA>   1963      31000        7000      5000
## 4 Africa <NA>   1964      43000        6000     14000
## 5 Africa <NA>   1965      34000        6000     12000
## # … with 9,892 more rows
```

`filter()`

picks observations (rows) based on their value



Artwork by Allison Horst

Useful `filter()` helpers

These functions and operators help you filter your observations:

- relational operators `<`, `>`, `==`, ...
- logical operators `&`, `|`, `!`
- `%in%` to filter multiple values
- `is.na()` to filter missing values
- `between()` to filter values that are between an upper and lower boundary
- `near()` to compare floating points (use instead of `==` for doubles)

filter()

Filter rows that contain the values for Germany

```
filter(soybean_use, entity == "Germany")
```

```
## # A tibble: 53 × 6
##   entity  code   year human_food animal_feed processed
##   <chr>   <chr> <dbl>      <dbl>       <dbl>     <dbl>
## 1 Germany DEU    1961          0        3000   1042000
## 2 Germany DEU    1962          0        3000    935000
## 3 Germany DEU    1963          0        3000   1092000
## 4 Germany DEU    1964          0        3000   1096000
## 5 Germany DEU    1965          0        3000   1435000
## # … with 48 more rows
```

`filter()` goes through each row of the data and return only those rows where the value for `entity` is `"Germany"`

filter() + %in%

Use the `%in%` operator to filter multiple countries

```
countries_select <- c("Germany", "Austria", "Switzerland")
filter(soybean_use, entity %in% countries_select)
```

```
## # A tibble: 159 × 6
##   entity  code   year human_food animal_feed processed
##   <chr>   <chr> <dbl>      <dbl>       <dbl>     <dbl>
## 1 Austria AUT    1961          0           0         0
## 2 Austria AUT    1962          0           0         0
## 3 Austria AUT    1963          0           0         0
## 4 Austria AUT    1964          0           0         0
## 5 Austria AUT    1965          0           0         0
## # … with 154 more rows
```

filter() + is.na()

Filter only rows that don't have a country code (i.e. the continents etc.)

```
filter(soybean_use, is.na(code))
```

```
## # A tibble: 1,734 × 6
##   entity code   year human_food animal_feed processed
##   <chr>  <chr> <dbl>      <dbl>       <dbl>     <dbl>
## 1 Africa <NA>   1961      33000        6000     14000
## 2 Africa <NA>   1962      43000        7000     17000
## 3 Africa <NA>   1963      31000        7000      5000
## 4 Africa <NA>   1964      43000        6000     14000
## 5 Africa <NA>   1965      34000        6000     12000
## # … with 1,729 more rows
```

Or the opposite: filter only the rows that have a country code with

```
filter(soybean_use, !is.na(code))
```

`filter()` + `between()`

Combine different filters:

Select rows where

- the value for `years` is between 1970 and 1980
- the value for `entity` is Germany

```
filter(soybean_use, between(year, 1970, 1980) & entity == "Germany")
```

```
## # A tibble: 11 × 6
##   entity  code   year human_food animal_feed processed
##   <chr>   <chr> <dbl>      <dbl>       <dbl>     <dbl>
## 1 Germany DEU    1970          0        3000   2118000
## 2 Germany DEU    1971          0        3000   2119000
## 3 Germany DEU    1972          0        5000   2271000
## 4 Germany DEU    1973          0        3000   2820000
## 5 Germany DEU    1974          0        3000   3704000
## # … with 6 more rows
```

`select()`

picks variables (columns) based on their names

Useful `select()` helpers

- `starts_with()` and `ends_with()`: variable names that start/end with a specific string
- `contains()`: variable names that contain a specific string
- `matches()`: variable names that match a regular expression
- `any_of()` and `all_of()`: variables that are contained in a character vector

select()

Select the variables entity, year and human food

```
select(soybean_use, entity, year, human_food)
```

```
## # A tibble: 9,897 × 3
##   entity  year human_food
##   <chr>  <dbl>      <dbl>
## 1 Africa  1961      33000
## 2 Africa  1962      43000
## # … with 9,895 more rows
```

Remove variables using `-`

```
select(soybean_use, -entity, -year, -human_food)
```

```
## # A tibble: 9,897 × 3
##   code  animal_feed processed
##   <chr>       <dbl>     <dbl>
## 1 <NA>         6000     14000
## 2 <NA>         7000     17000
## # … with 9,895 more rows
```

select() + ends_with()

Select all columns that end with `"d"`

```
select(soybean_use, ends_with("d"))
```

```
## # A tibble: 9,897 × 3
##   human_food animal_feed processed
##        <dbl>       <dbl>     <dbl>
## 1      33000        6000     14000
## 2      43000        7000     17000
## 3      31000        7000      5000
## # … with 9,894 more rows
```

You can use the same structure for `starts_with()` and `contains()`.

```
# this does not match any rows in the soy bean data set
# but combinations like this are helpful for research data
select(soybean_use, starts_with("sample_"))

select(soybean_use, contains("_id_"))
```

select() + any_of()/all_of()

Use a character vector in conjunction with column selection

```
cols <- c("sample_", "year", "processed", "entity")
```

`any_of()` returns any columns that match an element in `cols`

```
select(soybean_use, any_of(cols))
```

```
## # A tibble: 9,897 × 3
##    year processed entity
##   <dbl>     <dbl> <chr>
## 1  1961     14000 Africa
## # … with 9,896 more rows
```

`all_of()` tries to match all elements in `cols` and returns an error if an element does not exist

```
select(soybean_use, all_of(cols))
```

```
## Error in `select()`:
## ! Problem while evaluating `all_of(cols)`.
```

select() + from:to

Multiple consecutive columns can be selected using the `from:to` structure with either column id or variable name:

```
select(soybean_use, 1:3)
select(soybean_use, code:animal_feed)
```

```
## # A tibble: 9,897 × 4
##   code   year human_food animal_feed
##   <chr> <dbl>      <dbl>       <dbl>
## 1 <NA>   1961      33000        6000
## 2 <NA>   1962      43000        7000
## 3 <NA>   1963      31000        7000
## # … with 9,894 more rows
```

Be a bit careful with these commands: They are not robust if you e.g. change the order of your columns at some point.

`mutate()`

adds new variables

Artwork by Allison Horst

mutate()

New columns can be added based on values from other columns

```
mutate(soybean_use, sum_human_animal = human_food + animal_feed)
```

```
## # A tibble: 9,897 × 7
##   entity code   year human_food animal_feed processed sum_human_animal
##   <chr>  <chr> <dbl>      <dbl>       <dbl>     <dbl>            <dbl>
## 1 Africa <NA>   1961      33000        6000     14000            39000
## 2 Africa <NA>   1962      43000        7000     17000            50000
## 3 Africa <NA>   1963      31000        7000      5000            38000
## # … with 9,894 more rows
```

Add multiple new columns at once:

```
mutate(soybean_use,
  sum_human_animal = human_food + animal_feed,
  total = human_food + animal_feed + processed
)
```

mutate() + case_when()

Use `case_when` to add column values conditional on other columns.

`case_when()` can combine many cases into one.

```
mutate(soybean_use,
  legislation = case_when(
    year < 2000 & year >= 1980 ~ "legislation_1",     # case 1
    year >= 2000 ~ "legislation_2",                   # case 2
    TRUE ~ "no_legislation"                           # any other cases
  )
)
```

```
## # A tibble: 9,897 × 7
##   entity code   year human_food animal_feed processed legislation
##   <chr>  <chr> <dbl>      <dbl>       <dbl>     <dbl> <chr>
## 1 Africa <NA>   1961      33000        6000     14000 no_legislation
## 2 Africa <NA>   1962      43000        7000     17000 no_legislation
## 3 Africa <NA>   1963      31000        7000      5000 no_legislation
## # … with 9,894 more rows
```

`summarize()` + `group_by()`

summarizes data by group

summarize()

`summarize` will collapse the data to a single row

```
summarize(soybean_use,
          total_animal = sum(animal_feed, na.rm = TRUE),
          total_human = sum(human_food, na.rm = TRUE))
## # A tibble: 1 × 2
##   total_animal total_human
##          <dbl>       <dbl>
## 1    942503000  1589729000
```

`summarize()` and `group_by()`

`summarize` is much more useful in combination with `group_by()`.

If you group the data before summarizing it, the **summary** will be calculated **separately for each group**

```
# group the data by year
soybean_use_group <- group_by(soybean_use, year)
```

```
# summarize the grouped data
summarize(soybean_use_group,
          total_animal = sum(animal_feed, na.rm = TRUE),
          total_human = sum(human_food, na.rm = TRUE))
```

```
## # A tibble: 53 × 3
##    year total_animal total_human
##   <dbl>        <dbl>       <dbl>
## 1  1961      1503000    16994000
## 2  1962      1800000    17326000
## # … with 51 more rows
```

To ungroup data that was grouped before, you can use `ungroup()`

count()

Counts observations by group

```
# count rows grouped by year
count(soybean_use, year)

# or if the data is already grouped by year
count(soybean_use_group)
```

```
## # A tibble: 53 × 2
## # Groups:   year [53]
##    year     n
##   <dbl> <int>
## 1  1961   178
## 2  1962   178
## 3  1963   178
## 4  1964   178
## # … with 49 more rows
```

The pipe %>%

Combine multiple data operations into one command

The pipe %>%

Data transformation often requires **multiple operations** in sequence.

The pipe operator `%>%` helps to keep these operations clear and readable.

The pipe %>%

Let's look at an example without pipe:

```
# 1: filter rows that actually represent a country
soybean_new <- filter(soybean_use, !is.na(code))

# 2: group the data by year
soybean_new <- group_by(soybean_new, year)

# 3: summarize mean values by year
soybean_new <- summarize(soybean_new,
    mean_processed = mean(processed, na.rm=TRUE),
    sd_processed = sd(processed, na.rm = TRUE))
```

How could we make this more efficient?

The pipe %>%

We could do everything in one step without intermediate results by using use one **nested function**

```
soybean_new <- summarize(
  group_by(
    filter(soybean_use, !is.na(code)),
    year
  ),
  mean_processed = mean(processed, na.rm = TRUE),
  sd_processed = sd(processed, na.rm = TRUE)
)
```

But this gets complicated and error prone very quickly

The pipe `%>%`

The pipe operator (included in the `tidyverse`) makes it very easy to combine multiple operations:

```
soybean_new <- soybean_use %>%
  filter(!is.na(code)) %>%
  group_by(year) %>%
  summarize(
    mean_processed = mean(processed, na.rm = TRUE),
    sd_processed = sd(processed, na.rm = TRUE)
  )
```

You can read from top to bottom and interpret the `%>%` as an "and then do".

The pipe `%>%`

But what is happening?

The pipe is "pushing" the result of one line into the first argument of the function from the next line.

```
soybean_use %>%
  count(year)

# instead of
count(soybean_use, year)
```

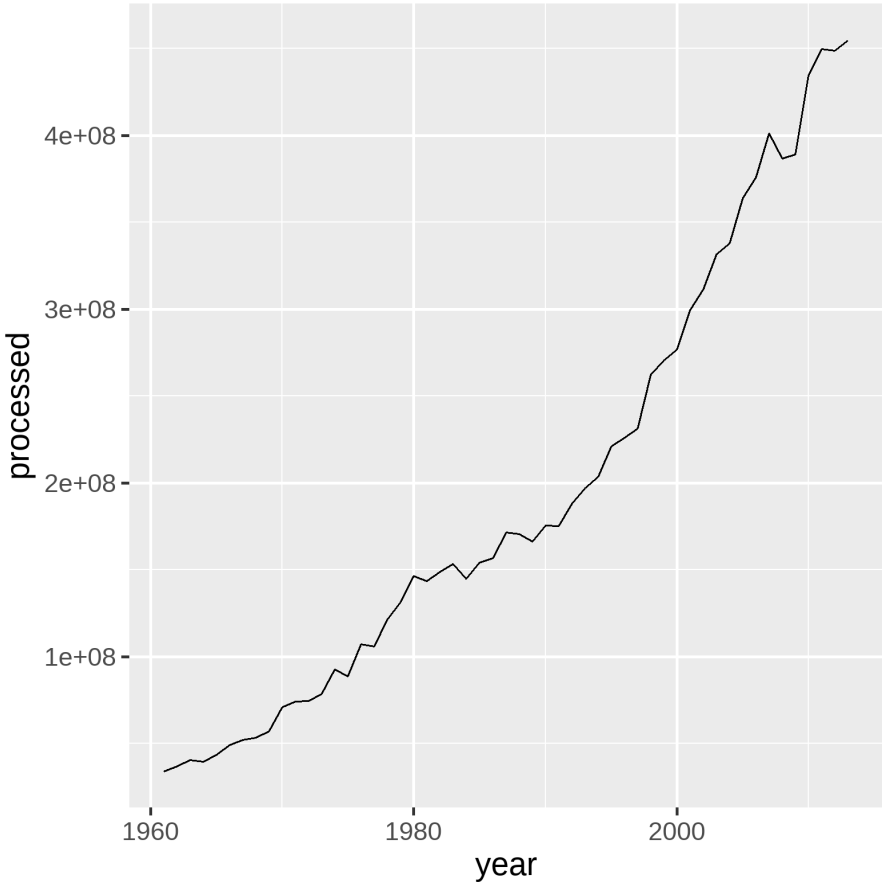
Piping works perfectly with the `tidyverse` functions because they are designed to return a tibble **and** take a tibble as first argument.

Use the keyboard shortcut `Ctrl/Cmd + Shift + M` to insert `%>%`

The pipe %>%

Piping also works well together with `ggplot`

```
soybean_use %>%
  filter(!is.na(code)) %>%
  select(year, processed) %>%
  group_by(year) %>%
  summarize(
    processed = sum(processed, na.rm = TRUE)
  ) %>%
  ggplot(aes(
    x = year,
    y = processed
  )) +
    geom_line()
```



Combining mulitiple tables into one

Combine two tibbles by row `bind_rows`

Situation: Two (or more) `tibbles` with the same variables (column names)

```
tbl_a <- soybean_use[1:2, ] # first two rows
tbl_b <- soybean_use[2:nrow(soybean_use), ] # the rest
```

```
tbl_a
```

```
## # A tibble: 2 × 6
##   entity code   year human_food animal_feed processed
##   <chr>  <chr> <dbl>      <dbl>       <dbl>     <dbl>
## 1 Africa <NA>   1961      33000        6000     14000
## 2 Africa <NA>   1962      43000        7000     17000
```

```
tbl_b
```

```
## # A tibble: 9,896 × 6
##   entity code   year human_food animal_feed processed
##   <chr>  <chr> <dbl>      <dbl>       <dbl>     <dbl>
## 1 Africa <NA>   1962      43000        7000     17000
## 2 Africa <NA>   1963      31000        7000      5000
## # … with 9,894 more rows
```

Combine two tibbles by row `bind_rows`

Bind the rows together with `bind_rows()`:

```
bind_rows(tbl_a, tbl_b)
```

```
## # A tibble: 9,898 × 6
##   entity code   year human_food animal_feed processed
##   <chr>  <chr> <dbl>      <dbl>       <dbl>     <dbl>
## 1 Africa <NA>   1961      33000        6000     14000
## 2 Africa <NA>   1962      43000        7000     17000
## # … with 9,896 more rows
```

You can also add an ID-column to indicate which line belonged to which table:

```
bind_rows(a = tbl_a, b = tbl_b, .id = "id")
```

```
## # A tibble: 9,898 × 7
##   id    entity code   year human_food animal_feed processed
##   <chr> <chr>  <chr> <dbl>      <dbl>       <dbl>     <dbl>
## 1 a     Africa <NA>   1961      33000        6000     14000
## 2 a     Africa <NA>   1962      43000        7000     17000
## 3 b     Africa <NA>   1962      43000        7000     17000
## # … with 9,895 more rows
```

Join tibbles with `left_join()`

Situation: Two tables that share some but not all columns.

```
soybean_use
```

```
## # A tibble: 9,897 × 6
##   entity code   year human_food animal_feed processed
##   <chr>  <chr> <dbl>      <dbl>       <dbl>     <dbl>
## 1 Africa <NA>   1961      33000        6000     14000
## 2 Africa <NA>   1962      43000        7000     17000
## # … with 9,895 more rows
```

```
# table with the gdp of the country/continent for each year
gdp
```

```
## # A tibble: 9,897 × 3
##   entity  year   gdp
##   <chr>  <dbl> <dbl>
## 1 Africa  1961  5.08
## 2 Africa  1962  5.08
## # … with 9,895 more rows
```

Join tibbles with `left_join()`

Join the two tables by the two common columns `entity` and `year`

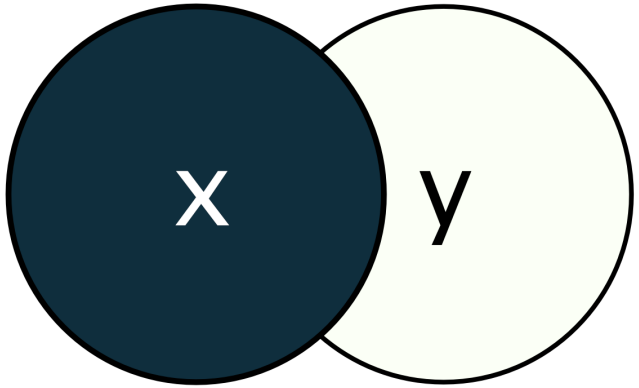
```
left_join(soybean_use, gdp, by = c("entity", "year"))
```

```
## # A tibble: 9,897 × 7
##   entity code   year human_food animal_feed processed   gdp
##   <chr>  <chr> <dbl>      <dbl>       <dbl>     <dbl> <dbl>
## 1 Africa <NA>   1961      33000        6000     14000  5.08
## 2 Africa <NA>   1962      43000        7000     17000  5.08
## 3 Africa <NA>   1963      31000        7000      5000  5.08
## # … with 9,894 more rows
```

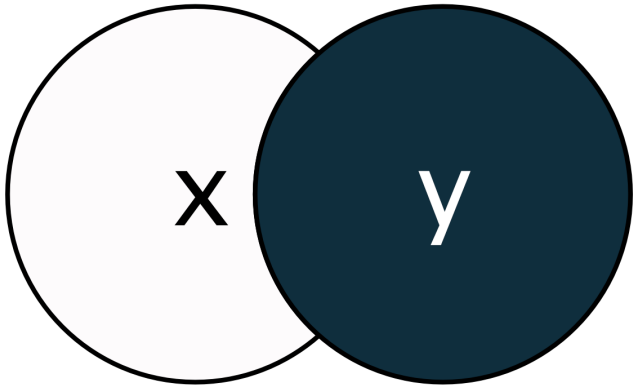
`left_join()` means that the resulting tibble will contain all rows of `soybean_use`, but not necessarily all rows of `gdp`

Different `*_join()` functions

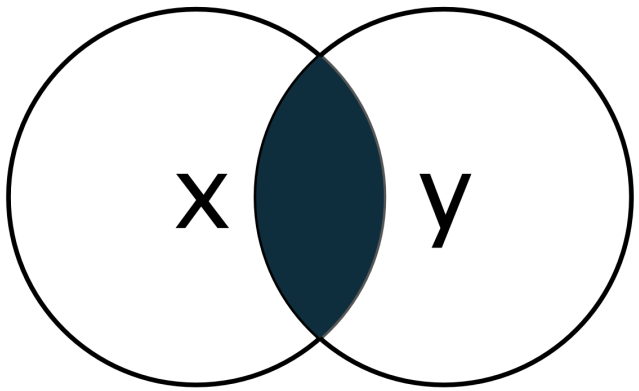
`left_join(x, y)`



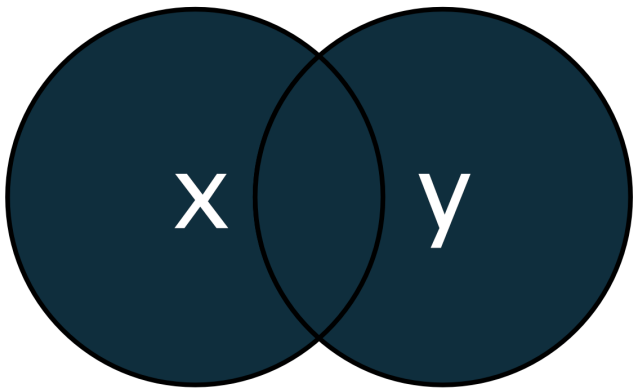
`right_join(x, y)`



`inner_join(x, y)`



`full_join(x, y)`



Summary I

All `dplyr` functions take a tibble as first argument and return a tibble.

`filter()`

- pick rows with helpers
  - relational and logical operators
  - `%in%`
  - `is.na()`
  - `between()`
  - `near()`

`select()`

- pick columns with helpers
  - `starts_with()`, `ends_with()`
  - `contains()`
  - `matches()`
  - `any_of()`, `all_of()`

Summary II

`arrange()`

- change order of rows (adscending)
  - or descending with `desc()`

`mutate()`

- add columns but keep all columns
  - `case_when()` for conditional values

Summary III

`summarize()` + `group_by()`

- collapse rows into one row by some summary
  - combine with `group_by()` to summarize by group
  - use `ungroup()` to ungroup grouped tibble

`count`

- count rows based on a group
  - can be used in combination with `group_by()`

Summary IV

`bind_rows()`

- combine rows of multiple tibbles into one
  - the tibbles need to have the same columns
  - add an id column with the argument `.id = "id"`
  - function `bind_cols()` works similarly just for columns

`left_join()`

- combine tables based on common columns

Now you

Task 2: Transforming the penguin data set (60 min)

Find the task description here