Data transformation with dplyr

Day 2 - Introduction to Data Analysis with R

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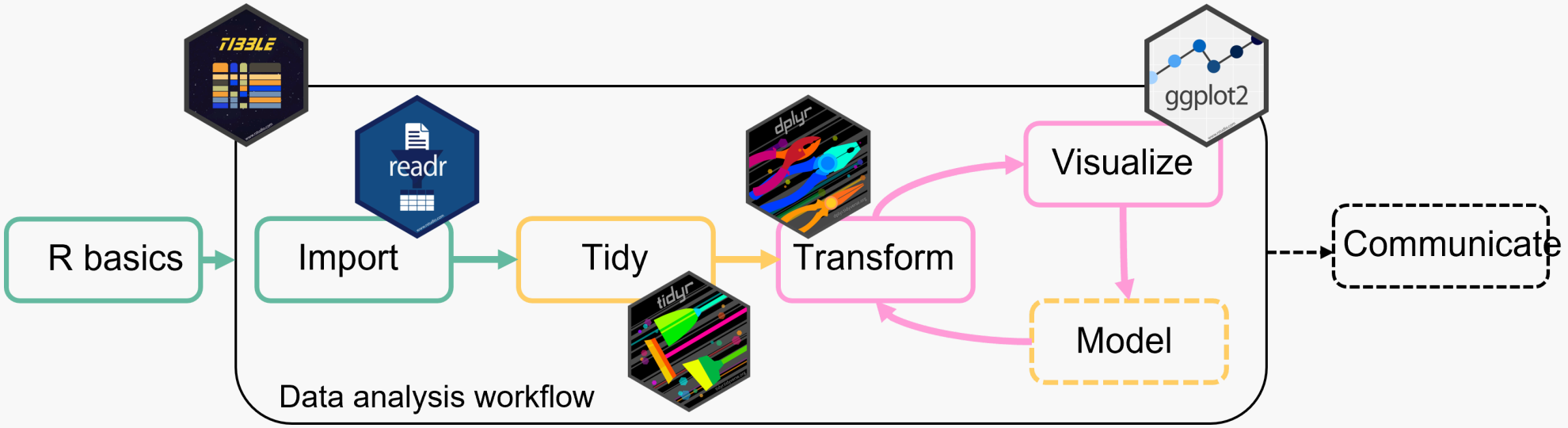
Data transformation

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`:

```
1 library(dplyr)
2 # or
3 library(tidyverse)
```

Dplyr basic vocuabulary 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

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

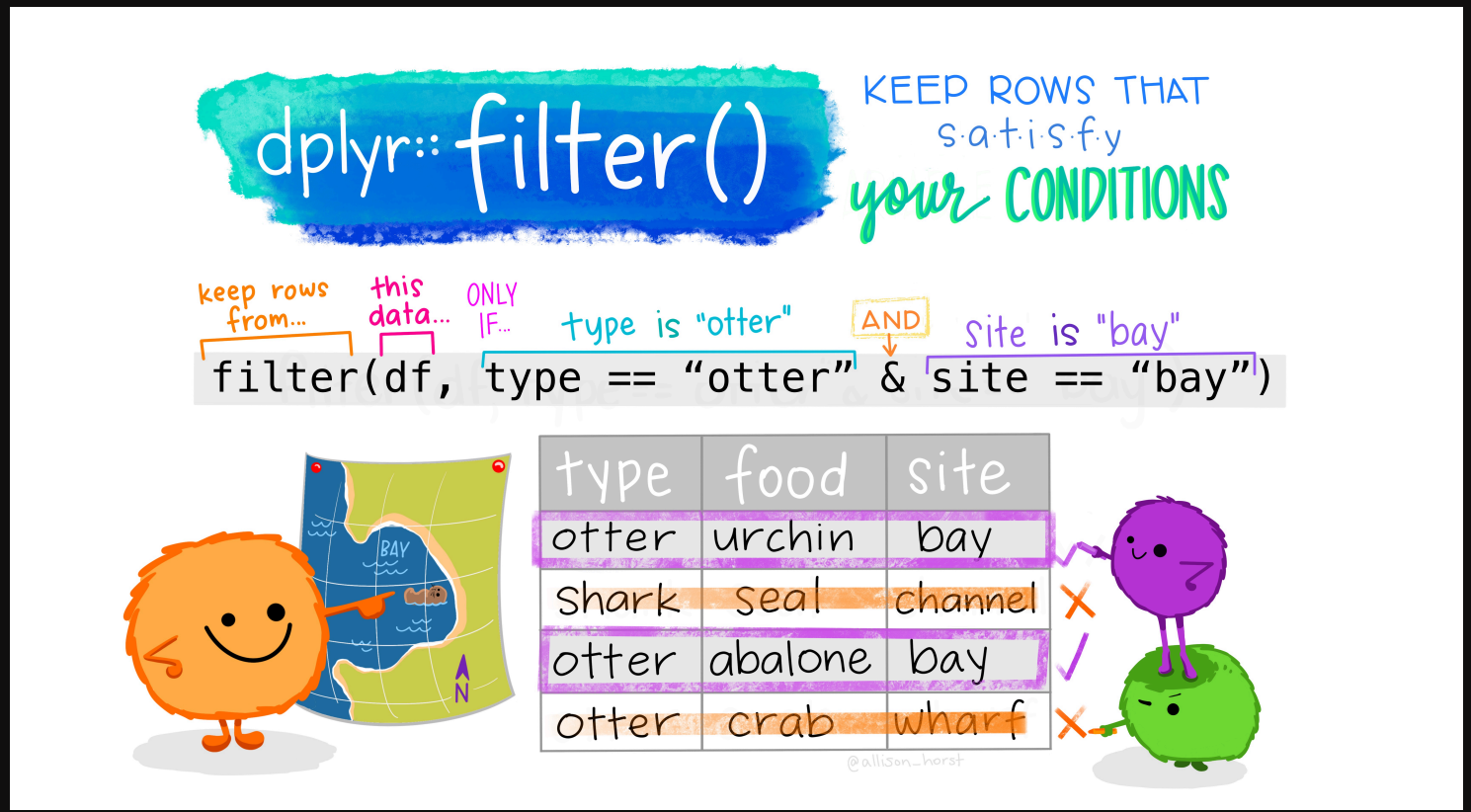
Example data

Soybean production for different use by year and country.

```
soybean_use <- readr::read_csv('https://raw.githubusercontent.com/rfordatasci
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
#>  6 Africa <NA>   1966      41000        6000      2000
#>  7 Africa <NA>   1967      47000        6000      4000
#>  8 Africa <NA>   1968      50000        7000      3000
#>  9 Africa <NA>   1969      52000        6000      6000
#> 10 Africa <NA>   1970      52000        6000      8000
#> # ℹ 9,887 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
#>  6 Germany DEU    1966          0        3000   1588000
#>  7 Germany DEU    1967          0        3000   1646000
#>  8 Germany DEU    1968          0        3000   1480000
#>  9 Germany DEU    1969          0        3000   1423000
#> 10 Germany DEU    1970          0        3000   2118000
#> # ℹ 43 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 rows based on multiple values, e.g. 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
#>  6 Austria AUT    1966          0           0         0
#>  7 Austria AUT    1967          0           0         0
#>  8 Austria AUT    1968          0           0         0
#>  9 Austria AUT    1969          0           0         0
#> 10 Austria AUT    1970          0           0         0
#> # ℹ 149 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
#>  6 Africa <NA>   1966      41000        6000      2000
#>  7 Africa <NA>   1967      47000        6000      4000
#>  8 Africa <NA>   1968      50000        7000      3000
#>  9 Africa <NA>   1969      52000        6000      6000
#> 10 Africa <NA>   1970      52000        6000      8000
#> # ℹ 1,724 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
#>  6 Germany DEU    1975          0        3000   3480000
#>  7 Germany DEU    1976          0        1000   3453000
#>  8 Germany DEU    1977          0        3000   3388000
#>  9 Germany DEU    1978          0        3000   3647000
#> 10 Germany DEU    1979          0        2000   3700000
#> 11 Germany DEU    1980          0        3000   3887000
```

`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
#>  3 Africa  1963      31000
#>  4 Africa  1964      43000
#>  5 Africa  1965      34000
#>  6 Africa  1966      41000
#>  7 Africa  1967      47000
#>  8 Africa  1968      50000
#>  9 Africa  1969      52000
#> 10 Africa  1970      52000
#> # ℹ 9,887 more rows
```

Remove variables using –

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

`select()` + `ends_with()`

Select all columns that end with `"d"`

```
1 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
#> # ℹ 9,894 more rows
```

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

```
1 # this does not match any rows in the soy bean data set
2 # but combinations like this are helpful for research data
3 select(soybean_use, starts_with("sample_"))
4
5 select(soybean_use, contains("_id_"))
```

select() + any_of()/all_of()

Use a character vector in conjunction with column selection

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

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

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

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

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

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

```
#> Error in `all_of()`:
#> ! Can't subset columns that don't exist.
#> ✖ Column `sample_` doesn't exist.
```

`select()` + `from:to`

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

```
1  select(soybean_use, 1:3)
2  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
#> # ℹ 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

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mutate()

New columns can be added based on values from other columns

```
1  mutate(soybean_use,
2    sum_human_animal = human_food + animal_feed
3  )
```

```
#> # 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
#> # ℹ 9,894 more rows
```

Add multiple new columns at once:

```
1  mutate(soybean_use,
2    sum_human_animal = human_food + animal_feed,
3    total = human_food + animal_feed + processed
4  )
```

mutate() + case_when()

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

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

```
 1  mutate(soybean_use,
 2    legislation = case_when(
 3      between(year, 1980, 2000) ~ "legislation_1",   # case 1
 4      year >= 2000 ~ "legislation_2",                # case 2
 5      .default = "no_legislation"                    # all other cases
 6    )
 7  )
 8  #> # A tibble: 9,897 × 7
 9  #>    entity code   year human_food animal_feed processed legislation
10  #>    <chr>  <chr> <dbl>      <dbl>       <dbl>     <dbl> <chr>
11  #>  1 Africa <NA>   1961      33000        6000     14000 no_legislation
12  #>  2 Africa <NA>   1962      43000        7000     17000 no_legislation
13  #>  3 Africa <NA>   1963      31000        7000      5000 no_legislation
14  #>  4 Africa <NA>   1964      43000        6000     14000 no_legislation
15  #>  5 Africa <NA>   1965      34000        6000     12000 no_legislation
16  #>  6 Africa <NA>   1966      41000        6000      2000 no_legislation
17  #>  7 Africa <NA>   1967      47000        6000      4000 no_legislation
18  #>  8 Africa <NA>   1968      50000        7000      3000 no_legislation
19  #>  9 Africa <NA>   1969      52000        6000      6000 no_legislation
```

`summarize()`

> summarizes data

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()` by group

`summarize` is much more useful in combination with the grouping argument `.by`

- **summary** will be calculated **separately for each group**

```
# summarize the grouped data
summarize(soybean_use,
  total_animal = sum(animal_feed, na.rm = TRUE),
  total_human = sum(human_food, na.rm = TRUE),
  .by = year
)
#> # A tibble: 53 × 3
#>     year total_animal total_human
#>    <dbl>        <dbl>       <dbl>
#>  1  1961      1503000    16994000
#>  2  1962      1800000    17326000
#>  3  1963      2060000    18667000
#>  4  1964      2002000    19639000
#>  5  1965      2162000    17796000
#>  6  1966      3096000    22179000
#>  7  1967      2818000    23282000
#>  8  1968      3361000    22747000
#>  9  1969      3084000    22212000
#> 10  1970      2496000    24119000
```

count()

Counts observations by group

```
# count rows grouped by year
count(soybean_use, year)
#> # A tibble: 53 × 2
#>     year     n
#>    <dbl> <int>
#>  1  1961   178
#>  2  1962   178
#>  3  1963   178
#>  4  1964   178
#>  5  1965   178
#>  6  1966   178
#>  7  1967   178
#>  8  1968   178
#>  9  1969   178
#> 10  1970   178
#> # ℹ 43 more rows
```

The pipe |>

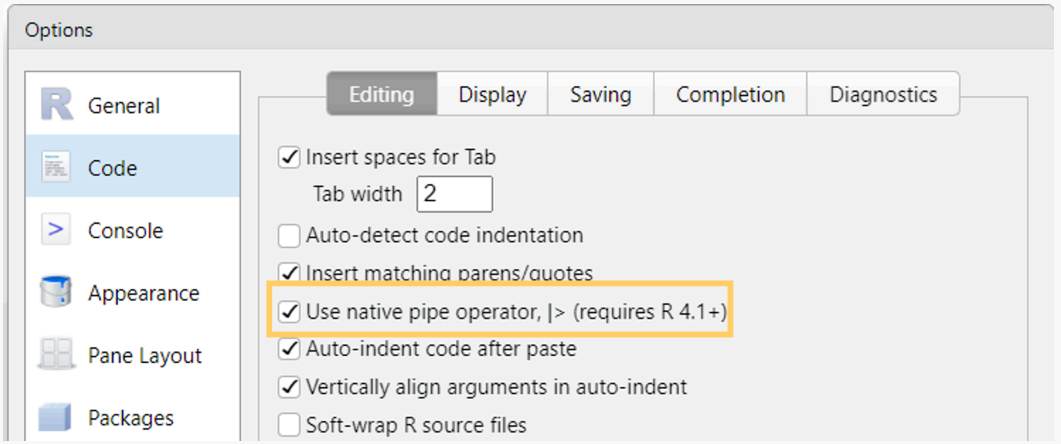
> Combine multiple data operations into one command

The pipe |>

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

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

- You may also see `%>%` from the `magrittr` package
- Turn on the native R pipe `|>` in **Tools -> Global Options -> Code**



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

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(
  filter(soybean_use, !is.na(code)),
  mean_processed = mean(processed, na.rm = TRUE),
  sd_processed = sd(processed, na.rm = TRUE),
  .by = year
)
```

But this gets complicated and error prone very quickly

The pipe |>

The pipe operator makes it very easy to combine multiple operations:

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

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.

```
1  soybean_use |>
2    count(year)
3
4  # instead of
5  count(soybean_use, year)
```

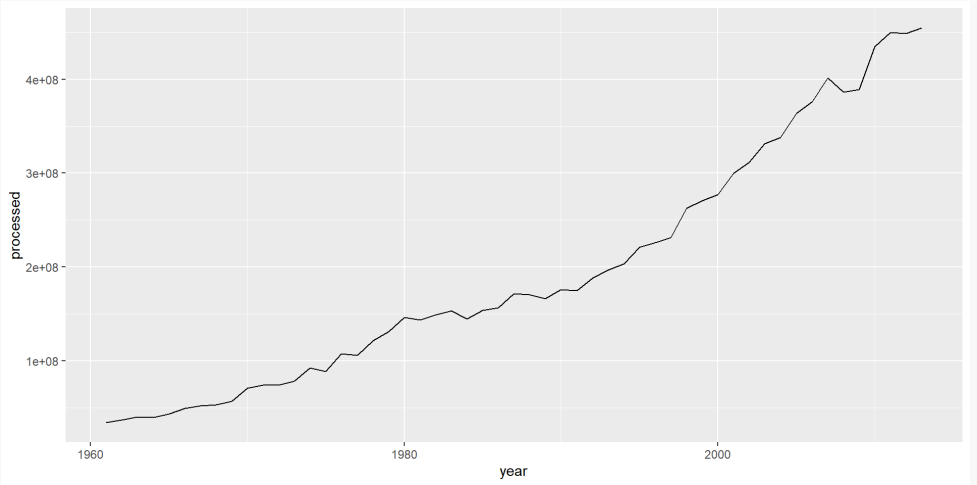
Piping works perfectly with the `tidyverse` functions because they are designed to return a tibble **and** take a tibble as first argument.

> **Tip**
>
> 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) |>
  summarize(
    processed = sum(processed,
      na.rm = TRUE
    ),
    .by = year
  ) |>
  ggplot(aes(
    x = year,
    y = processed
  )) +
  geom_line()
```



Combining mulitiple tables

Combine two tibbles by row `bind_rows`

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

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

```
1  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
```

```
1  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
#> # ℹ 9,894 more rows
```

Combine two tibbles by row `bind_rows`

Bind the rows together with `bind_rows()`:

```
1 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
#> # ℹ 9,896 more rows
```

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

```
1 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
#> # ℹ 9,895 more rows
```

You can use `bind_rows()` to bind as many tables as you want:

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

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
#> # ℹ 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  4.02
#> 2 Africa  1962  4.02
#> # ℹ 9,895 more rows
```

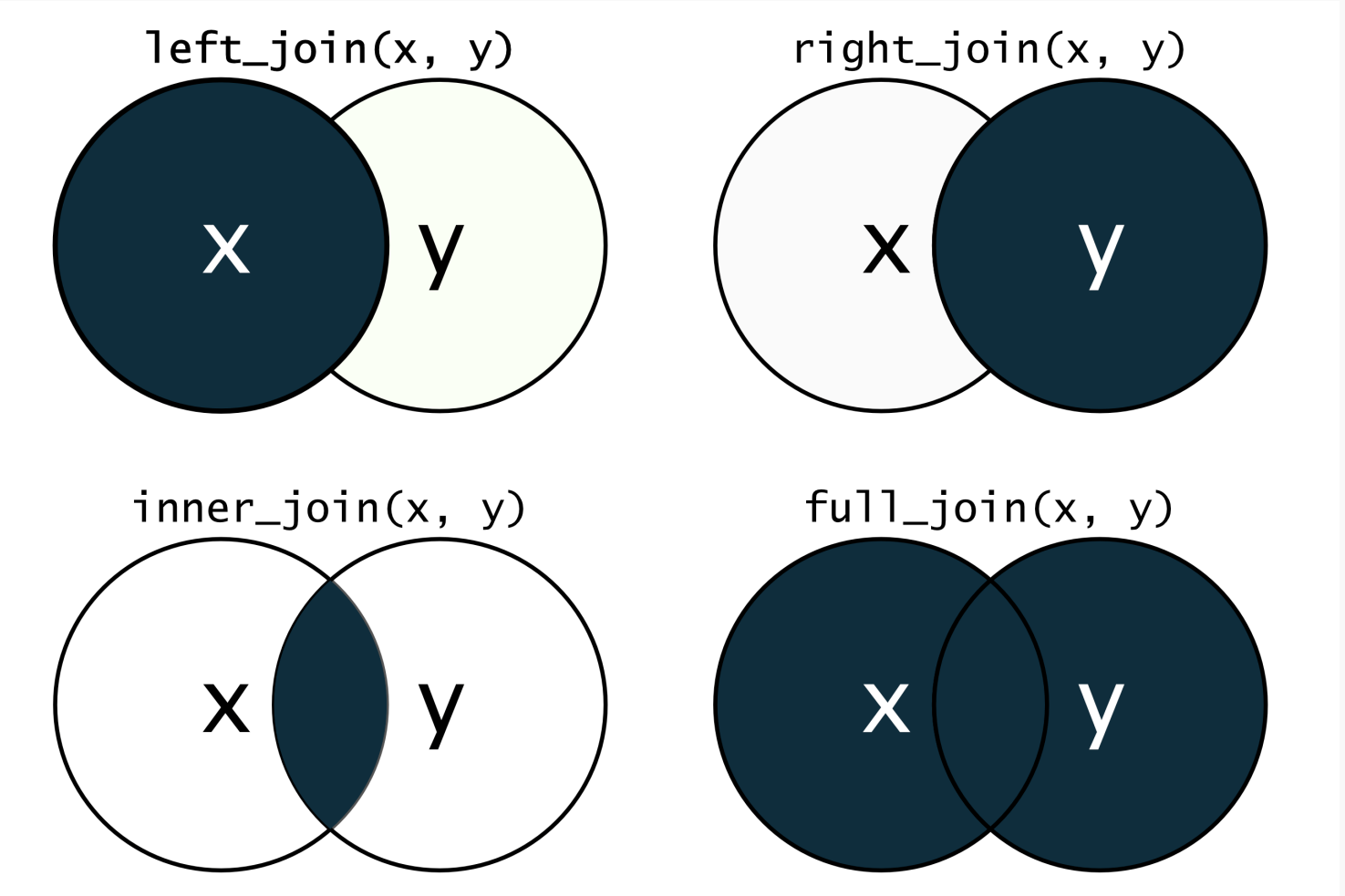
Join tibbles with `left_join()`

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  4.02
#>  2 Africa <NA>   1962      43000        7000     17000  4.02
#>  3 Africa <NA>   1963      31000        7000      5000  4.02
#>  4 Africa <NA>   1964      43000        6000     14000  4.02
#>  5 Africa <NA>   1965      34000        6000     12000  4.02
#>  6 Africa <NA>   1966      41000        6000      2000  4.02
#>  7 Africa <NA>   1967      47000        6000      4000  4.02
#>  8 Africa <NA>   1968      50000        7000      3000  4.02
#>  9 Africa <NA>   1969      52000        6000      6000  4.02
#> 10 Africa <NA>   1970      52000        6000      8000  4.02
#> # ℹ 9,887 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



Summary

> Data transformation with dplyr

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()`

Summary II

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

`select()`

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

Summary III

`arrange()`

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

`mutate()`

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

Summary IV

`summarize()`

- **collapse rows** into one row by some summary
  - use `.by` argument to summarize by group

`count`

- **count rows** based on a group

Summary V

`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 (60 min)

Transform the penguin data set

Find the task description here