# Introduction to the tidyverse

## Scientific workflows: Tools and Tips 

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# What is this lecture series?

## Scientific workflows: Tools and Tips 🛠️

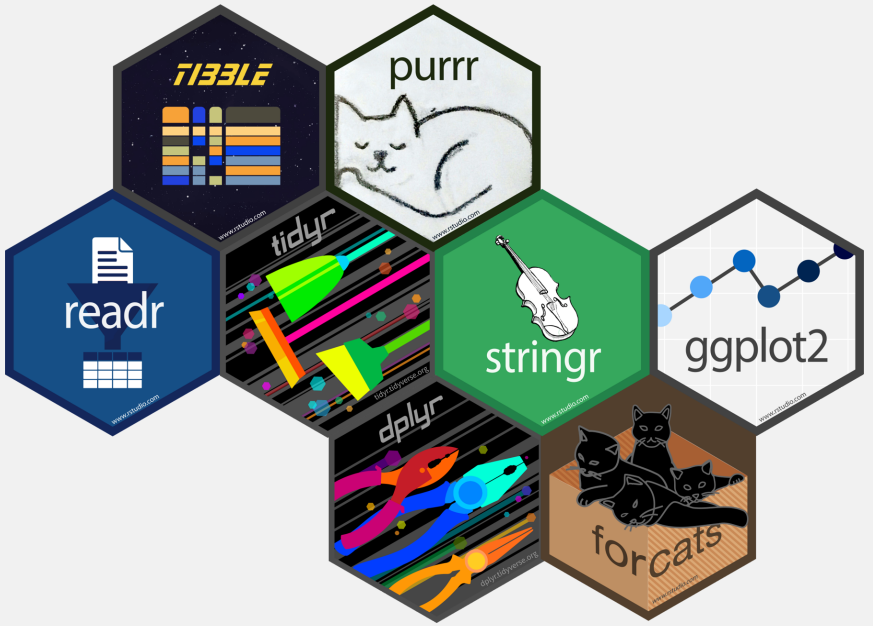
🗓️ Every 3rd Thursday 🕐 4-5 p.m. 📍 Webex

- One topic from the world of scientific workflows
- Material provided online
- If you don't want to miss a lecture
  - Subscribe to the mailing list

# What is the tidyverse?


> The tidyverse is an opinionated **collection of R packages** designed for data science. All packages **share** an underlying **design philosophy, grammar, and data structures**.
>
> www.tidyverse.org

## Tidyverse core packages



# Why the tidyverse?


Basic idea: Make data analysis **efficient** and **intuitive**

- Write code that is easy to **read**, **write** and **maintain**
- More time for **data interpretation**
- Tidyverse is **actively developed** and has a **large community**.

This facilitates

 Learning

 Collaboration

 Reproducible research

# Today

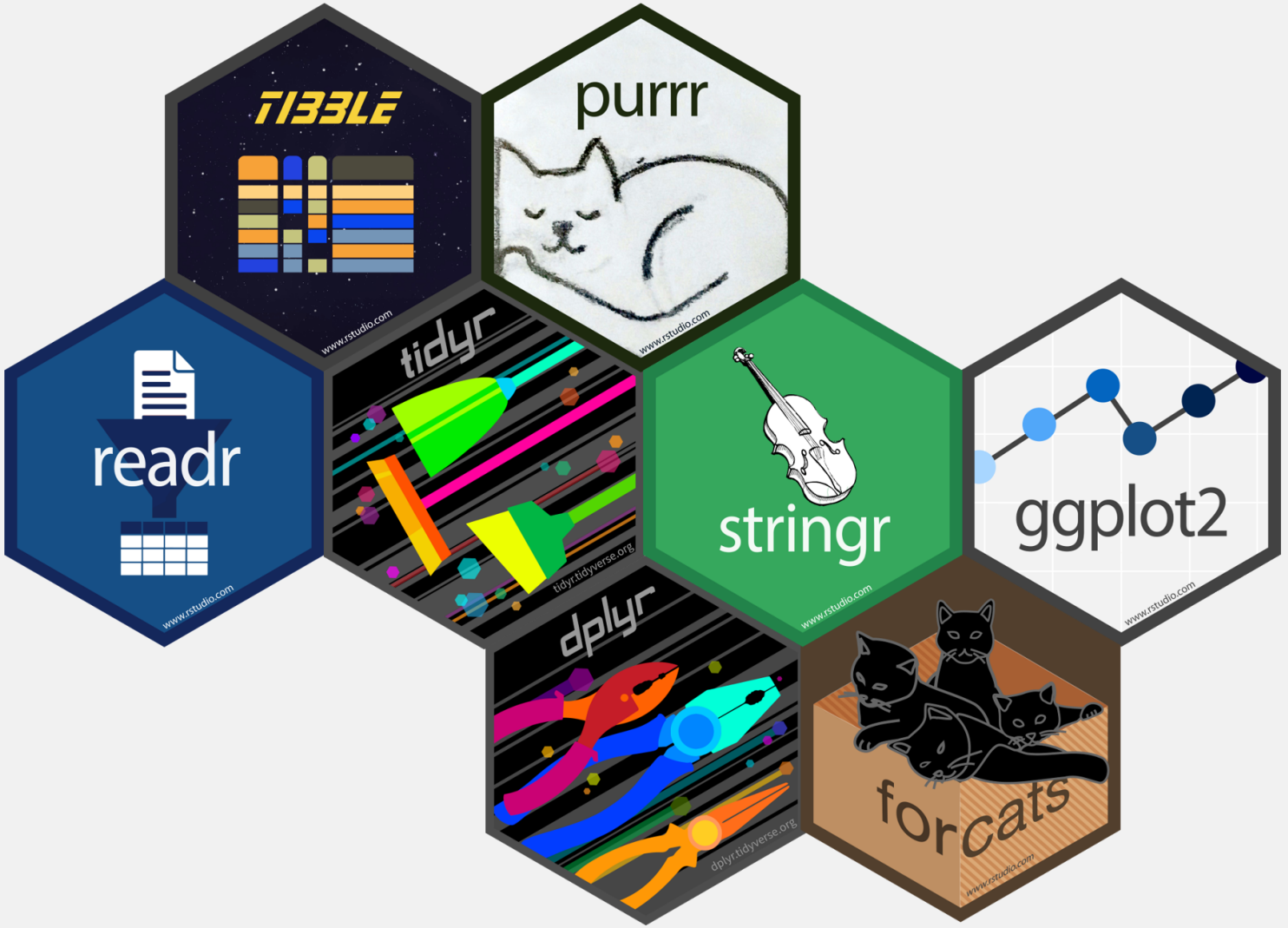

Overview of

- most important **packages and functions**
- how they work together in a **data analysis workflow**
- underlying **principles** of the tidyverse

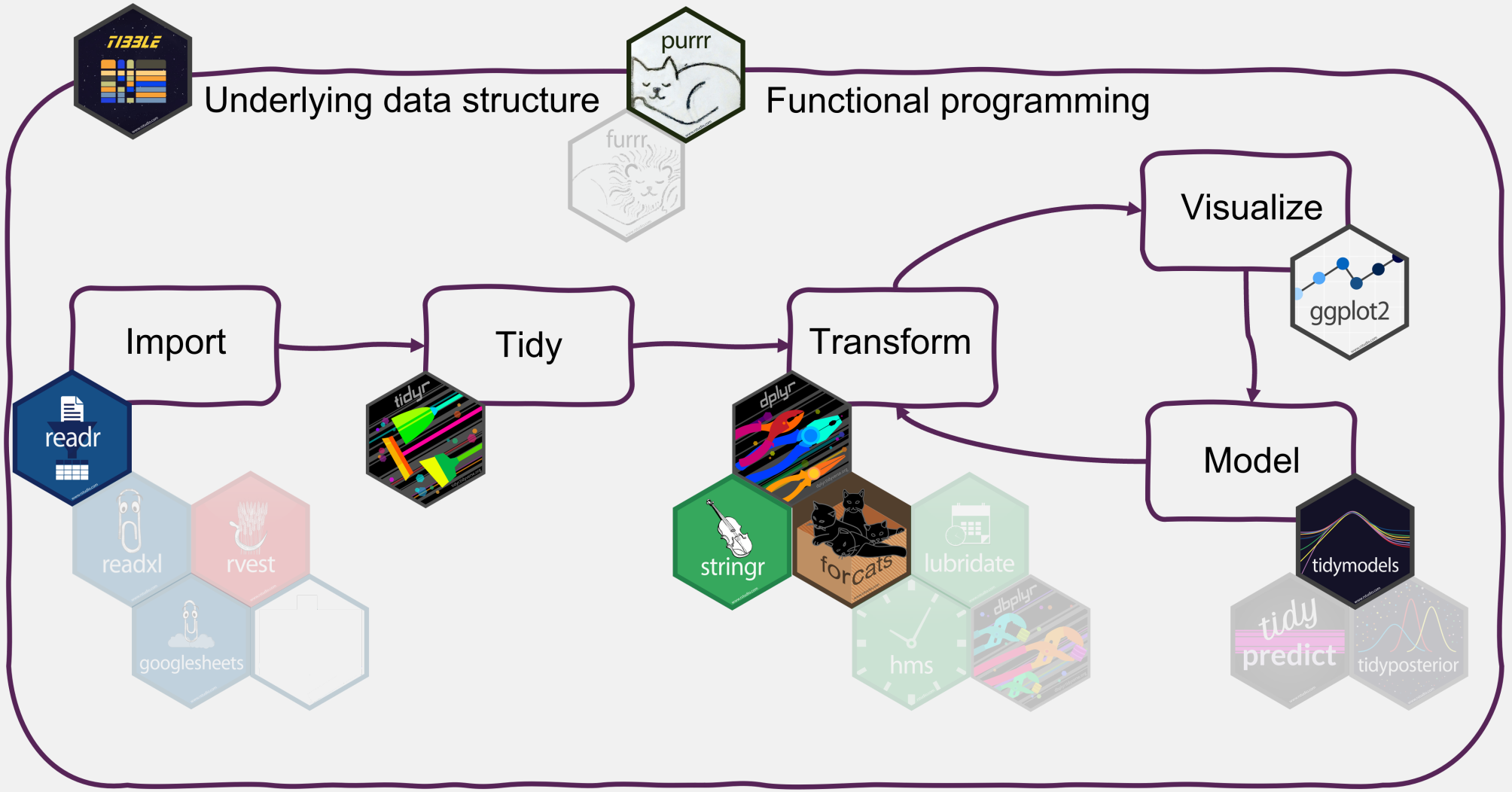
I can't show you everything. But the tidyverse has an excellent documentation and cheatsheets.

# Which tidyverse packages do you use?

Head over to the menti poll



# Data analysis with the tidyverse



# Getting the tidyverse

Install all tidyverse packages with

```
install.packages("tidyverse")
```

Load all core tidyverse packages with

```
library(tidyverse)
#> ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
#> ✓ dplyr     1.1.3     ✓ readr     2.1.4
#> ✓ forcats   1.0.0     ✓ stringr   1.5.0
#> ✓ ggplot2   3.4.4     ✓ tibble    3.2.1
#> ✓ lubridate 1.9.3     ✓ tidyr     1.3.0
#> ✓ purrr     1.0.2
#> ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
#> ✖ dplyr::filter() masks stats::filter()
#> ✖ dplyr::lag()    masks stats::lag()
#> ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to
```

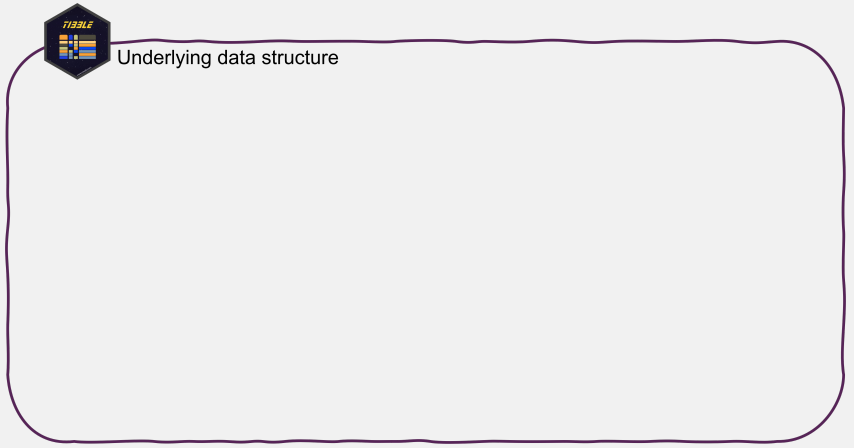
You can also load packages individually - But don't do both!

Non-core packages need to be loaded individually, e.g.

```
library(readxl)
```

# Tibbles from `tibble`

> The underlying data structure



# What are tibbles?


Tibbles are

> a **modern reimagining of the data frame**. Tibbles are designed to be (as much as possible) **drop-in replacements** for data frames.
>
> (Wickham, Advanced R)

- Tibbles have the **same basic properties** as data frames
- Everything that you can do with data frames, you can do with tibbles
- Main advantage: Tibbles **print much nicer** to the console

Have a look at this book chapter for a full list of the differences between data frames and tibbles and the advantages of using tibbles.

# How to create tibbles?


- Tidyverse functions return tibbles by default
- Create with `tibble` function (equivalent to `data.frame`)

# How to create tibbles?


## Creating a tibble

```
tibble(
  x = 1:26,
  y = letters,
  z = factor(LETTERS)
)
#> # A tibble: 26 × 3
#>        x y     z
#>    <int> <chr> <fct>
#>  1     1 a     A
#>  2     2 b     B
#>  3     3 c     C
#>  4     4 d     D
#>  5     5 e     E
#>  6     6 f     F
#>  7     7 g     G
#>  8     8 h     H
#>  9     9 i     I
#> 10    10 j     J
#> # ℹ 16 more rows
```

## Creating a data frame

```
data.frame(
  x = 1:26,
  y = letters,
  z = factor(LETTERS)
)
#>     x y z
#> 1   1 a A
#> 2   2 b B
#> 3   3 c C
#> 4   4 d D
#> 5   5 e E
#> 6   6 f F
#> 7   7 g G
#> 8   8 h H
#> 9   9 i I
#> 10 10 j J
#> 11 11 k K
#> 12 12 l L
#> 13 13 m M
#> 14 14 n N
#> 15 15 o O
```

# Import data with readr

Read in your files

# Most important `readr` functions


- `read_csv` to read **comma delimited** files
- `read_tsv` to read **tab delimited** files
- `read_delim` to read files with **any delimiter**

All `read_*` functions return a `tibble`.

# Example with arctic temperature data


Data modified from `lterdatasampler`

```
arc_weather <- read_csv(file = "data/arc_weather.csv")
arc_weather
```

```
#> # A tibble: 365 × 3
#>    Date       `FoolikMeanTemp°C` `PoolikMeanTemp°C`
#>    <date>                  <dbl>               <dbl>
#>  1 1988-06-01                8.4                11.7
#>  2 1988-06-02                6                   9.07
#>  3 1988-06-03                5.8                 8.69
#>  4 1988-06-04                1.8                 5.18
#>  5 1988-06-05                6.8                 9.54
#>  6 1988-06-06                5.2                 8.60
#>  7 1988-06-07                2.2                 4.41
#>  8 1988-06-08                9.4                12.2
#>  9 1988-06-09               13.1                16.5
#> 10 1988-06-10               17.7                20.9
#> # ℹ 355 more rows
```

Use readr functions with `janitor::clean_names`

Get consistent and good-practice use column names. Package documentation

# Example with arctic temperature data


Data modified from `lterdatasampler`

```
arc_weather <- janitor::clean_names(arc_weather)
arc_weather
```

```
#> # A tibble: 365 × 3
#>    date       foolik_mean_temp_c poolik_mean_temp_c
#>    <date>                  <dbl>               <dbl>
#>  1 1988-06-01                8.4                11.7
#>  2 1988-06-02                6                   9.07
#>  3 1988-06-03                5.8                 8.69
#>  4 1988-06-04                1.8                 5.18
#>  5 1988-06-05                6.8                 9.54
#>  6 1988-06-06                5.2                 8.60
#>  7 1988-06-07                2.2                 4.41
#>  8 1988-06-08                9.4                12.2
#>  9 1988-06-09               13.1                16.5
#> 10 1988-06-10               17.7                20.9
#> # ℹ 355 more rows
```

Use readr functions with `janitor::clean_names`

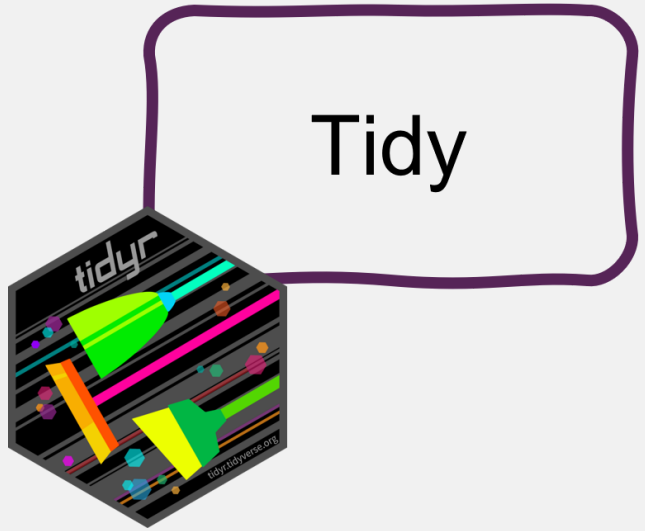
Get consistent and good-practice use column names. Package documentation

# Advantages of `readr`


- Faster than `read.table`/`read.csv`
- Better defaults than base R (e.g. guessing of data types)
- Returns tibbles
- Tidyverse packages for other data types:
  - `readxl` for Excel files
  - `haven` for SPSS, SAS, and Stata files
  - `googlesheets4` for Google sheets
  - ...

# Tidy data with `tidyr`

> Reorganize the data



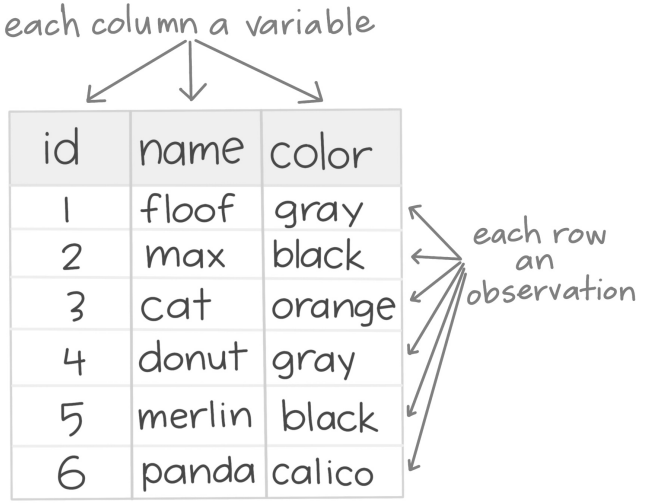
# What is tidy data?

"TIDY DATA is a standard way of mapping the meaning of a dataset to its structure."

–HADLEY WICKHAM

## In tidy data:

- each variable forms a column
- each observation forms a row
- each cell is a single measurement




Wickham, H. (2014). Tidy Data. Journal of Statistical Software *59* (10). DOI: 10.18637/jss.v059.i10

Illustration from the Openscapes blog *Tidy Data for reproducibility, efficiency, and collaboration* by Julia Lowndes and Allison Horst

# What is non-tidy data?

Tidy

| id | name | color |
|---|---|---|
| 1 | floof | gray |
| 2 | max | black |
| 3 | cat | orange |
| 4 | donut | gray |
| 5 | merlin | black |
| 6 | panda | calico |

Non-tidy

| floof | max | cat | donut | merlin | p |
|---|---|---|---|---|---|
| gray | black | orange | gray | black | c |

| gray | black | orange | calico |
|---|---|---|---|
| floof | max | cat | panda |
| donut | merlin | | |

Sometimes ***raw data*** is non-tidy because its structure is optimized for data entry or viewing rather than analysis.

# Advantages of tidy data

The main advantages of **tidy** data is that the `tidyverse` packages are built to work with it.

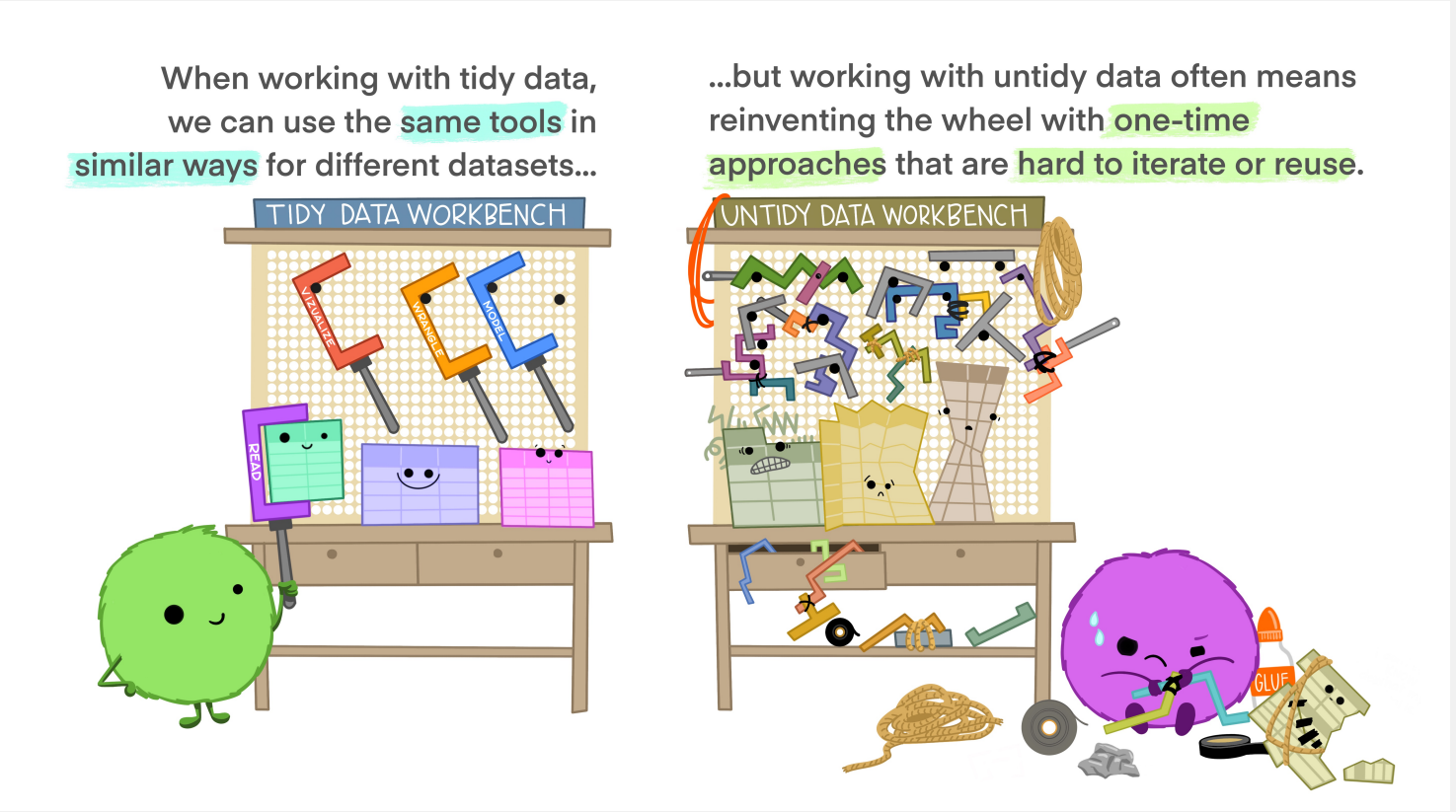



Illustration from the Openscapes blog *Tidy Data for reproducibility, efficiency, and collaboration* by Julia Lowndes and Allison Horst

# Tidy data with tidyr


- `Tidyr` **reorganizes** the data but **does not change** values
- Most important functionality:
  - **Pivoting**: `pivot_longer` and `pivot_wider`
  - **Splitting** and **combining** columns: `separate_wider_delim/position/regex` and `unite`
  - Handle **missing values**: `drop_na`, `replace_na`, `complete`

# Example


What is not tidy about our weather data?

```
arc_weather
#> # A tibble: 365 × 3
#>    date       foolik_mean_temp_c poolik_mean_temp_c
#>    <date>                  <dbl>               <dbl>
#>  1 1988-06-01                8.4                11.7
#>  2 1988-06-02                6                   9.07
#>  3 1988-06-03                5.8                 8.69
#>  4 1988-06-04                1.8                 5.18
#>  5 1988-06-05                6.8                 9.54
#>  6 1988-06-06                5.2                 8.60
#>  7 1988-06-07                2.2                 4.41
#>  8 1988-06-08                9.4                12.2
#>  9 1988-06-09               13.1                16.5
#> 10 1988-06-10               17.7                20.9
#> # ℹ 355 more rows
```

- Each row has multiple observations
- Variables are split across multiple columns

# Example


This can be solved with `pivot_longer`

```
pivot_longer(arc_weather,
             cols = c(foolik_mean_temp_c, poolik_mean_temp_c))
#> # A tibble: 730 × 3
#>    date       name                value
#>    <date>     <chr>               <dbl>
#>  1 1988-06-01 foolik_mean_temp_c   8.4
#>  2 1988-06-01 poolik_mean_temp_c  11.7
#>  3 1988-06-02 foolik_mean_temp_c   6
#>  4 1988-06-02 poolik_mean_temp_c   9.07
#>  5 1988-06-03 foolik_mean_temp_c   5.8
#>  6 1988-06-03 poolik_mean_temp_c   8.69
#>  7 1988-06-04 foolik_mean_temp_c   1.8
#>  8 1988-06-04 poolik_mean_temp_c   5.18
#>  9 1988-06-05 foolik_mean_temp_c   6.8
#> 10 1988-06-05 poolik_mean_temp_c   9.54
#> # ℹ 720 more rows
```

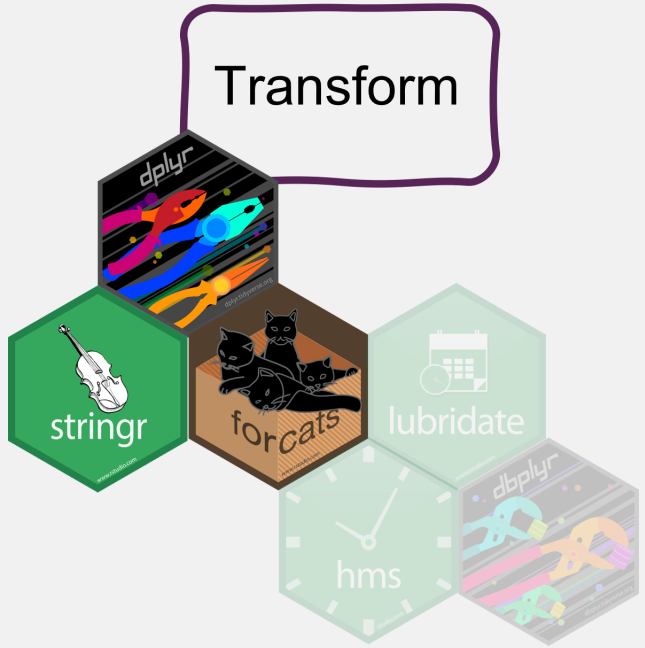
# Example


You can also directly name the new columns:

```
arc_weather <- pivot_longer(arc_weather,
  cols = c(foolik_mean_temp_c, poolik_mean_temp_c),
  names_to = "station",
  values_to = "mean_temp_c")
arc_weather
#> # A tibble: 730 × 3
#>    date       station             mean_temp_c
#>    <date>     <chr>                     <dbl>
#>  1 1988-06-01 foolik_mean_temp_c         8.4
#>  2 1988-06-01 poolik_mean_temp_c        11.7
#>  3 1988-06-02 foolik_mean_temp_c         6
#>  4 1988-06-02 poolik_mean_temp_c         9.07
#>  5 1988-06-03 foolik_mean_temp_c         5.8
#>  6 1988-06-03 poolik_mean_temp_c         8.69
#>  7 1988-06-04 foolik_mean_temp_c         1.8
#>  8 1988-06-04 poolik_mean_temp_c         5.18
#>  9 1988-06-05 foolik_mean_temp_c         6.8
#> 10 1988-06-05 poolik_mean_temp_c         9.54
#> # ℹ 720 more rows
```

# Transform data with `dplyr`

> How to actually change values



# Transform data with `dplyr`


- Data cleaning, adding new columns, summarizing, …
- Depending on the data type in combination with
  - `stringr` for character columns
  - `lubridate` for date-time columns
  - `forcats` for factor columns

# Data cleaning and filtering


`select` picks variables (columns) based on their names

```
select(arc_weather,
  date, mean_temp_c)
#> # A tibble: 730 × 2
#>    date       mean_temp_c
#>    <date>           <dbl>
#>  1 1988-06-01         8.4
#>  2 1988-06-01        11.7
#>  3 1988-06-02         6
#>  4 1988-06-02         9.07
#>  5 1988-06-03         5.8
#>  6 1988-06-03         8.69
#>  7 1988-06-04         1.8
#>  8 1988-06-04         5.18
#>  9 1988-06-05         6.8
#> 10 1988-06-05         9.54
#> # ℹ 720 more rows
```

`filter` picks observations (rows) based on their values

```
filter(arc_weather,
  station == "foolik_mean_temp_c")
#> # A tibble: 365 × 3
#>    date       station              mean_te
#>    <date>     <chr>                     <
#>  1 1988-06-01 foolik_mean_temp_c
#>  2 1988-06-02 foolik_mean_temp_c
#>  3 1988-06-03 foolik_mean_temp_c
#>  4 1988-06-04 foolik_mean_temp_c
#>  5 1988-06-05 foolik_mean_temp_c
#>  6 1988-06-06 foolik_mean_temp_c
#>  7 1988-06-07 foolik_mean_temp_c
#>  8 1988-06-08 foolik_mean_temp_c
#>  9 1988-06-09 foolik_mean_temp_c
#> 10 1988-06-10 foolik_mean_temp_c
#> # ℹ 355 more rows
```

# Combine `filter` with other packages


## `lubridate` to filter by month

```
# Filter rows from May
filter(arc_weather,
  month(date) == 5)
#> # A tibble: 62 × 3
#>    date       station                mean_te
#>    <date>     <chr>                       <
#>  1 1989-05-01 foolik_mean_temp_c         -3
#>  2 1989-05-01 poolik_mean_temp_c         -0
#>  3 1989-05-02 foolik_mean_temp_c         -0
#>  4 1989-05-02 poolik_mean_temp_c          1
#>  5 1989-05-03 foolik_mean_temp_c          0
#>  6 1989-05-03 poolik_mean_temp_c          4
#>  7 1989-05-04 foolik_mean_temp_c         -2
#>  8 1989-05-04 poolik_mean_temp_c          0
#>  9 1989-05-05 foolik_mean_temp_c         -2
#> 10 1989-05-05 poolik_mean_temp_c          0
#> # ℹ 52 more rows
```

## `stringr` to filter characters

```
# Filter rows where the station contains "f
filter(arc_weather,
  str_detect(station, "foolik"))
#> # A tibble: 365 × 3
#>    date       station                mean_te
#>    <date>     <chr>                       <
#>  1 1988-06-01 foolik_mean_temp_c
#>  2 1988-06-02 foolik_mean_temp_c
#>  3 1988-06-03 foolik_mean_temp_c
#>  4 1988-06-04 foolik_mean_temp_c
#>  5 1988-06-05 foolik_mean_temp_c
#>  6 1988-06-06 foolik_mean_temp_c
#>  7 1988-06-07 foolik_mean_temp_c
#>  8 1988-06-08 foolik_mean_temp_c
#>  9 1988-06-09 foolik_mean_temp_c
#> 10 1988-06-10 foolik_mean_temp_c
#> # ℹ 355 more rows
```

# Change and add values


## Add columns with `mutate`

```
# Add column with temperature in K
mutate(arc_weather,
  mean_temp_k = mean_temp_c + 274.15)
#> # A tibble: 730 × 4
#>    date       station             mean_temp_c mean_temp_k
#>    <date>     <chr>                     <dbl>       <dbl>
#>  1 1988-06-01 foolik_mean_temp_c        8.4          283.
#>  2 1988-06-01 poolik_mean_temp_c       11.7          286.
#>  3 1988-06-02 foolik_mean_temp_c        6            280.
#>  4 1988-06-02 poolik_mean_temp_c        9.07         283.
#>  5 1988-06-03 foolik_mean_temp_c        5.8          280.
#>  6 1988-06-03 poolik_mean_temp_c        8.69         283.
#>  7 1988-06-04 foolik_mean_temp_c        1.8          276.
#>  8 1988-06-04 poolik_mean_temp_c        5.18         279.
#>  9 1988-06-05 foolik_mean_temp_c        6.8          281.
#> 10 1988-06-05 poolik_mean_temp_c        9.54         284.
#> # ℹ 720 more rows
```

# Change and add values


## Change the values of existing columns with `mutate`

```
# Remove _mean_temp_c from station
arc_weather <- mutate(arc_weather,
                      station = str_remove(station, "_mean_temp_c"))
arc_weather
#> # A tibble: 730 × 3
#>    date       station mean_temp_c
#>    <date>     <chr>         <dbl>
#>  1 1988-06-01 foolik         8.4
#>  2 1988-06-01 poolik        11.7
#>  3 1988-06-02 foolik         6
#>  4 1988-06-02 poolik         9.07
#>  5 1988-06-03 foolik         5.8
#>  6 1988-06-03 poolik         8.69
#>  7 1988-06-04 foolik         1.8
#>  8 1988-06-04 poolik         5.18
#>  9 1988-06-05 foolik         6.8
#> 10 1988-06-05 poolik         9.54
#> # ℹ 720 more rows
```

# Summarize data


## `summarize` will **collapse the data** to a **single row**

```
# Calculate the overall mean temperature
summarize(arc_weather,
            overall_mean = mean(mean_temp_c, na.rm = TRUE))
#> # A tibble: 1 × 1
#>   overall_mean
#>          <dbl>
#> 1        -7.07
```

# Summarizing data by group


`summarize` in combination with `group_by` will **collapse the data** to a **single row per group**

```
# Calculate the mean temperature for each s
arc_weather_group <- group_by(arc_weather,
summarize(arc_weather_group,
  overall_mean = mean(mean_temp_c, na.rm =
#> # A tibble: 2 × 2
#>   station overall_mean
#>   <chr>          <dbl>
#> 1 foolik         -8.60
#> 2 poolik         -5.55
```

```
# Alternatively, use `.by` to specify the
# grouping variable (new feature).
summarize(arc_weather,
  overall_mean = mean(mean_temp_c, na.rm =
  .by = station)
#> # A tibble: 2 × 2
#>   station overall_mean
#>   <chr>          <dbl>
#> 1 foolik         -8.60
#> 2 poolik         -5.55
```

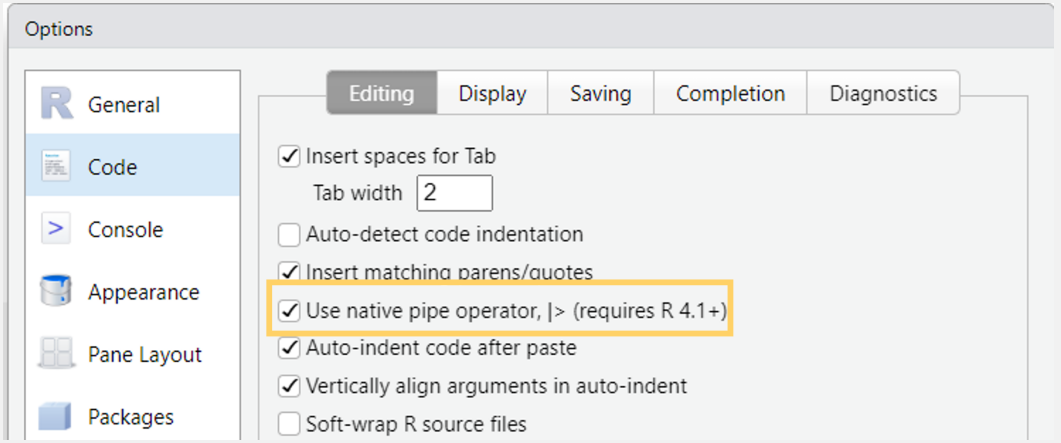
- `group_by` can be used for any dplyr function to perform the operation by group

# 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 (tidyverse)
- Turn on the native R pipe `|>` in **Tools -> Global Options -> Code**



# The pipe |>

Let's look at an example without the pipe:

```
arc_weather_group <- group_by(arc_weather, station)
summarize(arc_weather_group,
          overall_mean = mean(mean_temp_c, na.rm = TRUE))
```

The pipe operator makes it very easy to combine these operations

```
arc_weather |>
  group_by(station) |>
  summarize(overall_mean = mean(mean_temp_c, 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.

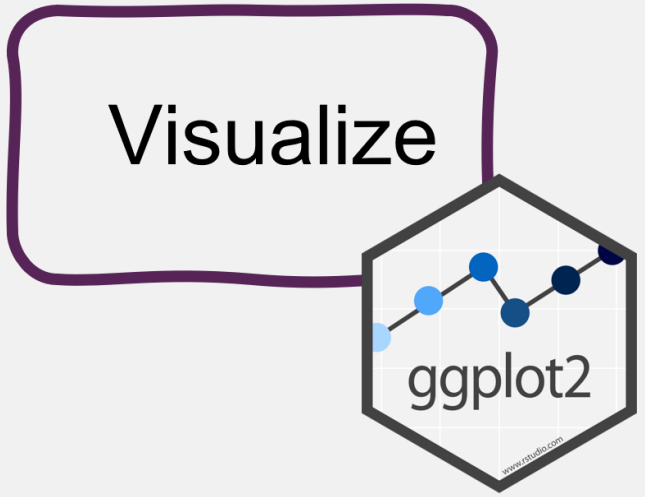
```
arc_weather |>
  group_by(station)

# instead of
group_by(arc_weather, station)
```

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

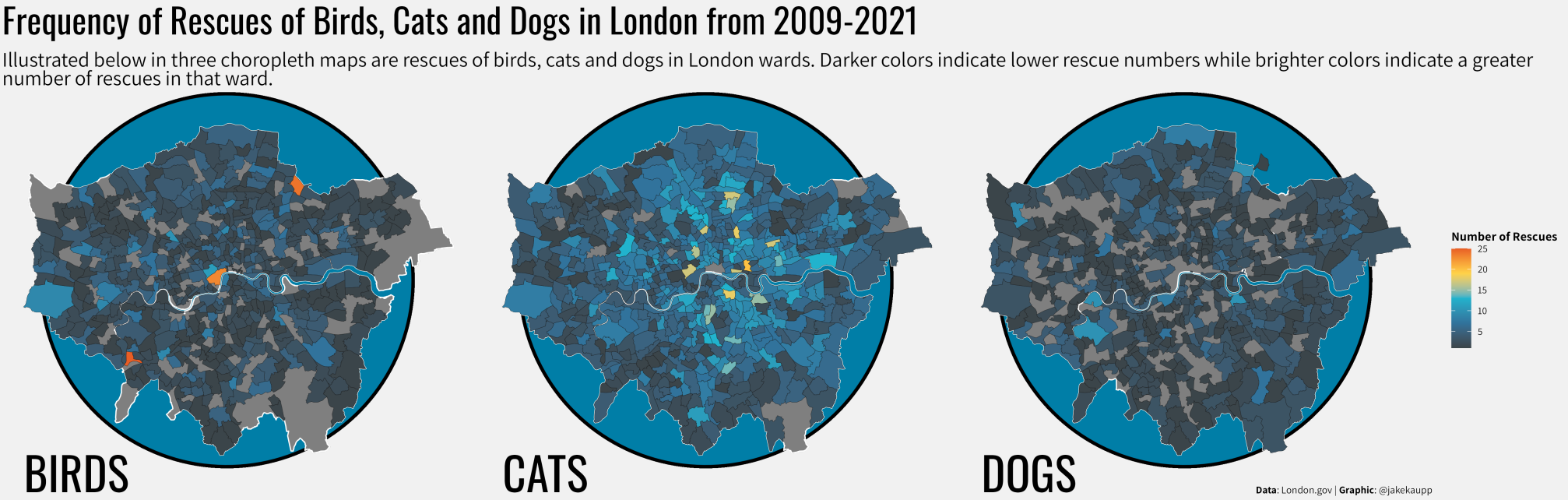
> **Tip**
>
> Use the keyboard shortcut `Ctrl/Cmd + Shift + M` to insert `|>`

# Visualize data with ggplot2

> Quick exploratory plots and data masterpieces

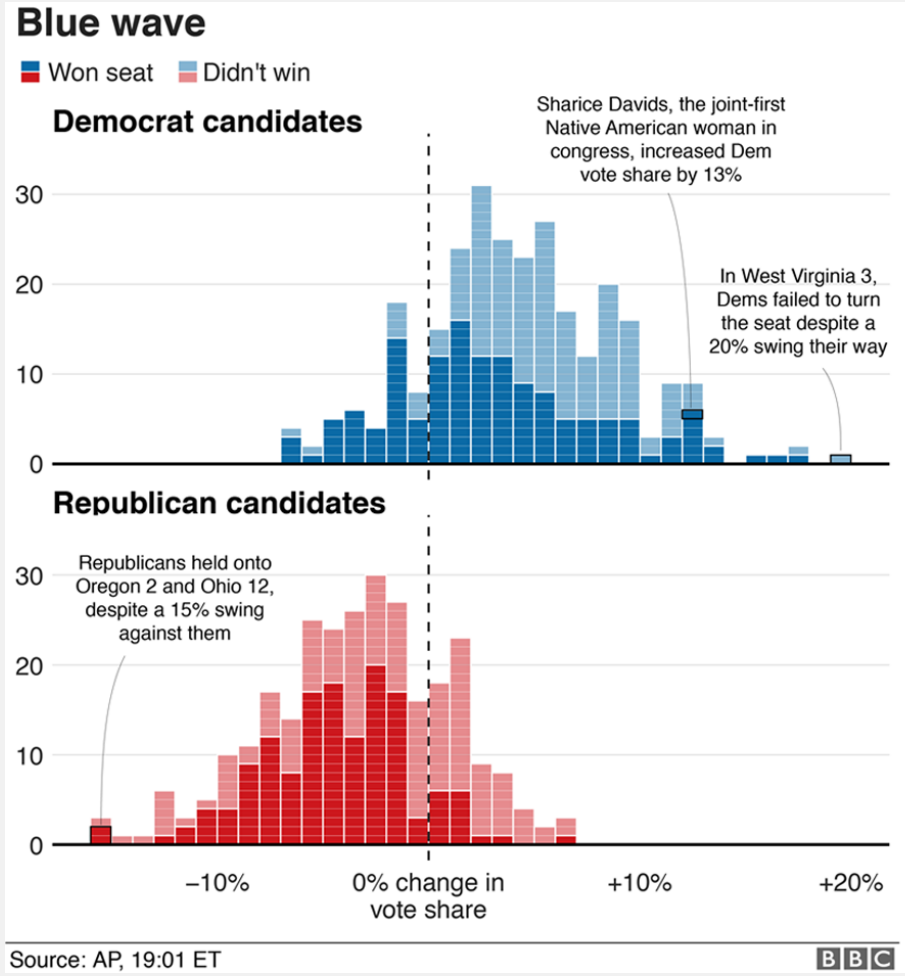


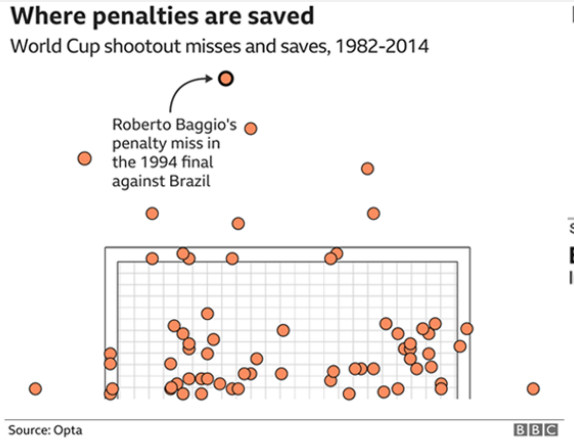
# A ggplot showcase

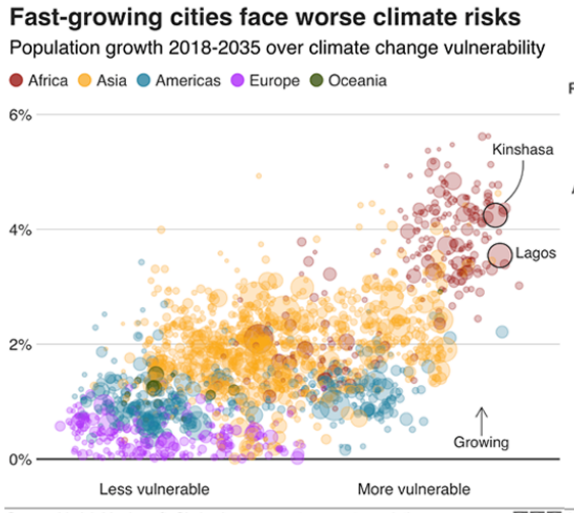



Visualization by Jake Kaupp, code available on Github

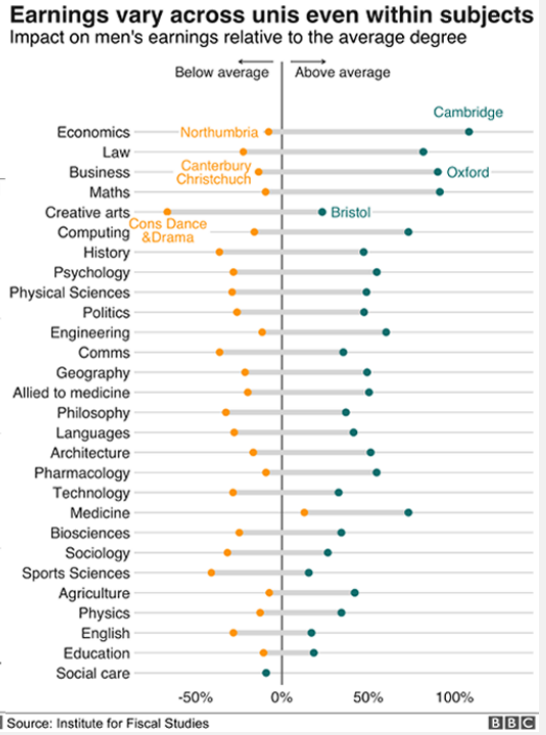
# A ggplot showcase



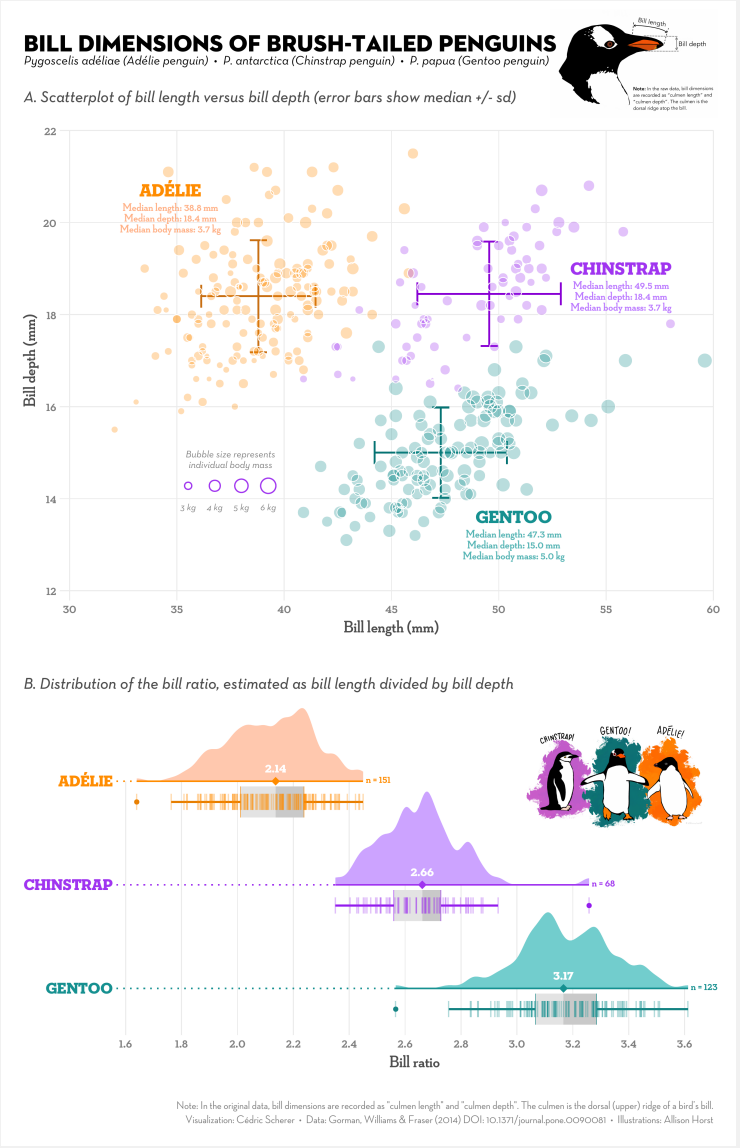








Visualizations produced by the BBC News data team

# A ggplot showcase




Visualization by Cédric Scherer, code available on Github

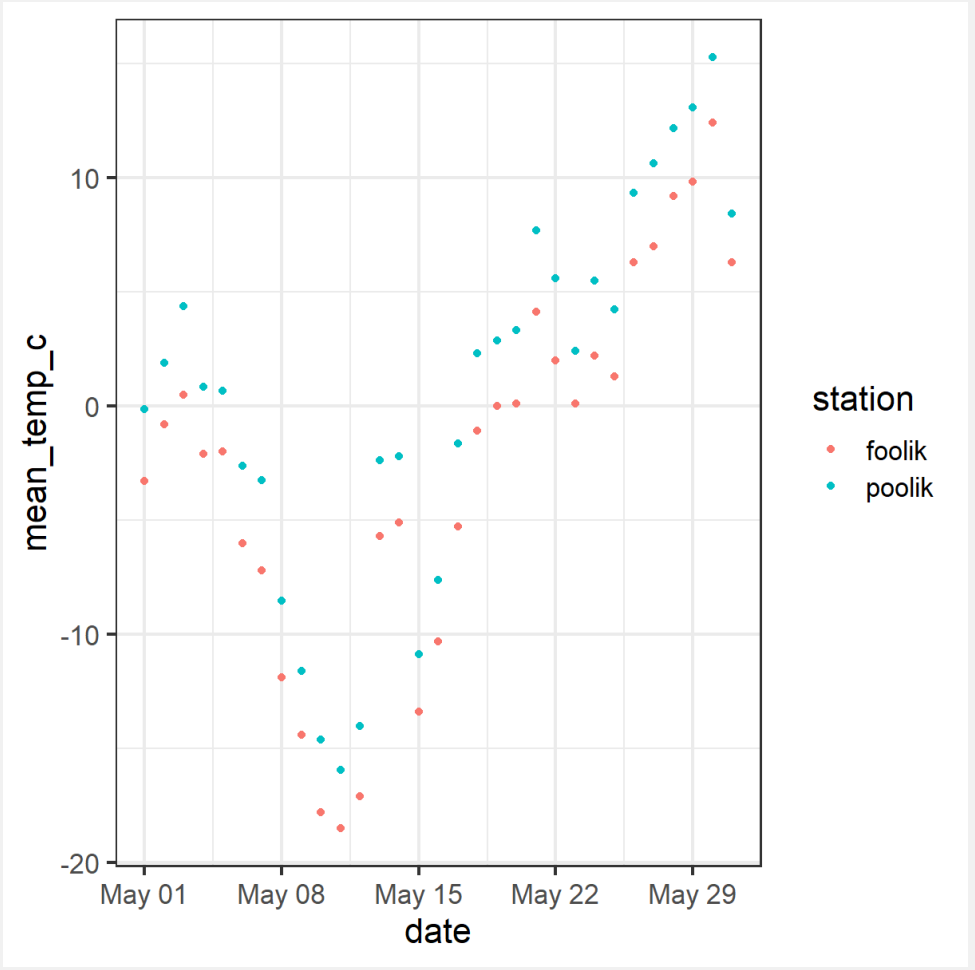
# Advantages of ggplot


- **Consistent** grammar
- **Flexible** structure allows you to produce any type of plots
- Highly **customizable appearance** (themes)
- Many **extension packages** that provide additional plot types, themes, colors, animation, ...
  - Find a list of ggplot extensions here
- Perfect package for **exploratory data analysis** and **beautiful plots**

# Basic ggplot

Basic idea: Stack layers of the plot on top of each other with +

```
arc_weather_may <- filter(arc_weather,
  month(date) == 5)
ggplot(data = arc_weather_may,
  aes(
    x = date,
    y = mean_temp_c,
    color = station
)) +
  geom_point()
```

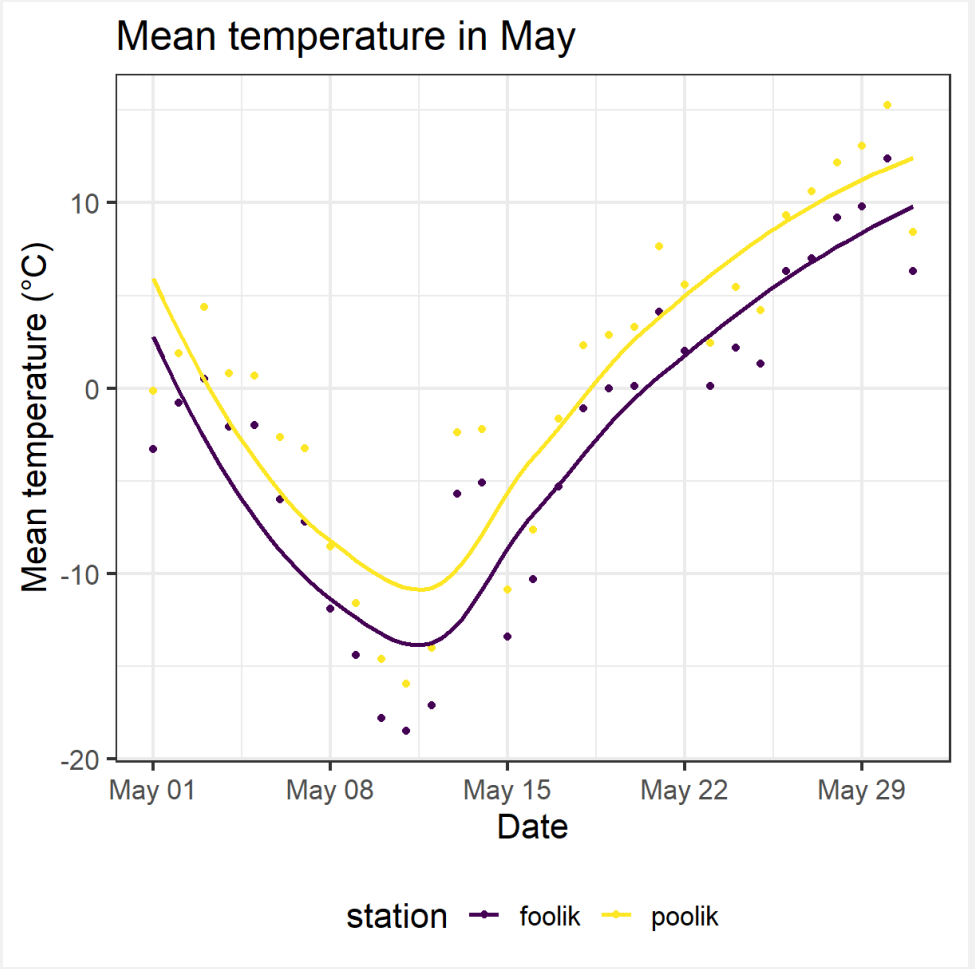



- **aes**thetics define how data variables are mapped onto plot properties
- **geoms** define the type of plot (e.g. points, lines, bars, ...)

# Basic ggplot


- ggplot offers many more customization options and layers
- works well with the pipe |>

```
arc_weather |>
  filter(month(date) == 5) |>
  ggplot(aes(
    x = date,
    y = mean_temp_c,
    color = station)) +
  geom_point() +
  geom_smooth() +
  labs(
    title = "Mean temperature in May",
    x = "Date",
    y = "Mean temperature (°C)") +
  scale_color_viridis_d()
```



# Functional programming with `purrr`


Functional programming

# Functional programming with `purrr`


- Apply functions to multiple elements of a list/vector/…
  - Replace e.g. for loops/apply-functions
  - Often `purrr` functions are more intuitive
  - See here for a full comparison between base R functions and purr functions
- Most important function: `map`
  - Comes in different versions, depending on the input and the desired output

# A simple example


Draw 4 numbers from normal distribution with means 1, 2, 3, 4.

## Do it by hand

```
# Do it by hand
set.seed(123)
rnorm(n = 4, mean = 1, sd = 1)
#> [1] 0.4395244 0.7698225 2.5587083 1.0705
rnorm(n = 4, mean = 2, sd = 1)
#> [1] 2.1292877 3.7150650 2.4609162 0.7349
rnorm(n = 4, mean = 3, sd = 1)
#> [1] 2.313147 2.554338 4.224082 3.359814
rnorm(n = 4, mean = 4, sd = 1)
#> [1] 4.400771 4.110683 3.444159 5.786913
```

## Use purrr

```
# Use purrr
set.seed(123)
means <- 1:4
samples <- map(means, rnorm, n = 4, sd = 1)
str(samples)
#> List of 4
#>  $ : num [1:4] 0.44 0.77 2.56 1.07
#>  $ : num [1:4] 2.129 3.715 2.461 0.735
#>  $ : num [1:4] 2.31 2.55 4.22 3.36
#>  $ : num [1:4] 4.4 4.11 3.44 5.79
```

This can also be combined with the pipe:

```
means |>
  map(rnorm, n = 4, sd = 1) |>
  str()
#> List of 4
#>  $ : num [1:4] 1.498 -0.967 1.701 0.527
#>  $ : num [1:4] 0.932 1.782 0.974 1.271
```

# Different versions of the `map` function


These are just some examples, there are many more options:

| Output | Input | Purr function |
|---|---|---|
| List | 1 Vector | map |
| List | 2 Vectors | map2 |
| Vector of desired type | 1 Vector | map_lgl |
| Vector of desired type | 2 Vectors | map2_lgl |
| Data frame | 1 Vector | map_df |
| Data frame | 2 Vectors | map2_df |

# A more complex example


Read in and analyse multiple files with the same structure at once.

```
# Step 1: List all files in your data directory
paths <- list.files("data")
```

```
#> [1] "foolik.csv" "poolik.csv"
```

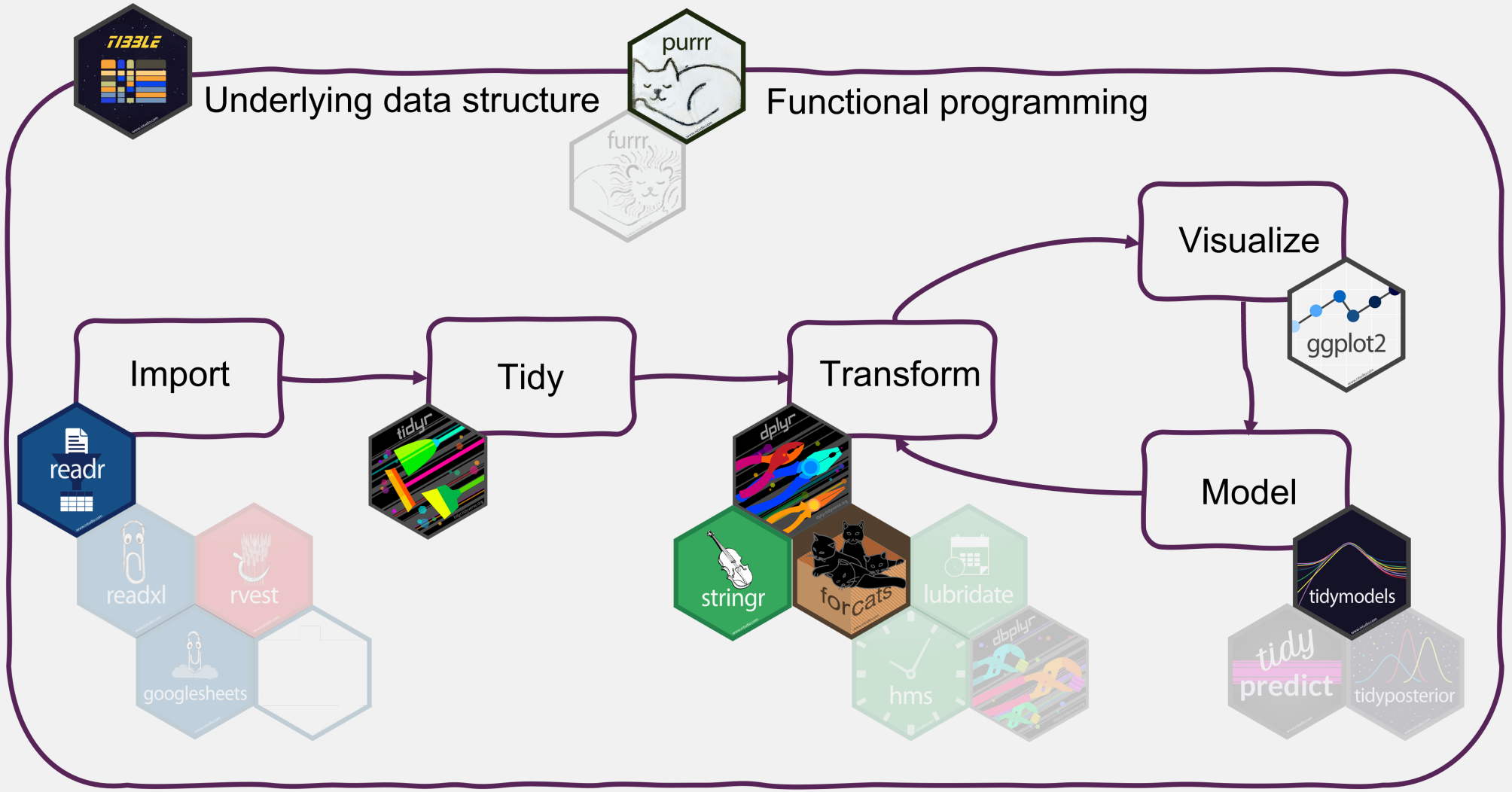
```
# Step 2: Read all files into a list of tib
arc_weather_files <- map(paths, read_csv)
arc_weather_files
#> [[1]]
#> # A tibble: 365 × 3
#>    date       station mean_temp_c
#>    <date>     <chr>         <dbl>
#>  1 1988-06-01 foolik          8.4
#>  2 1988-06-02 foolik          6
#>  3 1988-06-03 foolik          5.8
#>  4 1988-06-04 foolik          1.8
#>  5 1988-06-05 foolik          6.8
#>  6 1988-06-06 foolik          5.2
#>  7 1988-06-07 foolik          2.2
#>  8 1988-06-08 foolik          9.4
#>  9 1988-06-09 foolik         13.1
#> 10 1988-06-10 foolik         17.7
#> # ℹ 355 more rows
#>
#> [[2]]
```

# A more complex example


Read in and analyse multiple files with the same structure at once.

```
# Step 3: Apply a linear model to each station file,
# get the model summary of each model and extract the coefficients
arc_weather_files |>
  map(\(x) lm(mean_temp_c ~ date, data = x)) |>
  map(summary) |>
  map_dbl("r.squared")
#> [1] 0.2018279 0.2000210
```

# Summary


tibble
Underlying data structure
purrr
furrr
Functional programming
Visualize
ggplot2
Import
Tidy
Transform
Model
readr
tidyr
dplyr
readxl
rvest
googlesheets
stringr
forcats
lubridate
hms
dbplyr
tidymodels
tidy predict
tidyposterior

# Summary

Tidyverse makes data analysis

- efficient
- intuitive
- consistent

Tidyverse code is more **readable** and **easier to write & maintain**.

This facilitates

 Learning

 Collaboration

 Reproducible research

# Summary

Where to get started with the tidyverse?

- Check out the lecture website for links to documenation, cheatsheets and books
- Use the cheatsheets as reference while working

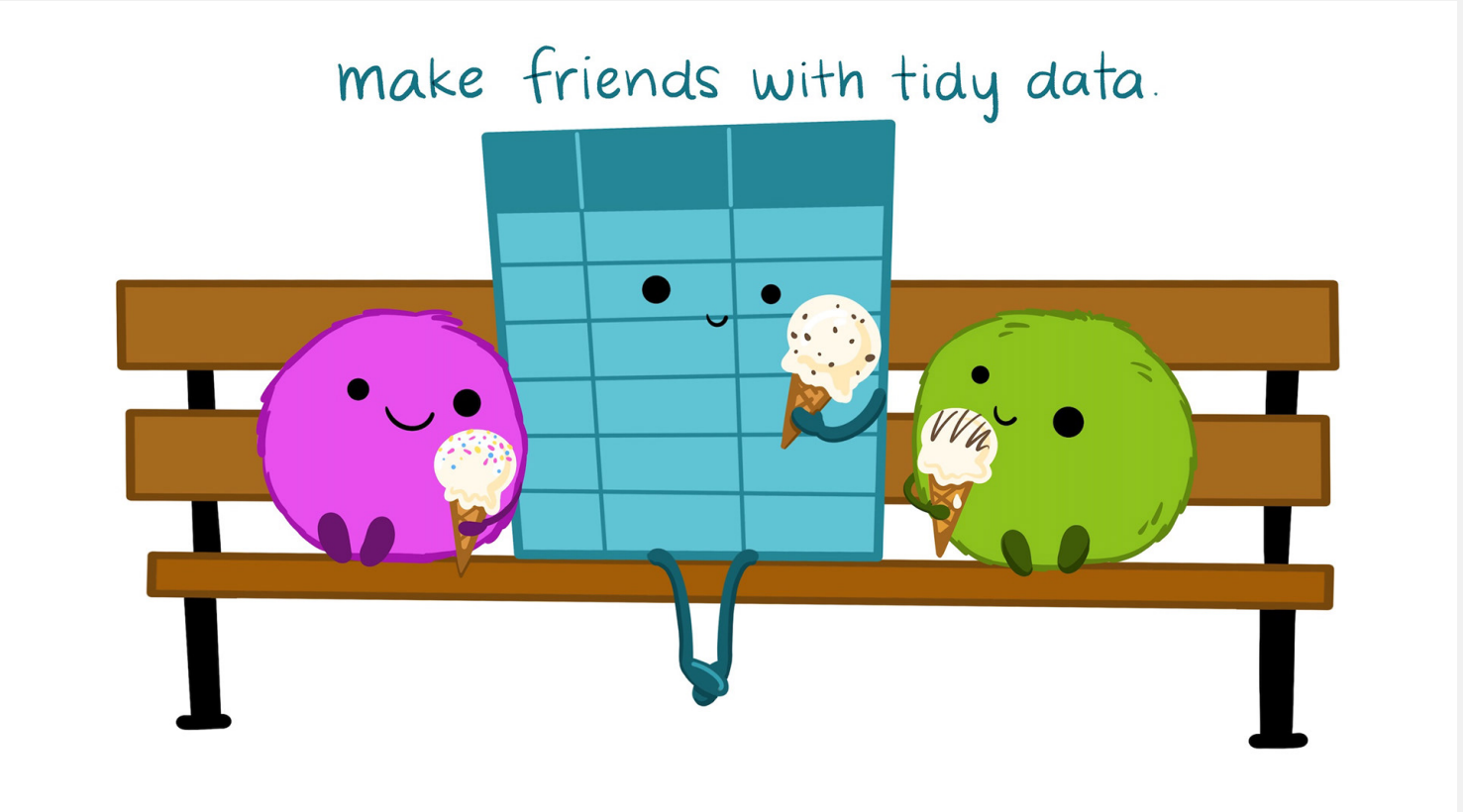



Illustration from the Openscapes blog *Tidy Data for reproducibility, efficiency, and collaboration* by Julia Lowndes and Allison Horst

# Next lecture

Semester break in March!

**Topic t.b.a.**

 18th April  4-5 p.m.  Webex

 Subscribe to the mailing list

 For topic suggestions and/or feedback send me an email

# Thank you for your attention :)

Questions?

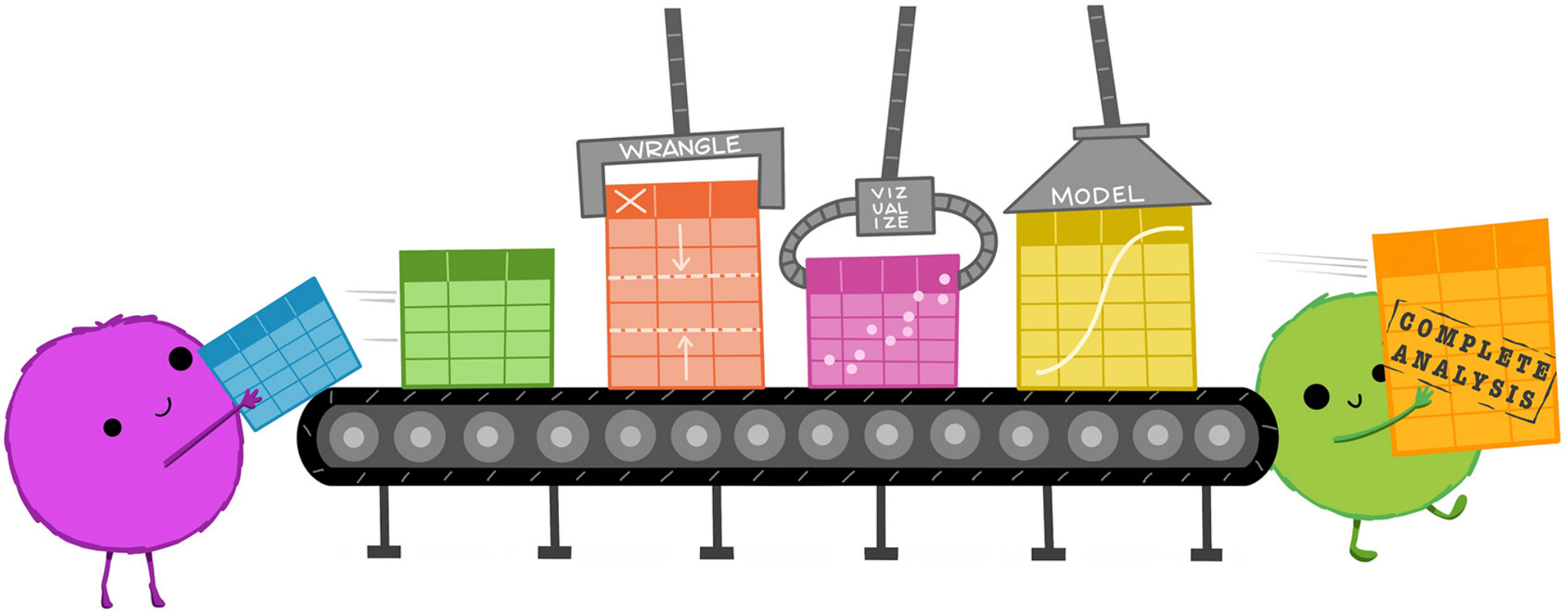



Illustration from the Openscapes blog *Tidy Data for reproducibility, efficiency, and collaboration* by Julia Lowndes and Allison

# References

- Tidyverse website: find links to all package documentations
- Cheatsheets
- R for Data Science book: Learn data analysis with the tidyverse