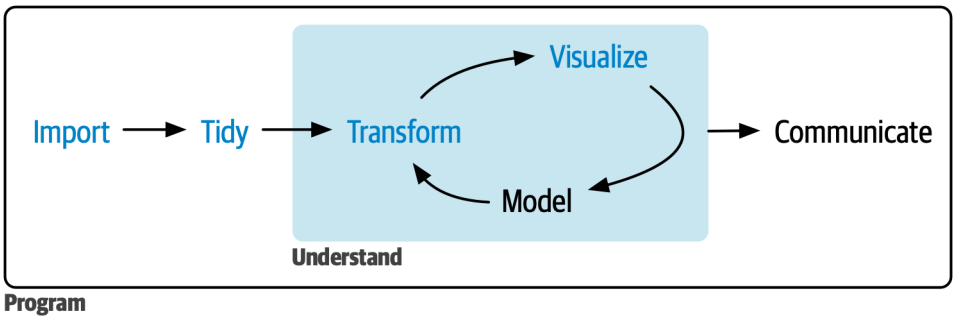
The Data Analysis Workflow



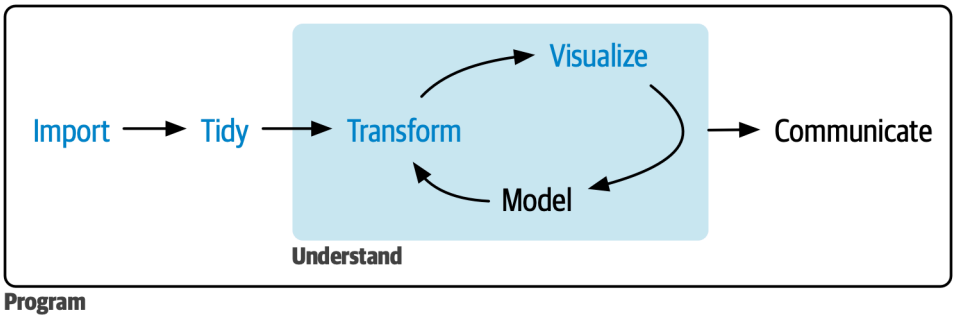
Source: H. Wickham, M. Cetinkaya-Rundel, and G. Grolemund [1], R. A. Poldrack [2]

The process of statistical modeling

There is a set of steps that we generally go through when we want to use our statistical model to test a scientific hypothesis:

1. Specify your question of interest
2. Identify or collect the appropriate data
3. Prepare the data for analysis
4. Determine the appropriate model
5. Fit the model to the data
6. Criticize the model to make sure it fits properly
7. Test hypothesis and quantify effect size
8. Communicate your analysis

Data Analysis Workflow



Import

Throughout, we have been using the `tidyverse` library of packages for data analysis.

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

```
library(tidyverse)
```

Import

- There are tools for reading data from almost any source:
  - `read_csv()`, `read_excel()`, `read_rds()`, ...
- When we load a dataset with a `tidyverse()` function, it will return a `tibble`

```
data <- read_csv("data/Apple_Emissions/greenhouse_gas_emissions.csv")
```

Tidy

The same data can be represented in multiple ways. Here's the same data organized three different ways:

Each dataset shows the same values of four variables: country, year, population, and number of documented cases of TB (tuberculosis), but each dataset organizes the values in a different way.

```
table1
```

```
# A tibble: 6 × 4
  country      year  cases population
  <chr>       <dbl>  <dbl>      <dbl>
1 Afghanistan  1999    745   19987071
2 Afghanistan  2000   2666   20595360
3 Brazil       1999  37737  172006362
4 Brazil       2000  80488  174504898
5 China        1999 212258 1272915272
6 China        2000 213766 1280428583
```

```
table3
```

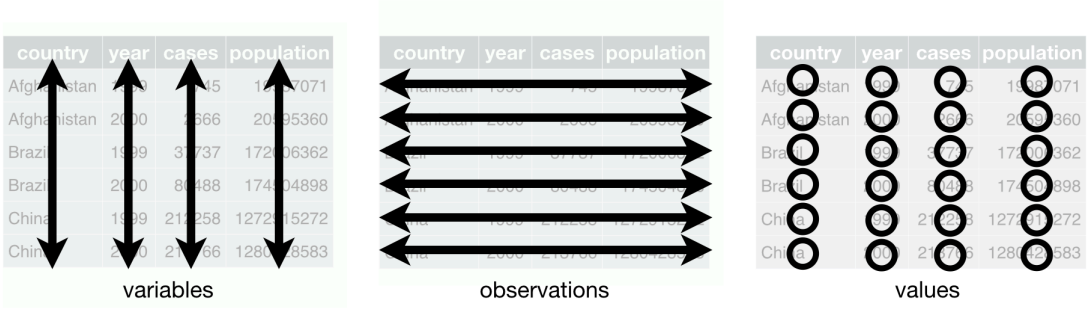
```
# A tibble: 6 × 3
  country      year rate
  <chr>       <dbl> <chr>
1 Afghanistan  1999 745/19987071
2 Afghanistan  2000 2666/20595360
3 Brazil       1999 37737/172006362
4 Brazil       2000 80488/174504898
5 China        1999 212258/1272915272
6 China        2000 213766/1280428583
```

```
table2
```

```
# A tibble: 12 × 4
   country      year type            count
   <chr>       <dbl> <chr>           <dbl>
 1 Afghanistan  1999 cases             745
 2 Afghanistan  1999 population   19987071
 3 Afghanistan  2000 cases            2666
 4 Afghanistan  2000 population   20595360
 5 Brazil       1999 cases           37737
 6 Brazil       1999 population  172006362
 7 Brazil       2000 cases           80488
 8 Brazil       2000 population  174504898
```

```
 9 China        1999 cases          212258
10 China        1999 population 1272915272
11 China        2000 cases          213766
12 China        2000 population 1280428583
```

- There are three rules that make a dataset tidy:
  1. Each variable is a column; each column is a variable.
  2. Each observation is a row; each row is an observation.
  3. Each value is a cell; each cell is a single value.



Why ensure your data is tidy?

1. There's a general advantage to picking one consistent way of storing data. If you have a consistent data structure, it's easier to learn the tools that work with it because they have an underlying uniformity.
2. There's a specific advantage to placing variables in columns because it allows R's vectorized nature to shine. That makes transforming tidy data feel particularly natural.

So, our first task after importing the data is to make sure it's tidy. In addition to the rules above, this can also include things like:

- ensure the data types are correct
- clean up the column names
- make sure we know what the variables represent

For the .csv data we loaded, our column names can be a bit difficult to work with since they have spaces in them. We can use a function from the `janitor` package to clean these:

```
data <- data |>
  janitor::clean_names()
data
```

```
# A tibble: 127 × 6
   fiscal_year category           type           scope   description emissions
         <dbl> <chr>              <chr>          <chr>   <chr>           <dbl>
 1        2022 Corporate emissions Gross emissions Scope 1 Natural ga…     39700
 2        2022 Corporate emissions Gross emissions Scope 1 Fleet vehi…     12600
 3        2022 Corporate emissions Gross emissions Scope 1 Other (R&D…      2900
 4        2022 Corporate emissions Gross emissions Scope … Electricity         0
 5        2022 Corporate emissions Gross emissions Scope … Steam, hea…      3000
 6        2022 Corporate emissions Gross emissions Scope 3 Business t…    113500
 7        2022 Corporate emissions Gross emissions Scope 3 Employee c…    134200
 8        2022 Corporate emissions Gross emissions Scope 3 Upstream f…     10600
 9        2022 Corporate emissions Gross emissions Scope 3 Work from …      7500
10        2022 Corporate emissions Gross emissions Scope 3 Transmissi…         0
# ℹ 117 more rows
```

Transform

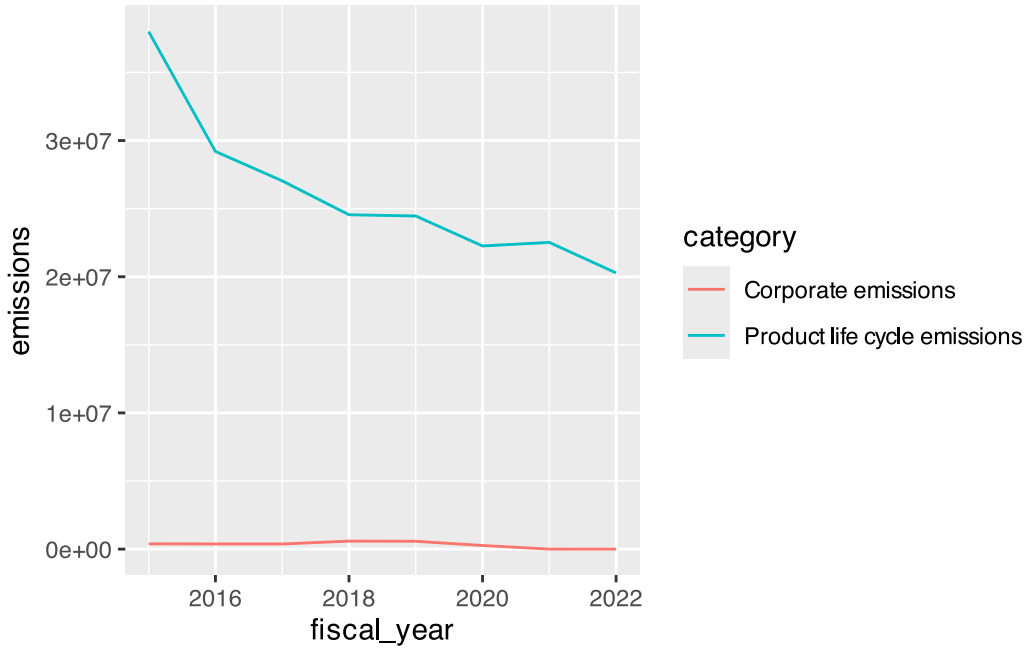
We've dealt with data transformations quite a bit already. This includes operations like calculating the mean for different groups, or for multiple groups:

```
data |>
  group_by(category) |>
  summarise(
    mean_emissions = mean(emissions, na.rm = TRUE),
  )
```

```
# A tibble: 2 × 2
  category                    mean_emissions
  <chr>                                <dbl>
1 Corporate emissions                 35594.
2 Product life cycle emissions      5630000
```

Visualize

```
data |>
  group_by(category, fiscal_year) |>
  summarise(emissions = sum(emissions, na.rm = TRUE)) |>
  ggplot(aes(x = fiscal_year, y = emissions, color = category)) +
  geom_line()
```



Communicate

This is where we will dive into using Quarto. Start by downloading the Apple Emissions dataset from Moodle and open RStudio.

We'll go through how to create and write a full analysis in a `.qmd` file using this dataset.

Refer to our lecture notes specifically on using Quarto

Assignment - Deceptive Visualisation

References

Bibliography

[1] H. Wickham, M., Cetinkaya-Rundel, and G. Grolemund, *R for Data Science: Import, Tidy, Transform, Visualize, and Model Data*, Second edition. Beijing ; Sebastopol, CA: O'Reilly, 2023.

[2] R. A. Poldrack, *Statistical Thinking. Analyzing Data in an Uncertain World*. Princeton: Princeton University Press, 2023. [Online]. Available: https://statsthinking21.github.io/statsthinking21-core-site/