Dr Andrew Mitchell

Lecturer in AI and Machine Learning for Sustainable Construction

Introduction

> “The simple graph has brought more information to the data analyst’s mind than any other device.” — John Tukey

R has several systems for making graphs, but `ggplot2` is one of the most elegant and most versatile.

`ggplot2` implements the *grammar of graphics*, a coherent system for describing and building graphs. With `ggplot2`, you can do more and faster by learning one system and applying it in many places.

This presentation is based on the Data Visualization chapter of the R for Data Science book by Hadley Wickham and Garrett Grolemund.

Introduction

In this tutorial, we will create this plot:

The Grammar of Graphics

In 1999, a statistician named Leland Wilkinson published the first edition of what has been the most influential work in data visualization, The Grammar of Graphics.

The most complete implementation of the grammar is found in an R package called `ggplot2` by Hadley Wickham.

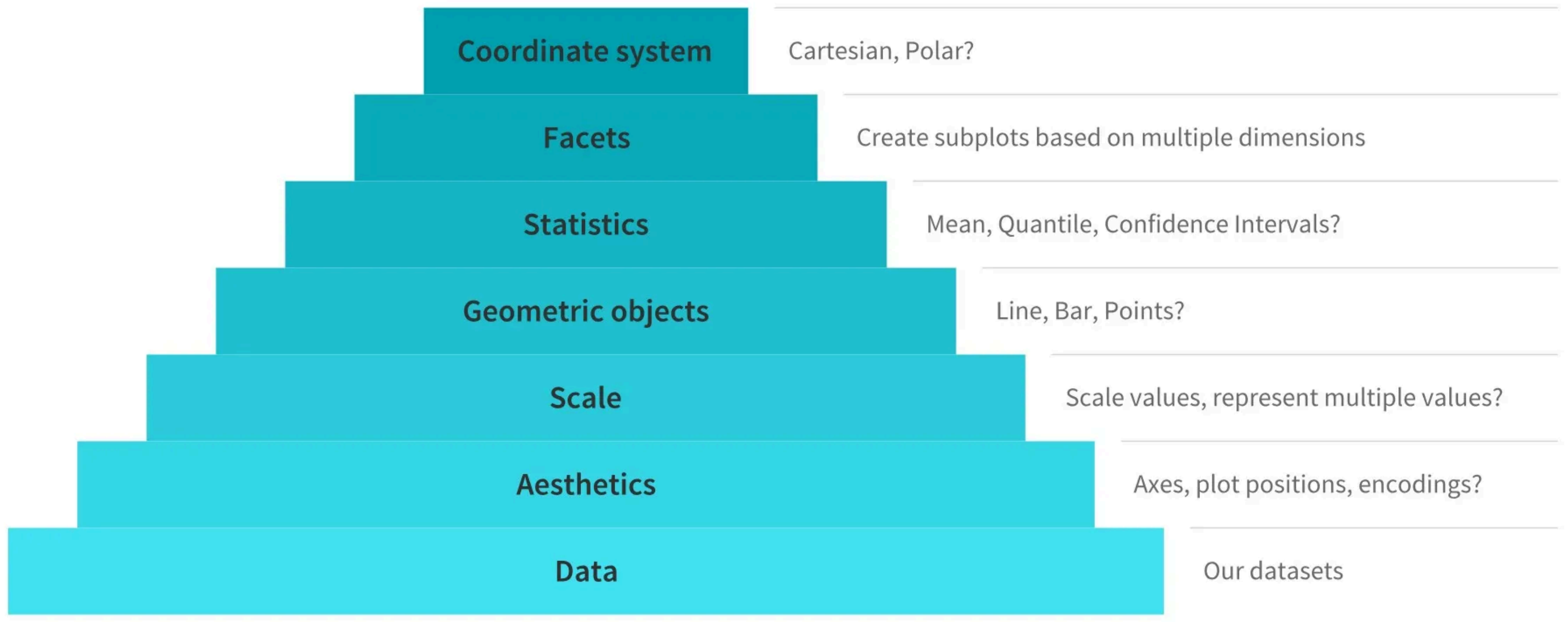
The Grammar of Graphics

A plot can be decomposed into three primary elements

1. the **data**
2. the **aesthetic mapping** of the variables in the data to visual cues
3. the **geometry** used to encode the observations on the plot.

The Grammar of Graphics

Major Components of the Grammar of Graphics


Coordinate system
Cartesian, Polar?
Facets
Create subplots based on multiple dimensions
Statistics
Mean, Quantile, Confidence Intervals?
Geometric objects
Line, Bar, Points?
Scale
Scale values, represent multiple values?
Aesthetics
Axes, plot positions, encodings?
Data
Our datasets

Getting Started

Throughout this lecture, we will be writing code together inside this webpage.

Hints:

You can type code into the cells and run them by clicking the “Run” button.

Getting Started

Packages

We begin by loading the `tidyverse` and `ggplot2` packages.

We almost always begin our work by loading the tidyverse package. Note that the terms "package" and "library" are used interchangeably but that there is no package() function. To load a package, you need to use library().

Getting Started

Loading the Data

Load the `palmerpenguins` package using library().

This package contains the `penguins` dataset, which we will use for this tutorial.

Getting Started

Getting help

If you are unsure about how to use a function, you can use the `?` operator to get help.

For a data package like `palmerpenguins`, you can use `?penguins` to get help on the dataset.

The Grammar of Graphics

The Data

- A **variable** is a quantity, quality, or property that you can measure.

- A **value** is the state of a variable when you measure it. The value of a variable may change from measurement to measurement.

- An **observation** is a set of measurements made under similar conditions. An observation will contain several values, each associated with a different variable. We'll sometimes refer to an observation as a data point.

- **Tabular data** is a set of values, each associated with a variable and an observation. Tabular data is *tidy* if each value is placed in its own "cell", each variable in its own column, and each observation in its own row.

The Grammar of Graphics

The Data

- `species`: a penguin's species (Adelie, Chinstrap, or Gentoo).
- `flipper_length_mm`: length of a penguin's flipper, in millimeters.
- `body_mass_g`: body mass of a penguin, in grams.

Formulating our Research Question(s)

- Do penguins with longer flippers weigh more or less than penguins with shorter flippers? You probably already have an answer, but try to make your answer precise.

Formulating our Research Question(s)

- Do penguins with longer flippers weigh more or less than penguins with shorter flippers? You probably already have an answer, but try to make your answer precise.
- What does the relationship between flipper length and body mass look like? Is it positive? Negative? Linear? Nonlinear?

Formulating our Research Question(s)

- Do penguins with longer flippers weigh more or less than penguins with shorter flippers? You probably already have an answer, but try to make your answer precise.
- What does the relationship between flipper length and body mass look like? Is it positive? Negative? Linear? Nonlinear?
- Does the relationship vary by the species of the penguin? How about by the island where the penguin lives?

Building up a plot

Creating a ggplot

With **ggplot2**, you begin a plot with the function `ggplot()`, defining a plot object that you then add layers to.

The first argument of `ggplot()` is the dataset to use in the graph and so `ggplot(data = penguins)` creates an empty graph that is primed to display the penguins data, but since we haven't told it how to visualize it yet, for now it's empty.

Tip

input `ggplot(data = penguins)`

Building up a plot

This is not a very exciting plot, but you can think of it like an empty canvas you'll paint the remaining layers of your plot onto.

Next, we need to tell `ggplot()` how the information from our data will be visually represented. The mapping argument of the `ggplot()` function defines how variables in your dataset are mapped to visual properties (**aesthetics**) of your plot.

. . .

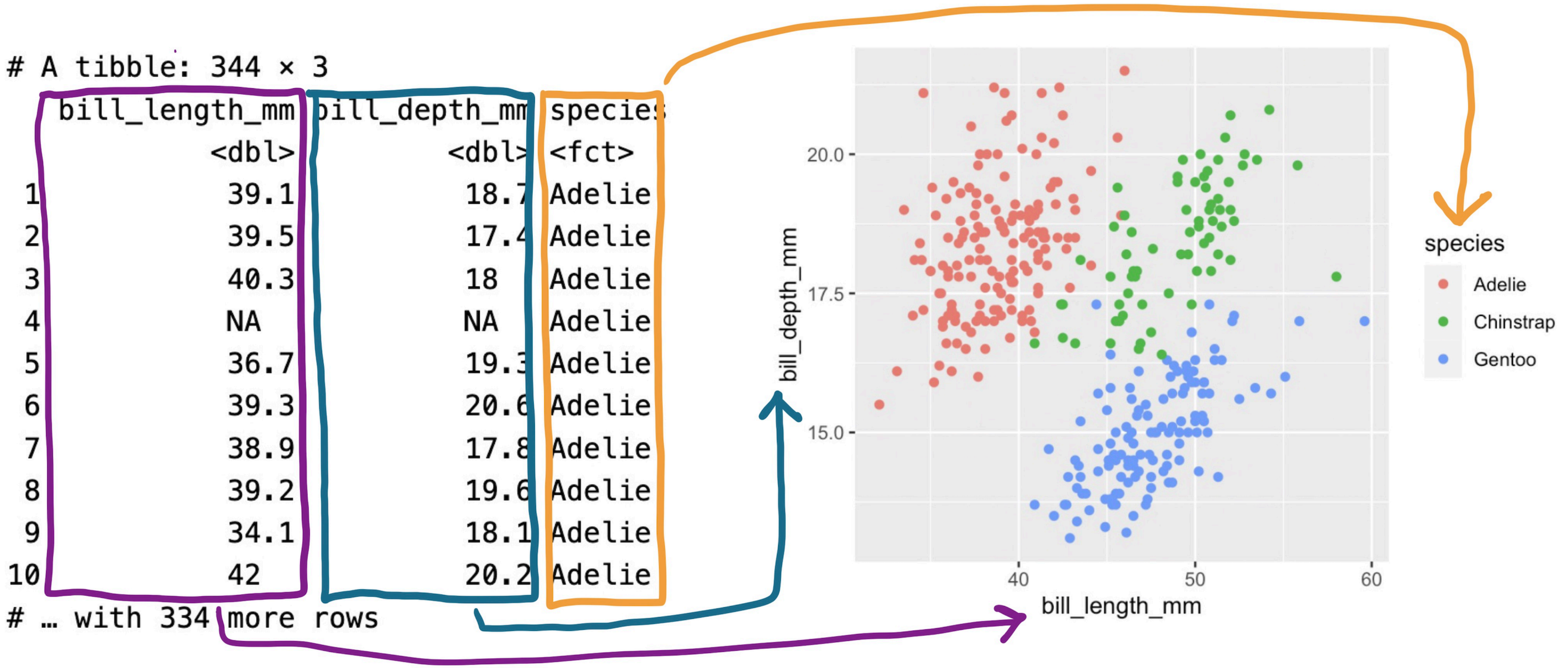
For now, we will only map flipper length to the `x` aesthetic and body mass to the `y` aesthetic.

Building up a plot

The Grammar of Graphics

Aesthetics

The Grammar of Graphics



```
# A tibble: 344 × 3
   bill_length_mm bill_depth_mm species
            <dbl>         <dbl> <fct>
 1           39.1          18.7 Adelie
 2           39.5          17.4 Adelie
 3           40.3          18   Adelie
 4           NA            NA   Adelie
 5           36.7          19.3 Adelie
 6           39.3          20.6 Adelie
 7           38.9          17.8 Adelie
 8           39.2          19.6 Adelie
 9           34.1          18.1 Adelie
10           42            20.2 Adelie
# … with 334 more rows
```

Building up a plot

Aesthetic mappings

The mapping argument is always defined in the `aes()` function, and the `x` and `y` arguments of `aes()` specify which variables to map to the `x` and `y` axes.

For now, we will only map flipper length to the `x` aesthetic and body mass to the `y` aesthetic. **ggplot2** looks for the mapped variables in the `data` argument, in this case, `penguins`.

Tip

add `mapping = aes(x = flipper_length_mm, y = body_mass_g)`

Our empty canvas now has more structure – it's clear where flipper lengths will be displayed (on the x-axis) and where body masses will be displayed (on the y-axis). But the penguins

Building up a plot

themselves are not yet on the plot. This is because we have not yet articulated, in our code, how to represent the observations from our data frame on our plot.

Building up a plot

Adding layers

We need to define a **geom**: the geometrical object that a plot uses to represent data. These geometric objects are made available in **ggplot2** with functions that start with `geom_`.

People often describe plots by the type of geom that the plot uses:

- bar charts use bar geoms (geom_bar()),

Building up a plot

Adding layers

We need to define a **geom**: the geometrical object that a plot uses to represent data. These geometric objects are made available in **ggplot2** with functions that start with `geom_`.

People often describe plots by the type of geom that the plot uses:

- bar charts use bar geoms (geom_bar()),
- line charts use line geoms (geom_line()),

Building up a plot

Adding layers

We need to define a **geom**: the geometrical object that a plot uses to represent data. These geometric objects are made available in **ggplot2** with functions that start with `geom_`.

People often describe plots by the type of geom that the plot uses:

- bar charts use bar geoms (geom_bar()),
- line charts use line geoms (geom_line()),
- boxplots use boxplot geoms (geom_boxplot()),

Building up a plot

Adding layers

We need to define a **geom**: the geometrical object that a plot uses to represent data. These geometric objects are made available in **ggplot2** with functions that start with `geom_`.

People often describe plots by the type of geom that the plot uses:

- bar charts use bar geoms (geom_bar()),
- line charts use line geoms (geom_line()),
- boxplots use boxplot geoms (geom_boxplot()),
- scatterplots use point geoms (geom_point()), and so on.

The function `geom_point()` adds a **layer** of points to your plot, which creates a scatterplot.

Building up a plot

Add a scatter point layer to the plot:

Tip

add + `geom_point()`

Now we have a scatterplot of flipper length (x-axis) and body mass (y-axis) for penguins. The plot displays a positive, linear, and relative strong relationship between these two variables.

Before we add more layers to this plot, let's pause for a moment and review the warning message we got:

We're seeing this message because there are two penguins in our dataset with missing body mass and/or flipper length values and ggplot2 has no way of representing them on the plot

Building up a plot

without both of these values. Like R, ggplot2 subscribes to the philosophy that missing values should never silently go missing. This type of warning is probably one of the most common types of warnings you will see when working with real data – missing values are a very common issue and you'll learn more about them later. For the remaining plots we will suppress this warning so it's not printed alongside every single plot we make.

Building up a plot

Adding aesthetics

It’s always a good idea to be skeptical of any apparent relationship between two variables and ask if there may be other variables that explain or change the nature of this apparent relationship.

For example, does the relationship between flipper length and body mass differ by species?

When exploring relationships between variables, it’s important to consider other variables that might affect the relationship. Let’s incorporate `species` into our plot using color:

Tip

Building up a plot

Scatterplots are useful for displaying the relationship between two numerical variables, but it's always a good idea to be skeptical of any apparent relationship between two variables and ask if there may be other variables that explain or change the nature of this apparent relationship.

For example, does the relationship between flipper length and body mass differ by species? Let's incorporate species into our plot and see if this reveals any additional insights into the apparent relationship between these variables. We will do this by representing species with different colored points.

To achieve this, will we need to modify the aesthetic or the geom? If you guessed "in the aesthetic mapping, inside of `aes()`", you're already getting the hang of creating data visualizations with ggplot2! And if not, don't worry.

Add `color = species` to the aesthetic mapping. This tells ggplot2 to color the points by species.

Building up a plot

When we map a categorical variable to an aesthetic, ggplot2 automatically: - Assigns a unique value to each level (here, a unique color for each species) - Adds a legend explaining the mapping

Building up a plot

Add a trend line to see the relationship more clearly using `geom_smooth()`

Tip

Add a trendline (`geom_smooth(method = "lm")`) layer to the plot.

Now let's add one more layer: a smooth curve displaying the relationship between body mass and flipper length. Before you proceed, refer back to the code above, and think about how we can add this to our existing plot.

Since this is a new geometric object representing our data, we will add a new geom as a layer on top of our point geom: `geom_smooth()`. And we will specify that we want to draw the line of best fit based on a linear model with `method = "lm"`.

Building up a plot

Add `geom_smooth(method = "lm")` to the plot.

The method = “lm” argument tells geom_smooth() to use a linear model. Notice how the color aesthetic is inherited by both geoms, creating separate trend lines for each species.

Building up a plot

Adding smooth curves

It’s important to recognise how the **color aesthetic** is inherited by both **geoms**, creating separate trend lines for each species.

```r
ggplot(
  data = penguins,
  mapping = aes(x = flipper_length_mm, y = body_mass_g, color = species)
) +
  geom_point() +
  geom_smooth(method = "lm")
```

We have successfully added lines, but this plot doesn’t look like our ultimate goal plot, which only has one line for the entire dataset as opposed to separate lines for each of the penguin species.

Building up a plot

When aesthetic mappings are defined in `ggplot()`, at the *global* level, they're passed down to each of the subsequent geom layers of the plot. However, each geom function in ggplot2 can also take a `mapping` argument, which allows for aesthetic mappings at the *local* level that are added to those inherited from the global level. Since we want points to be colored based on species but don't want the lines to be separated out for them, we should specify `color = species` for `geom_point()` only.

Building up a plot

Adding smooth curves

It’s important to recognise how the **color aesthetic** is inherited by both **geoms**, creating separate trend lines for each species.

```
ggplot(
  data = penguins,
  mapping = aes(x = flipper_length_mm, y = body_mass_g,
  color = species)
) +
  geom_point( <color = species> ) +
  geom_smooth(method = "lm")
```

Building up a plot

Adding smooth curves

It's important to recognise how the **color aesthetic** is inherited by both **geoms**, creating separate trend lines for each species.

```r
ggplot(
  data = penguins,
  mapping = aes(x = flipper_length_mm, y = body_mass_g,
  color = species)
) +
  geom_point() +
  geom_smooth(method = "lm", <color = species>)
```

Pay attention to how the aesthetic mappings propagate through the layers of the plot.

This can be useful for creating complex plots with multiple layers, but it can also lead to unexpected results if you're not careful.

Building up plots

Global vs Local aesthetics

In the previous plot, the color aesthetic was defined in the global mapping. This means that it applies to all geoms in the plot.

To get a single trend line while keeping colored points, we move the color aesthetic to `geom_point()`:

Tip

Aesthetic mappings can be defined at the global level (in ggplot()) or at the local level (in individual geoms). Local aesthetics override global ones.

Building up plots

Voila! We have something that looks very much like our ultimate goal, though it’s not yet perfect. We still need to use different shapes for each species of penguins and improve labels.

It’s generally not a good idea to represent information using only colors on a plot, as people perceive colors differently due to color blindness or other color vision differences. Therefore, in addition to color, we can also map `species` to the `shape` aesthetic.

Building up a plot

Other aesthetics - shapes

In addition to color, we can also map out variables to other aesthetic elements.

Here, we map `species` to the `shape` aesthetic.

Tip

It’s generally not a good idea to represent information using only colors on a plot, as people perceive colors differently due to color blindness or other color vision differences. Therefore, in addition to color, we can also map `species` to the `shape` aesthetic.

Building up a plot

Final touches

The **data portions** of our plot are now complete. But data visualization is not just about the data – it's also about the **visual elements** that make the plot accessible and informative.

We also need the plot itself to communicate:

- What the plot is about (title)

Building up a plot

Final touches

The **data portions** of our plot are now complete. But data visualization is not just about the data – it's also about the **visual elements** that make the plot accessible and informative.

We also need the plot itself to communicate:

- What the plot is about (title)
- What the axes represent, including units (labels)

Building up a plot

Final touches

The **data portions** of our plot are now complete. But data visualization is not just about the data – it's also about the **visual elements** that make the plot accessible and informative.

We also need the plot itself to communicate:

- What the plot is about (title)
- What the axes represent, including units (labels)
- What the colors and shapes represent (legends)

Building up a plot

Final touches

The **data portions** of our plot are now complete. But data visualization is not just about the data – it's also about the **visual elements** that make the plot accessible and informative.

We also need the plot itself to communicate:

- What the plot is about (title)
- What the axes represent, including units (labels)
- What the colors and shapes represent (legends)
- Additional context such as the source of the data (subtitle or caption)

Building up a plot

We can now add this information to our plot

Tip

To add:

```
title = "Body Mass and Flipper Length",
subtitle = "Dimensions for Adelie, Chinstrap, and Gentoo Penguins",
x = "Flipper Length (mm)",
y = "Body Mass (g)",
color = "Species",
shape = "Species"
```

Building up a plot

And finally, we can improve the labels of our plot using the `labs()` function in a new layer. Some of the arguments to `labs()` might be self explanatory:

- `title` adds a title and `subtitle` adds a subtitle to the plot

Other arguments match the aesthetic mappings:

- `x` is the x-axis label
- `y` is the y-axis label
- `color` and `shape` define the label for the legend.

In addition, we can improve the color palette to be colorblind safe with the `scale_color_colorblind()` function from the ggthemes package.

Some notes on `ggplot()` calls

So far, we've written the code in a very explicit way, with each argument named. This is a good practice when you're learning, but it can be a bit verbose.

Typically, the first one or two arguments to a function are so important that you should know them by heart. The first two arguments to `ggplot()` are **data** and **mapping**.

You'll often see them left out. This is true for other functions as well.

When leaving the names out, the order of the arguments matters.

```r
ggplot(
  data = penguins,
  mapping = aes(x = flipper_length_mm, y = body_mass_g)
) +
  geom_point()
```

Some notes on `ggplot()` calls

```r
ggplot(
  data = penguins,
  mapping = aes(x = flipper_length_mm, y = body_mass_g)
) +
  geom_point()
```

```r
ggplot(penguins, aes(x = flipper_length_mm, y = body_mass_g)) +
  geom_point()
```

Some notes on `ggplot()` calls

In the future, you'll also learn about the pipe, `|>`, which operates similarly to the + operator in ggplot2.

It lets you chain together a series of operations, passing the output of one function to the input of the next.

```r
penguins |>
  ggplot(aes(x = flipper_length_mm, y = body_mass_g)) +
  geom_point()
```

Some notes on `ggplot()` calls

In the future, you'll also learn about the pipe, `|>`, which operates similarly to the + operator in ggplot2.

It lets you chain together a series of operations, passing the output of one function to the input of the next.

```
penguins |>
  ggplot(<penguins>, aes(x = flipper_length_mm, y = body_mass_g)) +
  geom_point()
```

Don't worry if you don't understand this yet. It's just a sneak peek at what's to come.

Summary

The basic idea that underpins ggplot2: **a visualization is a mapping from variables in your data to aesthetic properties like position, color, size and shape.**

- The grammar of graphics provides a systematic way to build visualizations
- Start with data and aesthetic mappings
- Add layers with geoms
- Use different geoms for different types of variables
- Enhance plots with labels, colors, and facets
- Make sure your plots are clear and honest

Key takeaways: - Build plots layer by layer - Choose appropriate visualizations for your variable types - Consider your audience when making design choices - Use aesthetics and facets to show additional variables - Always aim for clear and accessible visualizations

That’s it!

With our remaining time, I’d like you to practice with `ggplot2` using the DataAnalytics exercise. You should have already installed DataAnalytics with:

```r
devtools::install_github("antoinevernet/DataAnalytics")
```

You can then run the following code to get started:

```r
learnr::run_tutorial("02-Visualisation", package = "DataAnalytics")
```

Continuous Module Dialogue

Menti Survey

Continuous Module Dialogue

Figure 1: https://www.menti.com/al7gkr8qhntz

Visualizing distributions

The following are some additional slides on dealing with other data types and visualizing distributions in `ggplot2`. Explore them at your own pace.

Visualizing distributions

Categorical variables

For categorical variables like `species`, we use bar charts:

A bar chart shows: - Categories on one axis - Counts (frequencies) on the other axis - Height of bars represents number of observations in each category

Visualizing distributions

Improving categorical plots

We can reorder bars by frequency for better visualization:

fct_infreq() is a function from forcats package that reorders factor levels by their frequencies. This makes the plot easier to read and interpret patterns.

Visualizing distributions

Numerical variables

For numerical variables like `body_mass_g`, we use histograms:

A histogram: - Divides the x-axis into bins - Height shows number of observations in each bin - binwidth controls the size of the bins - Different binwidths can reveal different patterns

Visualizing distributions

Exploring binwidth

The choice of binwidth affects what patterns we can see:

- Too small binwidth: too many bars, noisy pattern
- Too large binwidth: too few bars, loses detail
- Need to experiment to find the right balance

Visualizing distributions

Density plots

An alternative to histograms is the density plot:

Density plots: - Show the shape of the distribution smoothly - Easier to compare multiple groups - Like a smoothed histogram - Think of it as draping a string over a histogram

Visualizing relationships

Numerical and categorical variables

To compare a numerical variable across categories, use boxplots:

A boxplot shows: - Median (middle line) - IQR (box) - Whiskers (extend to most extreme non-outlier points) - Individual points for outliers

Visualizing relationships

Alternative views

We can also use density plots to compare distributions:

- color and fill aesthetics distinguish species
- alpha controls transparency
- Overlapping distributions show how groups compare

Visualizing relationships

Two categorical variables

For two categorical variables, use stacked bar plots:

position = “fill”: - Standardizes bars to same height - Shows proportions instead of counts - Better for comparing distributions across groups

Visualizing relationships

Three or more variables

Use facets to split plots by a categorical variable:

facet_wrap(): - Creates separate plots for each category - Maintains same scales across plots - Useful for seeing patterns within groups - Alternative to mapping variables to aesthetics