

# Week 2: Data visualization

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## Materials

- [Slides](#)
- Demo

### Acknowledgement

These notes are adapted from [Ch 2 Data visualization](#) and [Ch 10 Layers](#) in R for Data Science

## 0.1 Visualization with ggplot2

There are many ways to visualize data with R. One great option is [ggplot2](#). Note that `ggplot2` is one of the core packages in the `tidyverse`, a family of packages for datascience with R. We'll learn more about this package next week.

- `ggplot2` makes use of a system for describing and creating graphics known as the layered **grammar of graphics**
- learning this one simple system allows you to generate many different types of plots

To create a plot with `ggplot2`, you call the function `ggplot()`, which creates a **plot object**. Then you add **layers** to the object. There are 3 basic requirements for every `ggplot`:

1. **data** - what dataset are you plotting? Including only data generates an empty canvas
2. **aesthetics** - define how variables in your dataset are mapped to visual properties in the plot
3. **geoms** - determine the geometrical object that a plot uses to represent the data

We can think of the following as a basic template for any `ggplot`:

```
ggplot(  
  data = <DATA>,  
  mapping = aes(<MAPPINGS>)  
) +  
  <GEOM_FUNCTION>
```

One common **warning** you will encounter is about missing values. `ggplot2` will always let you know that some of your data could not be plotted in the way you specified. Usually this is good to know, but nothing to worry about:

Removed n rows containing missing values

*We won't cover everything you can do with `ggplot2` (that would be a lot!) In lecture we'll demo the most common features, but you should feel comfortable using [ggplot2's function reference](#) to figure out how to do other things.*

## 0.2 Aesthetics

There are two ways we can determine the aesthetics of a plot:

- **mapping** allows us to determine aesthetics based on a variable, which are passed as arguments. e.g. `mapping=aes(color=var)`.
- **setting** allows us to set aesthetics to a constant value, which are passed as their own argument e.g. `color=var`

When we **map** categorical variables to aesthetics, `ggplot2` assigns a unique value of the aesthetic to each unique value of the variable.

- This process is known as **scaling**; we can override the scale `ggplot2` selected by adding a `scales` layer.
- `ggplot2` also automatically creates a legend to describe the mapping for us (except for x and y aesthetics, where `ggplot2` simply creates the axis – no legend is necessary).

When we **set** aesthetics, we must select the value for the aesthetic manually.

- **color** and **fill** - set name of a color as a string, e.g. `color="blue"`
- **alpha** - set value between 0 and 1, where 0 is most transparent, e.g. `alpha=0.5`
- **size** - set size of point in mm, e.g. `size=1`
- **shape** - set shape of point as a number 1-25, e.g. `shape=1`. There are 25 built in shapes (see below)
- **linetype** - a name of “blank”, “solid”, “dashed”, “dotted”, “dotdash”, “longdash”, “twodash”, e.g. `linetype="dotted"`

There are **3 common warnings** people encounter when **mapping categorical variables**

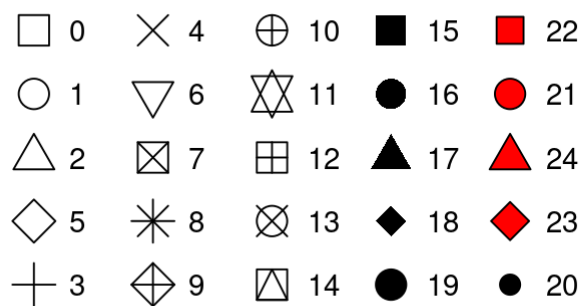


Figure 1: from R4DS's figure 10.1 showing the available shapes

1. The shape palette can deal with a maximum of 6 discrete values
  2. Removed n rows containing missing values
  3. Using alpha for a discrete value is not advised.
- The first two happen when mapping **shape**, because by default ggplot2 will use no more than 6 shapes at a time (and any additional levels are discarded)
  - The last one happens when mapping **size** or **alpha**, because it is strange to map an unordered categorical variable to an ordered aesthetic. Size and alpha imply there is some ranking but there is none!

### 0.3 Geoms

**Geoms** are the geometric objects used to represent the data in your plot. To change the geom, simply change the geom function

- `geom_histogram()` - histogram, distribution of a continuous variable
- `geom_density()` - distribution of a continuous variable
- `geom_bar()` - distribution of categorical data
- `geom_point()` - scatterplot
- `geom_smooth()` - smoothed line of best fit
- [All available geoms](#)

**Mapping and data:** Every geom function takes a **mapping** argument and a **data** argument, both can be defined either globally in the `ggplot()` layer or locally in the geom layer. When defining mappings or data locally in the geom layer, remember:

- they are *local*, meaning they only apply to *that specific layer*
- they will extend or override any *global* mappings or data you specified in `ggplot()`

- they (usefully!) allow you to specify different aesthetics or data in different layers

**Position:** Every geom also takes a **position** argument, which adjusts the position of the geom. We will encounter this most often in `geom_bar()` and `geom_point()`:

- For `geom_bar()`, the default position is **stacked**, e.g. `position="stacked"`, but there are 3 other options: (1) **dodge** would place overlapping bars next to each other, (2) **fill** would make each set of stacked bars the same height (a relative frequency plot), (3) **identity** would make the bars overlapping (which isn't very useful – we'd only see the tallest one!)
- For `geom_point()`, set `position="jitter"` to add a small amount of random noise to each point, which spreads them out! Technically makes your plot less accurate, but can also reveal important information. (`geom_jitter()` is shorthand for `geom_point(position="jitter")`)

**Stat:** All geoms also take a **stat** argument, which is short for **statistical transformation**. Many geoms have `stat="identity"` as their default argument, which means they plot the raw (untransformed) data from your dataset (`geom_point()` is one of them!). But some geoms *do* calculate new values to plot by default. For example:

- `geom_bar()` and `geom_histogram()` bin the data and plot the **bin counts** (the number of points that fall in each bin) by default
- `geom_smooth()` fits a model to your data and plots the prediction from the model
- `geom_boxplot()` computes the five-number summary of the distribution (more on this next week!) and then display that number as a summary

Usually we use the default stat, so we don't need to specify it at all. But sometimes when making `geom_bar()` plots, we want to override the default to `stat="identity"` to make the height of the bars map to the raw values of a y variable.

**Other geom-specific arguments:** Certain geoms make frequent use of other more specific arguments. Two we will encounter often are:

- For `geom_smooth()`, we set the smoothing method with the **method** argument, e.g. `method="lm"`
- For `geom_histogram()`, we set the number of bins with the **bins** argument or the width of the bins with the **binwidth** argument, e.g. `binwidth=30`.

## 0.4 Other layers

There are many other layers that can be specified in ggplot2 to create more complex plots. I find this figure helpful in understanding the layered nature of the **grammar of graphics**:

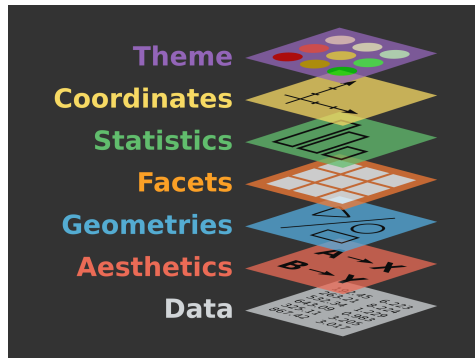


Figure 2: Adapted from The Grammar of Graphics by Leland Wilkinson

Below we'll outline some common uses for the following layers. We demoed most of this in class, but a few of them might be new to you!

- **facets** - display subsets of data
- **labels** - modifies axis, legend and plot labels
- **themes** - overall visuals
- **scales** - map data values to visual values of aesthetic

#### 0.4.1 Facets

Facets are smaller plots that display different subsets of the data. They are often used as an alternative to aesthetics to plot additional categorical variables.

- **facet\_wrap(~var)** - splits a plot into subplots based on a categorical variable; each subplot displays a subset of the data. The **ncol** argument takes a number and specifies the number of columns.
- **facet\_grid(rows~cols)** - splits a plot into subplots with the combination of two variables, one as the rows of the facet and one as the columns. To leave off rows (or cols), use the **.**, e.g. **facet\_grid(.~species)**
- **scales** - by default facets share the same scale and range for x and y aesthetics. Set the **scales** argument to "free" to allow for different axis scales, e.g. **scales="free"**

#### 0.4.2 Labels

The **labs()** functions allows you to modify axis, legend, and plot labels. **labs()** takes several arguments.

Some are a straightforward name, like:

- **title** - plot title

- **subtitle** - plot subtitle
- **caption** - caption at bottom right of plot

Others are mapped to aesthetics, like:

- **x** - the x axis label
- **y** - the y axis label
- **color** - the legend for the color aesthetic
- **size** - the legend for the size aesthetic

### 0.4.3 Themes

ggplot2 comes with many [complete themes](#) which control how everything is displayed (except data!). A few favorites include:

- `theme_gray()` - the default
- `theme_bw()` - classic dark-on-light theme
- `theme_minimal()` - minimal theme with no background annotations
- `theme_classic()` - a classic looking theme with no gridlines

Themes take a few arguments, two of which we may use in the class:

- **base\_size** - base font size, given in pts
- **base\_family** - base font family to use

### 0.4.4 Scales

[Scales](#) control the details of how data values are translated to visual properties. Adding a scale layer overrides the default scales that ggplot2 uses automatically. There are many kinds of scales, but we will mostly encounter them when changing colors of things:

- `scale_color_brewer()` - changes the color, allows you to [select color palettes](#) from the RColorBrewer package with **palette** argument, e.g. `palette="Greens"`
- `scale_fill_manual()` - also changes the color, set to manual values with **values** argument, e.g. `values=c("green", "blue", "red")`

## 0.5 Shortcuts

When calling `ggplot2` (or any function!) we can specify argument names explicitly or leave them off (implicit). Leaving off the names makes code more concise, so you'll typically see it that way.

- **explicit** naming of arguments allow us to write them in any order (because we indicate them to `ggplot2` by their name)

```
ggplot(  
  data = my_data,  
  mapping = aes(x = weight, y = height)  
)
```

- **implicit** argument names means we have to specify them in a perscribed order (data first!) so `ggplot2` can identify them without their name

```
ggplot(  
  my_data,  
  aes(x = weight, y = height)  
)
```

Another shortcut you'll encounter is **the pipe operator**, `%>%`. The pipe takes the thing on its left and passes it along to the function on its right (as the function's first argument)

- `x %>% y` is equivalent to `f(x, y)`
- since the first argument to `ggplot()` is data, you'll typically see the pipe used like this:

```
my_data %>%  
ggplot(  
  aes(x = weight, y = height)  
)
```

## 0.6 Saving plots

Often we want to save a plot (to add it to a presentation or paper). We can accomplish this with `ggsave()`.

```
# save your most recent plot with the name  
ggsave("myfigurename.png")
```

```
# specify the width and height; can also specify which units you mean  
ggsave("myfigurename.png", width = 4, height = 4)  
ggsave("mtcars.pdf", width = 20, height = 20, units = "cm")
```

In Google Colab, you can find your saved plot by clicking the file icon on the left side bar.

## 0.7 Further reading

Recommended further reading:

- [Ch 2 Data visualization](#) in R for Data Science
- <https://moderndive.com/2-viz.html>
- [Ch 10 Layers](#) in R for Data Science

Other useful resources:

- [ggplot2 function reference](#)
- [ggplot2 cheat sheet](#)
- [introduction to palmerpenguins](#)