

Data Visualization

R Software Workshop

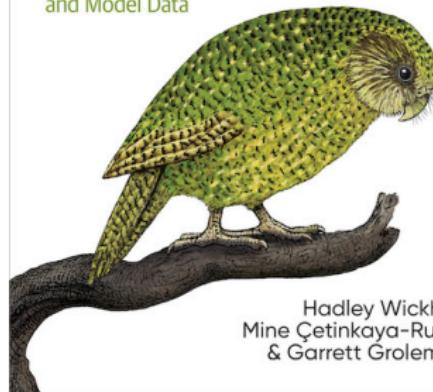
Department of Mathematics and Statistics
MSU - Iligan Institute of Technology

O'REILLY®

Second
Edition

R for Data Science

Import, Tidy, Transform, Visualize,
and Model Data



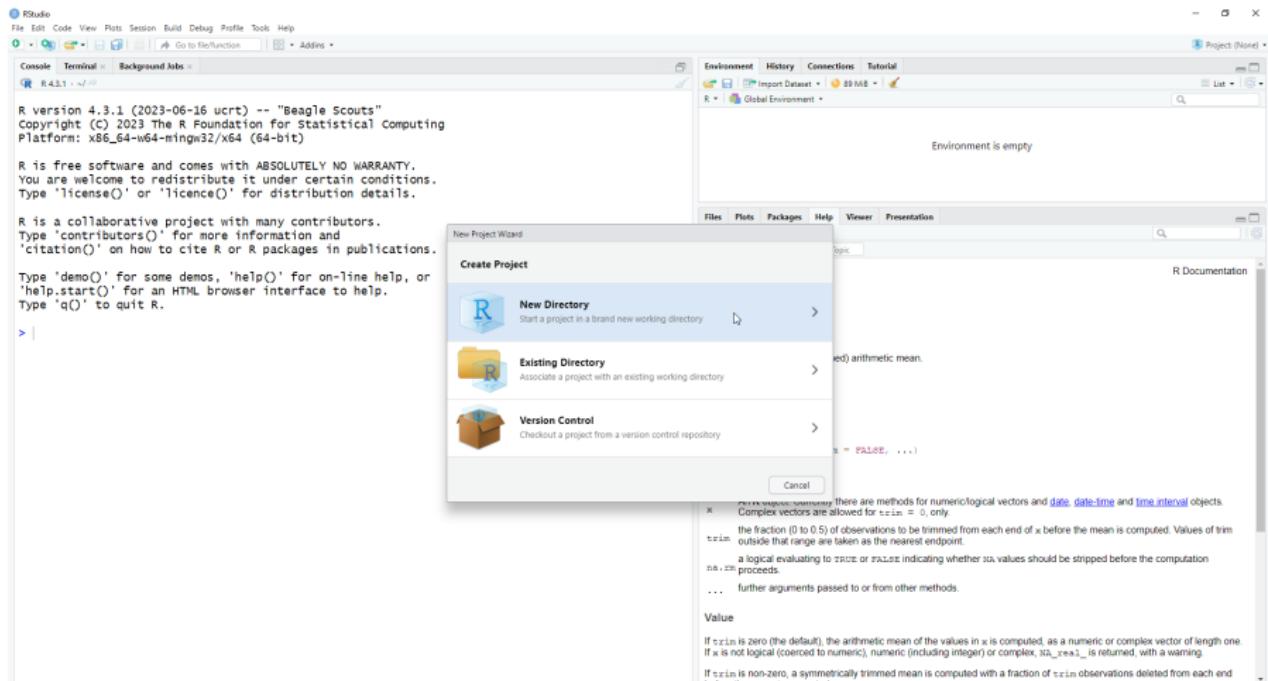
Hadley Wickham,
Mine Çetinkaya-Rundel
& Garrett Grolemund

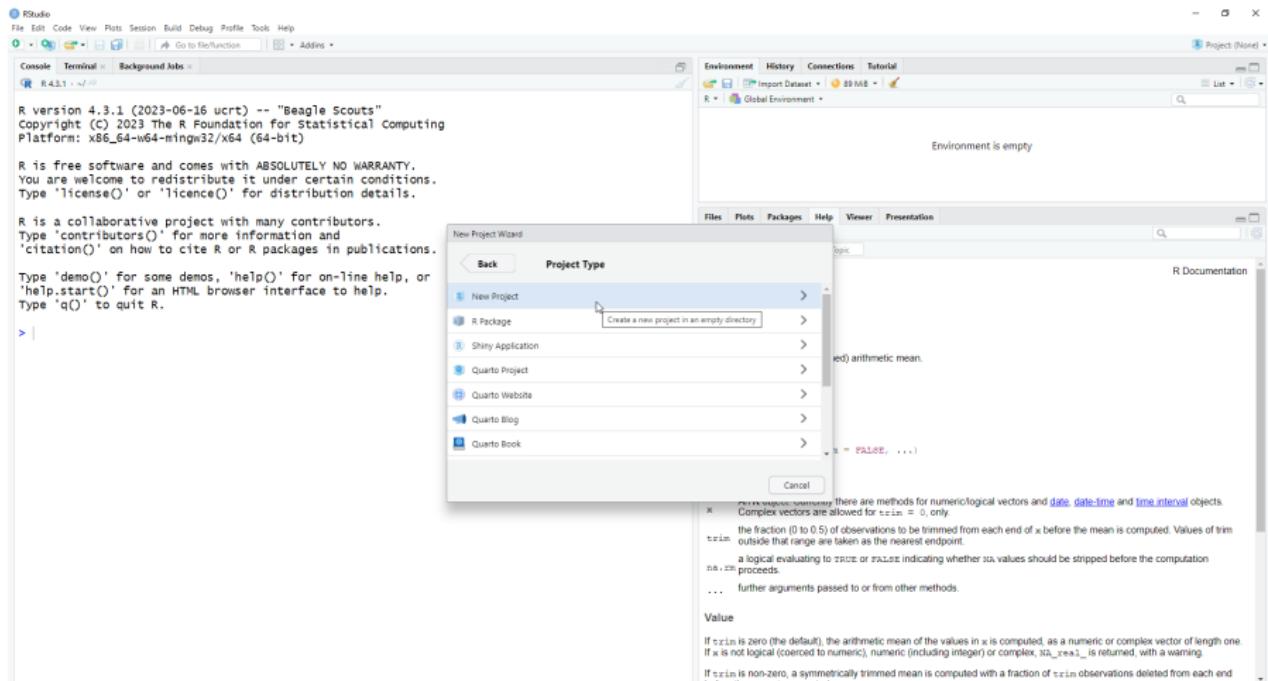
The BBC logo, consisting of four white squares arranged in a 2x2 grid, with the letters 'B', 'B', 'C' respectively in each square.

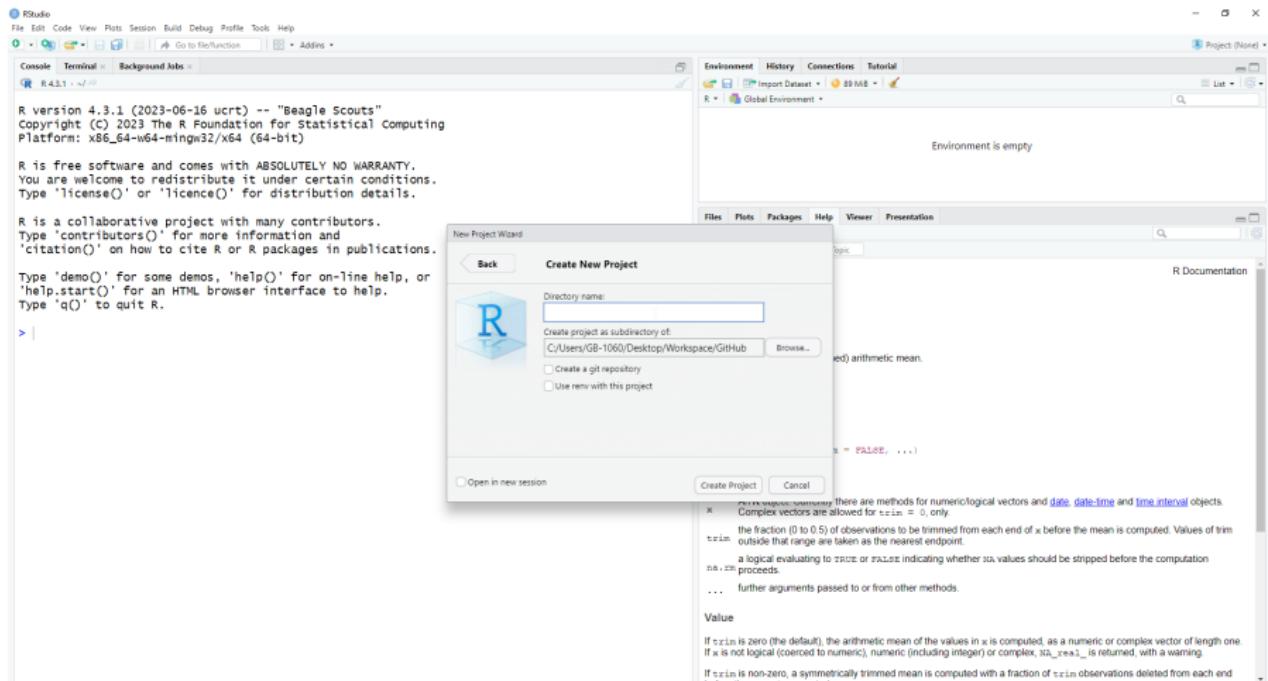
Penguin chicks rescued by unlikely hero | Spy in the Snow - BBC

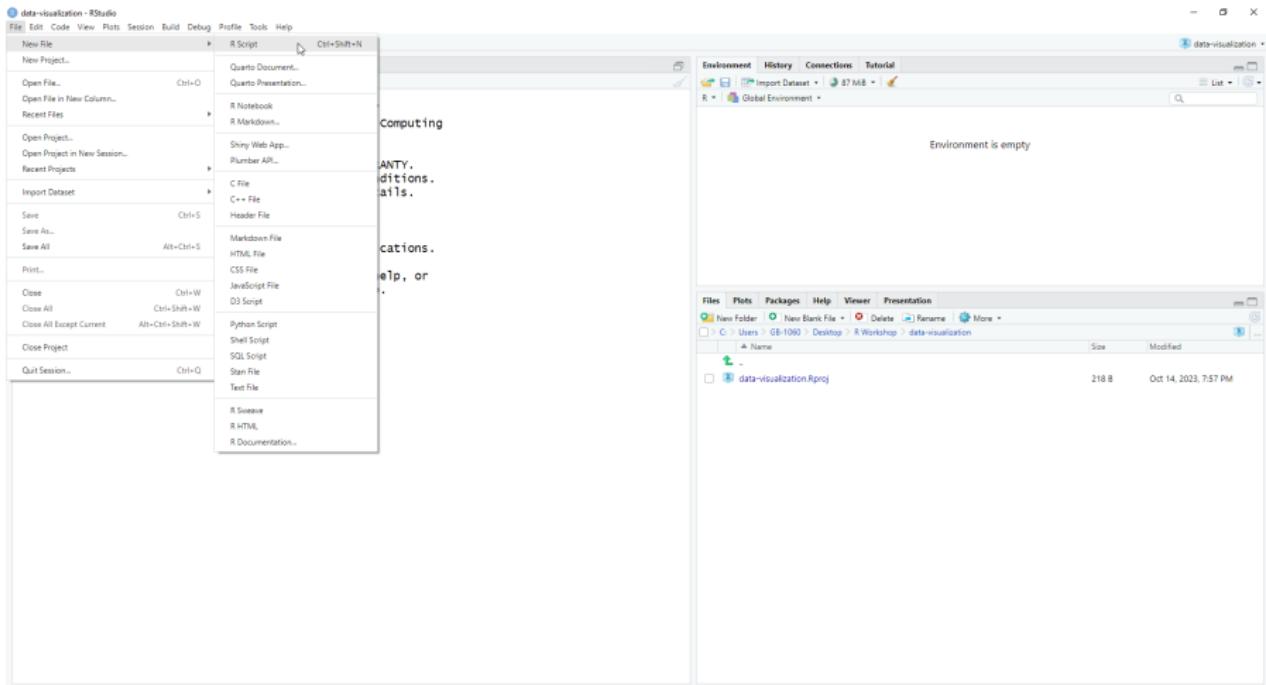
The screenshot shows the RStudio interface with the following details:

- File Menu:** Includes options like New File, Open File..., Open Project..., Import Dataset, Save, Print, Close, Close All, Close All Except Current, Close Project, and Quit Session... with their respective keyboard shortcuts.
- Environment Pane:** Shows the Global Environment with an empty list of objects.
- Help Pane:** Displays the documentation for the `mean` function.
 - Description:** Generic function for the (trimmed) arithmetic mean.
 - Usage:** `mean(x, ...)`
 - Arguments:**
 - x:** An R object. Currently there are methods for numeric/logical vectors and `date`, `date-time` and `time.interval` objects. Complex vectors are allowed for `trim = 0`, only.
 - trim:** the fraction (0 to 0.5) of observations to be trimmed from each end of `x` before the mean is computed. Values of `trim` outside that range are taken as the nearest endpoint.
 - na.rm:** a logical evaluating to `TRUE` or `FALSE` indicating whether `NA` values should be stripped before the computation proceeds.
 - ...** further arguments passed to or from other methods.
 - Value:** If `trim` is zero (the default), the arithmetic mean of the values in `x` is computed, as a numeric or complex vector of length one. If `x` is not logical (coerced to numeric), numeric (including integer) or complex, `na_real_` is returned, with a warning. If `trim` is non-zero, a symmetrically trimmed mean is computed with a fraction of `trim` observations deleted from each end before the mean is computed.









Prerequisites

This course focuses on **ggplot2**, one of the core packages in the tidyverse.

```
library(tidyverse)
```

```
library(palmerpenguins)
library(ggthemes)
```

```
install.packages("palmerpenguins")
install.packages("ggthemes")
```

The **palmerpenguins** package includes the penguins dataset containing body measurements for penguins on three islands in the Palmer Archipelago.

The **ggthemes** package offers a colorblind safe color palette.

The penguins data frame

- Do penguins with longer flippers weigh more or less than penguins with shorter flippers?

- What does the relationship between flipper length and body mass look like?

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- Does the relationship vary by the species of the penguin?

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- Does the relationship vary by the species of the penguin?
- Does the relationship vary by the island where the penguin lives?

`penguins` contains 344 observations collected and made available by Dr. Kristen Gorman and the Palmer Station, Antarctica LTER.¹

¹Horst AM, Hill AP, Gorman KB (2020). `palmerpenguins`: Palmer Archipelago (Antarctica) penguin data. R package version 0.1.0.
<https://allisonhorst.github.io/palmerpenguins/>. doi: 10.5281/zenodo.3960218.

penguins

```
glimpse(penguins)
```

Among the variables in penguins are:

- species: the penguin's species

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- flipper_length_mm: length of a penguin's flipper

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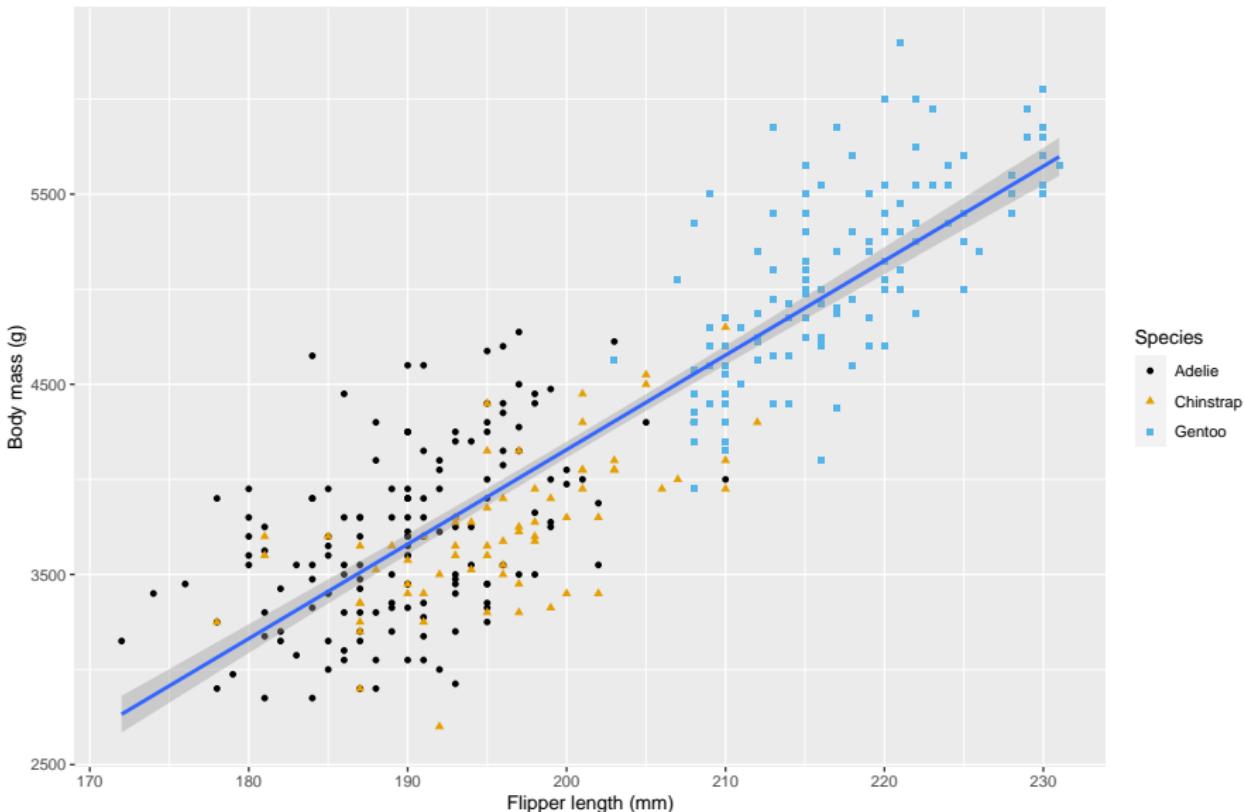
- species: the penguin's species
- flipper_length_mm: length of a penguin's flipper
- body_mass_g: body mass of a penguin

Ultimate goal

Our ultimate goal in this section is to create a visualization displaying *the relationship between flipper lengths and body masses of these penguins*, taking into consideration the species of the penguin.

Body mass and flipper length

Dimensions for Adelie, Chinstrap, and Gentoo Penguins



```
ggplot(data = penguins)
```

```
ggplot(data = penguins)
```

- The first argument of `ggplot()` is the dataset to use in the graph.

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

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

- The mapping argument of the `ggplot()` function defines how variables in your dataset are mapped to visual properties (**aesthetics**) of your plot.

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

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

- **geom**: the geometrical object that a plot uses to represent data

- Bar charts use bar geoms: `geom_bar()`

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- Line charts use line geoms: `geom_line()`

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- Boxplots use boxplot geoms: `geom_boxplot()`

- 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()`

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

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

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

What does the relationship between flipper length and body mass look like?

The relationship appears to be

- positive,

The relationship appears to be

- positive,
- fairly linear, and

The relationship appears to be

- positive,
- fairly linear, and
- moderately strong.

Penguins with longer flippers are generally larger in terms of their body mass.

```
#> Warning: Removed 2 rows containing  
#> missing values (`geom_point()`).
```

```
#> Warning: Removed 2 rows containing  
#> missing values (`geom_point()`).
```

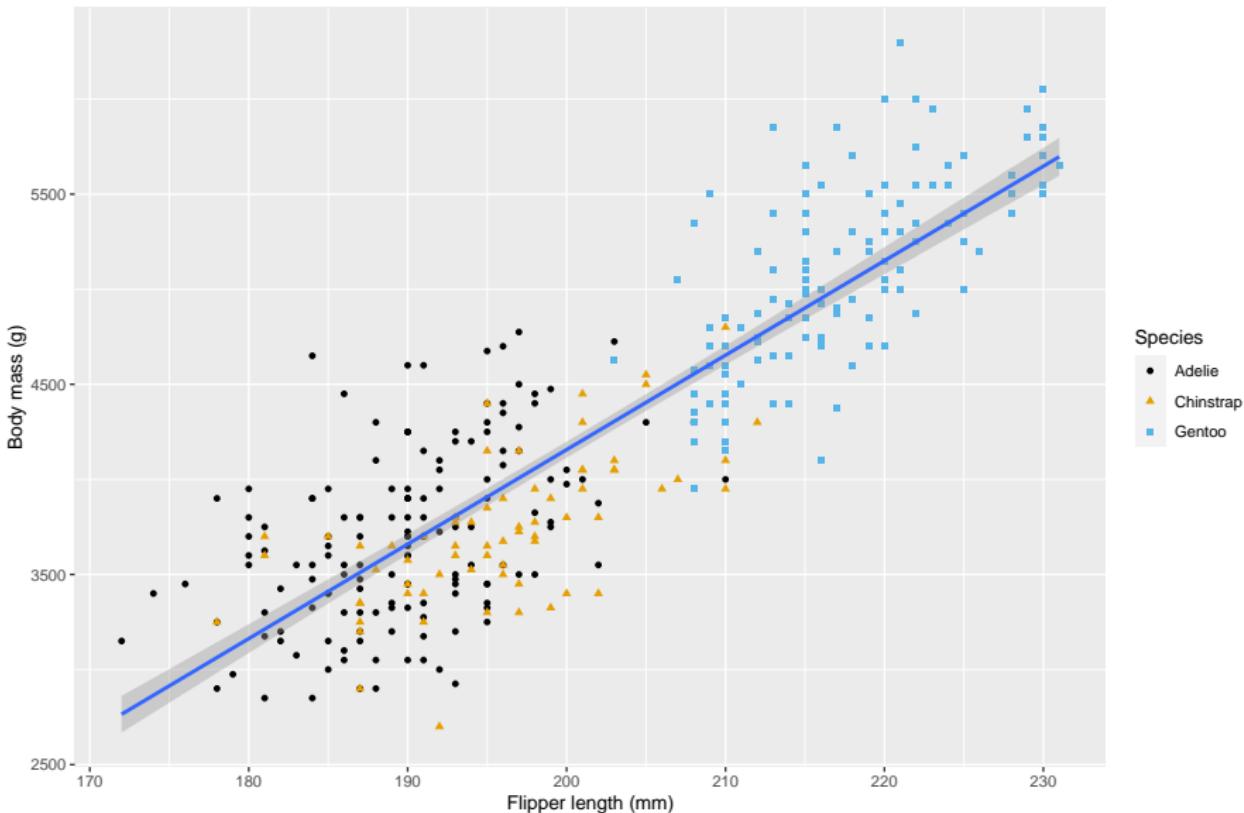
- There are two penguins in our dataset with missing body mass and/or flipper length values.

```
#> Warning: Removed 2 rows containing  
#> missing values (`geom_point()`).
```

- There are two penguins in our dataset with missing body mass and/or flipper length values.
- This type of warning is probably one of the most common types of warnings when working with real data.

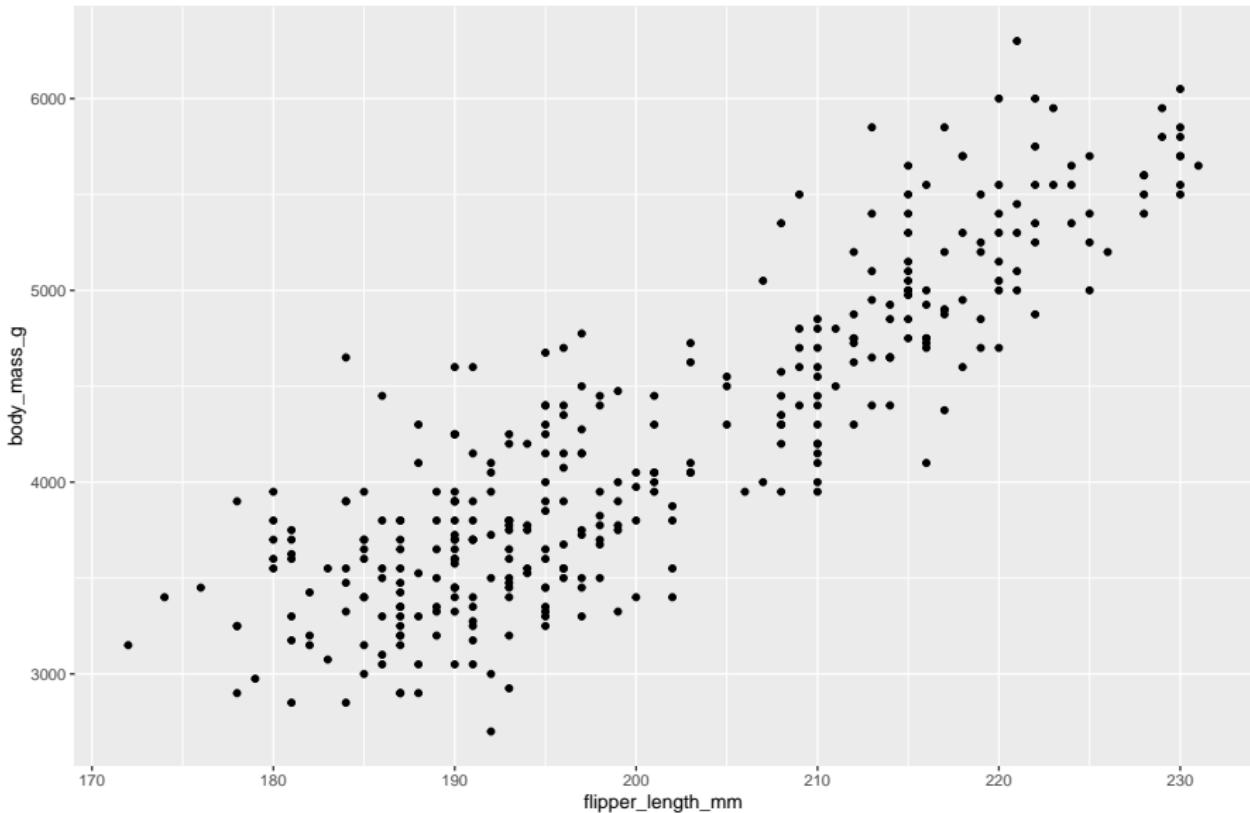
Body mass and flipper length

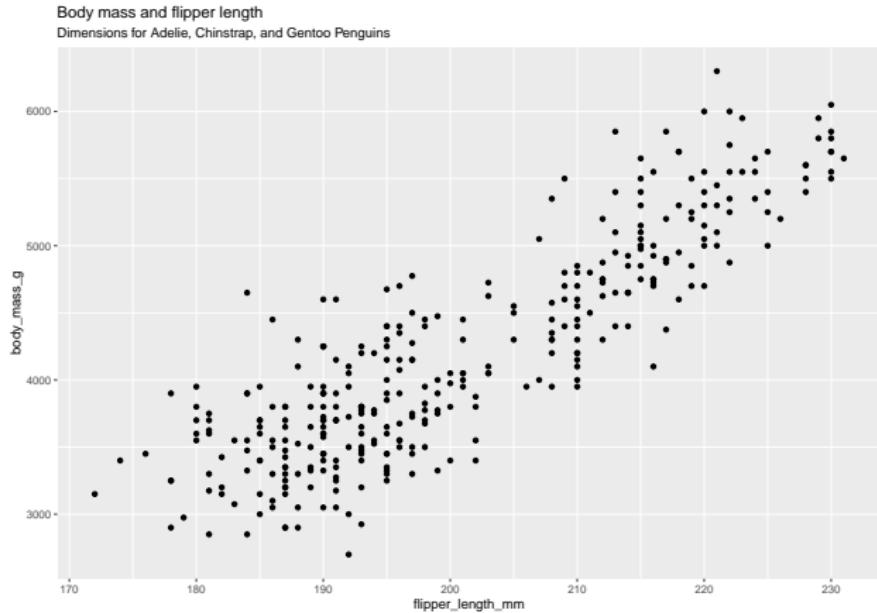
Dimensions for Adelie, Chinstrap, and Gentoo Penguins



Body mass and flipper length

Dimensions for Adelie, Chinstrap, and Gentoo Penguins





Does the relationship between flipper length and body mass differ by species?

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

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

- When a categorical variable is mapped to an aesthetic, ggplot2 will automatically assign a unique value of the aesthetic to each unique level of the variable.

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

- ggplot2 will also add a legend that explains which values correspond to which levels.

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

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

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

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

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

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.

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

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.

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

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

```
ggsave(filename = "penguin-scatterplot.png")
```

ggplot2 calls

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

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

Visualizing distributions

How you visualize the distribution of a variable depends on the type of variable: **categorical** or **numerical**.

A categorical variable

```
glimpse(penguins)
```

```
ggplot(penguins, aes(x = species)) +  
  geom_bar()
```

```
ggplot(penguins,  
       aes(x = fct_infreq(species))) +  
       geom_bar()
```

A numerical variable

```
glimpse(penguins)
```

A **histogram** divides the x-axis into equally spaced bins and then uses the height of a bar to display the number of observations that fall in each bin.

```
ggplot(penguins, aes(x = body_mass_g)) +  
  geom_histogram(binwidth = 200)
```

Different binwidths can reveal different patterns.

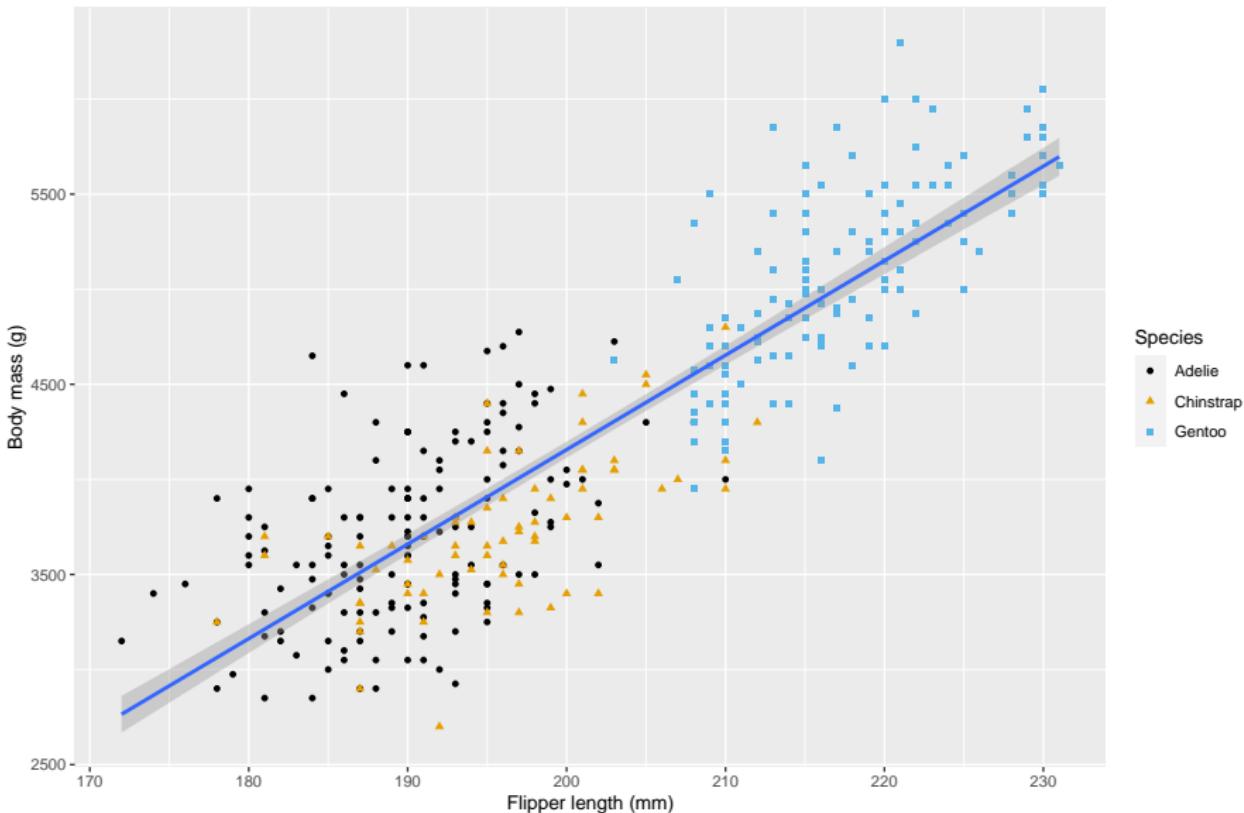
```
ggplot(penguins, aes(x = body_mass_g)) +  
  geom_histogram(binwidth = 20)
```

```
ggplot(penguins, aes(x = body_mass_g)) +  
  geom_histogram(binwidth = 2000)
```

```
ggplot(penguins, aes(x = body_mass_g)) +  
  geom_density()
```

Body mass and flipper length

Dimensions for Adelie, Chinstrap, and Gentoo Penguins



Checkpoint

- Create a bar plot of species of penguins, where you assign species to the y aesthetic.

Visualizing relationships

A numerical and a categorical variable

```
glimpse(penguins)
```

```
ggplot(penguins, aes(x = species,  
                      y = body_mass_g)) +  
  geom_boxplot()
```

```
ggsave(filename = "penguin-boxplot.png")
```

```
ggplot(penguins, aes(x = body_mass_g,  
                      color = species)) +  
  geom_density(linewidth = 0.75)
```

```
ggplot(penguins, aes(x = body_mass_g,  
                      color = species,  
                      fill = species)) +  
  geom_density(alpha = 0.5)
```

```
ggplot(penguins, aes(x = body_mass_g,  
                      color = species,  
                      fill = species)) +  
  geom_density(alpha = 0.5)
```

We **map** variables to aesthetics if we want the visual attribute represented by that aesthetic to vary based on the values of that variable.

```
ggsave(filename = "penguin-density-plot.png")
```

Two categorical variables

```
glimpse(penguins)
```

```
ggplot(penguins, aes(x = island,  
                      fill = species)) +  
  geom_bar()
```

```
ggsave(filename = "penguin-barplot.png")
```

```
ggplot(penguins, aes(x = island,  
                      fill = species)) +  
  geom_bar(position = "fill")
```

```
ggsave(filename =
  "penguin-relative-frequency.png")
```

Two numerical variables

```
glimpse(penguins)
```

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

```
ggsave(filename =
  "penguin-scatterplot-simple.png")
```

Three or more variables

```
glimpse(penguins)
```

```
ggplot(penguins, aes(x = flipper_length_mm,  
                      y = body_mass_g)) +  
  geom_point(aes(color = species,  
                 shape = island))
```

```
ggsave(filename =
        "penguin-scatterplot-islands.png")
```

```
ggplot(penguins, aes(x = flipper_length_mm,  
                      y = body_mass_g)) +  
  geom_point(aes(color = species,  
                  shape = species)) +  
  facet_wrap(~island)
```

```
ggplot(penguins, aes(x = flipper_length_mm,  
                      y = body_mass_g)) +  
  geom_point(aes(color = species,  
                  shape = species)) +  
  facet_wrap(~island)
```

- **facets**: subplots that each display one subset of the data.

```
ggsave(filename =
  "penguin-scatterplot-facets.png")
```

Checkpoint

- Create a scatterplot of bill_depth_mm vs. bill_length_mm and color the points by species.

Checkpoint

- Create a scatterplot of bill_depth_mm vs. bill_length_mm and color the points by species.
- What does adding coloring by species reveal about the relationship between these two variables?

Checkpoint

- Create a scatterplot of bill_depth_mm vs. bill_length_mm and color the points by species.
- What does adding coloring by species reveal about the relationship between these two variables?
- What about faceting by species?

Data visualization with ggplot2 :: CHEATSHEET

Basics

ggplot2 is based on the **grammar of graphics**, the idea that you can build every graph from the same components: a **data set**, a **coordinate system**, and **geoms**—visual marks that represent data points.



To display values, map variables in the data to visual properties of the geom (**aesthetics**) like **size**, **color**, and **x** and **y** locations.



Complete the template below to build a graph.

```
ggplot([data]) +
  <+GEOM_FUNCTIONS>(mapping = aes <+MAPPINGS>) +
  <+STAT_FUNCTIONS>(stat = <STAT>, position = <POSITION>) +
  <+COORDINATE_FUNCTIONS>+
  <+FACET_FUNCTIONS>-
  <+SCALE_FUNCTIONS>-
  <+THEME_FUNCTIONS>
```

Required
Not required,
sendable
defaults supplied

ggplot(data = mpg, aes(x = cyl, y = hwy)) Builds a plot that you finish by adding layers to. Add one geom function per layer.

last_plot() Returns the last plot.

ggsave("plot.png", width = 5, height = 5) Saves last plot as 5" x 5" file named "plot.png" in working directory. Matches file type to file extension.

Aes Common aesthetic values.

color and fill - string ("red", "#RRGGBB")

linetype - integer or string (0 = "blank", 1 = "solid", 2 = "dashed", 3 = "dotted", 4 = "dotteddash", 5 = "longdash", 6 = "twodash")

size - integer (line width in mm)

shape - integer/shape name or a single character ("a")

0	1	2	3	4	5	6	7	8	9	10	11	12
□	△	□	×	○	×	△	○	×	□	○	×	△
□	○	△	×	○	×	○	△	×	○	△	○	×
□	○	○	○	○	○	○	○	○	○	○	○	○

discrete

d <- ggplot(mpg, aes(lf))

Geoms

Use a geom function to represent data points, use the geom's aesthetic properties to represent variables. Each function returns a layer.

GRAPHICAL PRIMITIVES

```
a <- ggplot(economics, aes(date, unemploy))
b <- ggplot(seals, aes(x = long, y = lat))

a + geom_blank() and a + expand_limits()
Ensure limits include values across all plots.

b + geom_curve(aes(yend = lat + 1,
  xend = long + 1), curvature = 1) - y, xend, y, yend,
  alpha, angle, color, curvature, linetype, size,
  vjust, x, y, alpha, color, group, linetype, size

a + geom_path(lineend = "butt",
  linejoin = "round", linemethod = 1)
  x, y, alpha, color, group, linetype, size

a + geom_polygon(aes(alpha = 50)) - x, y, alpha,
  color, fill, group, subgroup, linetype, size

b + geom_rect(aes(xmin = long, ymin = lat,
  xmax = long + 1, ymax = lat + 1)) - xmax, xmin,
  ymax, ymin, alpha, color, fill, linetype, size

a + geom_ribbon(aes(ymin = unemploy - 900,
  ymax = unemploy + 900)) - x, ymax, ymin,
  alpha, color, fill, group, linetype, size
```

LINE SEGMENTS

```
common aesthetics: x, y, alpha, color, linetype, size

b + geom_abline(aes(intercept = 0, slope = 1))
b + geom_hline(aes(intercept = lat))
b + geom_vline(aes(xintercept = long))

b + geom_segment(aes(yend = lat + 1, xend = long + 1))
b + geom_spoke(aes(angle = 1:115, radius = 1))
```

ONE VARIABLE continuous

```
c <- ggplot(mpg, aes(hwy))
c + geom_area(stat = "bin")
c + geom_density(kernel = "gaussian")
c + geom_dotplot(binaxis = "y", stackdir = "center")
c + geom_freqpoly()
c + geom_histogram(binwidth = 5)
c + geom_qq(aes(sample = hwy))
c2 + geom_qq(aes(sample = hwy))
```

discrete

```
d <- ggplot(mpg, aes(lf))
d + geom_bar()
```

TWO VARIABLES both continuous

```
e <- ggplot(mpg, aes(cty, hwy))

e + geom_label(aes(label = cty), nudge_x = 1,
  nudge_y = 1) - x, y, label, alpha, color, angle, color,
  family, fontface, hjust, lineheight, size, vjust

e + geom_point()
  x, y, alpha, color, fill, shape, size, stroke

e + geom_quantile()
  x, y, alpha, color, group, linetype, size, weight

e + geom_rug(sides = "bl")
  x, y, alpha, color, linetype, size

b + geom_rect(aes(xmin = long, ymin = lat,
  xmax = long + 1, ymax = lat + 1)) - xmax, xmin,
  ymax, ymin, alpha, color, fill, linetype, size

a + geom_ribbon(aes(ymin = unemploy - 900,
  ymax = unemploy + 900)) - x, ymax, ymin,
  alpha, color, fill, group, linetype, size
```

one discrete, one continuous

```
f <- ggplot(mpg, aes(class, hwy))

f + geom_col()
  x, y, alpha, color, fill, group, linetype, size

f + geom_boxplot()
  x, y, lower, middle, upper, ymax, ymin, alpha,
  color, fill, group, linetype, shape, size, weight

f + geom_dotplot(binaxis = "y", stackdir = "center")
  x, y, alpha, color, fill, group, linetype, size

f + geom_violin(scale = "area")
  x, y, alpha, color, fill, group, linetype, size, weight
```

both discrete

```
g <- ggplot(diamonds, aes(cut, color))
g + geom_count()
g + geom_jitter(height = 2, width = 2)
```

THREE VARIABLES

```
seals$z <- with(seals, sqrt(delta_long^2 + delta_lat^2))
l <- ggplot(seals, aes(long, lat))

l + geom_contour(aes(z = z))
  x, y, z, alpha, color, group, linetype, size, weight

l + geom_contour_filled(aes(z = z))
  x, y, alpha, color, fill, group, linetype, size, subgroup
```

continuous bivariate distribution

```
h <- ggplot(diamonds, aes(carat, price))

h + geom_binned(binwidth = c(0.25, 500))
  x, y, alpha, color, fill, linetype, size, weight

h + geom_density_2d()
  x, y, alpha, color, group, linetype, size

h + geom_hex()
  x, y, alpha, color, fill, size
```

continuous function

```
i <- ggplot(economics, aes(date, unemploy))

i + geom_area()
  x, y, alpha, color, fill, linetype, size

i + geom_line()
  x, y, alpha, color, group, linetype, size

i + geom_step(direction = "hv")
  x, y, alpha, color, group, linetype, size
```

visualizing error

```
df <- data.frame(mu = c("A", "B"), fit = 4.5, se = 1.2)
j <- ggplot(df, aes(grp, fit, ymin = fit - se, ymax = fit + se))

j + geom_crossbar(fatten = 2) - x, y, max,
  ymin, alpha, color, fill, group, linetype, size

j + geom_errorbar() - x, ymax, ymin,
  alpha, color, group, linetype, size, width
  Also geom_errorbarh()

j + geom_linerange()
  x, ymin, ymax, alpha, color, group, linetype, size

j + geom_pointrange() - x, y, ymin, ymax,
  alpha, color, fill, group, linetype, shape, size
```

maps

```
data <- data.frame(murder = USArrests$Murder,
  state = tolower(stateNames(USArrests)))
map <- map_data("state")
k <- ggplot(data, aes(fill = murder))

k + geom_map(aes(map_id = state), map = map)
  + expand_limits(x = map$long, y = map$lat)
  map_id, alpha, color, fill, linetype, size
```

The ggplot2 logo is a hexagon containing a line graph with three data points connected by lines of increasing length, with a legend below it.

Stats

An alternative way to build a layer.

A stat builds new variables to plot (e.g., count, prop).



Visualize a stat by changing the default stat of a geom function, `geom_bar(stat="count")` or by using a stat function, `stat_count(geom="bar")`, which calls a default geom to make a layer (equivalent to a geom function). Use `after_stat(name)` syntax to map the stat variable `name` to an aesthetic.



```

c + stat_bin(binwidth = 1, boundary = 10)
x, y | count, density, density
c + stat_count(width = 1) x, y | count, prop
c + stat_density(adjust = 1, kernel = "gaussian")
x, y | count, density, scaled
  
```

```

e + stat_bin, 2d(bins = 30, drop = T)
x, y, fill | count, density
e + stat_bin, hex(bins = 30) x, y, fill | count, density
e + stat_dodge(dodge = "D", contour = TRUE, n = 100)
x, y, color, size | level
e + stat_elipse(level = 0.95, segments = 51, type = "t")
  
```

```

l + stat_contour(aes(z = z)) x, y, z, order | level
l + stat_summary_hex(bins = 20) x, bins = 30, fun = max
x, y, z, fill | value
l + stat_summary_2d(aes(z = z), bins = 30, fun = mean)
x, y, z, fill | value
  
```

```

f + stat_boxplot(coef = 1.5)
x, y | lower, middle, upper, width, ymin, ymax
  
```

```

f + stat_ydensity(kernel = "gaussian", scale = "area") x, y |
density, scaled, count, n, width, width, width
  
```

```

e + stat_ecdf(n = 40) x, y | x
e + stat_quantile(quantiles = c(0.1, 0.9),
formula = y ~ log(x), method = "rq") x, y | quantile
  
```

```

e + stat_smooth(method = "lm", formula = y ~ x, se = T,
level = 0.95) x, y | se, x, y, ymin, ymax
ggplot() + xlim(-5, 5) + stat_function(fun = dnorm,
n = 20, geom = "point") x, y
ggplot() + stat_qq(aes(sample = rnorm(100)))
x, y | sample, theoretical
  
```

```

e + stat_sum(x, y, size = 1, n, prop
  
```

```

e + stat_summary(fun.data = "mean_cl_boot")
h + stat_summary(bin = "mean", geom = "bar")
  
```

```

e + stat_identity()
  
```

```

e + stat_unique()
  
```



Scales

Override defaults with `scales` package.

`Scales` map data values to the visual values of an aesthetic. To change a mapping, add a new scale.



GENERAL PURPOSE SCALES

Use with most aesthetics

```

scale_continuous() Map cont. values to visual ones.
scale_discrete() Map discrete values to visual ones.
scale_binned() Map continuous values to discrete bins.
scale_identity() Use data values as visual ones.
scale_manual(values = c(0)) Map discrete values to manually chosen visual ones.
scale_date(date_labels = "%m/%d"),
date_breaks = "2 weeks") Treat date values as dates.
scale_datetime() Treat date values as date times. Same as scale_date(). See ?strptime for label formats.
  
```

X & Y AXIS SCALES

Use with x or y aesthetics (shown here)

```

scale_x_log10() Plot x on log10 scale.
scale_x_reverse() Reverse the direction of the x axis.
scale_x_sqrt() Plot x on square root scale.
  
```

COLOR AND FILL SCALES (DISCRETE)

```

n + scale_fill_brewer(palette = "Blues")
For palette choices:
RColorBrewer::display.brewer.all()
n + scale_fill_grey(start = 0.2,
end = 0.8, na.value = "red")
  
```

COLOR AND FILL SCALES (CONTINUOUS)

```

o <- c + geom_dotplot(aes(fill = x))
o + scale_fill_distiller(palette = "Blues")
o + scale_fill_gradient(low = "red", high = "yellow")
o + scale_fill_gradient2(low = "red", high = "blue",
mid = "white", midpoint = 25)
o + scale_fill_gradient3(colors = topo.colors(6))
Also: rainbow(), heat.colors(), terrain.colors(),
cm.colors(), RColorBrewer::brewer.pal()
  
```

SHAPE AND SIZE SCALES

```

p <- e + geom_point(aes(shape = fl, size = cyl))
p + scale_shape() + scale_size()
p + scale_shape_manual(values = c(3:7))
p + scale_size(range = c(1,6))
p + scale_size_area(max_size = 6)
  
```

Coordinate Systems

`r <- d + geom_bar()`

`r + coord_cartesian(xlim = c(0, 5))` -> the default cartesian coordinate system.

`r + coord_fixed(ratio = 1/2)`

ratio, xlim, ylim - Cartesian coordinates with fixed aspect ratio between x and y units.

`r + coord_flip()`

Flip cartesian coordinates by switching x and y aesthetic mappings.

`r + coord_polar(theta = "x", direction = 1)`

theta, start, direction - Polar coordinates.

`r + coord_trans(x = "sqrt")`

x and y axes transformed cartesian coordinates. See `trans` and `ytrans` to name of a function.

`r + coord_quickmap()`

`r + coord_map(projection = "ortho", orientation = c(41, -74, 0))` -> projection, xlim, ylim Map projections from the mapproj package (mercator (default), alazequalarea, lagrange, etc.).

Position Adjustments

Position adjustments determine how to arrange geoms that otherwise occupy the same space.

`s <- ggplot(mpg, aes(fl, fill = drv))`

`s + geom_bar(position = "dodge")` Arrange elements side by side.

`s + geom_bar(position = "fill")` Stack elements on top of one another, normalize height.

`e + geom_point(position = "jitter")` Add random noise to X and Y position of each element to avoid overlapping.

`e + geom_label(position = "nudge")` Nudge labels away from points.

`s + geom_bar(position = "stack")` Stack elements on top of one another.

Each position adjustment can be recast as a function with manual `width` and `height` arguments:

`s + geom_bar(position = position_dodge(width = 1))`

Themes

`r + theme_bw()` White background with grid lines.

`r + theme_gray()` Grey background (default theme).

`r + theme_minimal()` Minimal theme.

`r + theme_dark()` Dark for contrast.

`r + theme_void()` Empty theme.

`r + theme()` Customize aspects of the theme such as axis, legend, panel, and font properties.

`r + theme(panel.background = element_rect(fill = "blue"))`

Faceting

Facets divide a plot into subplots based on the values of one or more discrete variables.

`t <- ggplot(mpg, aes(cty, hwy)) + geom_point()`

`t + facet_grid(~ fl)` Facet into columns based on fl.

`t + facet_grid(~ year -)` Facet into rows based on year.

`t + facet_grid(~ fl * year -)` Facet into both rows and columns.

`t + facet_wrap(~ fl)` Wrap facets into a rectangular layout.

Set `scales` to let axis limits vary across facets.

`t + facet_grid(~ fl, scales = "free")` x and y axis limits adjust to individual facets:

"free_x" - x axis limits adjust

"free_y" - y axis limits adjust

Set `labeler` to adjust facet label:

`t + facet_grid(~ fl, labeler = label_bquote(alpha ^ .(fl)))`

`alpha^a alpha^b alpha^c alpha^d alpha^e`

Labels and Legends

Use `label()` to label the elements of your plot.

`t + labs(x = "New x axis label", y = "New y axis label", title = "New title", subtitle = "New subtitle", caption = "Add a caption below plot", alt = "Add alt text to the plot", `<AES>` = "New <AES> legend title")`

`t + annotate(gemot = "hex", x = 0, y = 0, label = "A")` Places a geom with manually selected aesthetics.

`p + guides(x = guide_axis_nudge(dodge = 2))` Avoid crowded legends with guides that have dodged or dodge or angle.

`n + guides(fill = "none")` Set legend type for each aesthetic: colorbar, legend, or none (no legend).

`n + theme(legend.position = "bottom")` Place legend at "bottom", "top", "left", or "right".

`n + scale_fill_discrete(name = "Title", labels = c("A", "B", "C", "D", "E"))` Set legend title and labels with a scale function.

Zooming

Without clipping (preferred):

`t + coord_cartesian(xlim = c(0, 100), ylim = c(10, 20))`

With clipping (removes unseeen data points):

`t + xlim(0, 100) + ylim(10, 20)`

`t + scale_x_continuous(limits = c[0, 100]) + scale_y_continuous(limits = c[0, 100])`