University of BRISTOL

Visualisation with R

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Statistical Computing & Empirical Methods (EMATM0061)

MSc in Data Science, Teaching block 1, 2021.

What will we cover today?

- We discuss why visualisation is a crucial skill for data scientists.
- We consider the difference between various visual cues within plots.
- We will take a brief look at the ggplot2 library within R.
- We will also think about basic data types and shapes.

The importance of visualisation

1. **Exploring data**:

   Many people are skilled at thinking visually.

   Plotting data is often the fastest way to gain insights

   - Identifying outliers
   - Determining the “shape” of a data distribution
   - Identifying relationships between variables
   - Spotting trends over time

The importance of visualisation

2. **Communicating your insights:**

   Data scientists must do more than understand and gain insight from data.

   That insight must also be communicated to others within their organization.

   Remember that your audience is often:

   - very short on time

   - from a non-technical background.

   Effective visualisations often allow us to bridge that gap.

A case study: The Challenger

In January 1986 the Challenger rocket was due to be launched by NASA.

A group of engineers who designed motors for NASA requested a delay.

It was argued that the rubber O-rings would not withstand the cold.

The advice was disregarded with dire consequences.

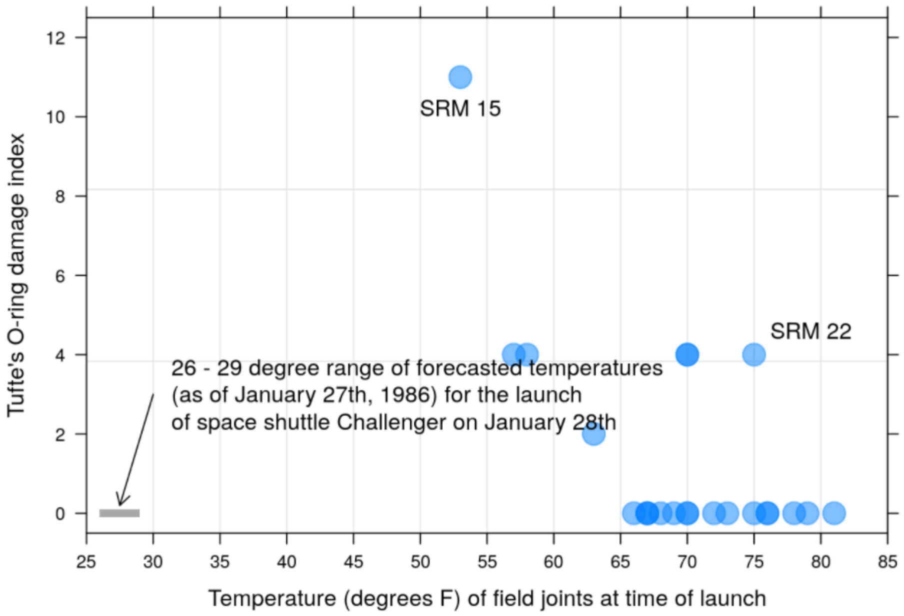
The rocket exploded 73 seconds after the launch.

A case study: The Challenger

Tufte (1997) has argued that this could have been avoided by better presentation.

HISTORY OF O-RING TEMPERATURES
(DEGREES - F)

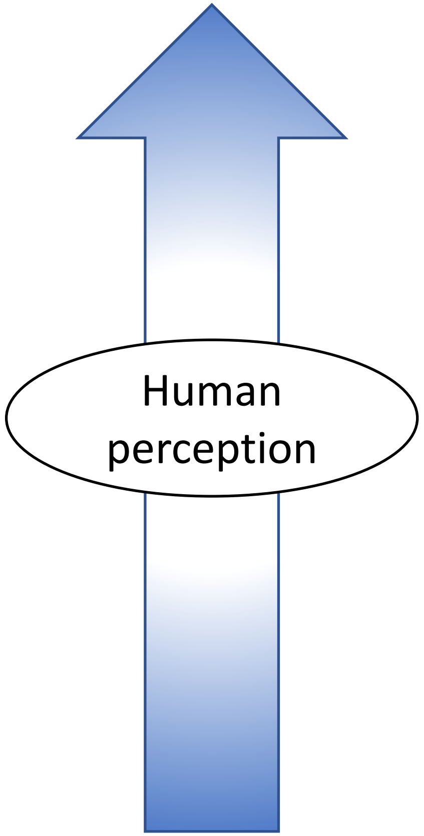
MOTOR	MBT	AMB	O-RING	WIND
DM-4	68	36	47	10 MPH
DM-2	76	45	52	10 MPH
QM-3	72.5	40	48	10 MPH
QM-4	76	48	51	10 MPH
SRM-15	52	64	53	10 MPH
SRM-22	77	78	75	10 MPH
SRM-25	55	26	29 27	10 MPH 25 MPH



Visual cues

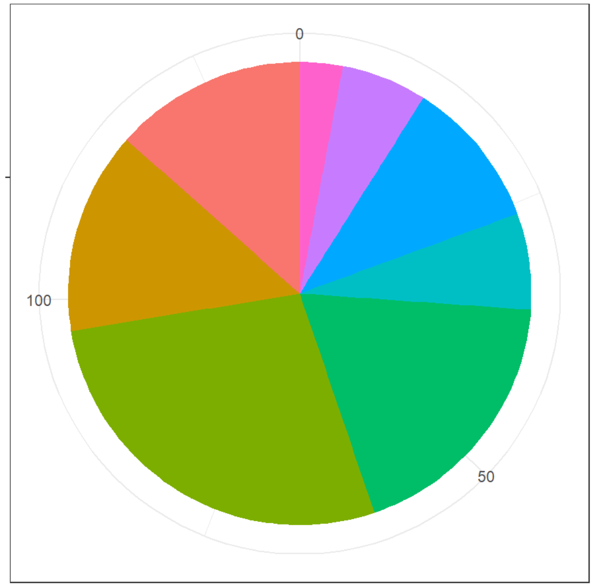
Visual cues are components of a plot or graph which draw the attention of your audience.

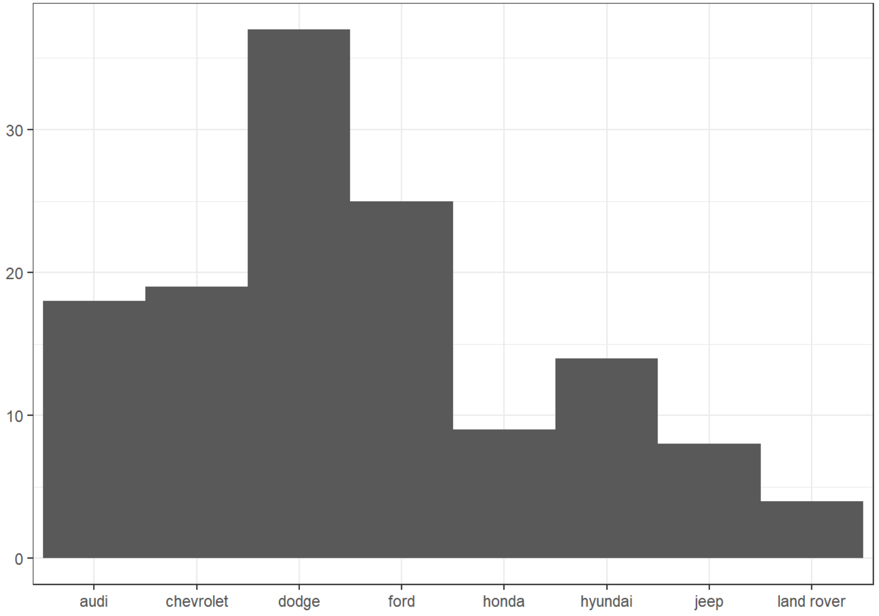
1. **Position** (numerical): Where in relation to other things?
2. **Length** (numerical): How large (in one dimension)?
3. **Angle** (numerical): How wide is something?
4. **Direction** (numerical): At what slope?
5. **Shape** (numerical): Which group?
6. **Area** (numerical): How big (in two dimensions)?
7. **Volume** (numerical): How big (in three dimensions)?
8. **Shade** (numerical or categorical): How dark is something?
9. **Colour** (numerical or categorical): What colour is something?

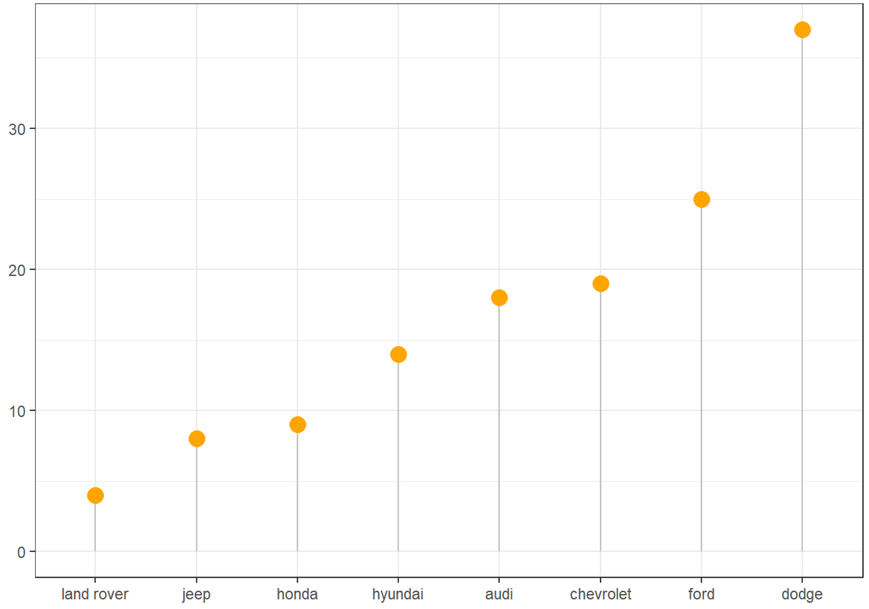


Visual cues

Visual cues are components of a plot or graph which draw the attention of your audience.







Which of these plots do you think is easiest to interpret?

Now take a break!

Visualisation in R with ggplot2

- Hadley Wickham's ggplot2 package allows us to quickly generate impressive plots within R.

- The ggplot2 package implements Leland Wilkinson's Grammar of Graphics:

    - An **aesthetic** is a mapping between a variable and visual cue.
    - A **glyph** is a basic graphical element e.g. a mark or symbol.
    - A **guide** is an annotation which provides context.

Visualisation in R with ggplot2

- First install & load the tidyverse library:

```
install.packages("tidyverse")

library(tidyverse)
```

In addition to ggplot2 for graphics this includes:

dplyr for data wrangling

tidyr for tidying data

purrr for functional programming with R

- Note that you only need to install a package once.

The Palmer penguins data set

- We will also make use of the Palmer penguins data set.

- Introduced by Alison Hill, Allison Horst, Kristen Gorman.

The Palmer penguins data set

- First load the palmer penguins library.

```
library(palmerpenguins)
```

- We can take a look at the data set by using the head function.

```
head(penguins)
```

```
# A tibble: 6 x 8
  species island    bill_length_mm bill_depth_mm flipper_length_mm body_mass_g sex     year
  <fct>   <fct>              <dbl>         <dbl>             <int>       <int> <fct>  <int>
1 Adelie  Torgersen           39.1          18.7               181        3750 male    2007
2 Adelie  Torgersen           39.5          17.4               186        3800 female  2007
3 Adelie  Torgersen           40.3          18                 195        3250 female  2007
4 Adelie  Torgersen           NA            NA                  NA          NA NA      2007
5 Adelie  Torgersen           36.7          19.3               193        3450 female  2007
6 Adelie  Torgersen           39.3          20.6               190        3650 male    2007
```

Types of variables

```
# A tibble: 6 x 8
  species island    bill_length_mm bill_depth_mm flipper_length_mm body_mass_g sex     year
  <fct>   <fct>              <dbl>         <dbl>             <int>       <int> <fct>  <int>
1 Adelie  Torgersen           39.1          18.7               181        3750 male    2007
2 Adelie  Torgersen           39.5          17.4               186        3800 female  2007
3 Adelie  Torgersen           40.3          18                 195        3250 female  2007
```

Continuous Numeric variables that can take any value on an interval

E.g. Bill length, bill depth, flipper length, body mass.

Discrete Numeric variables for which there is a minimum gap between possible values.

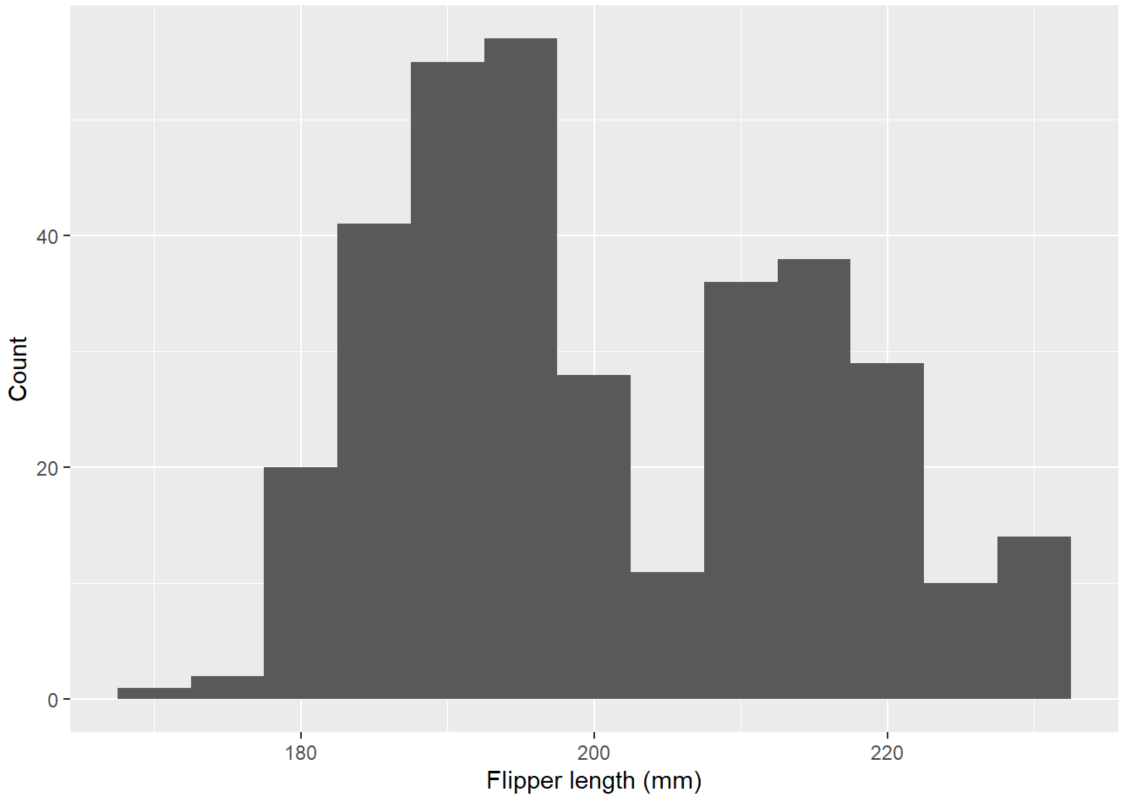
e.g. year the observation was recorded.

Categorical Variables that can take on only a specific set of values representing distinct categories

e.g. species, island, etc.

Univariate plots

```
univar_plot<-ggplot(data=penguins,aes(x=flipper_length_mm))+xlab("Flipper length (mm)")
univar_plot+geom_histogram(binwidth=5)+ylab("Count")
```

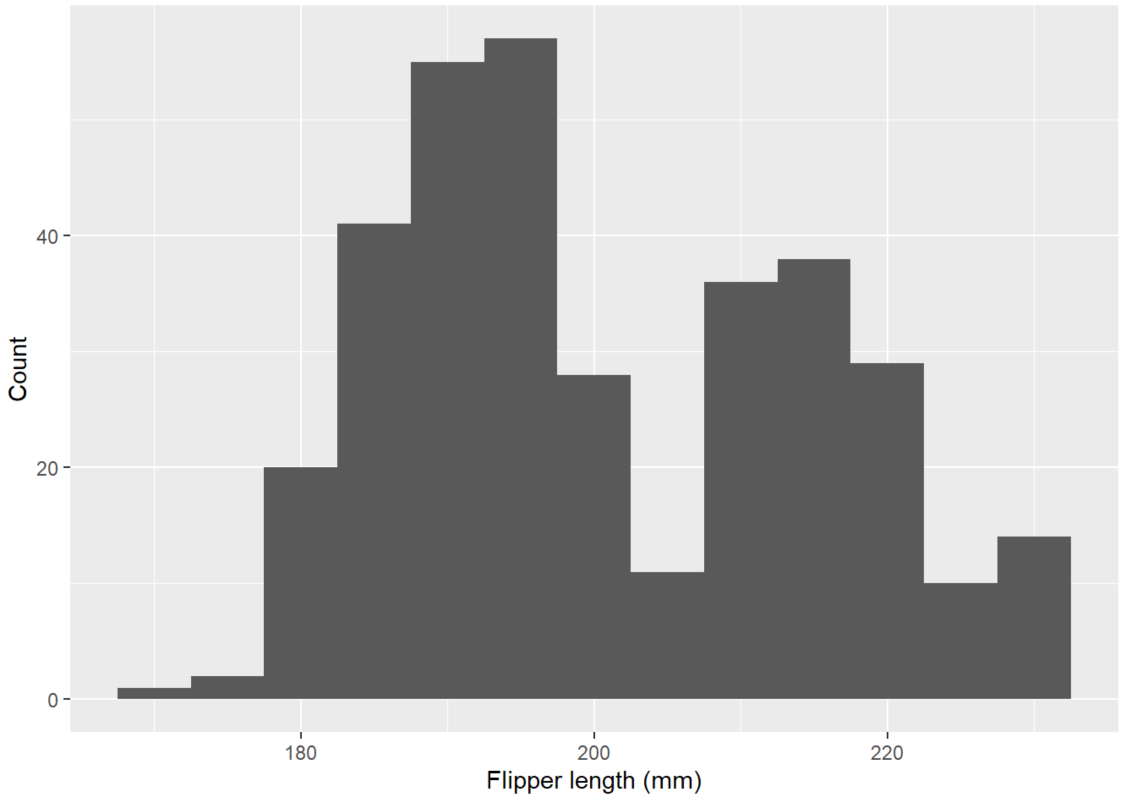


Each bar represents the number of penguins

with flipper length within the window.

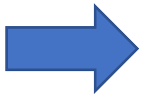
Univariate plots

```
univar_plot<-ggplot(data=penguins,aes(x=flipper_length_mm))+xlab("Flipper length (mm)")
univar_plot+geom_histogram(binwidth=5)+ylab("Count")
```



Aesthetic

A mapping between a variable and visual cue.

Flipper length  horizontal position.

Guide

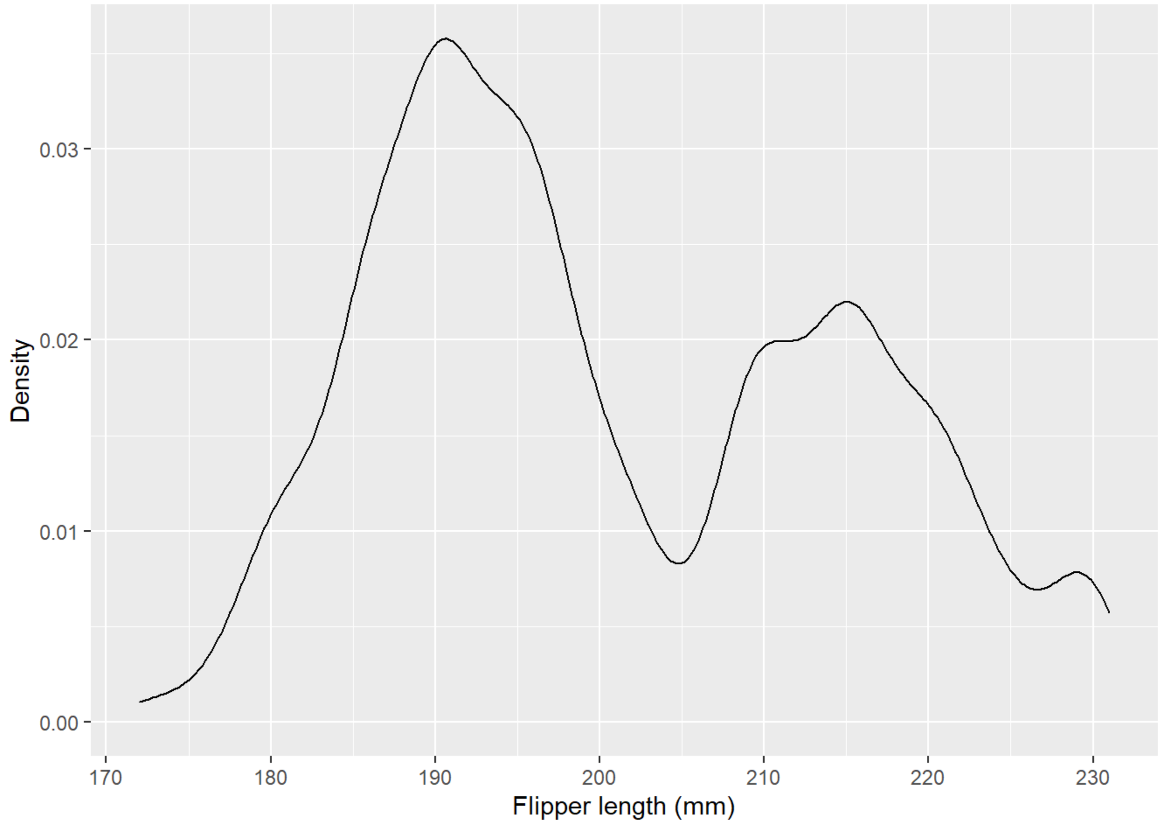
An annotation which provides context.

Glyph

A glyph is a basic graphical element.

Univariate plots

```
univar_plot+geom_density(adjust=0.5)+ylab("Density")
```

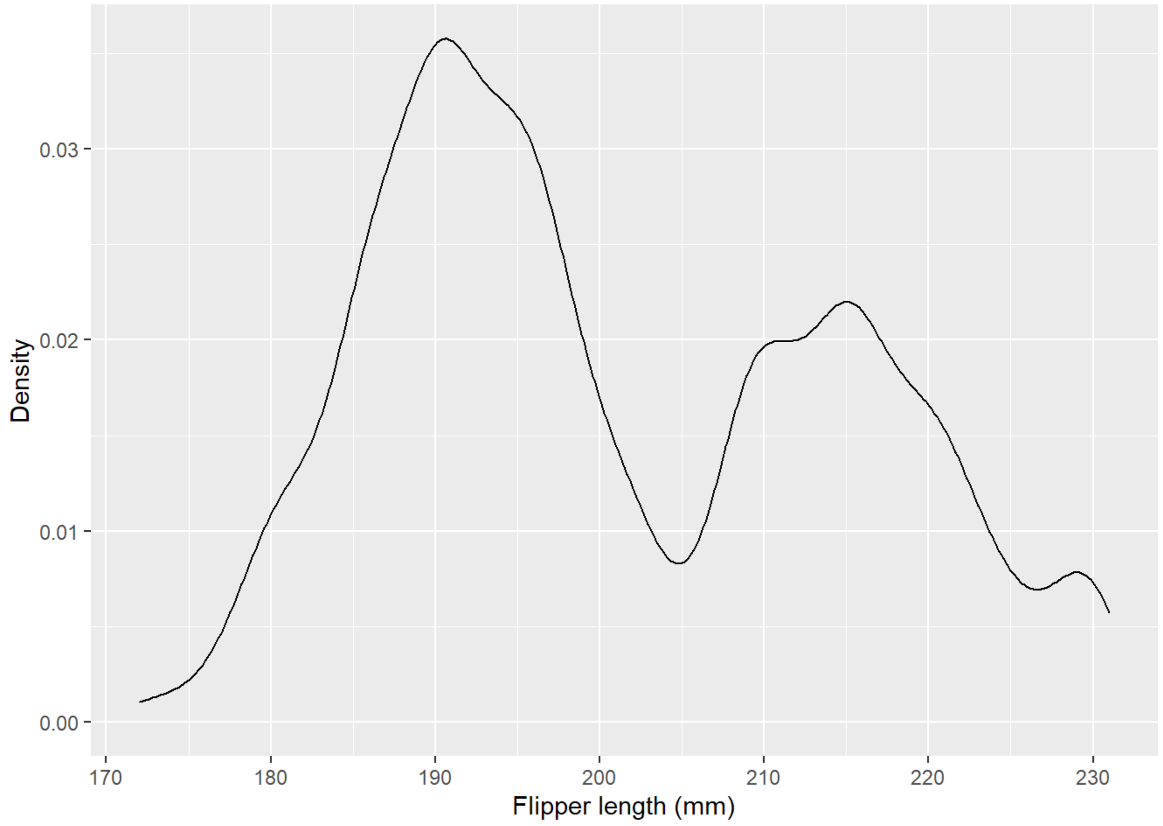


A density plot is a smoothed analogue of a histogram.

Counts are replaced with smoothed bump functions ie. kernels.

Univariate plots

```
univar_plot+geom_density(adjust=0.5)+ylab("Density")
```



Aesthetic

A mapping between a variable and visual cue.

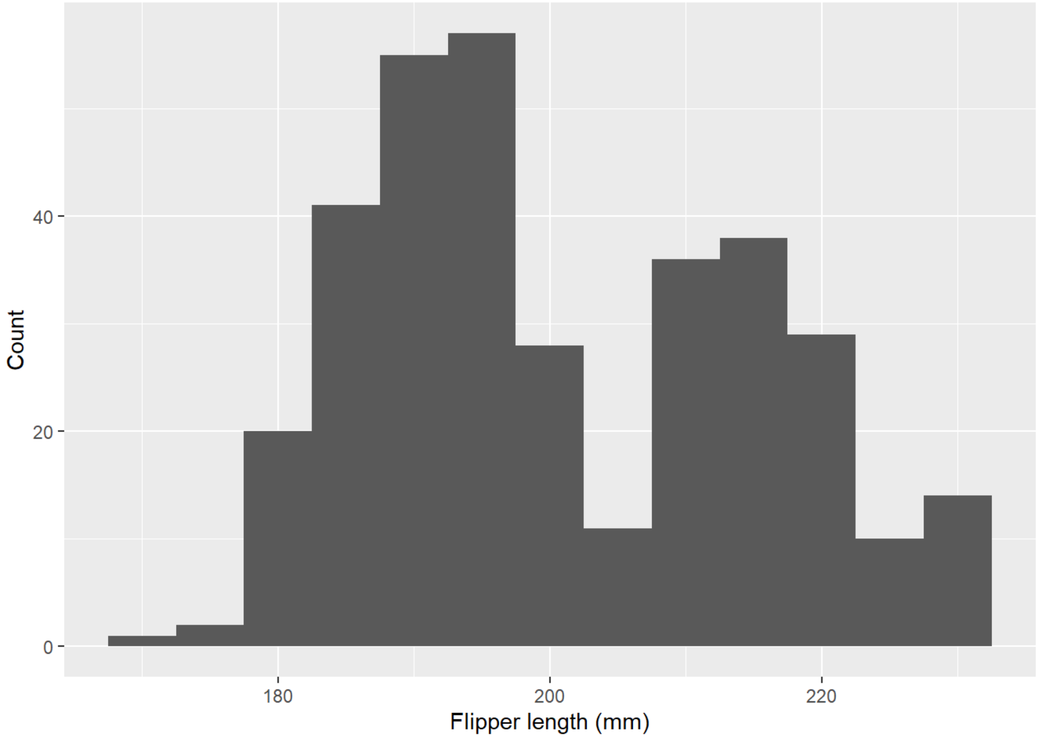
Flipper length → horizontal position.

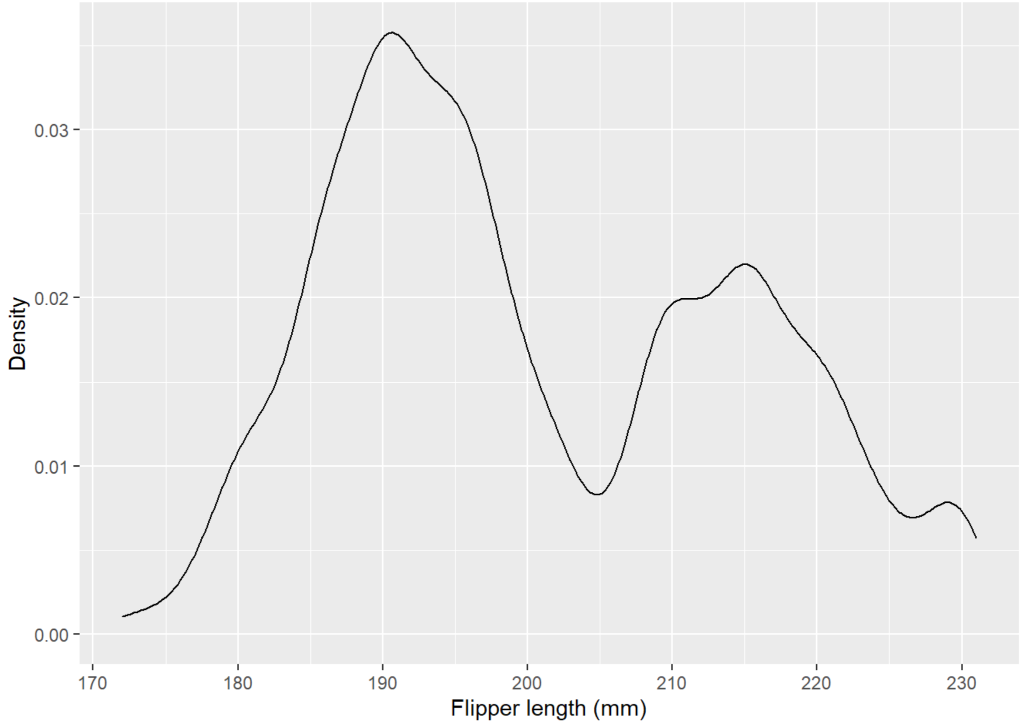
Glyph

A glyph is a basic graphical element.

The line within the density plot.

Univariate plots

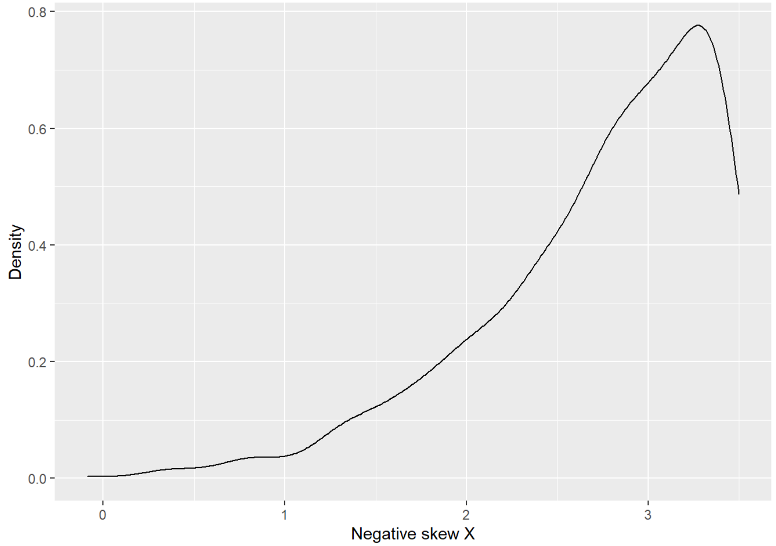


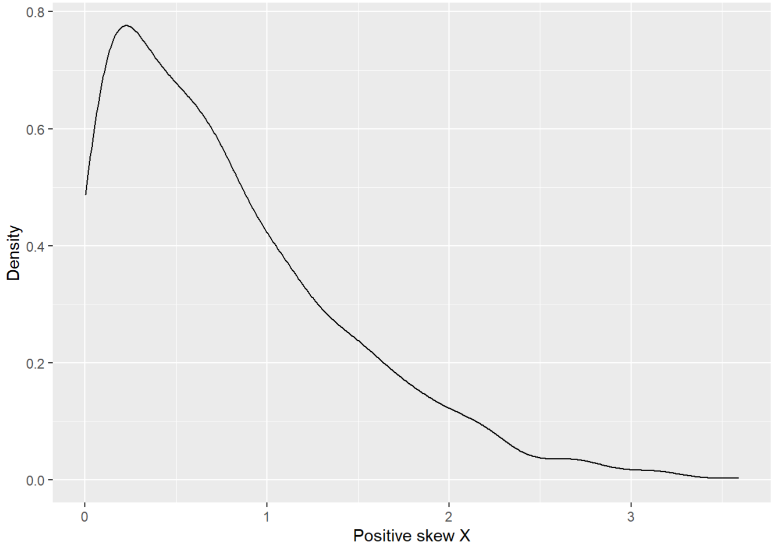


Histograms and density plots display the shape of the data distribution.

Skewness

Negative skewed data occurs when there is a large **left tail** consisting of a relatively small number of relatively low values, but most of the data is towards the upper end of the plot.



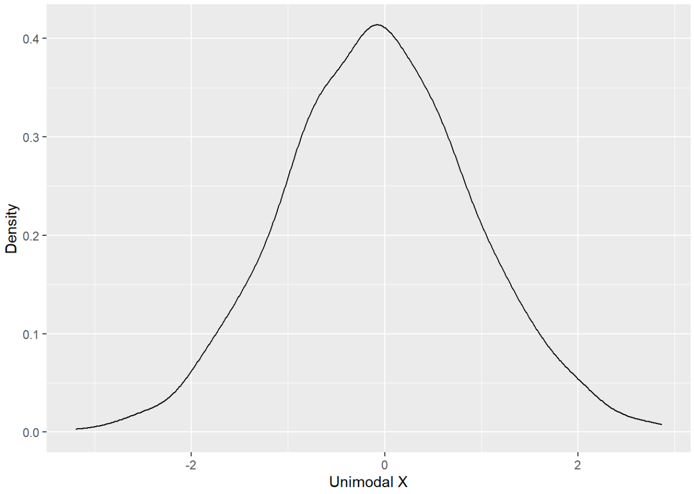


Positively skewed data occurs when there is a large **right tail** consisting of a relatively small number of relatively high values, but most of the data is towards the lower end of the plot.

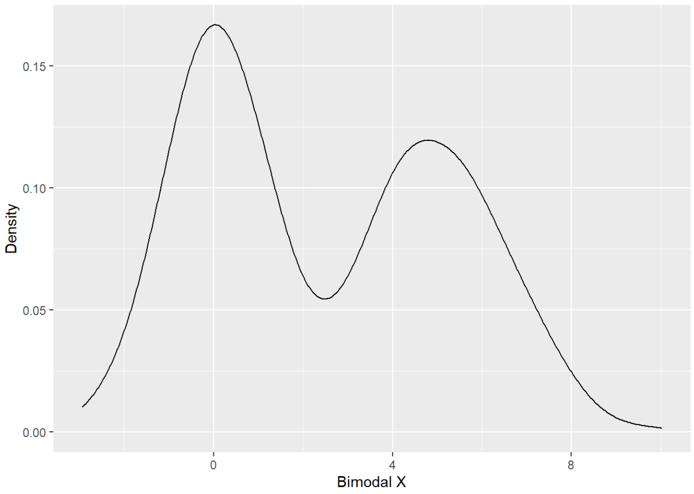
Unimodal vs. multi-modal

The number of modes refers to the number of peaks within the data.

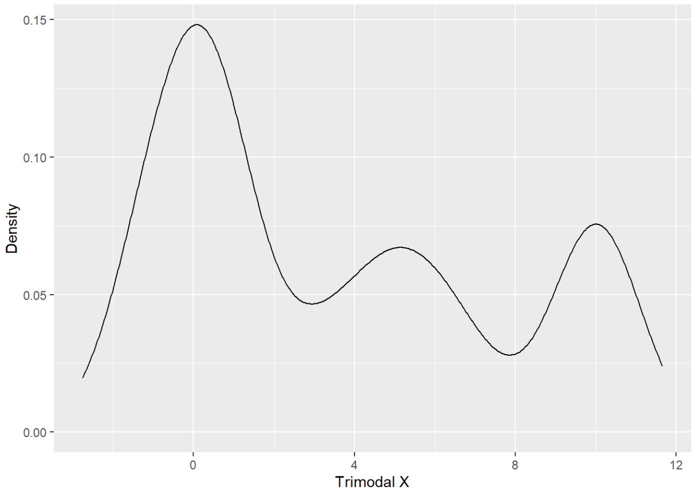
Unimodal



Bimodal

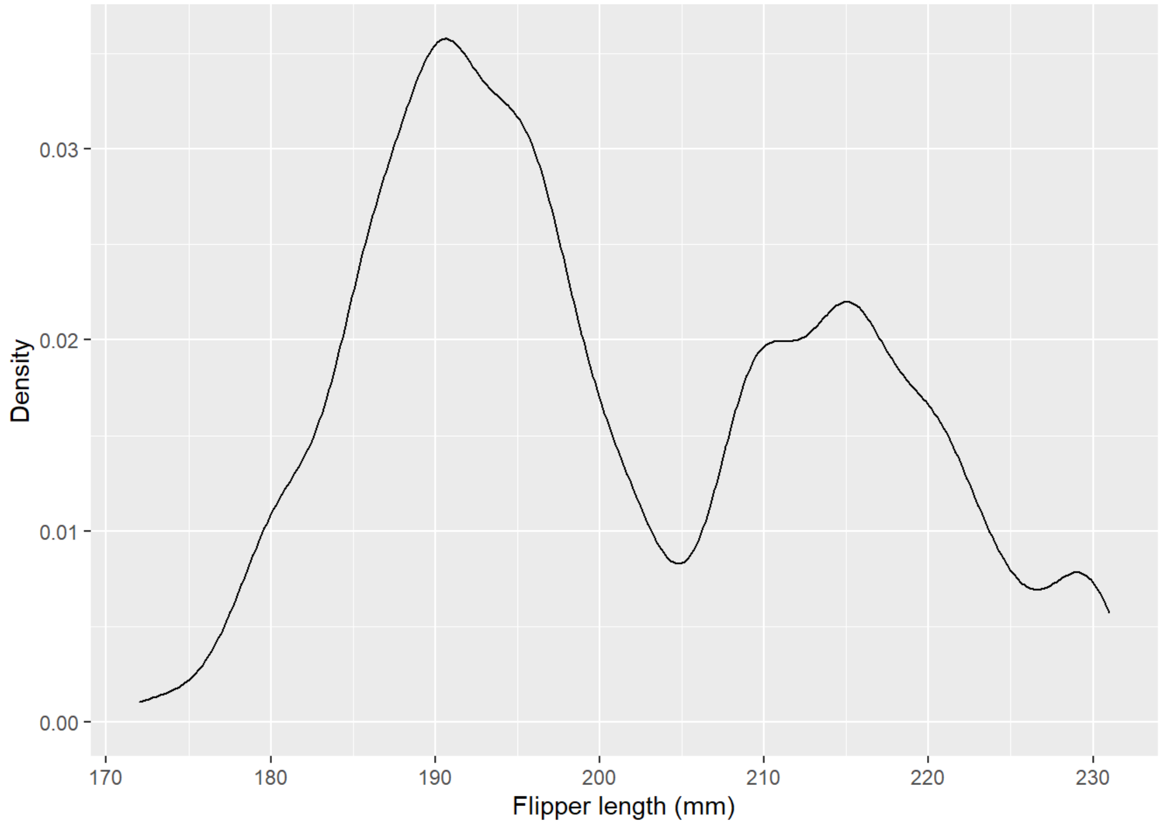


Trimodal



Univariate plots

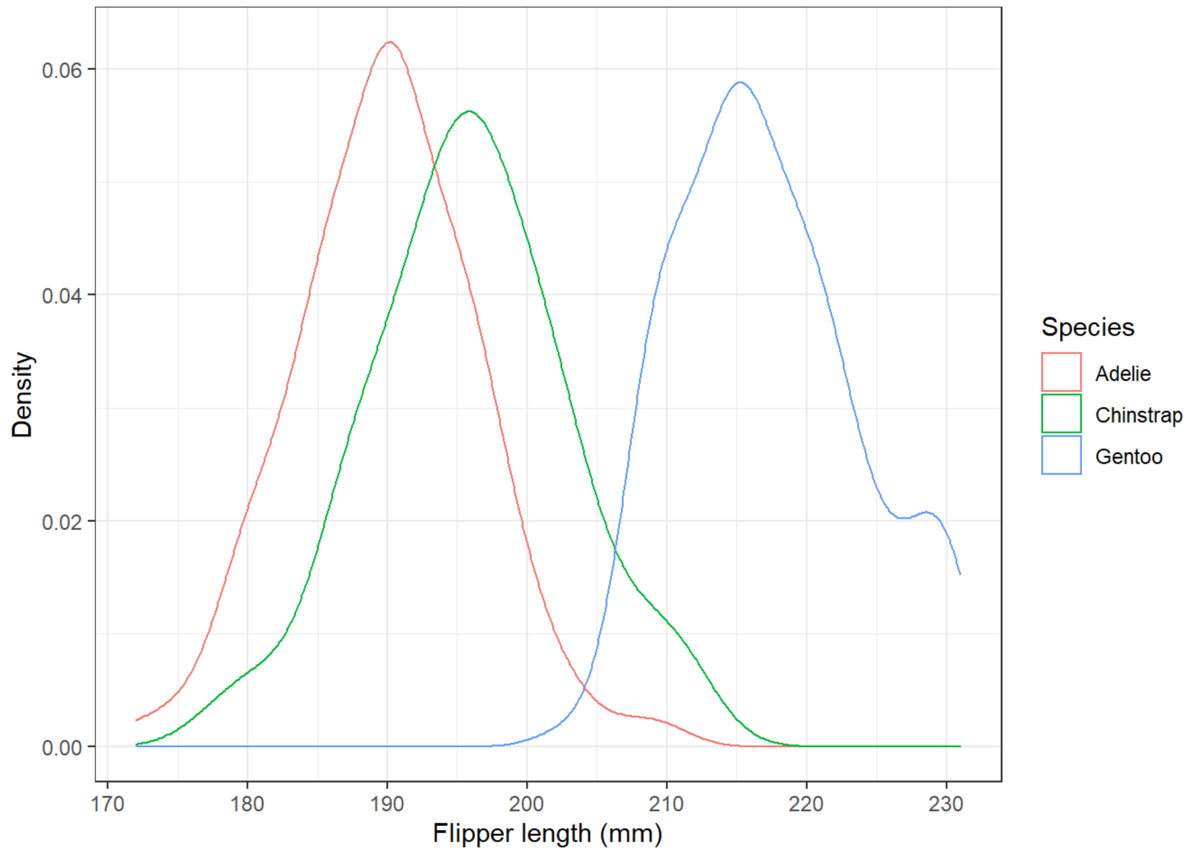
```
univar_plot+geom_density(adjust=0.5)+ylab("Density")
```



A bimodal distribution.

Bivariate plots

```
ggplot(data=rename(penguins,Species=species),aes(x=flipper_length_mm,color=Species))+
  geom_density()+theme_bw()+xlab("Flipper length (mm)")+ylab("Density")
```



Aesthetics

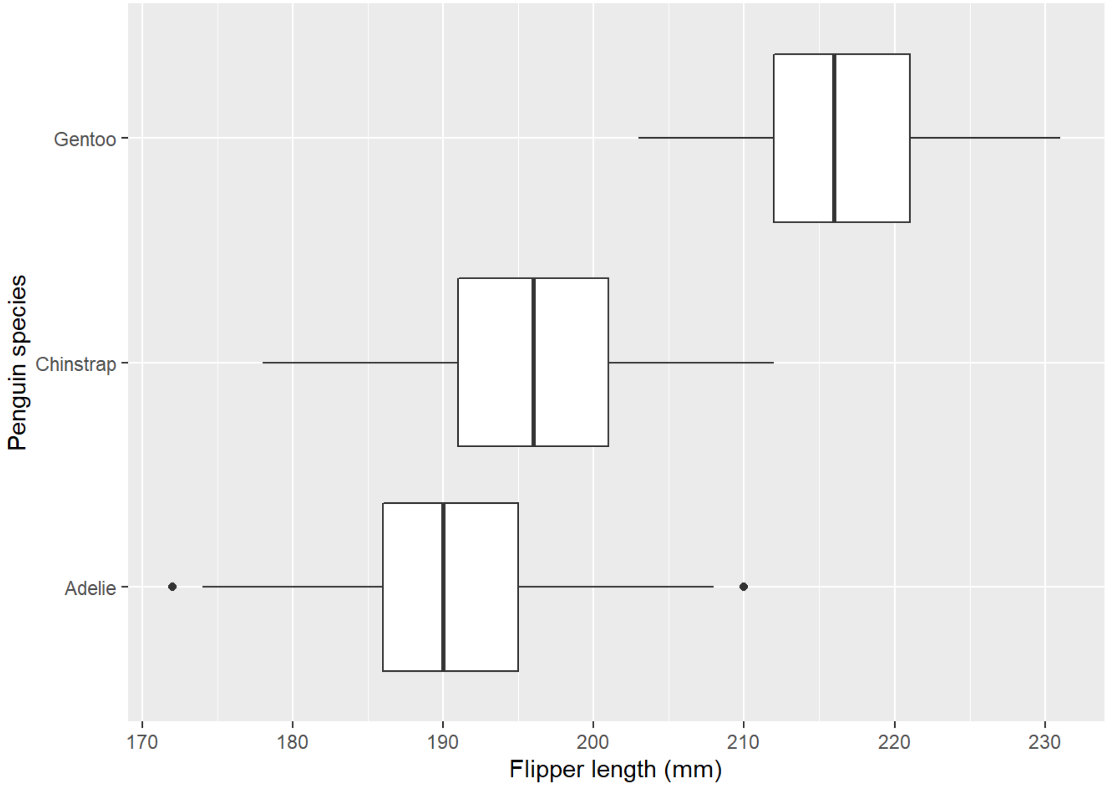
Mappings between a variable and visual cue.

Flipper length → horizontal position.

Species → color

Bivariate plots

```
ggplot(data=penguins,aes(x=flipper_length_mm,y=species))+geom_boxplot()+
  xlab("Flipper length (mm)")+ylab("Penguin species")
```



Aesthetics

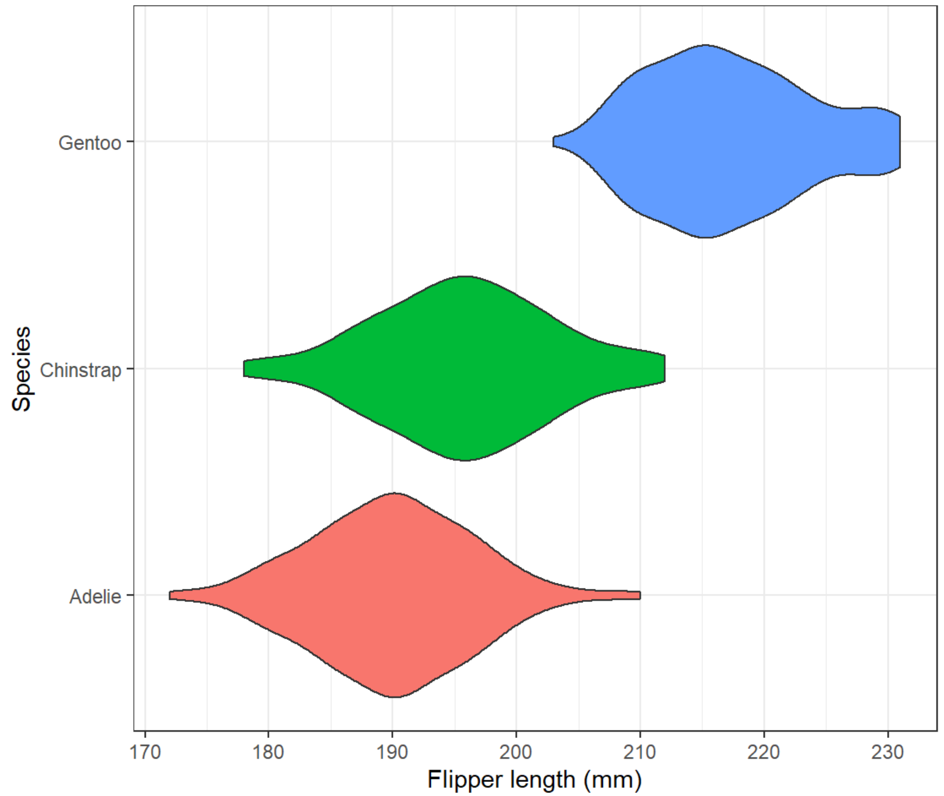
Mappings between a variable and visual cue.

Flipper length → horizontal position.

Species → vertical position.

Bivariate plots

```
ggplot(data=rename(penguins,Species=species),aes(x=flipper_length_mm,y=Species,fill=Species))+
  geom_violin()+theme_bw()+xlab("Flipper length (mm)")
```



Aesthetics

Mappings between a variable and visual cue.

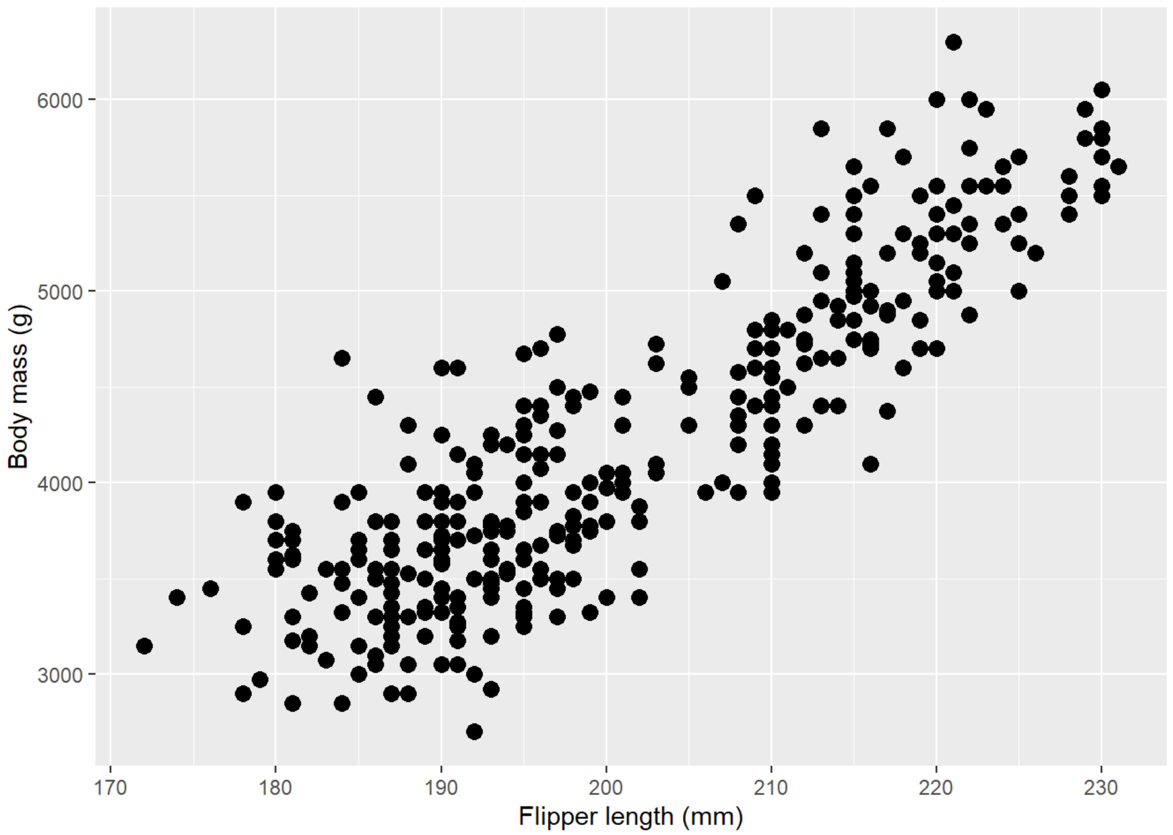
Flipper length → horizontal position.

Species → vertical position.

Species → colour

Bivariate plots

```
mass_flipper_scatter<-ggplot(data=penguins,aes(y=body_mass_g,x=flipper_length_mm))+
  xlab("Flipper length (mm)")+ylab("Body mass (g)")
mass_flipper_scatter+geom_point(size=3)
```



Aesthetics

Flipper length → horizontal position.

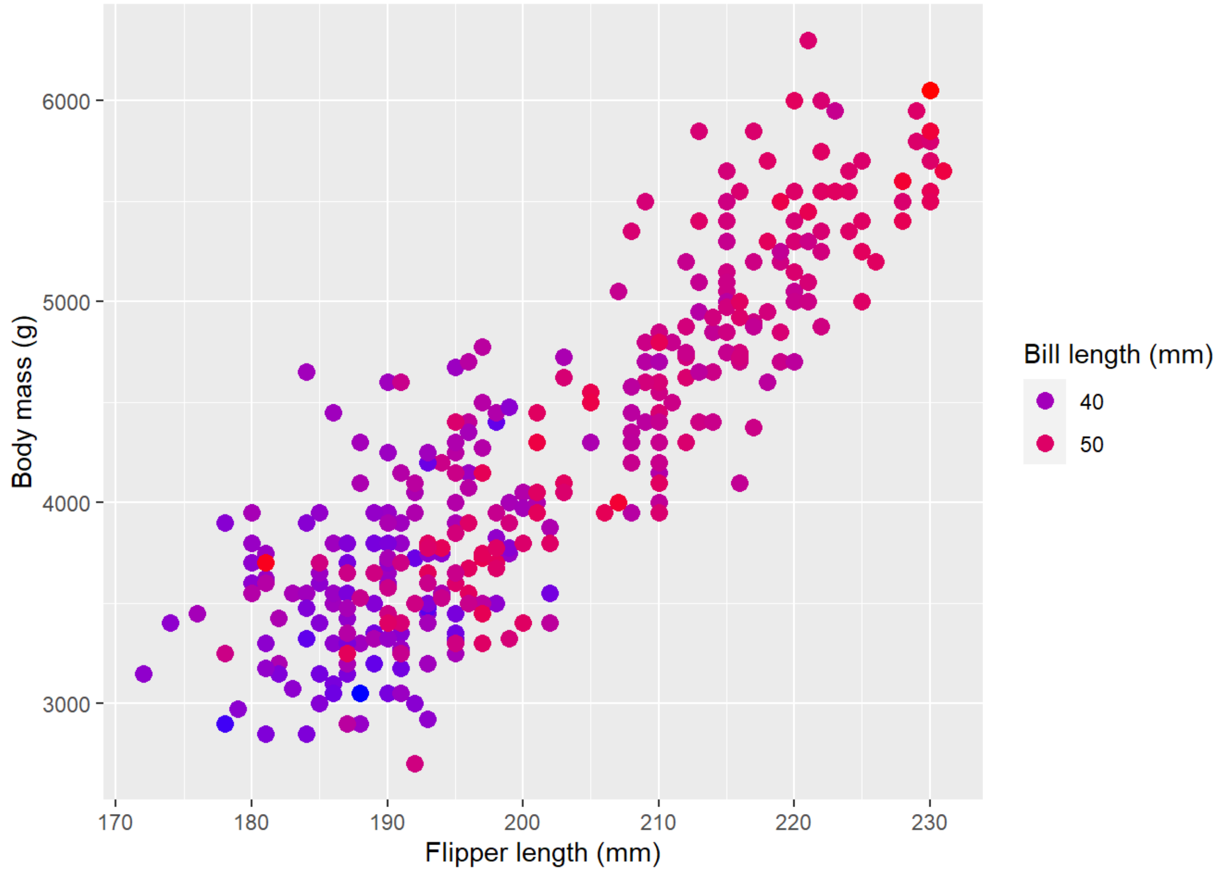
Body mass → vertical position.

Glyph

Points.

Multivariate plots

```
mass_flipper_scatter+geom_point(aes(color=bill_length_mm),size=3)+
  scale_color_gradient(low="blue", high="red")+guides(color=guide_legend("Bill length (mm)"))
```



Aesthetics

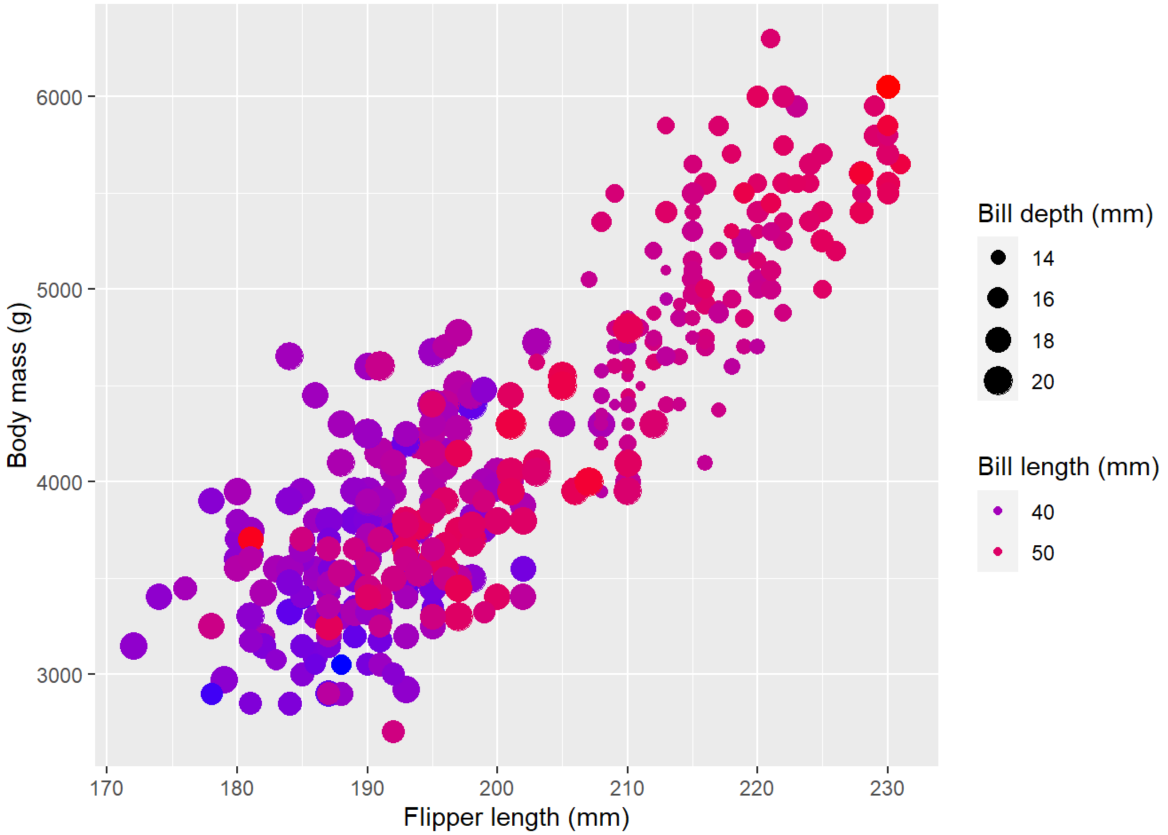
Flipper length → horizontal position.

Body mass → vertical position.

Bill length → color

Multivariate plots

```
mass_flipper_scatter+geom_point(aes(color=bill_length_mm,size=bill_depth_mm))+
  scale_color_gradient(low="blue", high="red")+
  guides(color=guide_legend("Bill length (mm)"),size=guide_legend("Bill depth (mm)"))
```



Aesthetics

Flipper length → horizontal position.

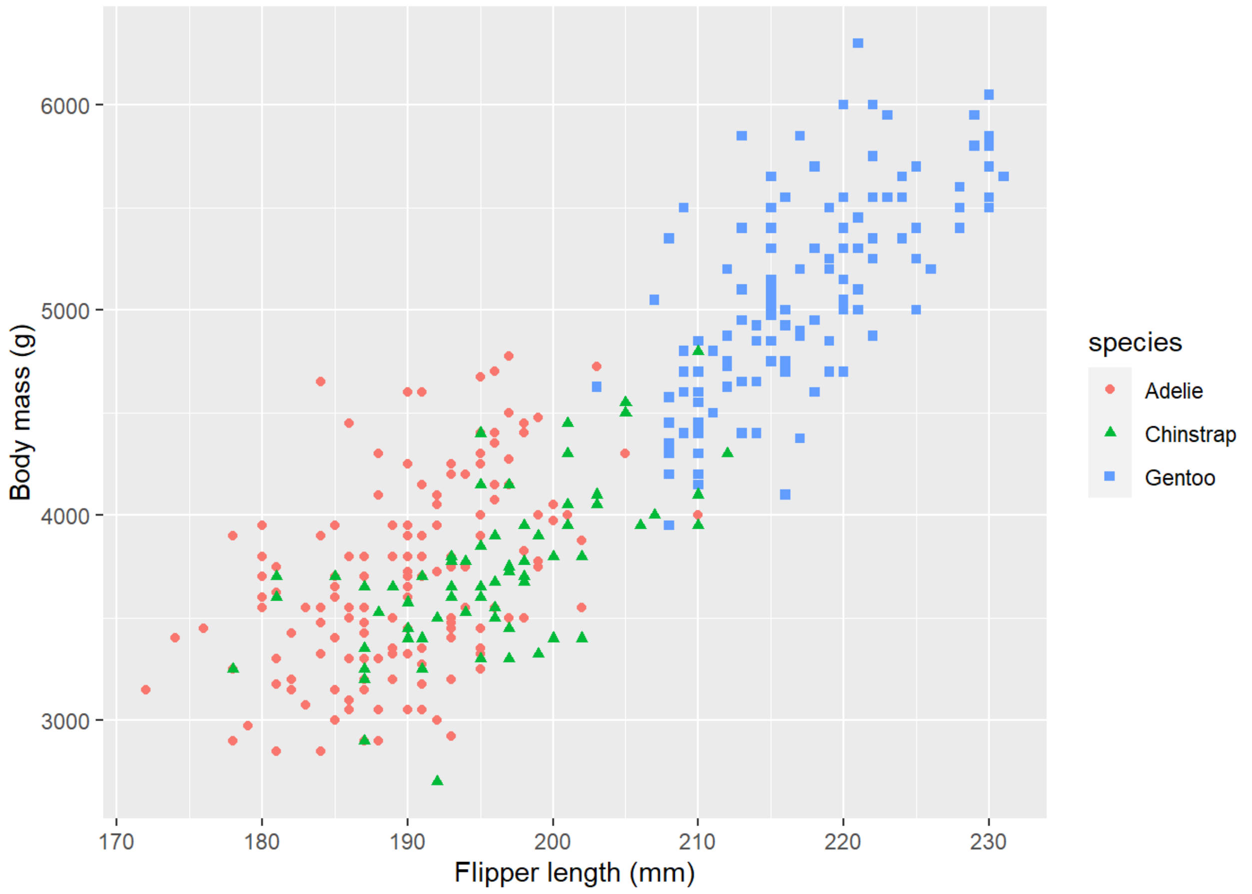
Body mass → vertical position.

Bill length → color

Bill depth → size

Multivariate plots

```
mass_flipper_scatter+geom_point(aes( color=species, shape = species))
```



Aesthetics

Flipper length → horizontal position.

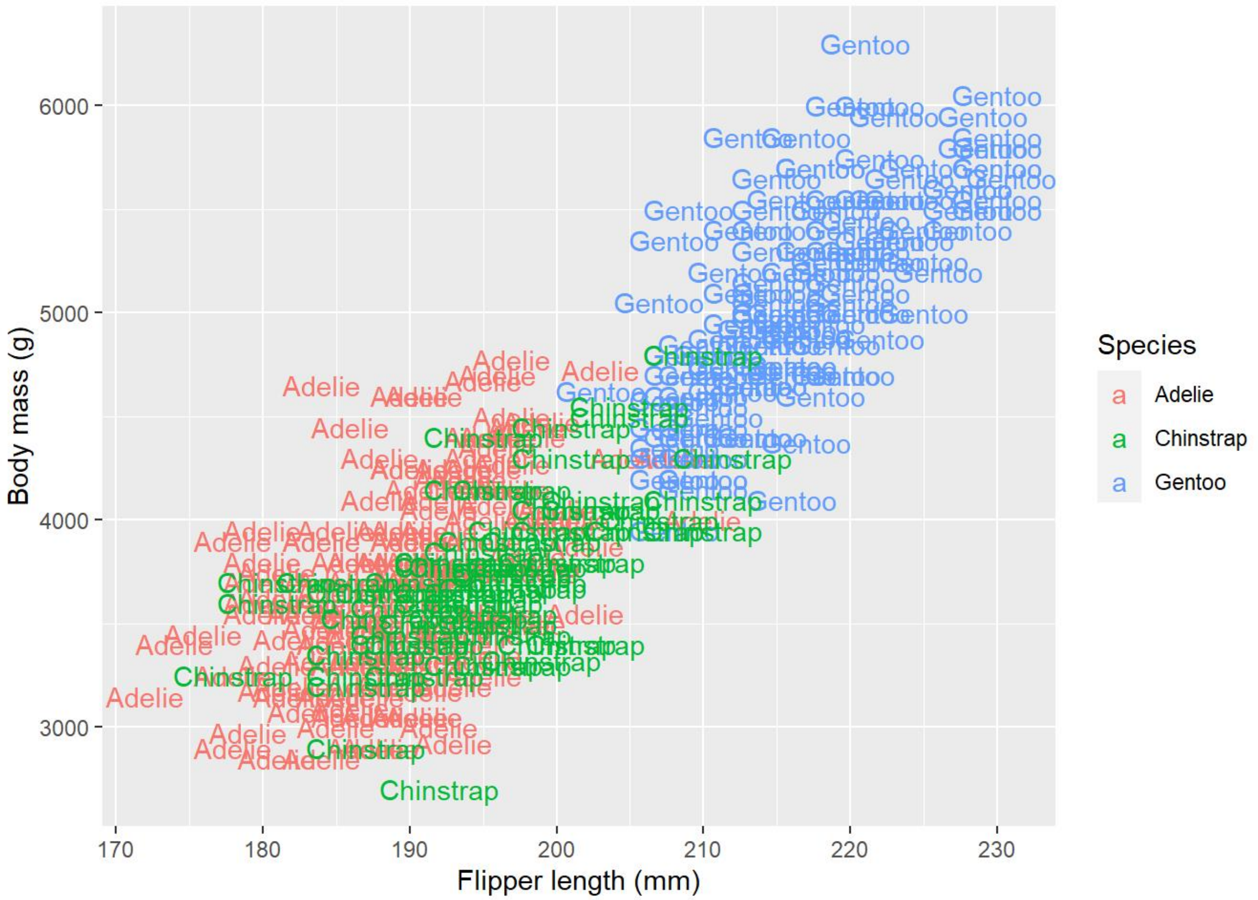
Body mass → vertical position.

Species → color

Species → shape

Multivariate plots

```
mass_flipper_scatter+geom_text(aes(label=species, color=species))+guides(color=guide_legend("Species"))
```



Aesthetics

Flipper length → horizontal position.

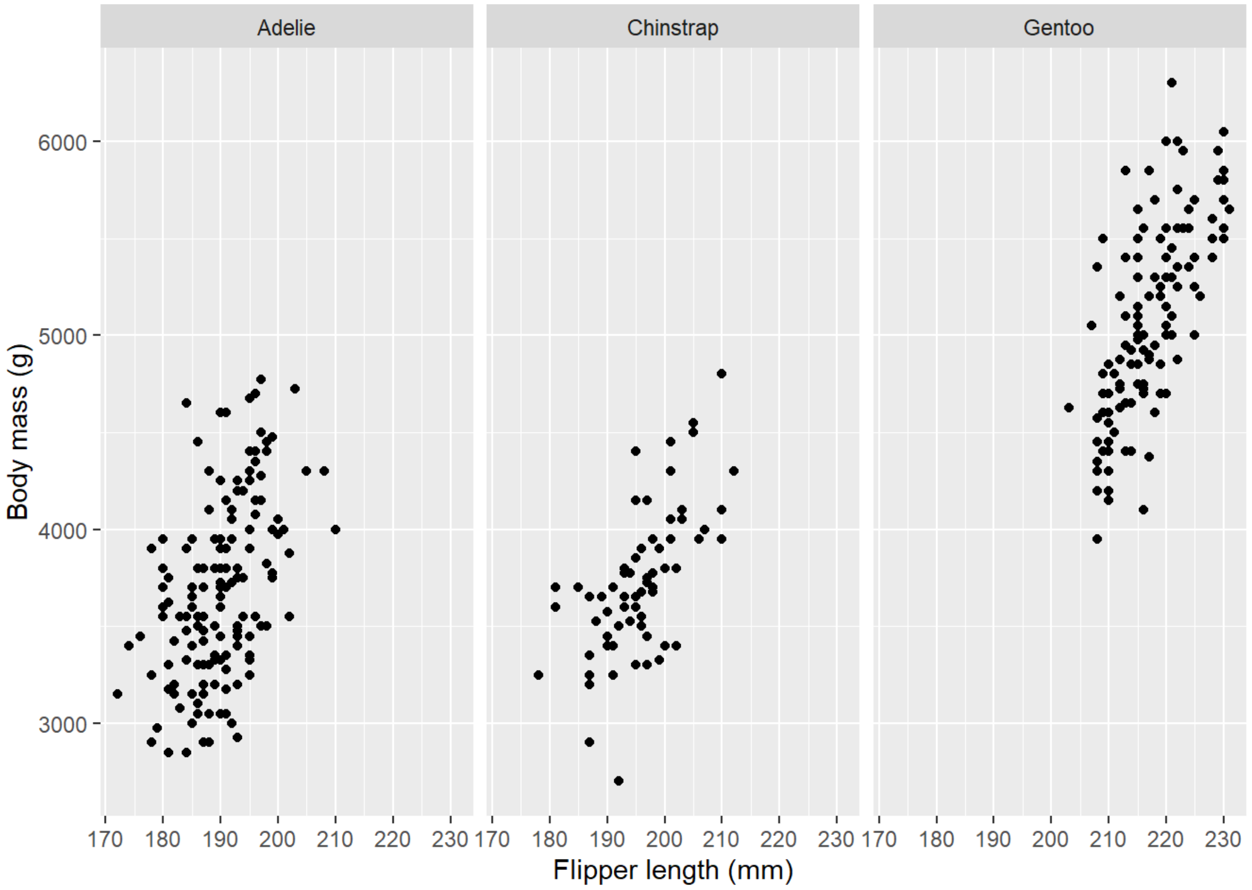
Body mass → vertical position.

Species → color

Species → text

Facets

```
mass_flipper_scatter+geom_point()+facet_wrap(~species)
```



Aesthetics

Flipper length → horizontal position.

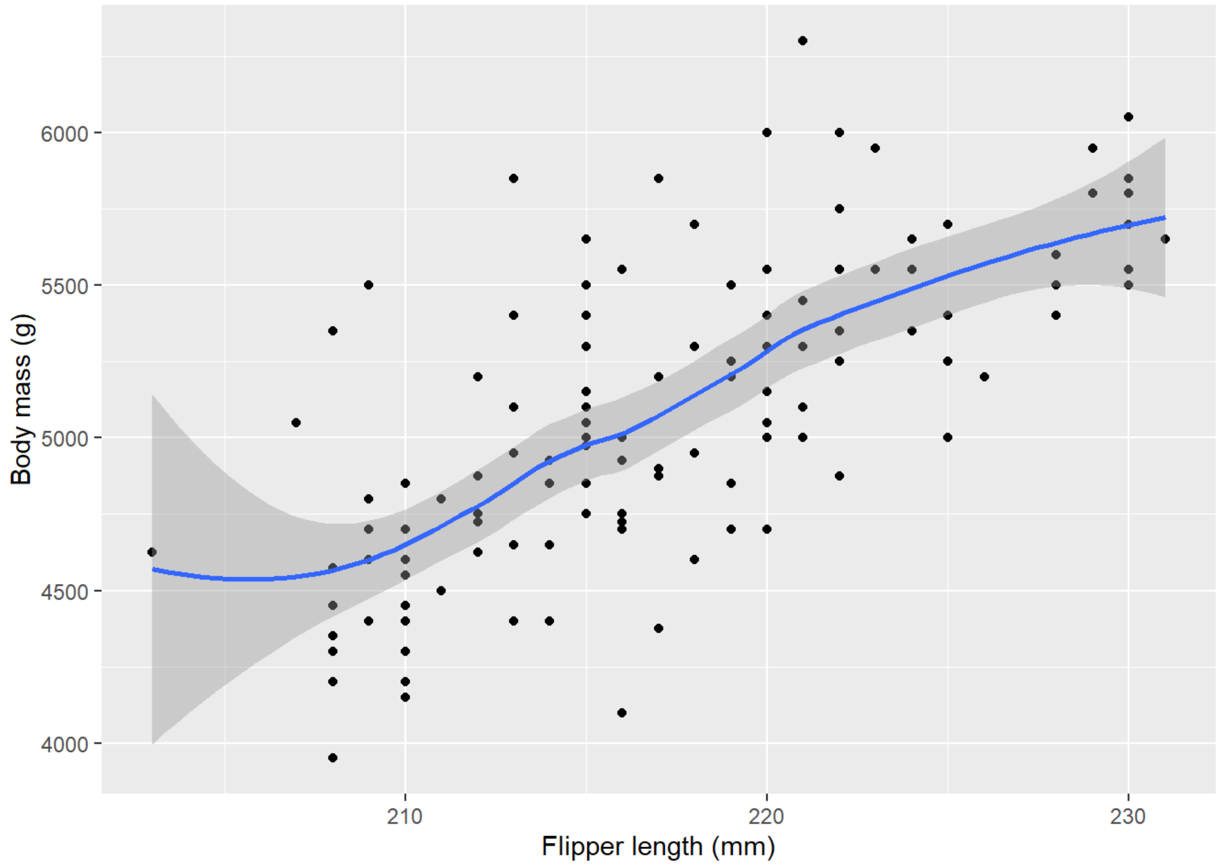
Body mass → vertical position

Facets

Species

Trend lines

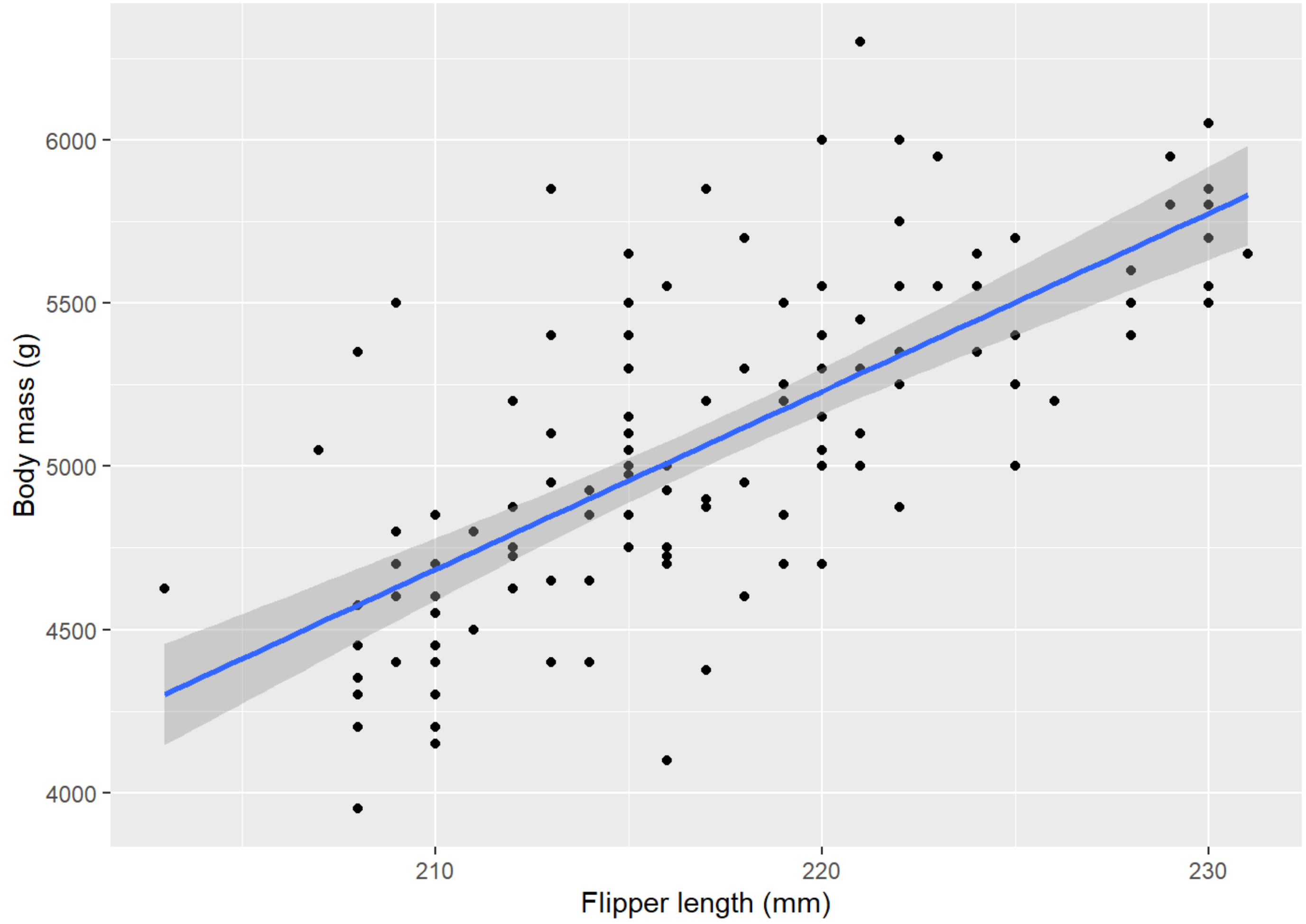
```
trend_plot<-ggplot(data=filter(penguins,species == "Gentoo"),aes(y=body_mass_g,x=flipper_length_mm))+
  xlab("Flipper length (mm)")+ylab("Body mass (g)")+geom_point()
trend_plot+geom_smooth()
```



Trend lines illustrate the relationship between two variables.

Trend lines

```
trend_plot+geom_smooth(method="lm")
```

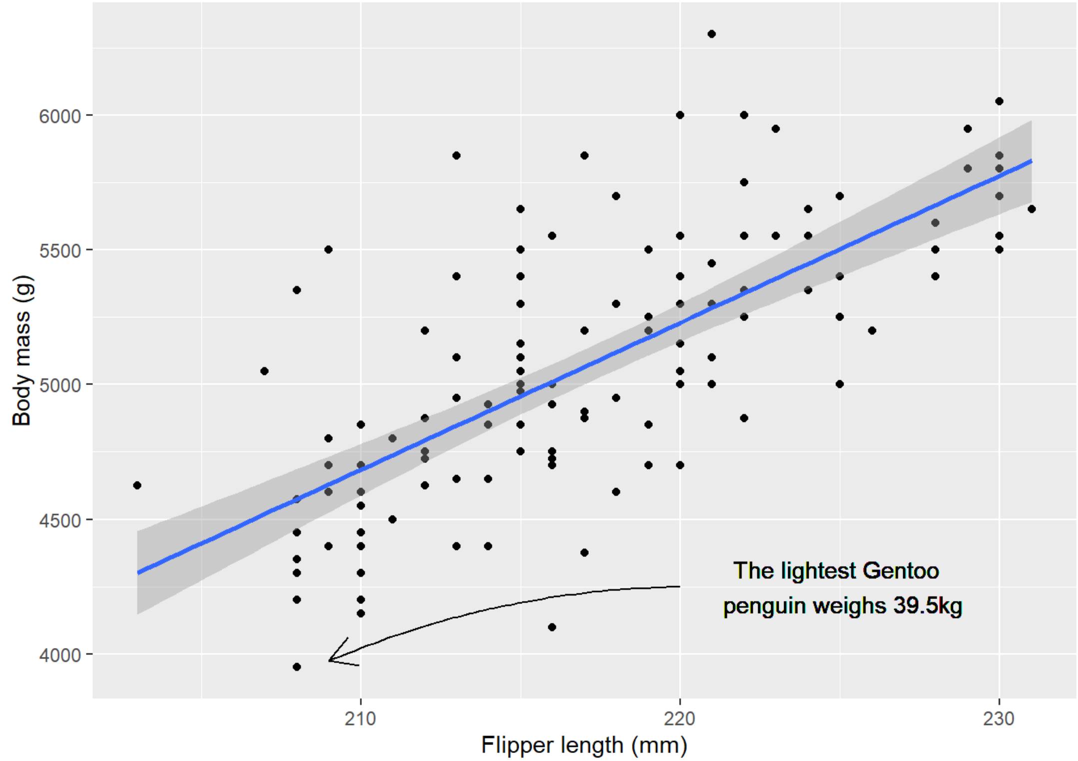


Annotation

```
min(filter(penguins,species == "Gentoo")$body_mass_g,na.rm=TRUE)
```

```
## [1] 3950
```

```
trend_plot+geom_smooth(method="lm")+
  geom_curve(x=220,xend=209,y=4250,yend=3975,arrow=arrow(length=unit(0.5,"cm")),curvature=0.1)+
  geom_text(x=225,y=4250,label="The lightest Gentoo \n penguin weighs 39.5kg")
```



GGplot2 gallery:

https://exts.ggplot2.tidyverse.org/gallery/

What have we covered?

- We discussed the importance of visualizations for data science:
  - To explore data
  - To explain your insights to colleagues.
- We have discussed the difference between various visual cues.
- We have had a brief look at the power of the ggplot2 library within R.

University of BRISTOL

Thanks for listening!

Henry W J Reeve

Any questions to: henry.reeve@bristol.ac.uk

With subject including: EMATM0061