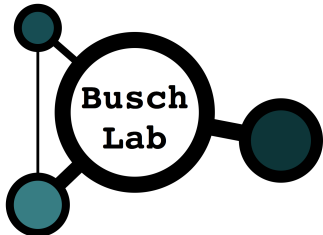


# Tidy data and visualisation with R

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# Topics

- Data manipulation
  - Introduction to the tidyverse
  - loading data (readr)
  - tidy data (tidyr)
  - selecting, filtering and creating new columns (dplyr)
- ggplot2
  - geoms
  - aesthetics
  - shapes and colours
  - facets
  - themes

# Preliminaries

- Code is shown in a different font with a grey background  
e.g. `head(data_frame)`

- lines that start with a `#` are comments  
e.g.

```
# this shows the top 6 lines of a data frame  
head(data_frame)
```

- The pipe operator `%>%`

- Provided by the `magrittr` package

- Equivalent of the unix pipe `|`  
`cut -f1,2,4 data.txt | head`

```
# select 3 columns and see the top lines  
select(data, c(1,2,4)) %>% head()
```

- Allows sending the results of one function into another
- Since v4.1.0, R has had its own version `|>`  
Has different functionality (see [here](#))

# Nested functions are hard to read

```
eat(slice(bake(put(pour(mix(ingredients), into = baking_mould),  
    into = oven), time = 30), pieces = 6), 1)
```

Even if you format the code nicely

```
eat(  
    slice(  
        bake(  
            put(  
                pour(  
                    mix(ingredients),  
                    into = baking_mould),  
                into = oven),  
            time = 30),  
        pieces = 6),  
    1)
```

# The pipe makes code easier to read

```
ingredients %>%  
  mix() %>%  
  pour(into = baking_mould) %>%  
  put(into = oven) %>%  
  bake(time = 30) %>%  
  slice(pieces = 6) %>%  
  eat(1)
```

from @dmi3k on Twitter

# Tidyverse

Tidyverse

[Packages](#) [Blog](#) [Learn](#) [Help](#) [Contribute](#)



## R packages for data science

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

Install the complete tidyverse with:

```
install.packages("tidyverse")
```

[tidyverse.org](https://tidyverse.org)

# Tidyverse packages



readr



dplyr



tidyr



ggplot2

# readr

- `read_tsv()`
  - reads in tab-delimited data and tries to guess the data type of each column
  - character, integer, numeric, logical
- `read_csv()`
  - same for comma-separated files



[readr.tidyverse.org](https://readr.tidyverse.org)



# read\_tsv

```
data_file <- 'assets/test-data.tsv'  
mock_data <- read_tsv(data_file)
```

```
## Rows: 2000 Columns: 7  
## — Column specification —————  
## Delimiter: "\t"  
## chr (2): Gene, Chr  
## dbl (5): pval, adjp, Start, End, Strand  
##  
## i Use `spec()` to retrieve the full column specification for this data.  
## i Specify the column types or set `show_col_types = FALSE` to quiet this m
```

```
head(mock_data, 3)
```

```
## # A tibble: 3 × 7  
##   Gene          pval  adjp Chr   Start   End Strand  
##   <chr>        <dbl> <dbl> <chr> <dbl> <dbl> <dbl>  
## 1 ENSDARG000000000001 0.771     1 14     5352   5542    -1  
## 2 ENSDARG000000000002 0.643     1 19    261334 261907    -1  
## 3 ENSDARG000000000003 0.687     1 13    604674 605540     1
```

# Column types

`readr` tries to correctly guess the data types

It does this by randomly sampling rows from the dataset (1000 rows by default).

If you find that `readr` is not correctly guessing the data types there are two solutions.

1. increase `guess_max`

2. define the column types explicitly

```
read_tsv(data_file, guess_max = 5000)
```

```
read_tsv(data_file, col_types = "cddciif")
```

```
read_tsv(data_file,  
  col_types = cols(Chr = col_character(),  
                   Strand = col_factor(levels = c("1", "-1"))))
```

# Factors

- Factors are used to work with categorical variables
- variables that have a fixed and known set of possible values

```
(genotype <- rep(c('wt', 'het', 'hom'), each = 3))
```

```
## [1] "wt" "wt" "wt" "het" "het" "het" "hom" "hom" "hom"
```

```
factor(genotype)
```

```
## [1] wt wt wt het het het hom hom hom  
## Levels: het hom wt
```

```
factor(genotype,  
       levels = c("wt", "het", "hom"))
```

```
## [1] wt wt wt het het het hom hom hom  
## Levels: wt het hom
```

# Factors

```
factor(c(genotype, 'hot'),  
       levels = c("wt", "het", "hom"))
```

```
## [1] wt wt wt het het het hom hom hom <NA>  
## Levels: wt het hom
```



[forcats.tidyverse.org](https://forcats.tidyverse.org)

# Tidy data

1. Every column is a variable.
2. Every row is an observation.
3. Every cell is a single value.

name	gene	sample	count	normalised_count
slc35a5	ENSDARG000000000001	sample_1	35	36.28
ccdc80	ENSDARG000000000002	sample_1	75	75.51
slc35a5	ENSDARG000000000001	sample_2	30	33.43
ccdc80	ENSDARG000000000002	sample_2	115	113.15

# Tidy data

Data is often not in this format. Often for very good reasons.  
One common arrangement for RNA-seq data is like this:

name	description	s1_count	s2_count	s1_norm_count	s2_norm_count
slc35a5	ENSDARG000000000001	35	30	36.28	33.43
ccdc80	ENSDARG000000000002	75	115	75.51	113.15
nrf1	ENSDARG000000000003	300	283	305.95	281.17

For example the Amphetamine dataset has 32520 rows (Genes) and 55 columns (18 Mb)

In tidy format it would be 715440 rows and 14 columns (130 Mb)

For plotting with `ggplot`, tidy data is required.

The `tidyr` package is designed to do this kind of rearrangement.



[tidyr.tidyverse.org](https://tidyr.tidyverse.org)

# Wide vs long data

id	x	y	z
1	a	c	e
2	b	d	f

id	name	val
1	x	a
1	y	c
1	z	e
2	x	b
2	y	d
2	z	f

# pivot\_longer()

```
df
```

```
## # A tibble: 2 × 4
##   id x     y     z
##   <dbl> <chr> <chr> <chr>
## 1     1 a     c     e
## 2     2 b     d     f
```

```
pivot_longer(df, cols = c(x, y, z),
              names_to = 'sample',
              values_to = 'count')
```

```
## # A tibble: 6 × 3
##   id sample count
##   <dbl> <chr>   <chr>
## 1     1 x     a
## 2     1 y     c
## 3     1 z     e
## 4     2 x     b
## 5     2 y     d
## 6     2 z     f
```



# pivot\_wider()

```
df_long
```

```
## # A tibble: 6 × 3
##   id sample count
##   <dbl> <chr> <chr>
## 1     1 x     a
## 2     1 y     b
## 3     1 z     c
## 4     2 x     d
## 5     2 y     e
## 6     2 z     f
```

```
pivot_wider(df_long, id_cols = id,
            names_from = 'sample',
            values_from = 'count')
```

```
## # A tibble: 2 × 4
##   id x     y     z
##   <dbl> <chr> <chr> <chr>
## 1     1 a     b     c
## 2     2 d     e     f
```

# Data manipulation

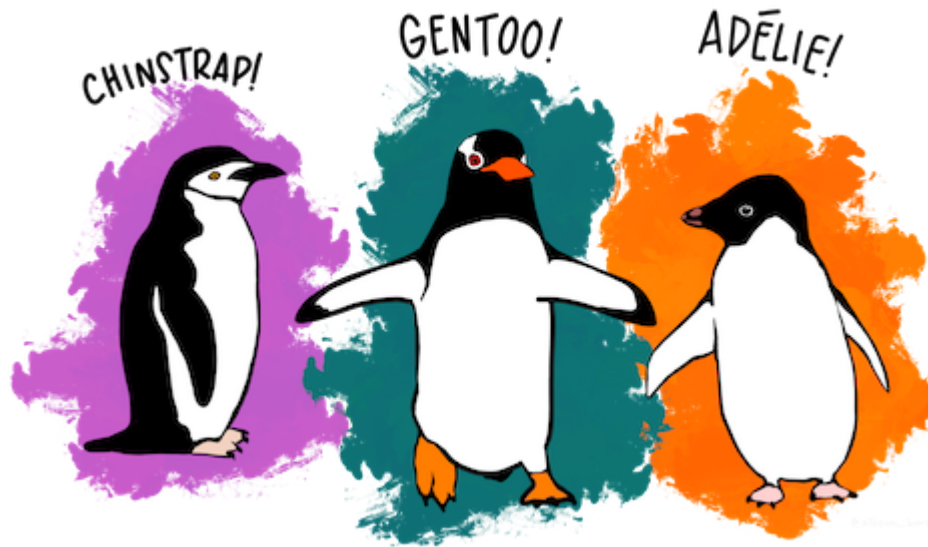
- `select()` - pick variables
- `filter()` - pick rows
- `arrange()` - sort rows
- `mutate()` - create new variables
- `summarise()` - reduce multiple values down to a single summary (mean, min, max etc.)



[dplyr.tidyverse.org](https://dplyr.tidyverse.org)

# Palmer Penguins

This dataset is available in the `palmerpenguins` package. It contains data for 3 different species of penguins (344 individuals), collected from 3 islands in the Palmer Archipelago, Antarctica.



Data were collected and made available by Dr. Kristen Gorman and the Palmer Station, Antarctica LTER, a member of the Long Term Ecological Research Network.

<https://allisonhorst.github.io/palmerpenguins>

# Palmer Penguins

```
library(palmerpenguins)  
head(penguins)
```

species	island	bill_length_mm	bill_depth_mm	flipper_length_mm	body_mass_g	sex	year
Adelie	Torgersen	39.1	18.7	181	3750	male	2007
Adelie	Torgersen	39.5	17.4	186	3800	female	2007
Adelie	Torgersen	40.3	18.0	195	3250	female	2007
Adelie	Torgersen	NA	NA	NA	NA	NA	2007
Adelie	Torgersen	36.7	19.3	193	3450	female	2007
Adelie	Torgersen	39.3	20.6	190	3650	male	2007

# select()

- Choose variables from a table
  - use column names explicitly: `select(data, GeneID)`
  - or positions: `select(data, c(1,5,9))`
  - column names can be used as if they are positions  
e.g. `select(data, GeneID:Name)`
  - or search functions
    - `starts_with()` `select(data, starts_with('Ctrl'))`
    - `ends_with()` `select(data, ends_with('count'))`
    - `contains()` `select(data, contains('3dpf'))`
    - `matches()` `select(data, matches('3dpf.*count'))`

# select()

```
select(penguins, species, year, body_mass_g) %>% head(4)
```

```
## # A tibble: 4 × 3
##   species year body_mass_g
##   <fct>   <int>     <int>
## 1 Adelie  2007         3750
## 2 Adelie  2007         3800
## 3 Adelie  2007         3250
## 4 Adelie  2007          NA
```

```
select(penguins, -species, -flipper_length_mm) %>% head(4)
```

```
## # A tibble: 4 × 6
##   island      bill_length_mm bill_depth_mm body_mass_g sex      year
##   <fct>          <dbl>         <dbl>     <int> <fct> <int>
## 1 Torgersen      39.1           18.7         3750 male   2007
## 2 Torgersen      39.5           17.4         3800 female 2007
## 3 Torgersen      40.3           18           3250 female 2007
## 4 Torgersen      NA              NA              NA <NA> 2007
```

# select()

```
select(penguins, starts_with('bill')) %>% head(4)
```

```
## # A tibble: 4 × 2
##   bill_length_mm bill_depth_mm
##           <dbl>         <dbl>
## 1           39.1           18.7
## 2           39.5           17.4
## 3           40.3            18
## 4            NA            NA
```

```
select(penguins, ends_with('mm')) %>% head(4)
```

```
## # A tibble: 4 × 3
##   bill_length_mm bill_depth_mm flipper_length_mm
##           <dbl>         <dbl>         <int>
## 1           39.1           18.7            181
## 2           39.5           17.4            186
## 3           40.3            18            195
## 4            NA            NA             NA
```

# select()

```
select(penguins, species, contains('length')) %>% head(4)
```

```
## # A tibble: 4 × 3
##   species bill_length_mm flipper_length_mm
##   <fct>      <dbl>          <int>
## 1 Adelie     39.1             181
## 2 Adelie     39.5             186
## 3 Adelie     40.3             195
## 4 Adelie     NA                NA
```

```
select(penguins, matches('_[mg]')) %>% head(4)
```

```
## # A tibble: 4 × 4
##   bill_length_mm bill_depth_mm flipper_length_mm body_mass_g
##   <dbl>          <dbl>          <int>        <int>
## 1 39.1            18.7             181         3750
## 2 39.5            17.4             186         3800
## 3 40.3            18                195         3250
## 4 NA              NA                NA           NA
```



# filter()

- Choose rows where conditions are true  
If there are multiple conditions, they must all be true
- check equality with == (!= for not equal to)
- Also <, >, <= ( $\leq$ ), >= ( $\geq$ )
- combine operators with & (AND), | (OR), ! (NOT)

# filter() equality

```
filter(penguins, species == "Gentoo")
```

```
## # A tibble: 124 × 8
##   species island bill_length_mm bill_depth_mm flipper_len...1 body_...2 sex
##   <fct>   <fct>         <dbl>         <dbl>         <int>     <int> <fct>
## 1 Gentoo  Biscoe           46.1           13.2           211       4500 fema..
## 2 Gentoo  Biscoe            50            16.3           230       5700 male
## 3 Gentoo  Biscoe           48.7           14.1           210       4450 fema..
## 4 Gentoo  Biscoe            50            15.2           218       5700 male
## 5 Gentoo  Biscoe           47.6           14.5           215       5400 male
## 6 Gentoo  Biscoe           46.5           13.5           210       4550 fema..
## 7 Gentoo  Biscoe           45.4           14.6           211       4800 fema..
## 8 Gentoo  Biscoe           46.7           15.3           219       5200 male
## 9 Gentoo  Biscoe           43.3           13.4           209       4400 fema..
## 10 Gentoo Biscoe           46.8           15.4           215       5150 male
## # ... with 114 more rows, and abbreviated variable names 1flipper_length_mm,
## # 2body_mass_g
```

# filter() greater than

```
filter(penguins, bill_length_mm > 50)
```

```
## # A tibble: 52 × 8
##   species island bill_length_mm bill_depth_mm flipper_len...1 body...2 sex
##   <fct>   <fct>      <dbl>          <dbl>          <int>      <int> <fct>
## 1 Gentoo  Biscoe         50.2           14.3            218        5700 male
## 2 Gentoo  Biscoe         59.6            17              230        6050 male
## 3 Gentoo  Biscoe         50.5           15.9            222        5550 male
## 4 Gentoo  Biscoe         50.5           15.9            225        5400 male
## 5 Gentoo  Biscoe         50.1            15              225        5000 male
## 6 Gentoo  Biscoe         50.4           15.3            224        5550 male
## 7 Gentoo  Biscoe         54.3           15.7            231        5650 male
## 8 Gentoo  Biscoe         50.7            15              223        5550 male
## 9 Gentoo  Biscoe         51.1           16.3            220        6000 male
## 10 Gentoo Biscoe         52.5           15.6            221        5450 male
## # ... with 42 more rows, and abbreviated variable names 1flipper_length_mm,
## # 2body_mass_g
```

# filter() combine conditions

```
filter(penguins, bill_length_mm > 50, flipper_length_mm >= 230)
```

```
## # A tibble: 5 × 8
##   species island bill_length_mm bill_depth_mm flipper_leng...1 body_...2 sex
##   <fct>   <fct>         <dbl>         <dbl>         <int>     <int> <fct>
## 1 Gentoo  Biscoe             59.6           17            230      6050 male
## 2 Gentoo  Biscoe             54.3           15.7          231      5650 male
## 3 Gentoo  Biscoe             52.1           17            230      5550 male
## 4 Gentoo  Biscoe             51.5           16.3          230      5500 male
## 5 Gentoo  Biscoe             55.1           16            230      5850 male
## # ... with abbreviated variable names 1flipper_length_mm, 2body_mass_g
```

# arrange()

```
arrange(penguins, bill_length_mm) %>% head(4)
```

```
## # A tibble: 4 × 8
##   species island      bill_length_mm bill_depth_mm flipper_l...1 body...2 sex
##   <fct>   <fct>          <dbl>          <dbl>          <int>    <int> <fct>
## 1 Adelie  Dream              32.1           15.5            188     3050 fema..
## 2 Adelie  Dream              33.1           16.1            178     2900 fema..
## 3 Adelie  Torgersen          33.5            19              190     3600 fema..
## 4 Adelie  Dream              34              17.1            185     3400 fema..
## # ... with abbreviated variable names 1flipper_length_mm, 2body_mass_g
```

```
# reverse order
arrange(penguins, desc(bill_length_mm)) %>% head(4)
```

```
## # A tibble: 4 × 8
##   species   island bill_length_mm bill_depth_mm flipper_le...1 body...2 sex
##   <fct>    <fct>          <dbl>          <dbl>          <int>    <int> <fct>
## 1 Gentoo   Biscoe          59.6            17              230     6050 male
## 2 Chinstrap Dream          58              17.8            181     3700 fema..
## 3 Gentoo   Biscoe          55.9            17              228     5600 male
## 4 Chinstrap Dream          55.8            19.8            207     4000 male
## # ... with abbreviated variable names 1flipper_length_mm, 2body_mass_g
```

# arrange()

```
arrange(penguins, species) %>% head(3)
```

```
## # A tibble: 3 × 8
##   species island      bill_length_mm bill_depth_mm flipper_l...1 body_...2 sex
##   <fct>   <fct>          <dbl>          <dbl>          <int>     <int> <fct>
## 1 Adelie  Torgersen          39.1           18.7           181       3750 male
## 2 Adelie  Torgersen          39.5           17.4           186       3800 fema..
## 3 Adelie  Torgersen          40.3           18             195       3250 fema..
## # ... with abbreviated variable names 1flipper_length_mm, 2body_mass_g
```

```
# data frames arranged by factor are
# sorted according to the levels of the factor
arrange(penguins, island) %>% head(3)
```

```
## # A tibble: 3 × 8
##   species island bill_length_mm bill_depth_mm flipper_leng...1 body_...2 sex
##   <fct>   <fct>          <dbl>          <dbl>          <int>     <int> <fct>
## 1 Adelie  Dream           39.5           16.7           178       3250 fema..
## 2 Adelie  Dream           37.2           18.1           178       3900 male
## 3 Adelie  Dream           39.5           17.8           188       3300 fema..
## # ... with abbreviated variable names 1flipper_length_mm, 2body_mass_g
```

# mutate ( )

- mutate makes new columns
- mutate keeps the original column
- transmute keeps only the new variables you create

# mutate()

```
mutate(penguins,  
       mass_by_bill_length = body_mass_g/bill_length_mm) %>%  
head()
```

```
## # A tibble: 6 × 5  
##   species island   body_mass_g bill_length_mm mass_by_bill_length  
##   <fct>   <fct>         <int>         <dbl>         <dbl>  
## 1 Adelie  Torgersen         3750          39.1          95.9  
## 2 Adelie  Torgersen         3800          39.5          96.2  
## 3 Adelie  Torgersen         3250          40.3          80.6  
## 4 Adelie  Torgersen          NA           NA            NA  
## 5 Adelie  Torgersen         3450          36.7          94.0  
## 6 Adelie  Torgersen         3650          39.3          92.9
```



# mutate()

```
mutate(penguins,  
  bill_depth_mm_transformed = case_when(  
    species == "Adelie" ~ bill_depth_mm * 10,  
    species == "Chinstrap" ~ bill_depth_mm / 10,  
    TRUE ~ bill_depth_mm  
  ))
```

```
## # A tibble: 6 × 4  
##   species    island  bill_depth_mm bill_depth_mm_transformed  
##   <fct>      <fct>          <dbl>                <dbl>  
## 1 Adelie    Torgersen      18.7                  187  
## 2 Adelie    Torgersen      17.4                  174  
## 3 Chinstrap Dream        17.9                   1.79  
## 4 Chinstrap Dream        19.5                   1.95  
## 5 Gentoo   Biscoe        13.2                   13.2  
## 6 Gentoo   Biscoe        16.3                   16.3
```

# summarise()

```
summarise(penguins,  
          min_weight = min(body_mass_g, na.rm = TRUE),  
          mean_weight = mean(body_mass_g, na.rm = TRUE),  
          max_weight = max(body_mass_g, na.rm = TRUE))
```

```
## # A tibble: 1 × 3  
##   min_weight mean_weight max_weight  
##   <int>      <dbl>      <int>  
## 1      2700      4202.      6300
```

```
group_by(penguins, species) %>%  
  summarise(min_weight = min(body_mass_g, na.rm = TRUE),  
            mean_weight = mean(body_mass_g, na.rm = TRUE),  
            max_weight = max(body_mass_g, na.rm = TRUE))
```

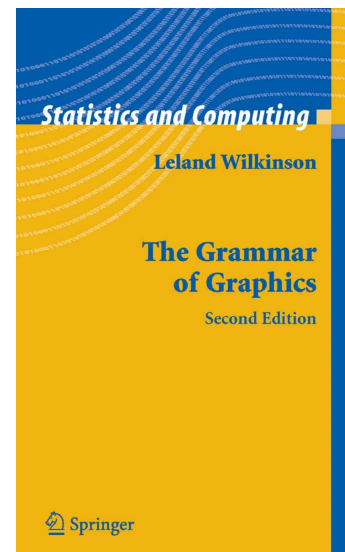
```
## # A tibble: 3 × 4  
##   species    min_weight mean_weight max_weight  
##   <fct>      <int>      <dbl>      <int>  
## 1 Adelie      2850      3701.      4775  
## 2 Chinstrap  2700      3733.      4800  
## 3 Gentoo     3950      5076.      6300
```

# Exercises

Open [r-data-vis-exercises.pdf](#) and do the **Tidy Data** exercises

# ggplot2

- Grammar of Graphics
  - Leland Wilkinson (2005)
- Components of a plot
  1. data
  2. geom
    - How the data is represented e.g. points, lines, bars, text
  3. aesthetics
    - attributes of a plot that variables in the data are mapped to
    - x, y, colour, shape, length, size, linetype



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

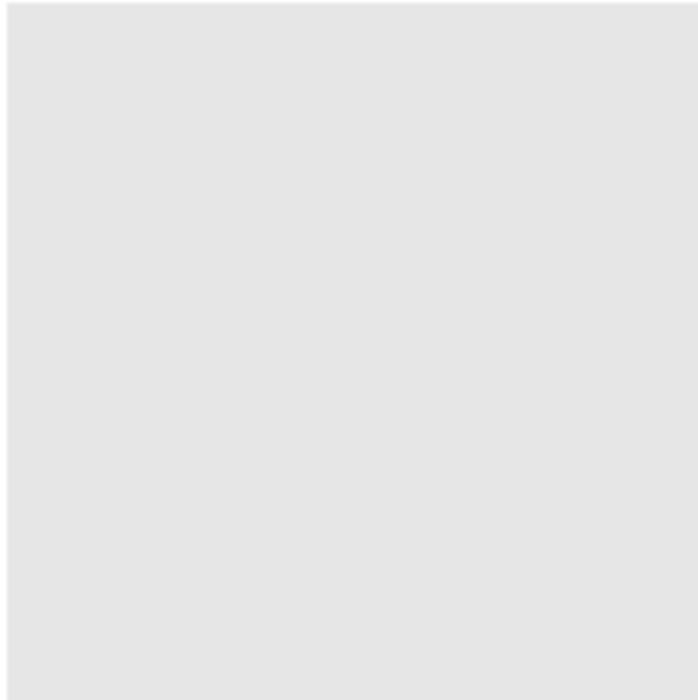


ggplot2

[ggplot2.tidyverse.org](http://ggplot2.tidyverse.org)

# Base plot

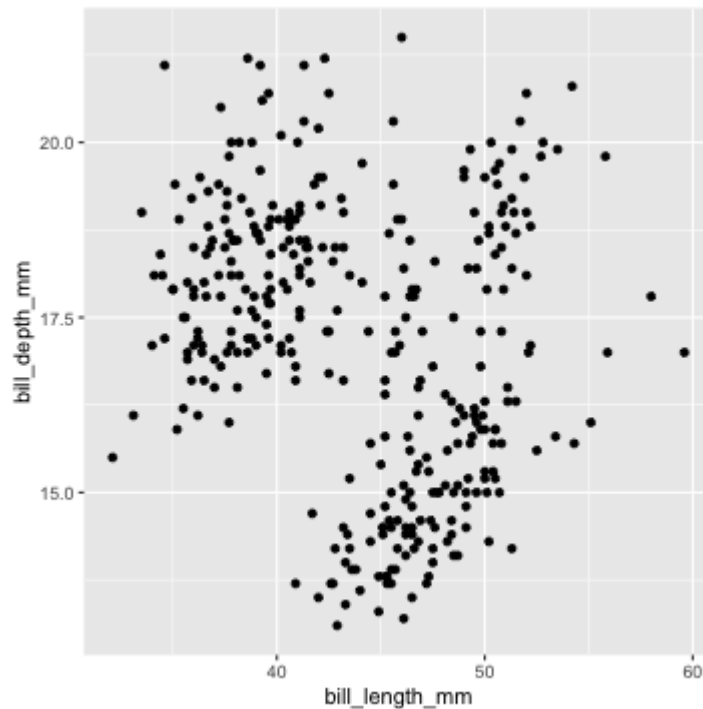
```
ggplot(data = penguins)
```



# Scatterplot

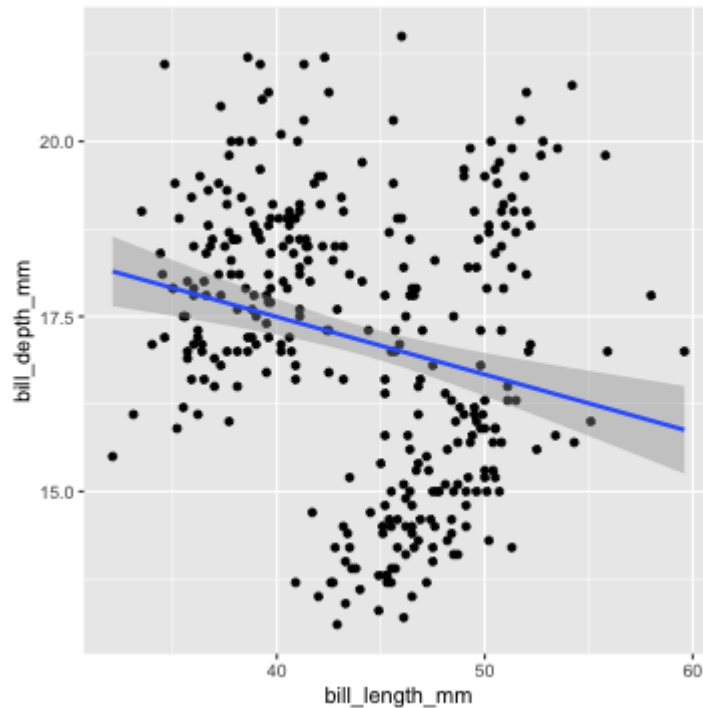
```
ggplot(data = penguins) +  
  geom_point(mapping = aes(x = bill_length_mm, y = bill_depth_mm))
```

## Warning: Removed 2 rows containing missing values (geom\_point).



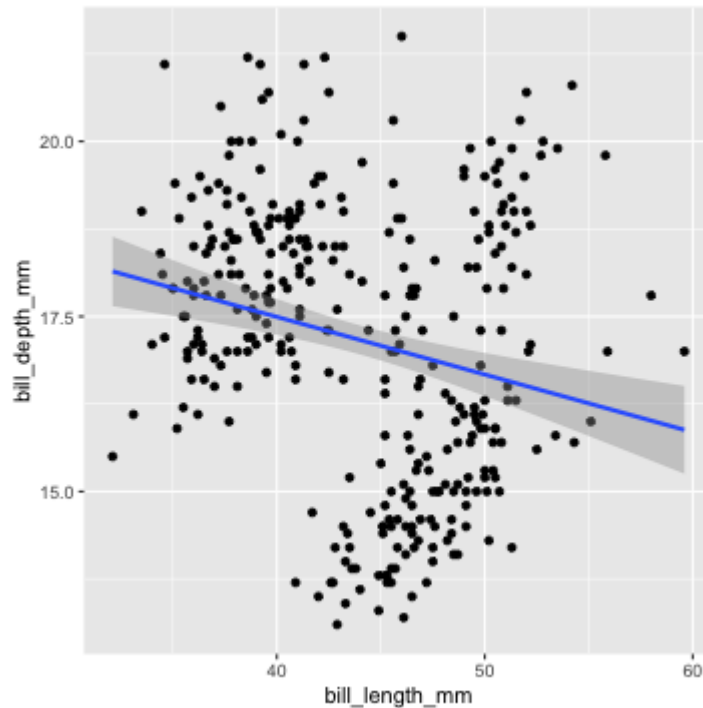
# Add another geom

```
ggplot(data = penguins) +  
  geom_point(mapping = aes(x = bill_length_mm, y = bill_depth_mm)) +  
  geom_smooth(mapping = aes(x = bill_length_mm, y = bill_depth_mm),  
             method = "lm", formula = y ~ x)
```



# Set the aesthetics for the whole plot

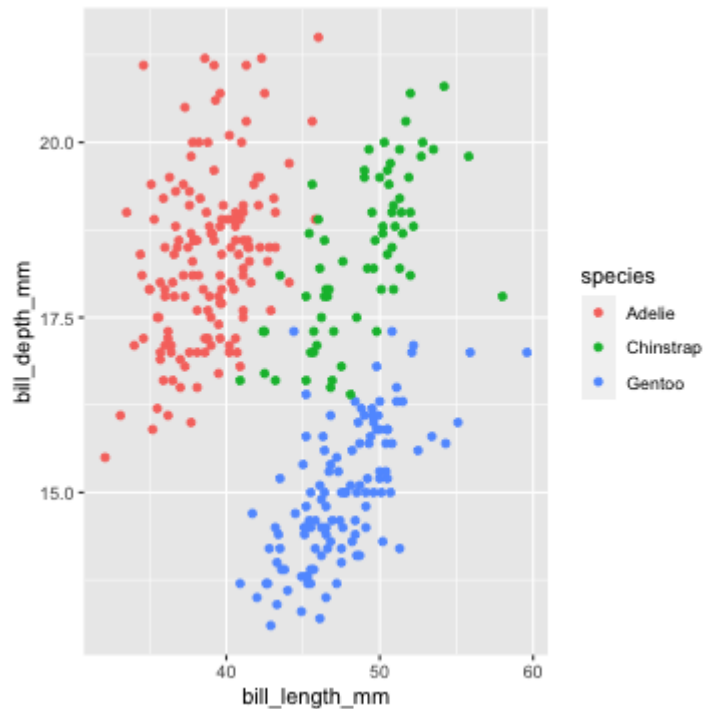
```
ggplot(data = penguins,  
       mapping = aes(x = bill_length_mm, y = bill_depth_mm)) +  
  geom_point() +  
  geom_smooth(method = "lm", formula = y ~ x)
```





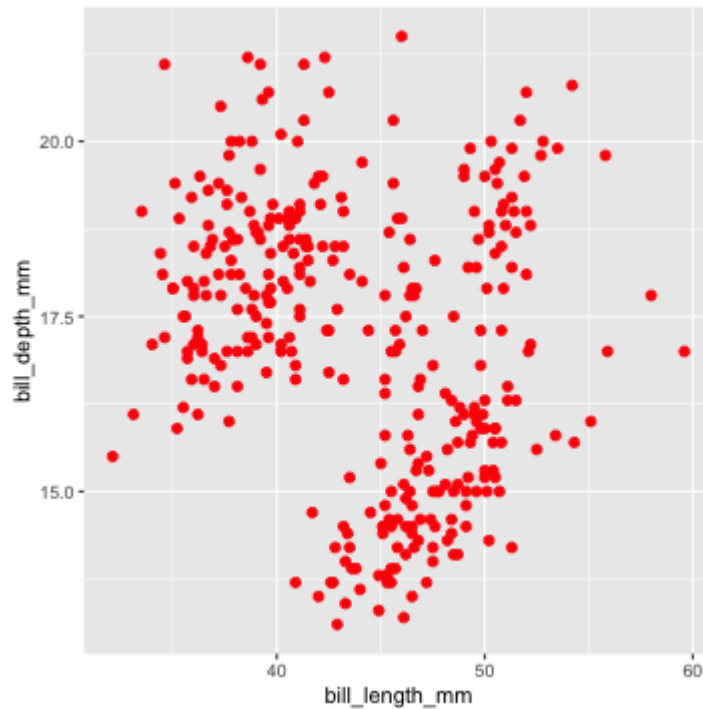
# Map categorical variable to colour

```
ggplot(data = penguins) +  
  geom_point(mapping = aes(x = bill_length_mm, y = bill_depth_mm,  
                           colour = species))
```



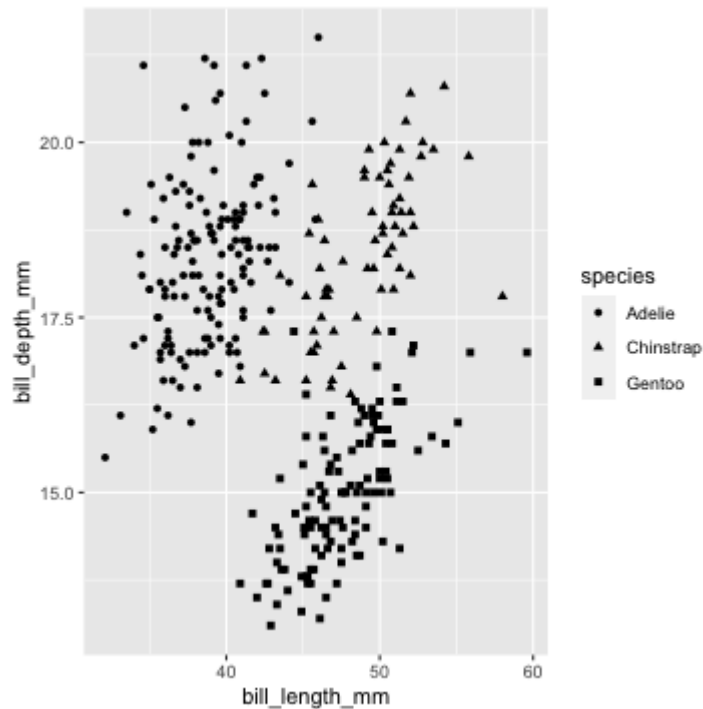
# Setting arguments outside of aes ( )

```
ggplot(data = penguins) +  
  geom_point(mapping = aes(x = bill_length_mm, y = bill_depth_mm),  
             colour = 'red', size = 2)
```



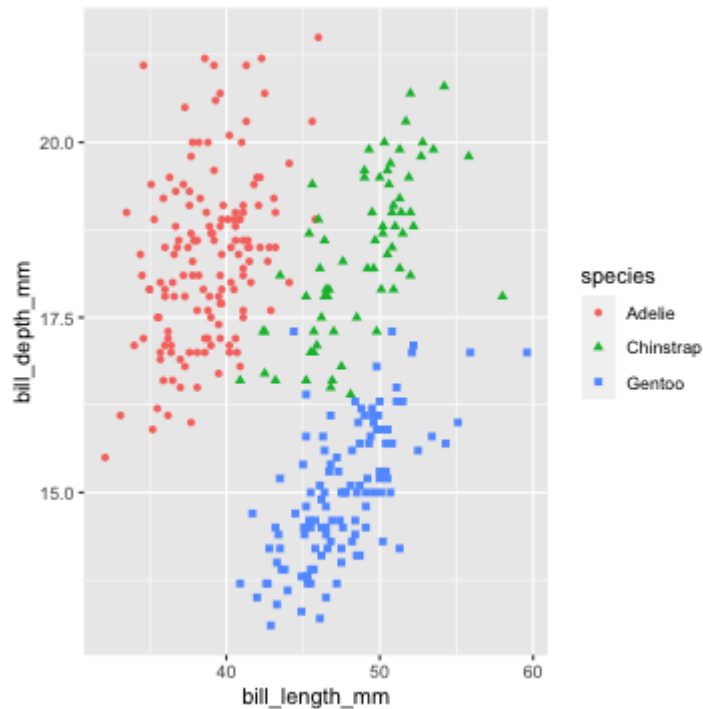
# Map categorical variable to shape

```
ggplot(data = penguins) +  
  geom_point(mapping = aes(x = bill_length_mm, y = bill_depth_mm,  
                           shape = species))
```



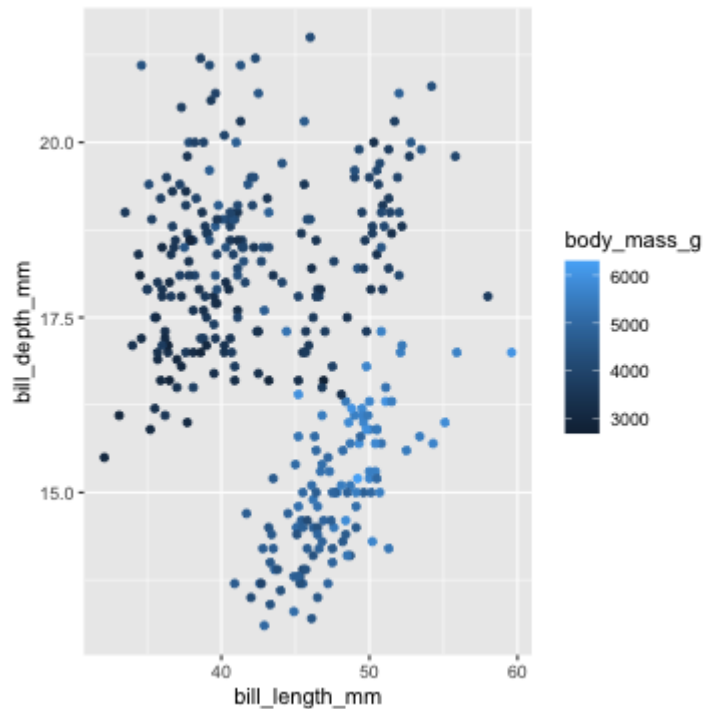
# Map to colour and shape

```
ggplot(data = penguins) +  
  geom_point(mapping = aes(x = bill_length_mm, y = bill_depth_mm,  
                           colour = species, shape = species))
```



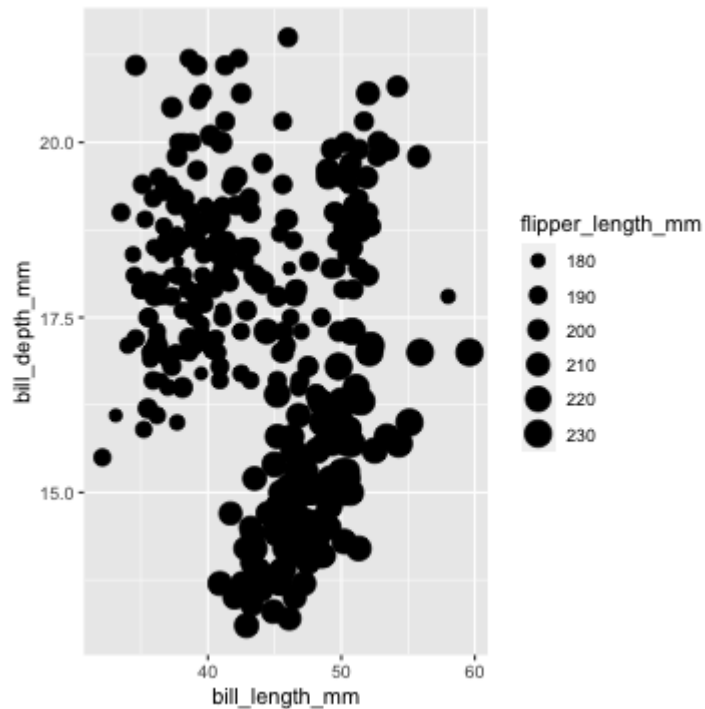
# Map continuous variable to colour

```
ggplot(data = penguins) +  
  geom_point(mapping = aes(x = bill_length_mm, y = bill_depth_mm,  
                           colour = body_mass_g))
```



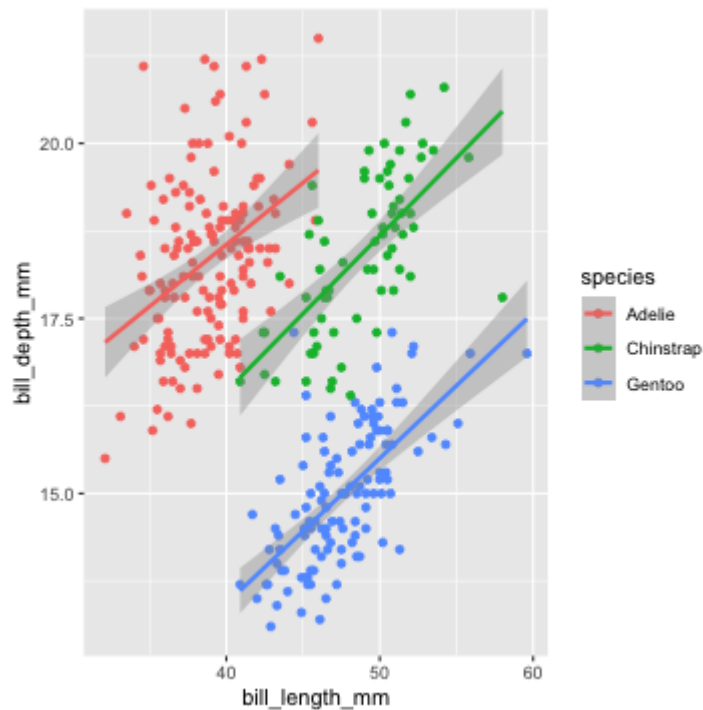
# Map continuous variable to size

```
ggplot(data = penguins) +  
  geom_point(mapping = aes(x = bill_length_mm, y = bill_depth_mm,  
                           size = flipper_length_mm))
```



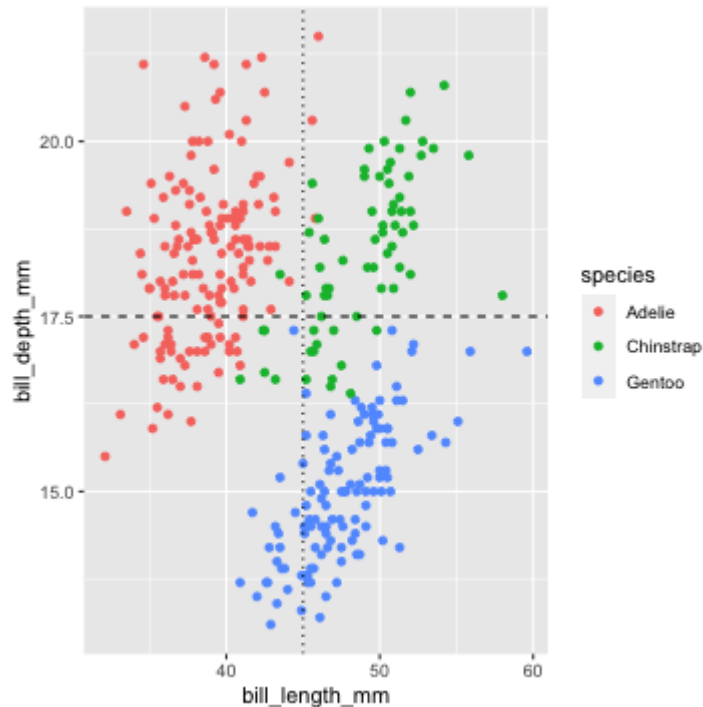
# Add extra geoms

```
ggplot(data = penguins,  
       mapping = aes(x = bill_length_mm, y = bill_depth_mm,  
                     colour = species)) +  
  geom_point() + geom_smooth(method = 'lm', formula = y ~ x)
```



# Add extra geoms

```
ggplot(data = penguins,  
       mapping = aes(x = bill_length_mm, y = bill_depth_mm,  
                     colour = species)) +  
  geom_point() +  
  geom_hline(yintercept = 17.5, linetype = "dashed") +  
  geom_vline(xintercept = 45, linetype = "dotted")
```

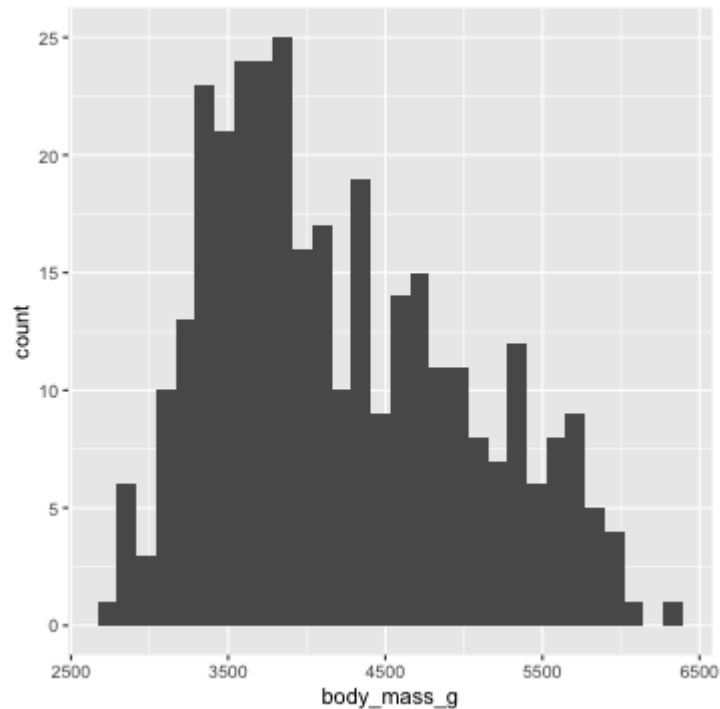




# geom\_histogram

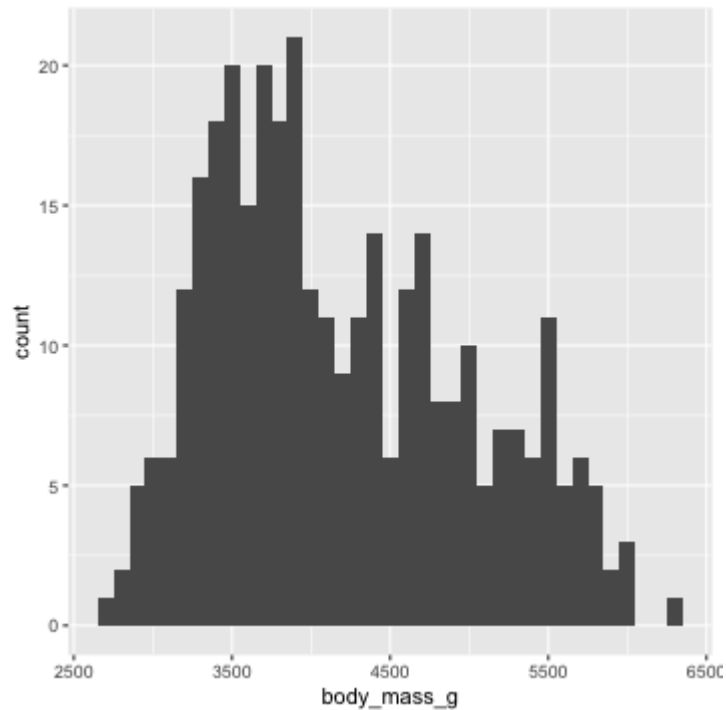
```
ggplot(data = penguins) +  
  geom_histogram(mapping = aes(x = body_mass_g))
```

## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



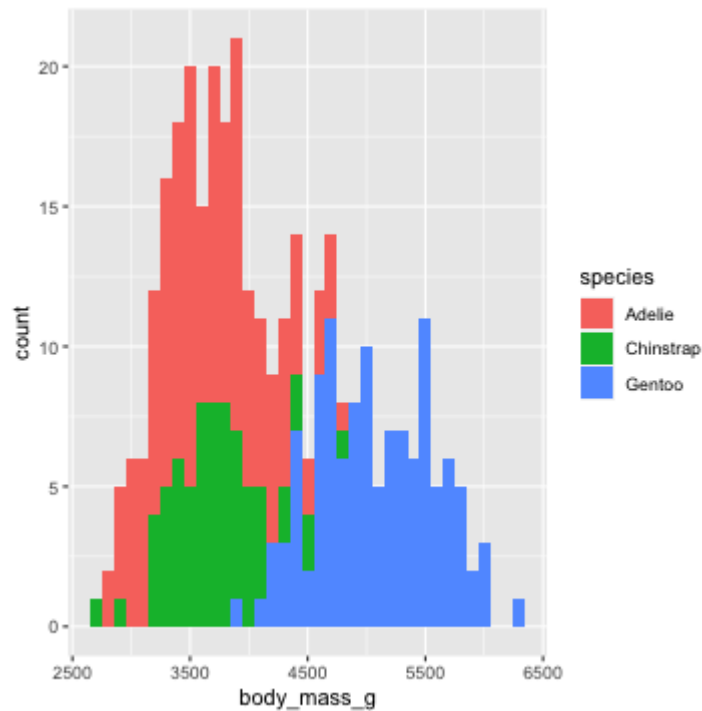
# geom\_histogram

```
ggplot(data = penguins) +  
  geom_histogram(mapping = aes(x = body_mass_g),  
                 binwidth = 100)
```



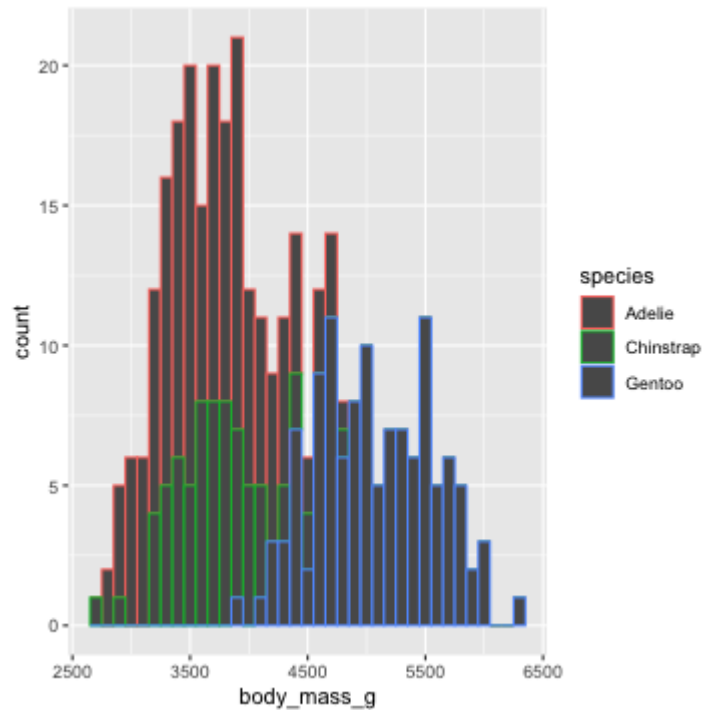
# geom\_histogram

```
ggplot(data = penguins) +  
  geom_histogram(mapping = aes(x = body_mass_g, fill = species),  
                 binwidth = 100)
```



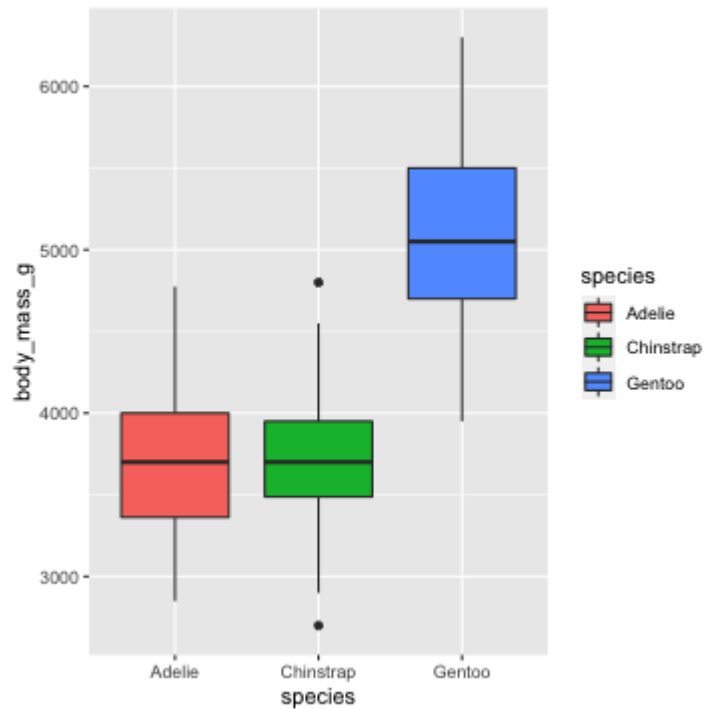
# geom\_histogram

```
ggplot(data = penguins) +  
  geom_histogram(mapping = aes(x = body_mass_g, colour = species),  
                 binwidth = 100)
```



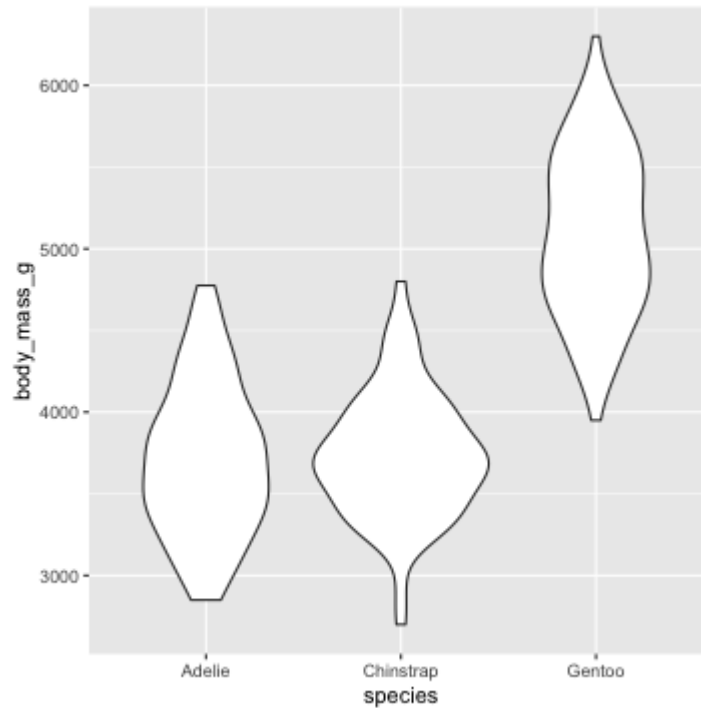
# Boxplots

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



# Violin plot

```
ggplot(data = penguins) +  
  geom_violin(mapping = aes(x = species, y = body_mass_g))
```



# colours ( )

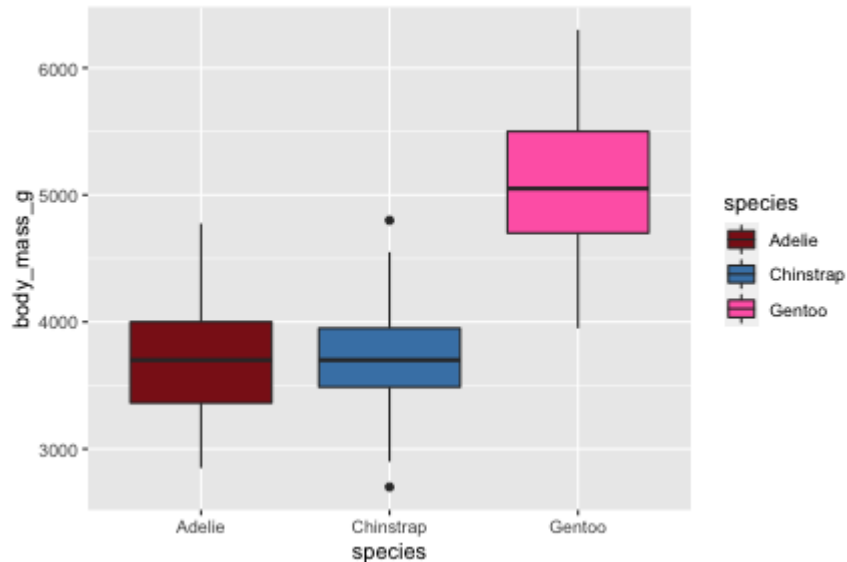
```
colours() %>% head()
```

```
## [1] "white" "aliceblue" "antiquewhite" "antiquewhite1"
## [5] "antiquewhite2" "antiquewhite3"
```

white	coral4	deepekyblue	gray28	gray88	gray40	grey100	lightpink2	mistyrose3	plum	slategray2
aliceblue	cornflowerblue	deepekyblue1	gray29	gray89	gray41	honeydew	lightpink3	mistyrose3	plum1	slategray3
antiquewhite	cornsilk	deepekyblue2	gray30	gray90	gray42	honeydew1	lightpink4	mistyrose4	plum2	slategray4
antiquewhite1	cornsilk1	deepekyblue3	gray31	gray91	gray43	honeydew2	lightsalmon	moccasin	plum3	slategray
antiquewhite2	cornsilk2	deepekyblue4	gray32	gray92	gray44	honeydew3	lightsalmon1	navajowhite	plum4	snow
antiquewhite3	cornsilk3	dimgray	gray33	gray93	gray45	honeydew4	lightsalmon2	navajowhite1	powderblue	snow1
antiquewhite4	cornsilk4	dimgray	gray34	gray94	gray46	hotpink	lightsalmon3	navajowhite2	purple	snow2
aquamarine	cyan	dodgerblue	gray35	gray95	gray47	hotpink	lightsalmon4	navajowhite3	purple1	snow3
aquamarine1	cyan1	dodgerblue1	gray36	gray96	gray48	hotpink2	lightseagreen	navajowhite4	purple2	snow4
aquamarine2	cyan2	dodgerblue2	gray37	gray97	gray49	hotpink3	lightskyblue	navy	purple3	springgreen
aquamarine3	cyan3	dodgerblue3	gray38	gray98	gray50	hotpink4	lightskyblue1	navyblue	purple4	springgreen1
aquamarine4	cyan4	dodgerblue4	gray39	gray99	gray51	indianred	lightskyblue2	oldlace	red	springgreen2
azure	darkblue	firebrick	gray40	gray100	gray52	indianred1	lightskyblue3	olivedrab	red1	springgreen3
azure1	darkcyan	firebrick1	gray41	green	gray53	indianred2	lightskyblue4	olivedrab1	red2	springgreen4
azure2	darkgoldenrod	firebrick2	gray42	green1	gray54	indianred3	lightslateblue	olivedrab2	red3	steelblue
azure3	darkgoldenrod1	firebrick3	gray43	green2	gray55	indianred3	lightslategray	olivedrab3	red4	steelblue1
azure4	darkgoldenrod2	firebrick4	gray44	green3	gray56	ivory	lightslategray	olivedrab4	rosybrown	steelblue2
beige	darkgoldenrod3	floralwhite	gray45	green4	gray57	ivory1	lightsteelblue	orange	rosybrown1	steelblue3
bisque	darkgoldenrod4	forestgreen	gray46	greenyellow	gray58	ivory2	lightsteelblue1	orange1	rosybrown2	steelblue4
bisque1	darkgray	gainsboro	gray47	grey	gray59	ivory3	lightsteelblue2	orange2	rosybrown3	tan
bisque2	darkgreen	ghostwhite	gray48		gray60	ivory4	lightsteelblue3	orange3	rosybrown4	tan1
bisque3	darkgray	gold	gray49		gray61	khaki	lightsteelblue4	orange4	royalblue	tan2
bisque4	darkkhaki	gold1	gray50		gray62	khaki1	lightyellow	orange4	royalblue1	tan3
	darkmagenta	gold2	gray51		gray63	khaki2	lightyellow1	orange4	royalblue2	tan4
	darkolivegreen	gold3	gray52		gray64	khaki3	lightyellow2	orange4	royalblue3	thistle
blanchedalmond	darkolivegreen1	gold4	gray53		gray65	khaki4	lightyellow3	orange4	royalblue4	thistle1
blue	darkolivegreen2	goldenrod	gray54		gray66	lavender	lightyellow4	orange4	saddlebrown	thistle2
blue1	darkolivegreen3	goldenrod1	gray55		gray67	lavenderblush	limegreen	orchid	salmon	thistle3
blue2	darkolivegreen2	goldenrod2	gray56		gray68	lavenderblush1	limegreen	orchid1	salmon1	thistle4
blue3	darkolivegreen4	goldenrod3	gray57		gray69	lavenderblush2	magenta	orchid2	salmon2	tomato
blueviolet	darkorange	goldenrod4	gray58		gray70	lavenderblush3	magenta1	orchid3	salmon3	tomato1
brown	darkorange1	gray	gray59		gray71	lavenderblush4	magenta2	orchid4	salmon4	tomato2
brown1	darkorange2		gray60		gray72	lavenderblush4	magenta3	palegoldenrod	sandybrown	tomato3
brown2	darkorange3		gray61		gray73	lemonchiffon	magenta4	palegreen	seagreen	tomato4
brown3	darkorange4		gray62		gray74	lemonchiffon1	maroon	palegreen1	seagreen1	turquoise
brown4	darkorchid		gray63		gray75	lemonchiffon2	maroon1	palegreen2	seagreen2	turquoise1
burlywood	darkorchid1		gray64		gray76	lemonchiffon3	maroon2	palegreen3	seagreen3	turquoise2
burlywood1	darkorchid2		gray65		gray77	lemonchiffon4	maroon3	palegreen4	seagreen4	turquoise3
burlywood2	darkorchid3		gray66		gray78	lightblue	maroon4	paleturquoise	seashell	turquoise4
burlywood3	darkorchid4		gray67		gray79	lightblue1	mediumaquamarine	paleturquoise1	seashell1	violet
burlywood4	darksalmon		gray68		gray80	lightblue2	mediumslateblue	paleturquoise2	seashell2	violet1
cadetblue	darkseagreen		gray69		gray81	lightblue3	mediumorchid	paleturquoise3	seashell3	violet2
cadetblue1	darkseagreen1		gray70		gray82	lightblue4	mediumorchid1	paleturquoise4	seashell4	violetred1
cadetblue2	darkseagreen2		gray71		gray83	lightcoral	mediumorchid2	palevioletred	sienna	violetred2
cadetblue3	darkseagreen3		gray72		gray84	lightcyan	mediumorchid3	palevioletred1	sienna1	violetred3
cadetblue4	darkseagreen4		gray73		gray85	lightcyan1	mediumorchid4	palevioletred2	sienna2	violetred4
chartreuse	darkslateblue		gray74		gray86	lightcyan2	mediumpurple	palevioletred3	sienna3	wheat1
chartreuse1	darkslategray		gray75		gray87	lightcyan3	mediumpurple1	palevioletred4	sienna4	wheat2
chartreuse2	darkslategray1		gray76		gray88	lightcyan4	mediumpurple2	papayawhip	skyblue	wheat3
chartreuse3	darkslategray2		gray77		gray89	lightgoldenrod	mediumpurple3	peachpuff	skyblue1	wheat4
chartreuse4	darkslategray3		gray78		gray90	lightgoldenrod1	mediumpurple4	peachpuff1	skyblue2	whitesmoke
chocolate	darkslategray4		gray79		gray91	lightgoldenrod2	mediumpurple4	peachpuff2	skyblue3	yellow
chocolate1	darkslategray1		gray80		gray92	lightgoldenrod3	mediumslateblue	peachpuff3	skyblue4	yellow1
chocolate2	darkturquoise		gray81		gray93	lightgoldenrod4	mediumslateblue1	peachpuff4	slateblue	yellow2
chocolate3	darkviolet		gray82		gray94	lightgoldenrodyellow	mediumslateblue2	peru	slateblue1	yellow3
chocolate4	deeppink		gray83		gray95	lightgray	mediumslateblue3	pink	slateblue2	yellow4
coral	deeppink1		gray24		gray96	lightgreen	mediumslateblue4	pink1	slateblue3	yellowgreen
coral1	deeppink2		gray25		gray97	lightgray	mediumvioletred	pink2	slateblue4	
coral2	deeppink3		gray26		gray98	lightpink	mediumvioletred1	mintcream	pink3	
coral3	deeppink4		gray27		gray99	lightpink1	mistyrose	lightpink	pink4	
							mistyrose1			

# Using colours in ggplot

```
ggplot(data = penguins, mapping = aes(x = species, y = body_mass_g,  
                                       fill = species)) +  
  geom_boxplot() +  
  scale_fill_manual(values = c('firebrick4', 'steelblue', 'hotpink'))
```

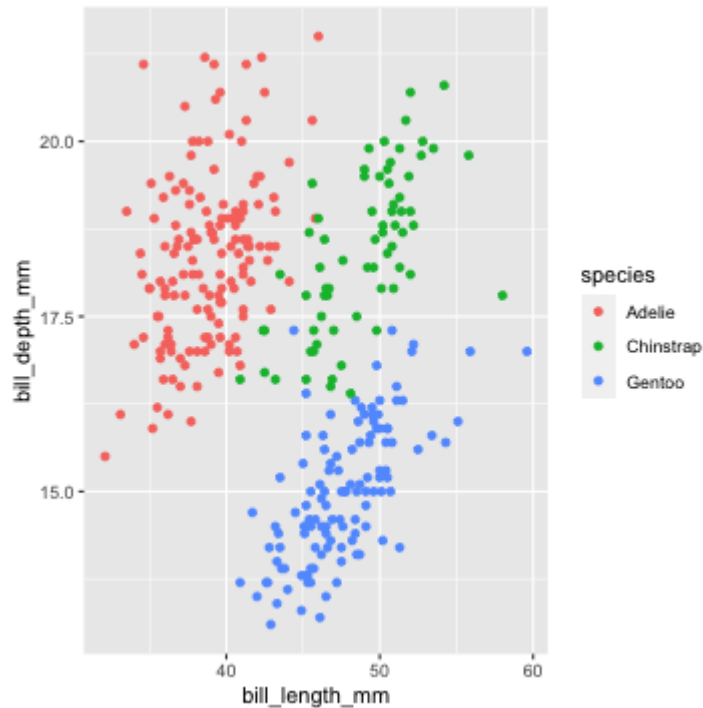


[ggplot2.tidyverse.org/reference/#scales](https://ggplot2.tidyverse.org/reference/#scales)



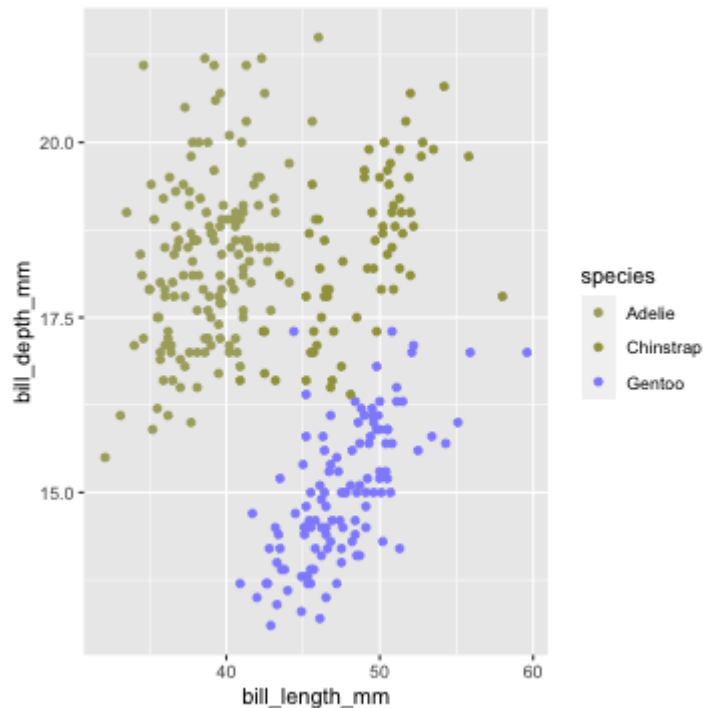
# Colour-blind friendly palettes

```
ggplot(data = penguins) +  
  geom_point(mapping = aes(x = bill_length_mm,  
                           y = bill_depth_mm,  
                           colour = species))
```



# Colour-blind friendly palettes

```
library(dichromat)
ggplot(data = penguins) +
  geom_point(mapping = aes(x = bill_length_mm, y = bill_depth_mm,
                           colour = species)) +
  scale_colour_manual(values = dichromat(scales::hue_pal()(3)))
```



# Colour-blind friendly palettes

**Set of colors that is unambiguous both to colorblinds and non-colorblinds**

Original	Simulation				Hue	for Photoshop, Illustrator, Freehand, etc.		for Word, Power Point, Canvas, etc.	
	Protan	Deutan	Tritan			C,M,Y,K (%)	R,G,B (0-255)	R,G,B (%)	
1					Black	-°	(0,0,0,100)	(0,0,0)	(0,0,0)
2					Orange	41°	(0,50,100,0)	(230,159,0)	(90,60,0)
3					Sky Blue	202°	(80,0,0,0)	(86,180,233)	(35,70,90)
4					bluish Green	164°	(97,0,75,0)	(0,158,115)	(0,60,50)
5					Yellow	56°	(10,5,90,0)	(240,228,66)	(95,90,25)
6					Blue	202°	(100,50,0,0)	(0,114,178)	(0,45,70)
7					Vermillion	27°	(0,80,100,0)	(213,94,0)	(80,40,0)
8					reddish Purple	326°	(10,70,0,0)	(204,121,167)	(80,60,70)

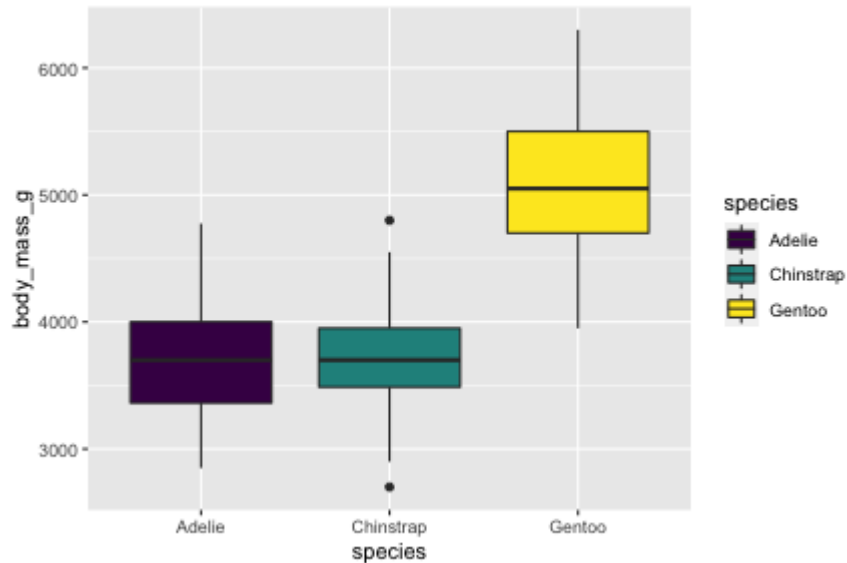
<https://jfly.uni-koeln.de/color/#pallet>

# Viridis: perceptually uniform scales



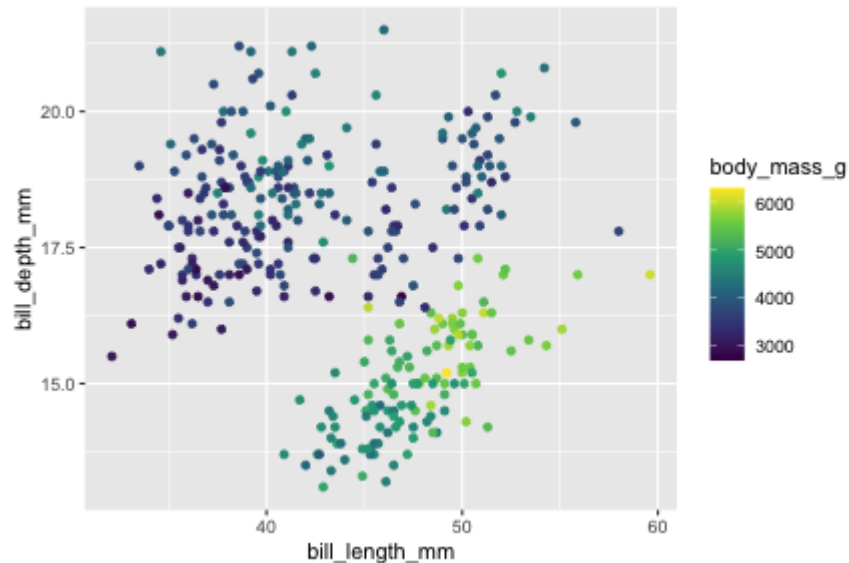
# Viridis: perceptually uniform scales

```
ggplot(data = penguins,  
       mapping = aes(x = species, y = body_mass_g, fill = species)) +  
  geom_boxplot() +  
  scale_fill_viridis_d()
```



# Viridis: perceptually uniform scales

```
ggplot(data = penguins, mapping = aes(x = bill_length_mm,  
  y = bill_depth_mm, colour = body_mass_g)) +  
  geom_point() +  
  scale_colour_viridis_c()
```



# Shapes

- There are 26 shapes available in R for plotting that are identified by numbers

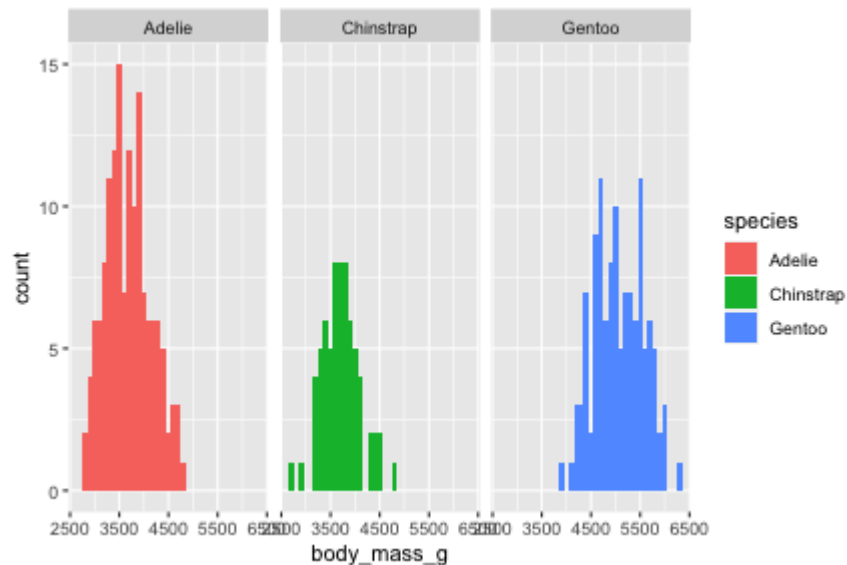


- 0-14 are hollow. The border colour is determined by the `colour` aesthetic
- 15-20 are solid. The colour is determined by the `colour` aesthetic
- 21-25 are filled shapes that have a border `colour` and a `fill` colour

[ggplot2.tidyverse.org/reference/aes\\_linetype\\_size\\_shape.html](https://ggplot2.tidyverse.org/reference/aes_linetype_size_shape.html)

# Facets

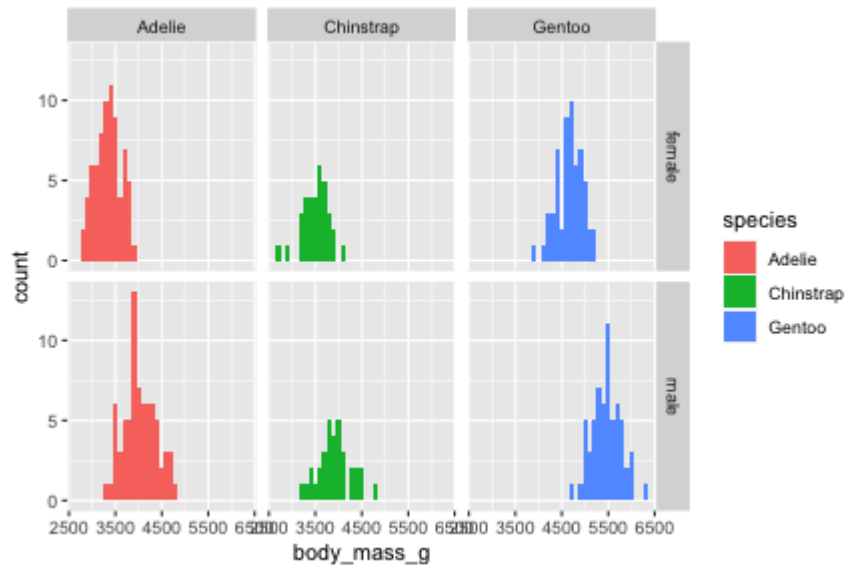
```
ggplot(data = penguins,  
       mapping = aes(x = body_mass_g, fill = species)) +  
  geom_histogram(binwidth = 100) +  
  facet_wrap(vars(species))
```





# Facets

```
ggplot(data = penguins,  
       mapping = aes(x = body_mass_g, fill = species)) +  
  geom_histogram(binwidth = 100) +  
  facet_grid(cols = vars(species),  
            rows = vars(sex))
```



# Themes

- `theme()` is ggplot's way of controlling the overall look of a plot
- Change axis titles, labels, lines and ticks
- Change the look of the legend (title, text, position, direction)
- Change the look of the panels (title, background, grid lines)
- A set of complete themes already exist



Reference

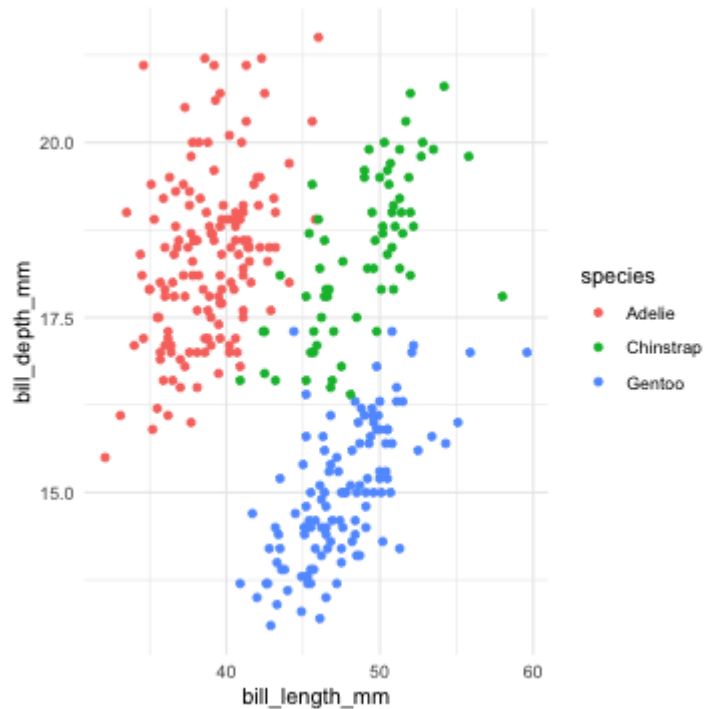
## Modify components of a theme

Source: `R/theme.r`

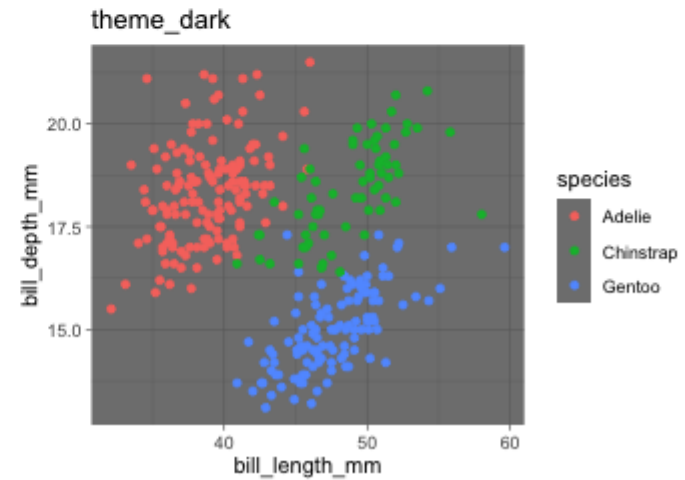
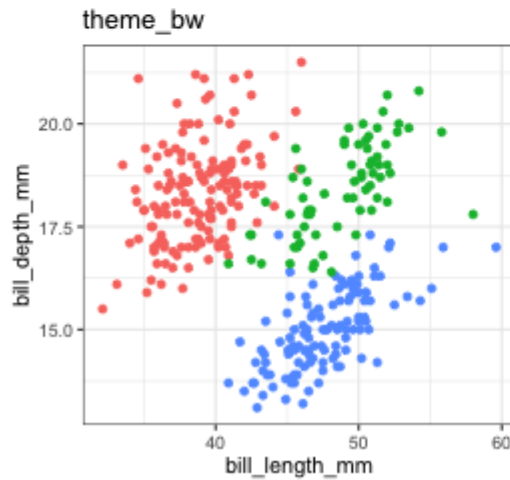
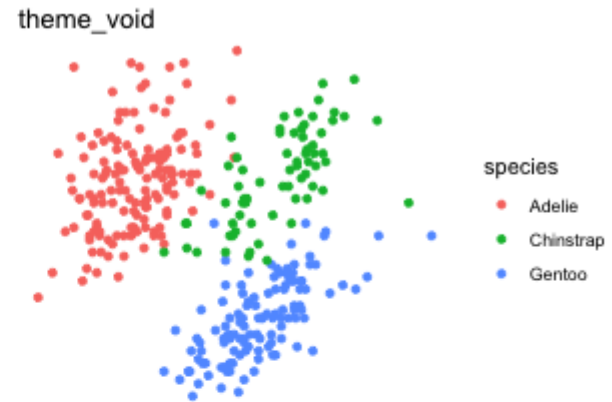
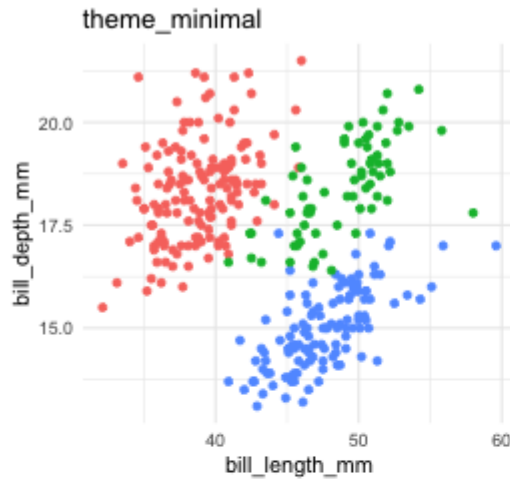
Themes are a powerful way to customize the non-data components of your plots: i.e. titles, labels, fonts, background, gridlines, and legends. Themes can be used to give plots a consistent customized look. Modify a single plot's theme using `theme()`; see `theme_update()` if you want modify the active theme, to affect all subsequent plots. Theme elements are documented together according to inheritance, read more about theme inheritance below.

# Themes

```
ggplot(data = penguins) +  
  geom_point(mapping = aes(x = bill_length_mm,  
                           y = bill_depth_mm,  
                           colour = species)) +  
  theme_minimal()
```

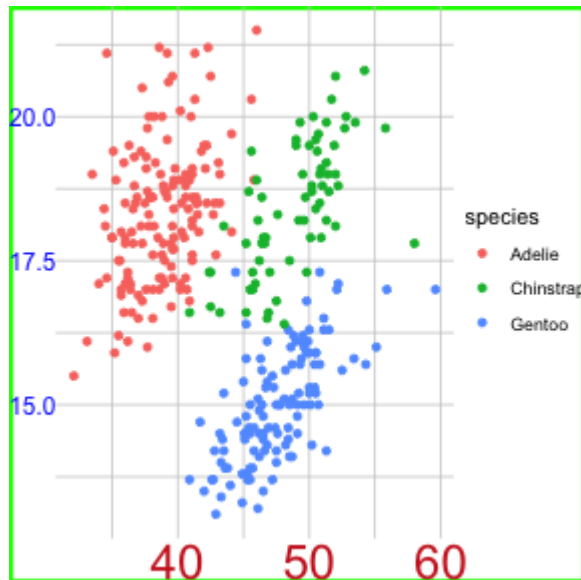


# Themes



# Customising themes

```
ggplot(data = penguins) +  
  geom_point(mapping = aes(x = bill_length_mm, y = bill_depth_mm,  
                           colour = species)) +  
  
  theme_void() +  
  theme(axis.text = element_text(colour = "blue", size = 12),  
        axis.text.x = element_text(colour = "firebrick3", size = 24),  
        panel.grid = element_line(colour = "grey80"),  
        plot.background = element_rect(colour = "green", size = 2))
```



# Further Reading

ggplot2 3.3.5 **Reference** News ▾ Articles ▾ Extensions

## Function reference



### Plot basics

All ggplot2 plots begin with a call to `ggplot()`, supplying default data and aesthetic mappings, specified by `aes()`. You then add layers, scales, coords and facets with `+`. To save a plot to disk, use `ggsave()`.

`ggplot()`

Create a new ggplot

`aes()`

Construct aesthetic mappings

``+` (<gg>)` ``%+%``

Add components to a plot

`ggsave()`

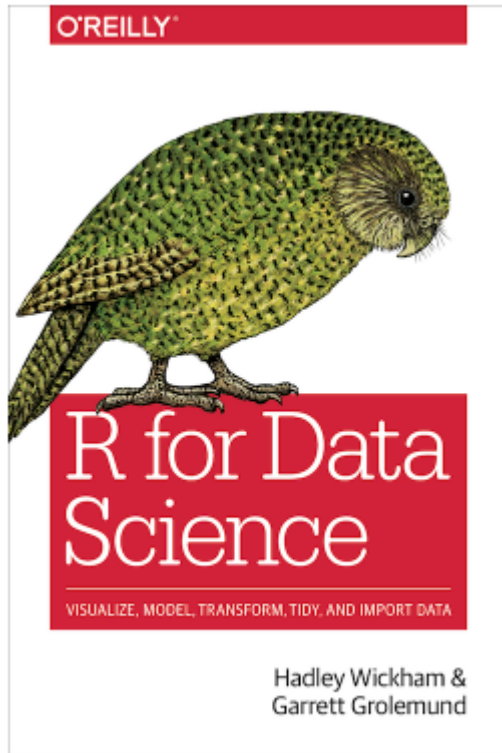
Save a ggplot (or other grid object) with sensible defaults

`qplot()` `quickplot()`

Quick plot

<https://ggplot2.tidyverse.org/reference>

# Further Reading



[r4ds.had.co.nz](http://r4ds.had.co.nz)

# Exercises