(A bit of) Advanced R

Part 3 - a tour of the `tidyverse`

Julien Chiquet

https://github.com/jchiquet/CourseAdvancedR

Université Paris Dauphine, Juin 2018

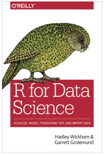
Outline

1. Introduction
2. Structures and types: `tibble`, `forcats`, `stringr`
3. data wrangling: `readr`, `tidyr`, `dplyr`
4. Manipulation: `magrittr`, `purrr`
5. Vizualization: `ggplot2`

References

Many ideas/examples inspired/stolen there:

R for data science (Wickham & Grolemund, 2016), http://r4ds.had.co.nz



Tidyverse website, https://www.tidyverse.org/

Prerequisites

Data Structures in base R

1. Atomic vector (integer, double, logical, character)
2. Recursive vector (list)
3. Factor
4. Matrix and array
5. Data Frame

R base programming

1. Control Statements
2. Functions
3. Functionals
4. Input/output
5. Rstudio API (application programming interface)

Outline

1. Introduction
2. Structures and types: `tibble`, `forcats`, `stringr`
3. data wrangling: `readr`, `tidyr`, `dplyr`
4. Manipulation: `magrittr`, `purrr`
5. Vizualization: `ggplot2`

Tidy data: motivation

Collected data are (never) under a proper canonical format

> *"Happy families are all alike; every unhappy family is unhappy in its own way." – Leo Tolstoy*

> *"Tidy datasets are all alike, but every messy dataset is messy in its own way." – Hadley Wickham*[1]

[1] Rstudio's chief scientific advisor

Tidy data: motivation

Collected data are (never) under a proper canonical format

> *"Happy families are all alike; every unhappy family is unhappy in its own way." – Leo Tolstoy*

> *"Tidy datasets are all alike, but every messy dataset is messy in its own way." – Hadley Wickham*[1]

[1] Rstudio's chief scientific advisor

Tidy data: what?

First, a subjective question

What is the *observation/statistical unit* in your data?

Definition

Tidy data is a standard way of mapping the meaning of a dataset to its structure. A dataset is messy or tidy depending on how rows, columns and tables are matched up with observations, variables and types.
In tidy data,

1. each variable forms a column,
2. each observation forms a row,
3. each type of observational unit forms a table.

Tidy data: what?

First, a subjective question

What is the *observation/statistical unit* in your data?

Definition

Tidy data is a standard way of mapping the meaning of a dataset to its structure. A dataset is messy or tidy depending on how rows, columns and tables are matched up with observations, variables and types.

In tidy data,

1. each variable forms a column,
2. each observation forms a row,
3. each type of observational unit forms a table.

Tidy data: what?

First, a subjective question

What is the *observation/statistical unit* in your data?

Definition

Tidy data is a standard way of mapping the meaning of a dataset to its structure. A dataset is messy or tidy depending on how rows, columns and tables are matched up with observations, variables and types.

In tidy data,

1. each variable forms a column,
2. each observation forms a row,
3. each type of observational unit forms a table.

Tidy data: why?

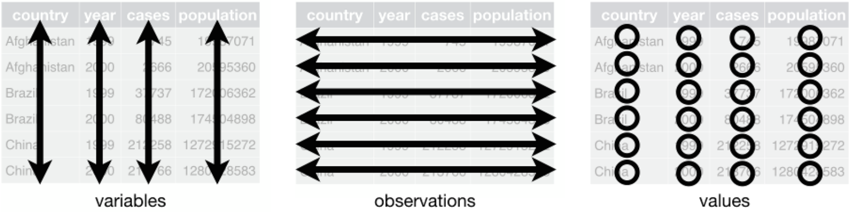


Figure 1: Tidy data

- make manipulation, visualization and modelling easier
- a common structure for all packages
- a philosophy for data representation (beyond the R framework)

Tidy or not ?

```r
tidyr::table3
```

```
## # A tibble: 6 x 3
##   country      year rate
## * <chr>       <int> <chr>
## 1 Afghanistan  1999 745/19987071
## 2 Afghanistan  2000 2666/20595360
## 3 Brazil       1999 37737/172006362
## 4 Brazil       2000 80488/174504898
## 5 China        1999 212258/1272915272
## 6 China        2000 213766/1280428583
```

Tidy or not ?

```
tidyr::table2
```

```
## # A tibble: 12 x 4
##    country      year type            count
##    <chr>       <int> <chr>           <int>
##  1 Afghanistan  1999 cases             745
##  2 Afghanistan  1999 population   19987071
##  3 Afghanistan  2000 cases            2666
##  4 Afghanistan  2000 population   20595360
##  5 Brazil       1999 cases           37737
##  6 Brazil       1999 population  172006362
##  7 Brazil       2000 cases           80488
##  8 Brazil       2000 population  174504898
##  9 China        1999 cases          212258
## 10 China        1999 population 1272915272
## 11 China        2000 cases          213766
## 12 China        2000 population 1280428583
```

Tidy or not ?

```r
tidyr::table1
```

```
## # A tibble: 6 x 4
##   country      year  cases population
##   <chr>       <int>  <int>      <int>
## 1 Afghanistan  1999    745   19987071
## 2 Afghanistan  2000   2666   20595360
## 3 Brazil       1999  37737  172006362
## 4 Brazil       2000  80488  174504898
## 5 China        1999 212258 1272915272
## 6 China        2000 213766 1280428583
```

The process of data analysis

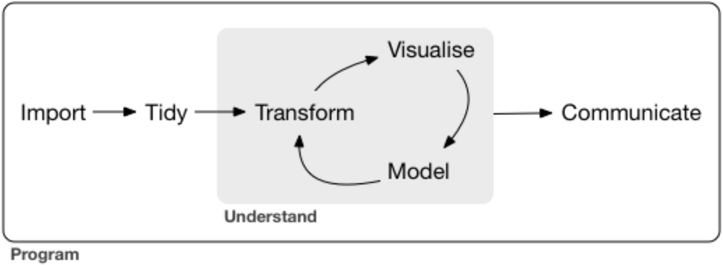


Figure 2: scheme for data analysis process

- **import:** read/load the data
- **tidy:** formating (individuals/variables data frame)
- **transform:** suppression/creation/filtering/selection
- **visualization:** representation and validation
- **model**: statistical fits
- **communication**: diffusion (web/talk/article)

The tidyverse

Definition

- contraction of ‘tidy’ (“well arranged) and ‘universe’.
- an *opinionated collection* of `R` packages designed for data science.
- all packages share an underlying *design philosophy*, *grammar*, and *data structures*

Phylosophy

allows the user to focus on the important statistical questions rather than focusing on the technical aspects of data analysis

Let's have a look

The core `tidyverse` loads `ggplot2`, `tibble`, `tidyr`, `readr`, `purrr`, `stringr`, `forecats`, `dplyr` and others in a fancy and unconflicted way.

```
library(tidyverse)
tidyverse:::tidyverse_conflicts()
```

```
## -- Conflicts ---------------------------------------------------------------
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
tidyverse:::tidyverse_deps()
```

```
## # A tibble: 25 x 4
##    package cran  local behind
##    <chr>   <chr> <chr> <lgl>
##  1 broom   0.4.4 0.4.3 TRUE
##  2 cli     1.0.0 1.0.0 FALSE
##  3 crayon  1.3.4 1.3.4 FALSE
##  4 dbplyr  1.2.1 1.2.1 FALSE
##  5 dplyr   0.7.5 0.7.4 TRUE
##  6 forcats 0.3.0 0.3.0 FALSE
##  7 ggplot2 2.2.1 2.2.1 FALSE
##  8 haven   1.1.1 1.1.1 FALSE
##  9 hms     0.4.2 0.4.2 FALSE
## 10 httr    1.3.1 1.3.1 FALSE
## # ... with 15 more rows
```

Packages roles and overview: types

tibble

a modern re-imagining of the data frame

stringr

a cohesive set of functions designed to make working with strings as easy as possible

forcats

a suite of useful tools that solve common problems with factors

Packages roles and overview: wrangling

readr

a fast and friendly way to read rectangular data (like csv, tsv, . . .)

tidyr

a set of functions that help you get to tidy data

dplyr

a consistent set of verbs that solve the most common data manipulation challenges

Packages roles and overview: manipulation

ggplot2

a system for declaratively creating graphics, based on The Grammar of Graphics

purrr

enhances R's functional programming (FP) toolkit

magrittr

offers a set of operators which make your code more readable

Data analysis with the tidyverse

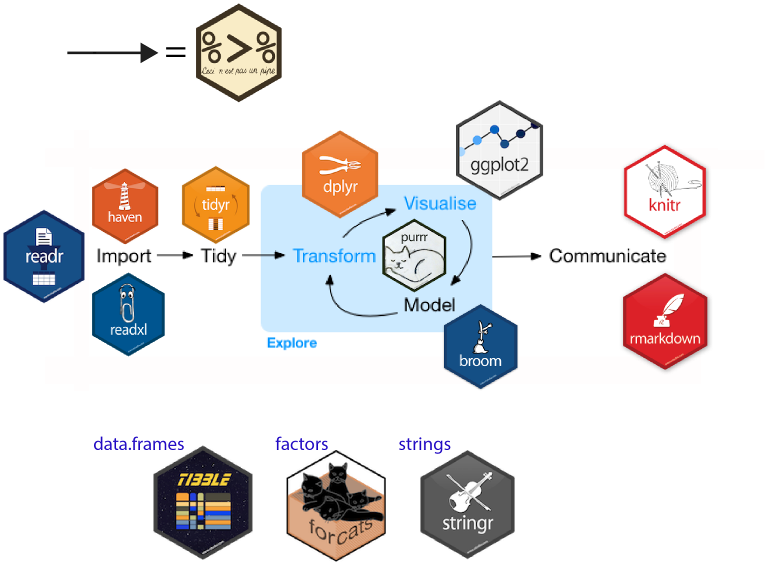


Figure 3: Updated scheme for data analysis process

Getting help

Rstudio's cheatsheets https://www.rstudio.com/resources/cheatsheets/

For a quick overview of the main features

Stackoverflow https://stackoverflow.com/

For all your specific questions

Tidyverse.org https://www.tidyverse.org

For an exhaustive documentation

Outline

{tibble}

Figure 4: a modern re-imagining of the data frame

`tibble` versus `data.frame`

`tibbles` (or `tbl_df`) are modern reimagining of the `data.frame`,

- *lazy*: do less (e.g. do not change variable names, types, no partial matching)
- *surly*: complain more (e.g. when a variable does not exist)

Conversion from a `data.frame`

```r
head(iris)
```

```
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1          5.1         3.5          1.4         0.2  setosa
## 2          4.9         3.0          1.4         0.2  setosa
## 3          4.7         3.2          1.3         0.2  setosa
## 4          4.6         3.1          1.5         0.2  setosa
## 5          5.0         3.6          1.4         0.2  setosa
## 6          5.4         3.9          1.7         0.4  setosa
```

```r
as_tibble(iris)
```

```
## # A tibble: 150 x 5
##    Sepal.Length Sepal.Width Petal.Length Petal.Width Species
##           <dbl>       <dbl>        <dbl>       <dbl> <fct>
##  1         5.10        3.50         1.40       0.200 setosa
##  2         4.90        3.00         1.40       0.200 setosa
##  3         4.70        3.20         1.30       0.200 setosa
##  4         4.60        3.10         1.50       0.200 setosa
##  5         5.00        3.60         1.40       0.200 setosa
##  6         5.40        3.90         1.70       0.400 setosa
##  7         4.60        3.40         1.40       0.300 setosa
##  8         5.00        3.40         1.50       0.200 setosa
##  9         4.40        2.90         1.40       0.200 setosa
## 10         4.90        3.10         1.50       0.100 setosa
## # ... with 140 more rows
```

Conversion from a data.frame

```r
head(iris)
```

```
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1          5.1         3.5          1.4         0.2  setosa
## 2          4.9         3.0          1.4         0.2  setosa
## 3          4.7         3.2          1.3         0.2  setosa
## 4          4.6         3.1          1.5         0.2  setosa
## 5          5.0         3.6          1.4         0.2  setosa
## 6          5.4         3.9          1.7         0.4  setosa
```

```r
as_tibble(iris)
```

```
## # A tibble: 150 x 5
##    Sepal.Length Sepal.Width Petal.Length Petal.Width Species
##           <dbl>       <dbl>        <dbl>       <dbl> <fct>
##  1         5.10        3.50         1.40       0.200 setosa
##  2         4.90        3.00         1.40       0.200 setosa
##  3         4.70        3.20         1.30       0.200 setosa
##  4         4.60        3.10         1.50       0.200 setosa
##  5         5.00        3.60         1.40       0.200 setosa
##  6         5.40        3.90         1.70       0.400 setosa
##  7         4.60        3.40         1.40       0.300 setosa
##  8         5.00        3.40         1.50       0.200 setosa
##  9         4.40        2.90         1.40       0.200 setosa
## 10         4.90        3.10         1.50       0.100 setosa
## # ... with 140 more rows
```

Creating a tibble

```
tibble(
  x = 1:5,
  y = 1,
  z = x ^ 2 + y
)
```

```
## # A tibble: 5 x 3
##       x     y     z
##   <int> <dbl> <dbl>
## 1     1    1.    2.
## 2     2    1.    5.
## 3     3    1.   10.
## 4     4    1.   17.
## 5     5    1.   26.
```

Column names of a tibble

Names can start by any character. To refer such variables, use the backticks

```
tibble(`:)` = "smile", ` ` = "space", `2000` = "number")
```

```
## # A tibble: 1 x 3
##   `:)`  ` `   `2000`
##   <chr> <chr> <chr>
## 1 smile space number
```

Creating a tibble

```
tibble(
  x = 1:5,
  y = 1,
  z = x ^ 2 + y
)
```

```
## # A tibble: 5 x 3
##       x     y     z
##   <int> <dbl> <dbl>
## 1     1    1.    2.
## 2     2    1.    5.
## 3     3    1.   10.
## 4     4    1.   17.
## 5     5    1.   26.
```

Column names of a tibble

Names can start by any character. To refer such variables, use the backticks

```
tibble(`:)` = "smile", ` ` = "space", `2000` = "number")
```

```
## # A tibble: 1 x 3
##   `:)`  ` `   `2000`
##   <chr> <chr> <chr>
## 1 smile space number
```

Row names

Row do not have names in a `tibble`

Solution

- one can use name by adding a specfic column
- `rownames_to_column ()` can help

Example

```
as_tibble(swiss, rownames = "Province")
```

```
## # A tibble: 47 x 7
##    Province     Fertility Agriculture Examination Education Catholic
##    <chr>            <dbl>       <dbl>       <int>     <int>    <dbl>
##  1 Courtelary        80.2        17.0          15        12     9.96
##  2 Delemont          83.1        45.1           6         9    84.8
##  3 Franches-Mnt      92.5        39.7           5         5    93.4
##  4 Moutier           85.8        36.5          12         7    33.8
##  5 Neuveville        76.9        43.5          17        15     5.16
##  6 Porrentruy        76.1        35.3           9         7    90.6
##  7 Broye             83.8        70.2          16         7    92.8
##  8 Glane             92.4        67.8          14         8    97.2
##  9 Gruyere           82.4        53.3          12         7    97.7
## 10 Sarine            82.9        45.2          16        13    91.4
## # ... with 37 more rows, and 1 more variable: Infant.Mortality <dbl>
```

Consistency in subsetting

```r
df <- data.frame(x = 1:9, y = LETTERS[1:9])
tbl <- tibble(x = 1:9, y = LETTERS[1:9])
```

```r
class(df[, 1:2])
```

```
## [1] "data.frame"
```

```r
class(tbl[, 1:2])
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

```r
class(df[, 1])
```

```
## [1] "integer"
```

```r
class(tbl[, 1])
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

Consistency in subsetting

```r
df <- data.frame(x = 1:9, y = LETTERS[1:9])
tbl <- tibble(x = 1:9, y = LETTERS[1:9])
```

```r
class(df[, 1:2])
```

```
## [1] "data.frame"
```

```r
class(tbl[, 1:2])
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

```r
class(df[, 1])
```

```
## [1] "integer"
```

```r
class(tbl[, 1])
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

Consistency in subsetting

```r
df <- data.frame(x = 1:9, y = LETTERS[1:9])
tbl <- tibble(x = 1:9, y = LETTERS[1:9])
```

```r
class(df[, 1:2])
```

```
## [1] "data.frame"
```

```r
class(tbl[, 1:2])
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

```r
class(df[, 1])
```

```
## [1] "integer"
```

```r
class(tbl[, 1])
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

List-column

The type `list` is available for a column in `tibble`

- a `tibble` allows cells containing lists
- a `tibble` allows cells containing data frames.

```
subset(starwars, select = c('name', 'height', 'mass', 'hair_color', 'films', 'vehicles'))
```

```
## # A tibble: 87 x 6
##    name               height  mass hair_color    films     vehicles
##    <chr>               <int> <dbl> <chr>         <list>    <list>
##  1 Luke Skywalker        172   77. blond         <chr [5]> <chr [2]>
##  2 C-3PO                 167   75. <NA>          <chr [6]> <chr [0]>
##  3 R2-D2                  96   32. <NA>          <chr [7]> <chr [0]>
##  4 Darth Vader           202  136. none          <chr [4]> <chr [0]>
##  5 Leia Organa           150   49. brown         <chr [5]> <chr [1]>
##  6 Owen Lars             178  120. brown, grey   <chr [3]> <chr [0]>
##  7 Beru Whitesun lars    165   75. brown         <chr [3]> <chr [0]>
##  8 R5-D4                  97   32. <NA>          <chr [1]> <chr [0]>
##  9 Biggs Darklighter     183   84. black         <chr [1]> <chr [0]>
## 10 Obi-Wan Kenobi        182   77. auburn, white <chr [6]> <chr [1]>
## # ... with 77 more rows
```

List-column: put a vector in each case

```r
head(starwars$films, 4)
```

```
## [[1]]
## [1] "Revenge of the Sith"     "Return of the Jedi"
## [3] "The Empire Strikes Back" "A New Hope"
## [5] "The Force Awakens"
##
## [[2]]
## [1] "Attack of the Clones"    "The Phantom Menace"
## [3] "Revenge of the Sith"     "Return of the Jedi"
## [5] "The Empire Strikes Back" "A New Hope"
##
## [[3]]
## [1] "Attack of the Clones"    "The Phantom Menace"
## [3] "Revenge of the Sith"     "Return of the Jedi"
## [5] "The Empire Strikes Back" "A New Hope"
## [7] "The Force Awakens"
##
## [[4]]
## [1] "Revenge of the Sith"     "Return of the Jedi"
## [3] "The Empire Strikes Back" "A New Hope"
```

{forcats}

Figure 5: a suite of useful tools that solve common problems with factor

`forcats` versus `base` factors

- easy use in conjuction with other tidyverse packages
- correct inconsistent behaviours of `R` base factors facilities

{stringr}

Figure 6: cohesive set of functions designed to make working with strings as easy as possible

`stringr` versus base string utilities

String manipulmtion is cumbersome in `R` base. However, string plays a big role in many data cleaning and preparation.

- easy use in conjuction with other tidyverse packages
- faster and correct implementations of common string manipulations

Outline

{readr}

Figure 7: a fast and friendly way to read rectangular data (like csv, tsv and so on)

- offer coherent/unified functions compared to `base::read.table` and friends
- offer interactive readinf
- output `tibble` rather than `data.frame`
- `read_csv`, `read_delim`, `read_rds`, `read_file`, `read_table`, etc

{tidyr}

Figure 8: a set of functions that help you get to tidy data

```
library(tidyr)
```

⇝ `tidyr` is a package which helps you to transform messy datasets into tidy datasets.

- evolution of base function `reshape`
- available functions are `spread`, `gather`, `unite`, `separate`

Grades dataset

```
grades <- tibble(
  Name = c("Tommy", "Mary", "Gary", "Cathy"),
  Sexage = c("m.15", "f.15", "m.16", "f.14"),
  Test1 = c(10, 15, 16, 14),
  Test2 = c(11, 13, 10, 12),
  Test3 = c(12, 13, 17, 10)
  )
grades
```

```
## # A tibble: 4 x 5
##   Name  Sexage Test1 Test2 Test3
##   <chr> <chr>  <dbl> <dbl> <dbl>
## 1 Tommy m.15     10.   11.   12.
## 2 Mary  f.15     15.   13.   13.
## 3 Gary  m.16     16.   10.   17.
## 4 Cathy f.14     14.   12.   10.
```

Name	Sexage	Test1	Test2	Test3
Tommy	m.15	10	11	12
Mary	f.15	15	13	13
Gary	m.16	16	10	17
Cathy	f.14	14	12	10

separate()

Separate one column into multiple columns

```
grades <- separate(grades, Sexage, into = c("Sex", "Age"))
grades
```

```
## # A tibble: 4 x 6
##   Name  Sex   Age   Test1 Test2 Test3
##   <chr> <chr> <chr> <dbl> <dbl> <dbl>
## 1 Tommy m     15      10.   11.   12.
## 2 Mary  f     15      15.   13.   13.
## 3 Gary  m     16      16.   10.   17.
## 4 Cathy f     14      14.   12.   10.
```

Name	Sex	Age	Test1	Test2	Test3
Tommy	m	15	10	11	12
Mary	f	15	15	13	13
Gary	m	16	16	10	17
Cathy	f	14	14	12	10

Remark

The inverse of separate() is unite()

separate()

Separate one column into multiple columns

```
grades <- separate(grades, Sexage, into = c("Sex", "Age"))
grades
```

```
## # A tibble: 4 x 6
##   Name  Sex   Age   Test1 Test2 Test3
##   <chr> <chr> <chr> <dbl> <dbl> <dbl>
## 1 Tommy m     15      10.   11.   12.
## 2 Mary  f     15      15.   13.   13.
## 3 Gary  m     16      16.   10.   17.
## 4 Cathy f     14      14.   12.   10.
```

Name	Sex	Age	Test1	Test2	Test3
Tommy	m	15	10	11	12
Mary	f	15	15	13	13
Gary	m	16	16	10	17
Cathy	f	14	14	12	10

Remark

The inverse of `separate()` is `unite()`

gather()

Gather Columns Into Key-Value Pairs

```r
grades <- gather(grades, Test1, Test2, Test3, key = Test, value = Grade)
head(grades, 5)
```

```
## # A tibble: 5 x 5
##   Name  Sex   Age   Test  Grade
##   <chr> <chr> <chr> <chr> <dbl>
## 1 Tommy m     15    Test1   10.
## 2 Mary  f     15    Test1   15.
## 3 Gary  m     16    Test1   16.
## 4 Cathy f     14    Test1   14.
## 5 Tommy m     15    Test2   11.
```

Name	Sex	Age	Test	Grade
Tommy	m	15	Test1	10
Mary	f	15	Test1	15
Gary	m	16	Test1	16
Cathy	f	14	Test1	14
Tommy	m	15	Test2	11

Remark

The inverse of gather() is spread()

gather()

Gather Columns Into Key-Value Pairs

```
grades <- gather(grades, Test1, Test2, Test3, key = Test, value = Grade)
head(grades, 5)
```

```
## # A tibble: 5 x 5
##   Name  Sex   Age   Test  Grade
##   <chr> <chr> <chr> <chr> <dbl>
## 1 Tommy m     15    Test1   10.
## 2 Mary  f     15    Test1   15.
## 3 Gary  m     16    Test1   16.
## 4 Cathy f     14    Test1   14.
## 5 Tommy m     15    Test2   11.
```

Name	Sex	Age	Test	Grade
Tommy	m	15	Test1	10
Mary	f	15	Test1	15
Gary	m	16	Test1	16
Cathy	f	14	Test1	14
Tommy	m	15	Test2	11

Remark

The inverse of `gather()` is `spread()`

dplyr

Figure 9: a consistent set of verbs (*a grammar*) that solves the most common data manipulation challenges

Typical operations

- create and pick variables
- pick and reorder observations
- create summaries
- ...

⇝ Functions in this package are verbs and work similarly

mtcars dataset

```r
data(mtcars)
as_tibble(mtcars)
```

```
## # A tibble: 32 x 11
##      mpg   cyl  disp    hp  drat    wt  qsec    vs    am  gear  carb
##  * <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
##  1  21.0    6.  160.  110.  3.90  2.62  16.5    0.    1.    4.    4.
##  2  21.0    6.  160.  110.  3.90  2.88  17.0    0.    1.    4.    4.
##  3  22.8    4.  108.   93.  3.85  2.32  18.6    1.    1.    4.    1.
##  4  21.4    6.  258.  110.  3.08  3.22  19.4    1.    0.    3.    1.
##  5  18.7    8.  360.  175.  3.15  3.44  17.0    0.    0.    3.    2.
##  6  18.1    6.  225.  105.  2.76  3.46  20.2    1.    0.    3.    1.
##  7  14.3    8.  360.  245.  3.21  3.57  15.8    0.    0.    3.    4.
##  8  24.4    4.  147.   62.  3.69  3.19  20.0    1.    0.    4.    2.
##  9  22.8    4.  141.   95.  3.92  3.15  22.9    1.    0.    4.    2.
## 10  19.2    6.  168.  123.  3.92  3.44  18.3    1.    0.    4.    4.
## # ... with 22 more rows
```

Select rows with `filter()`

Arguments

1. data
2. filtering expressions

Output

- a `tibble`
- **do not modify** the original data

Example

```r
filter(mtcars, cyl == 4, mpg > 30)
```

```
##    mpg cyl disp  hp drat    wt  qsec vs am gear carb
## 1 32.4   4 78.7  66 4.08 2.200 19.47  1  1    4    1
## 2 30.4   4 75.7  52 4.93 1.615 18.52  1  1    4    2
## 3 33.9   4 71.1  65 4.22 1.835 19.90  1  1    4    1
## 4 30.4   4 95.1 113 3.77 1.513 16.90  1  1    5    2
```

Reorder rows with `arrange()`

Principle

works like `filter()` but reorder rows according to a series of conditions

Example

```
as_tibble(arrange(mtcars, desc(carb), mpg))
```

```
## # A tibble: 32 x 11
##      mpg   cyl  disp    hp  drat    wt  qsec    vs    am  gear  carb
##    <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
##  1  15.0    8.  301.  335.  3.54  3.57  14.6    0.    1.    5.    8.
##  2  19.7    6.  145.  175.  3.62  2.77  15.5    0.    1.    5.    6.
##  3  10.4    8.  472.  205.  2.93  5.25  18.0    0.    0.    3.    4.
##  4  10.4    8.  460.  215.  3.00  5.42  17.8    0.    0.    3.    4.
##  5  13.3    8.  350.  245.  3.73  3.84  15.4    0.    0.    3.    4.
##  6  14.3    8.  360.  245.  3.21  3.57  15.8    0.    0.    3.    4.
##  7  14.7    8.  440.  230.  3.23  5.34  17.4    0.    0.    3.    4.
##  8  15.8    8.  351.  264.  4.22  3.17  14.5    0.    1.    5.    4.
##  9  17.8    6.  168.  123.  3.92  3.44  18.9    1.    0.    4.    4.
## 10  19.2    6.  168.  123.  3.92  3.44  18.3    1.    0.    4.    4.
## # ... with 22 more rows
```

Selecting columns with select() I

Similar to base::subsect(, select = c("",""))

With names

can be quoted or unquoted

```
as_tibble(select(mtcars, mpg, 'wt', cyl))
```

```
## # A tibble: 32 x 3
##      mpg    wt   cyl
##  * <dbl> <dbl> <dbl>
##  1  21.0  2.62    6.
##  2  21.0  2.88    6.
##  3  22.8  2.32    4.
##  4  21.4  3.22    6.
##  5  18.7  3.44    8.
##  6  18.1  3.46    6.
##  7  14.3  3.57    8.
##  8  24.4  3.19    4.
##  9  22.8  3.15    4.
## 10  19.2  3.44    6.
## # ... with 22 more rows
```

Selecting columns with `select()` II

With indexes

```r
as_tibble(select(mtcars, 1,2,5:7))
```

```
## # A tibble: 32 x 5
##      mpg   cyl  drat    wt  qsec
##  * <dbl> <dbl> <dbl> <dbl> <dbl>
##  1  21.0    6.  3.90  2.62  16.5
##  2  21.0    6.  3.90  2.88  17.0
##  3  22.8    4.  3.85  2.32  18.6
##  4  21.4    6.  3.08  3.22  19.4
##  5  18.7    8.  3.15  3.44  17.0
##  6  18.1    6.  2.76  3.46  20.2
##  7  14.3    8.  3.21  3.57  15.8
##  8  24.4    4.  3.69  3.19  20.0
##  9  22.8    4.  3.92  3.15  22.9
## 10  19.2    6.  3.92  3.44  18.3
## # ... with 22 more rows
```

Renaming columns with rename()

rename() keeps all variables

```r
as_tibble(rename(iris, petal_length = Petal.Length))
```

```
## # A tibble: 150 x 5
##    Sepal.Length Sepal.Width petal_length Petal.Width Species
##           <dbl>       <dbl>        <dbl>       <dbl> <fct>
##  1         5.10        3.50         1.40       0.200 setosa
##  2         4.90        3.00         1.40       0.200 setosa
##  3         4.70        3.20         1.30       0.200 setosa
##  4         4.60        3.10         1.50       0.200 setosa
##  5         5.00        3.60         1.40       0.200 setosa
##  6         5.40        3.90         1.70       0.400 setosa
##  7         4.60        3.40         1.40       0.300 setosa
##  8         5.00        3.40         1.50       0.200 setosa
##  9         4.40        2.90         1.40       0.200 setosa
## 10         4.90        3.10         1.50       0.100 setosa
## # ... with 140 more rows
```

Renaming columns with `select()`

Renaming can be done with `select()`

`select()` only keeps the variables specified

```r
as_tibble(select(iris, petal_length = Petal.Length))
```

```
## # A tibble: 150 x 1
##    petal_length
##           <dbl>
##  1         1.40
##  2         1.40
##  3         1.30
##  4         1.50
##  5         1.40
##  6         1.70
##  7         1.40
##  8         1.50
##  9         1.40
## 10         1.50
## # ... with 140 more rows
```

Add new variables with mutate()

mutate keeps the existing variables

```
as_tibble(
  mutate(mtcars,
         cyl2 = 2 * cyl,
         cyl4 = 2 * cyl2,
         disp = disp * 0.0163871,
         drat = NULL)
)
```

```
## # A tibble: 32 x 12
##      mpg   cyl  disp    hp    wt  qsec    vs    am  gear  carb  cyl2  cyl4
##    <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
##  1  21.0    6.  2.62  110.  2.62  16.5    0.    1.    4.    4.   12.   24.
##  2  21.0    6.  2.62  110.  2.88  17.0    0.    1.    4.    4.   12.   24.
##  3  22.8    4.  1.77   93.  2.32  18.6    1.    1.    4.    1.    8.   16.
##  4  21.4    6.  4.23  110.  3.22  19.4    1.    0.    3.    1.   12.   24.
##  5  18.7    8.  5.90  175.  3.44  17.0    0.    0.    3.    2.   16.   32.
##  6  18.1    6.  3.69  105.  3.46  20.2    1.    0.    3.    1.   12.   24.
##  7  14.3    8.  5.90  245.  3.57  15.8    0.    0.    3.    4.   16.   32.
##  8  24.4    4.  2.40   62.  3.19  20.0    1.    0.    4.    2.    8.   16.
##  9  22.8    4.  2.31   95.  3.15  22.9    1.    0.    4.    2.    8.   16.
## 10  19.2    6.  2.75  123.  3.44  18.3    1.    0.    4.    4.   12.   24.
## # ... with 22 more rows
```

Add new variables with `transmute()`

`transmute` drops the existing variables

```
as_tibble(
  transmute(mtcars,
         cyl2 = 2 * cyl,
         cyl4 = 2 * cyl2,
         disp = disp * 0.0163871,
         drat = NULL)
)
```

```
## # A tibble: 32 x 3
##     cyl2  cyl4  disp
##    <dbl> <dbl> <dbl>
##  1   12.   24.  2.62
##  2   12.   24.  2.62
##  3    8.   16.  1.77
##  4   12.   24.  4.23
##  5   16.   32.  5.90
##  6   12.   24.  3.69
##  7   16.   32.  5.90
##  8    8.   16.  2.40
##  9    8.   16.  2.31
## 10   12.   24.  2.75
## # ... with 22 more rows
```

Create summary statistics with summarise()

Reduction is done by means of statistical functions

- Center: `mean()`, `median()`
- Spread: `sd()`, `IQR()`, `mad()`
- Range: `min()`, `max()`, `quantile()`
- Position: `first()`, `last()`, `nth()`,
- Count: `n()`, `n_distinct()`
- Logical: `any()`, `all()`

Example

```
summarise(mtcars, Mean_mpg = mean(mpg),  Var_disp = var(disp))
```

```
##   Mean_mpg Var_disp
## 1 20.09062  15360.8
```

group rows according to factors with group_by()

group_by() does not do much visible expect creating a grouped data frame with type grouped_df

```
group_by(mtcars, cyl,am)
```

```
## # A tibble: 32 x 11
## # Groups:   cyl, am [6]
##      mpg   cyl  disp    hp  drat    wt  qsec    vs    am  gear  carb
##  * <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
##  1  21.0    6.  160.  110.  3.90  2.62  16.5    0.    1.    4.    4.
##  2  21.0    6.  160.  110.  3.90  2.88  17.0    0.    1.    4.    4.
##  3  22.8    4.  108.   93.  3.85  2.32  18.6    1.    1.    4.    1.
##  4  21.4    6.  258.  110.  3.08  3.22  19.4    1.    0.    3.    1.
##  5  18.7    8.  360.  175.  3.15  3.44  17.0    0.    0.    3.    2.
##  6  18.1    6.  225.  105.  2.76  3.46  20.2    1.    0.    3.    1.
##  7  14.3    8.  360.  245.  3.21  3.57  15.8    0.    0.    3.    4.
##  8  24.4    4.  147.   62.  3.69  3.19  20.0    1.    0.    4.    2.
##  9  22.8    4.  141.   95.  3.92  3.15  22.9    1.    0.    4.    2.
## 10  19.2    6.  168.  123.  3.92  3.44  18.3    1.    0.    4.    4.
## # ... with 22 more rows
```

Remark

ungroup() performs the reverse operation.

Combine summarise() and group_by()

Magic of group_by() comes true when used in conjunction with summarise()

```
grp_mtcars <- group_by(mtcars, cyl, carb)
summarise(grp_mtcars, Count = n(),  Mean_mpg = mean(mpg),  Var_disp = var(disp))
```

```
## # A tibble: 9 x 5
## # Groups:   cyl [?]
##     cyl  carb Count Mean_mpg Var_disp
##   <dbl> <dbl> <int>    <dbl>    <dbl>
## 1    4.    1.     5     27.6    457.
## 2    4.    2.     6     25.9    732.
## 3    6.    1.     2     19.8    544.
## 4    6.    4.     4     19.8     19.3
## 5    6.    6.     1     19.7     NA
## 6    8.    2.     4     17.2   1886.
## 7    8.    3.     3     16.3      0.
## 8    8.    4.     6     13.2   3341.
## 9    8.    8.     1     15.0     NA
```

Common remarks and extension

Remarks

Most primitive in `dyplr` do no modify the original table

Other verbs/functions

`rename`, `filter`, `select`, `summarise`, etc. all have *scoped* variant

- `rename_all()`: apply operation on all variables
- `rename_at()`: apply an operation on a subset of *specified* variables
- `rename_if()`:) apply an operation on the subset of *predicated* variables

Simple Exercise

Consider the grade student data set:

```
grades <- tibble(
  Name = c("Tommy", "Mary", "Gary", "Cathy"),
  Sexage = c("m.15", "f.15", "m.16", "f.14"),
  Math = c(10, 15, 16, 14),
  Philo = c(11, 13, 10, 12),
  English = c(12, 13, 17, 10)
  )
```

- Compute the mean by Topic
- Compute the mean by Student

Exercises in dplyr vs base R

Exercises adapted from UseR 2017 on data. table

```
set.seed(20170703L)## toy data.frames
DF1 = data.frame(id = sample(1:2, 9L, TRUE),
                 code = sample(letters[1:3], 9, TRUE),
                 valA = 1:9, valB = 10:18,
                 stringsAsFactors = FALSE)
DF2 = data.frame(id = c(3L, 1L, 1L, 2L, 3L),
                 code = c("b", "a", "c", "c", "d"),
                 mul = 5:1, stringsAsFactors = FALSE)
## corresponding data tibble
TB1 <- as.tibble(DF1)
TB2 <- as.tibble(DF2)
```

Question 1

Subset all rows where id column equals 1 & code column is not equal to “c”

base

```
base::subset(DF1, id == 1 & code != "c")
```

```
##   id code valA valB
## 2  1    b    2   11
## 7  1    b    7   16
```

```
with(DF1, DF1[id == 1 & code != "c",])
```

```
##   id code valA valB
## 2  1    b    2   11
## 7  1    b    7   16
```

dplyr

```
filter(TB1, id == 1 & code != "c")
```

```
## # A tibble: 2 x 4
##      id code   valA  valB
##   <int> <chr> <int> <int>
## 1     1 b         2    11
## 2     1 b         7    16
```

Question 1

Subset all rows where id column equals 1 & code column is not equal to "c"

base

```
base::subset(DF1, id == 1 & code != "c")
```

```
##   id code valA valB
## 2  1    b    2   11
## 7  1    b    7   16
```

```
with(DF1, DF1[id == 1 & code != "c",])
```

```
##   id code valA valB
## 2  1    b    2   11
## 7  1    b    7   16
```

dplyr

```
filter(TB1, id == 1 & code != "c")
```

```
## # A tibble: 2 x 4
##      id code   valA  valB
##   <int> <chr> <int> <int>
## 1     1 b         2    11
## 2     1 b         7    16
```

Question 1

Subset all rows where id column equals 1 & code column is not equal to "c"

base

```
base::subset(DF1, id == 1 & code != "c")
```

```
##   id code valA valB
## 2  1    b    2   11
## 7  1    b    7   16
```

```
with(DF1, DF1[id == 1 & code != "c",])
```

```
##   id code valA valB
## 2  1    b    2   11
## 7  1    b    7   16
```

dplyr

```
filter(TB1, id == 1 & code != "c")
```

```
## # A tibble: 2 x 4
##      id code   valA  valB
##   <int> <chr> <int> <int>
## 1     1 b         2    11
## 2     1 b         7    16
```

Question 2

Select valA and valB columns from DF1

base R

```
DF1[, c("valA", "valB")]
```

```
##   valA valB
## 1    1   10
## 2    2   11
## 3    3   12
## 4    4   13
## 5    5   14
## 6    6   15
## 7    7   16
## 8    8   17
## 9    9   18
```

dplyr

```
select(TB1, valA, valB)
```

```
## # A tibble: 9 x 2
##    valA  valB
##   <int> <int>
## 1     1    10
## 2     2    11
## 3     3    12
```

Question 2

Select valA and valB columns from DF1

base R

```
DF1[, c("valA", "valB")]
```

```
##   valA valB
## 1    1   10
## 2    2   11
## 3    3   12
## 4    4   13
## 5    5   14
## 6    6   15
## 7    7   16
## 8    8   17
## 9    9   18
```

dplyr

```
select(TB1, valA, valB)
```

```
## # A tibble: 9 x 2
##    valA  valB
##   <int> <int>
## 1     1    10
## 2     2    11
## 3     3    12
```

Question 2

Select valA and valB columns from DF1

base R

```
DF1[, c("valA", "valB")]
```

```
##   valA valB
## 1    1   10
## 2    2   11
## 3    3   12
## 4    4   13
## 5    5   14
## 6    6   15
## 7    7   16
## 8    8   17
## 9    9   18
```

dplyr

```
select(TB1, valA, valB)
```

```
## # A tibble: 9 x 2
##    valA  valB
##   <int> <int>
## 1     1    10
## 2     2    11
## 3     3    12
```

Question 3

Get sum(valA) and sum(valB) for id > 1 as a 1-row, 2-col data.frame

base R

```
colSums(DF1[ DF1$id > 1, c("valA", "valB")])
```

```
## valA valB
##   19   46
```

dplyr

```
TB1 %>% filter(id > 1) %>% select(valA, valB) %>% summarise_all(sum)
```

```
## # A tibble: 1 x 2
##    valA  valB
##   <int> <int>
## 1    19    46
```

Question 3

Get sum(valA) and sum(valB) for id > 1 as a 1-row, 2-col data.frame

base R

```
colSums(DF1[ DF1$id > 1, c("valA", "valB")])
```

```
## valA valB
##   19   46
```

dplyr

```
TB1 %>% filter(id > 1) %>% select(valA, valB) %>% summarise_all(sum)
```

```
## # A tibble: 1 x 2
##    valA  valB
##   <int> <int>
## 1    19    46
```

Question 3

Get sum(valA) and sum(valB) for id > 1 as a 1-row, 2-col data.frame

base R

```
colSums(DF1[ DF1$id > 1, c("valA", "valB")])
```

```
## valA valB
##   19   46
```

dplyr

```
TB1 %>% filter(id > 1) %>% select(valA, valB) %>% summarise_all(sum)
```

```
## # A tibble: 1 x 2
##    valA  valB
##   <int> <int>
## 1    19    46
```

Question 4

Replace valB with valB+1 for all rows where code == "c"

base R

```
DF1$valB[DF1$code == "c"] = DF1$valB[DF1$code == "c"] + 1
DF1
```

```
##   id code valA valB
## 1  1    c    1   11
## 2  1    b    2   11
## 3  1    c    3   13
## 4  1    c    4   14
## 5  2    a    5   14
## 6  2    a    6   15
## 7  1    b    7   16
## 8  2    a    8   17
## 9  1    c    9   19
```

dplyr

```
mutate(TB1, valB = ifelse(code == "c", valB + 1,valB))
```

```
## # A tibble: 9 x 4
##      id code   valA  valB
##   <int> <chr> <int> <dbl>
## 1     1 c         1   11.
## 2     1 b         2   11
```

Question 4

Replace valB with valB+1 for all rows where code == “c”

base R

```
DF1$valB[DF1$code == "c"] = DF1$valB[DF1$code == "c"] + 1
DF1
```

```
##   id code valA valB
## 1  1    c    1   11
## 2  1    b    2   11
## 3  1    c    3   13
## 4  1    c    4   14
## 5  2    a    5   14
## 6  2    a    6   15
## 7  1    b    7   16
## 8  2    a    8   17
## 9  1    c    9   19
```

dplyr

```
mutate(TB1, valB = ifelse(code == "c", valB + 1,valB))
```

```
## # A tibble: 9 x 4
##      id code   valA  valB
##   <int> <chr> <int> <dbl>
## 1     1 c         1   11.
## 2     1 b         2   11
```

Question 4

Replace valB with valB+1 for all rows where code == "c"

base R

```
DF1$valB[DF1$code == "c"] = DF1$valB[DF1$code == "c"] + 1
DF1
```

```
##   id code valA valB
## 1  1    c    1   11
## 2  1    b    2   11
## 3  1    c    3   13
## 4  1    c    4   14
## 5  2    a    5   14
## 6  2    a    6   15
## 7  1    b    7   16
## 8  2    a    8   17
## 9  1    c    9   19
```

dplyr

```
mutate(TB1, valB = ifelse(code == "c", valB + 1,valB))
```

```
## # A tibble: 9 x 4
##      id code   valA  valB
##   <int> <chr> <int> <dbl>
## 1     1 c         1   11.
## 2     1 b         2   11
```

Question 5

Add a new column valC column with values equal to valB^2 - valA^2

base R

```
DF1 <- transform(DF1, valC = valB^2 - valA^2)
## DF1$valC <- DF1$valB^2 - DF1$valA^2 # alternate solution
DF1
```

```
##   id code valA valB valC
## 1  1    c    1   11  120
## 2  1    b    2   11  117
## 3  1    c    3   13  160
## 4  1    c    4   14  180
## 5  2    a    5   14  171
## 6  2    a    6   15  189
## 7  1    b    7   16  207
## 8  2    a    8   17  225
## 9  1    c    9   19  280
```

dplyr

```
TB1 <- mutate(TB1, valC = valB^2 - valA^2)
TB1
```

```
## # A tibble: 9 x 5
##      id code   valA  valB  valC
##   <int> <chr> <int> <int> <dbl>
```

Question 5

Add a new column valC column with values equal to valB^2 - valA^2

base R

```
DF1 <- transform(DF1, valC = valB^2 - valA^2)
## DF1$valC <- DF1$valB^2 - DF1$valA^2 # alternate solution
DF1
```

```
##   id code valA valB valC
## 1  1    c    1   11  120
## 2  1    b    2   11  117
## 3  1    c    3   13  160
## 4  1    c    4   14  180
## 5  2    a    5   14  171
## 6  2    a    6   15  189
## 7  1    b    7   16  207
## 8  2    a    8   17  225
## 9  1    c    9   19  280
```

dplyr

```
TB1 <- mutate(TB1, valC = valB^2 - valA^2)
TB1
```

```
## # A tibble: 9 x 5
##      id code   valA  valB  valC
##   <int> <chr> <int> <int> <dbl>
```

Question 5

Add a new column valC column with values equal to valB^2 - valA^2

base R

```
DF1 <- transform(DF1, valC = valB^2 - valA^2)
## DF1$valC <- DF1$valB^2 - DF1$valA^2 # alternate solution
DF1
```

```
##   id code valA valB valC
## 1  1    c    1   11  120
## 2  1    b    2   11  117
## 3  1    c    3   13  160
## 4  1    c    4   14  180
## 5  2    a    5   14  171
## 6  2    a    6   15  189
## 7  1    b    7   16  207
## 8  2    a    8   17  225
## 9  1    c    9   19  280
```

dplyr

```
TB1 <- mutate(TB1, valC = valB^2 - valA^2)
TB1
```

```
## # A tibble: 9 x 5
##      id code   valA  valB  valC
##   <int> <chr> <int> <int> <dbl>
```

Question 6

Get sum(valA) and sum(valB) grouped by id and code (i.e., for each unique combination of id,code)

base

```
aggregate(.~ id + code, DF1, sum)
```

```
##   id code valA valB valC
## 1  2    a   19   46  585
## 2  1    b    9   27  324
## 3  1    c   17   57  740
```

```
aggregate(DF1[, c("valA", "valB")], list(DF1$id, DF1$code), sum)
```

```
##   Group.1 Group.2 valA valB
## 1       2       a   19   46
## 2       1       b    9   27
## 3       1       c   17   57
```

dplyr

```
TB1 %>% group_by(id, code) %>% summarise_all(sum)
```

```
## # A tibble: 3 x 5
## # Groups:   id [?]
##        id code    valA  valB  valC
```

Question 6

Get sum(valA) and sum(valB) grouped by id and code (i.e., for each unique combination of id,code)

base

```
aggregate(.~ id + code, DF1, sum)
```

```
##   id code valA valB valC
## 1  2    a   19   46  585
## 2  1    b    9   27  324
## 3  1    c   17   57  740
```

```
aggregate(DF1[, c("valA", "valB")], list(DF1$id, DF1$code), sum)
```

```
##   Group.1 Group.2 valA valB
## 1       2       a   19   46
## 2       1       b    9   27
## 3       1       c   17   57
```

dplyr

```
TB1 %>% group_by(id, code) %>% summarise_all(sum)
```

```
## # A tibble: 3 x 5
## # Groups:   id [?]
##      id code   valA  valB  valC
```

Question 6

Get sum(valA) and sum(valB) grouped by id and code (i.e., for each unique combination of id,code)

base

```
aggregate(.~ id + code, DF1, sum)
```

```
##   id code valA valB valC
## 1  2    a   19   46  585
## 2  1    b    9   27  324
## 3  1    c   17   57  740
```

```
aggregate(DF1[, c("valA", "valB")], list(DF1$id, DF1$code), sum)
```

```
##   Group.1 Group.2 valA valB
## 1       2       a   19   46
## 2       1       b    9   27
## 3       1       c   17   57
```

dplyr

```
TB1 %>% group_by(id, code) %>% summarise_all(sum)
```

```
## # A tibble: 3 x 5
## # Groups:   id [?]
##      id code   valA  valB  valC
```

Question 7

Get sum(valA) and sum(valB) grouped by id for id $>=$ 2 & code %in% c("a", "c")

base

```
aggregate(.~ id , subset(DF1, id >=2 & code %in% c("a","c"), -code), sum)
```

```
##   id valA valB valC
## 1  2   19   46  585
```

dplyr

```
TB1 %>%
  group_by(id) %>%
  filter(id >=2, code %in% c("a", "c")) %>%
  select(-code, -valC) %>%
  summarise_all(sum)
```

```
## # A tibble: 1 x 3
##      id  valA  valB
##   <int> <int> <int>
## 1     2    19    46
```

Question 7

Get sum(valA) and sum(valB) grouped by id for id >= 2 & code %in% c("a", "c")

base

```r
aggregate(.~ id , subset(DF1, id >=2 & code %in% c("a","c"), -code), sum)
```

```
##   id valA valB valC
## 1  2   19   46  585
```

dplyr

```r
TB1 %>%
  group_by(id) %>%
  filter(id >=2, code %in% c("a", "c")) %>%
  select(-code, -valC) %>%
  summarise_all(sum)
```

```
## # A tibble: 1 x 3
##      id  valA  valB
##   <int> <int> <int>
## 1     2    19    46
```

Question 7

Get sum(valA) and sum(valB) grouped by id for id >= 2 & code %in% c("a", "c")

base

```
aggregate(.~ id , subset(DF1, id >=2 & code %in% c("a","c"), -code), sum)
```

```
##   id valA valB valC
## 1  2   19   46  585
```

dplyr

```
TB1 %>%
  group_by(id) %>%
  filter(id >=2, code %in% c("a", "c")) %>%
  select(-code, -valC) %>%
  summarise_all(sum)
```

```
## # A tibble: 1 x 3
##      id  valA  valB
##   <int> <int> <int>
## 1     2    19    46
```

Question 8

Replace valA with max(valA)-min(valA) grouped by code

base

```
DF1 <- transform(DF1, valA = rep(tapply(valA, code, function(x) diff(range(x)))[code]))
DF1
```

```
##   id code valA valB valC
## 1  1    c    8   11  120
## 2  1    b    5   11  117
## 3  1    c    8   13  160
## 4  1    c    8   14  180
## 5  2    a    3   14  171
## 6  2    a    3   15  189
## 7  1    b    5   16  207
## 8  2    a    3   17  225
## 9  1    c    8   19  280
```

dplyr

```
TB1 <- TB1 %>% group_by(code) %>% mutate(valA= max(valA)-min(valA))
TB1
```

```
## # A tibble: 9 x 5
## # Groups:   code [3]
##      id code   valA  valB  valC
##   <int> <chr> <dbl> <int> <dbl>
```

Question 8

Replace valA with max(valA)-min(valA) grouped by code

base

```
DF1 <- transform(DF1, valA = rep(tapply(valA, code, function(x) diff(range(x)))[code]))
DF1
```

```
##   id code valA valB valC
## 1  1    c    8   11  120
## 2  1    b    5   11  117
## 3  1    c    8   13  160
## 4  1    c    8   14  180
## 5  2    a    3   14  171
## 6  2    a    3   15  189
## 7  1    b    5   16  207
## 8  2    a    3   17  225
## 9  1    c    8   19  280
```

dplyr

```
TB1 <- TB1 %>% group_by(code) %>% mutate(valA= max(valA)-min(valA))
TB1
```

```
## # A tibble: 9 x 5
## # Groups:   code [3]
##        id code   valA  valB  valC
##     <int> <chr> <dbl> <int> <dbl>
```

Question 8

Replace valA with max(valA)-min(valA) grouped by code

base

```
DF1 <- transform(DF1, valA = rep(tapply(valA, code, function(x) diff(range(x)))[code]))
DF1
```

```
##   id code valA valB valC
## 1  1    c    8   11  120
## 2  1    b    5   11  117
## 3  1    c    8   13  160
## 4  1    c    8   14  180
## 5  2    a    3   14  171
## 6  2    a    3   15  189
## 7  1    b    5   16  207
## 8  2    a    3   17  225
## 9  1    c    8   19  280
```

dplyr

```
TB1 <- TB1 %>% group_by(code) %>% mutate(valA= max(valA)-min(valA))
TB1
```

```
## # A tibble: 9 x 5
## # Groups:   code [3]
##      id code   valA  valB  valC
##   <int> <chr> <dbl> <int> <dbl>
```

Question 9

Create a new col named valD with max(valB)-min(valA) grouped by code

base

```
DF1 <- transform(DF1, valD = by(DF1, code, function(x) max(x$valB) - min(x$valA))[code])
DF1
```

```
##   id code valA valB valC valD
## 1  1    c    8   11  120   11
## 2  1    b    5   11  117   11
## 3  1    c    8   13  160   11
## 4  1    c    8   14  180   11
## 5  2    a    3   14  171   14
## 6  2    a    3   15  189   14
## 7  1    b    5   16  207   11
## 8  2    a    3   17  225   14
## 9  1    c    8   19  280   11
```

dplyr

```
TB1 <- TB1 %>% group_by(code) %>% mutate(valD= max(valB)-min(valA))
TB1
```

```
## # A tibble: 9 x 6
## # Groups:   code [3]
##        id code   valA  valB  valC  valD
##    <int> <chr> <dbl> <int> <dbl> <dbl>
```

Question 9

Create a new col named valD with max(valB)-min(valA) grouped by code

base

```
DF1 <- transform(DF1, valD = by(DF1, code, function(x) max(x$valB) - min(x$valA))[code])
DF1
```

```
##   id code valA valB valC valD
## 1  1    c    8   11  120   11
## 2  1    b    5   11  117   11
## 3  1    c    8   13  160   11
## 4  1    c    8   14  180   11
## 5  2    a    3   14  171   14
## 6  2    a    3   15  189   14
## 7  1    b    5   16  207   11
## 8  2    a    3   17  225   14
## 9  1    c    8   19  280   11
```

dplyr

```
TB1 <- TB1 %>% group_by(code) %>% mutate(valD= max(valB)-min(valA))
TB1
```

```
## # A tibble: 9 x 6
## # Groups:   code [3]
##      id code   valA  valB  valC  valD
##   <int> <chr> <dbl> <int> <dbl> <dbl>
```

Question 9

Create a new col named valD with max(valB)-min(valA) grouped by code

base

```
DF1 <- transform(DF1, valD = by(DF1, code, function(x) max(x$valB) - min(x$valA))[code])
DF1
```

```
##   id code valA valB valC valD
## 1  1    c    8   11  120   11
## 2  1    b    5   11  117   11
## 3  1    c    8   13  160   11
## 4  1    c    8   14  180   11
## 5  2    a    3   14  171   14
## 6  2    a    3   15  189   14
## 7  1    b    5   16  207   11
## 8  2    a    3   17  225   14
## 9  1    c    8   19  280   11
```

dplyr

```
TB1 <- TB1 %>% group_by(code) %>% mutate(valD= max(valB)-min(valA))
TB1
```

```
## # A tibble: 9 x 6
## # Groups:   code [3]
##      id code   valA  valB  valC  valD
##   <int> <chr> <dbl> <int> <dbl> <dbl>
```

Outline

1. Introduction
2. Structures and types: `tibble`, `forcats`, `stringr`
3. data wrangling: `readr`, `tidyr`, `dplyr`
4. Manipulation: `magrittr`, `purrr`
5. Vizualization: `ggplot2`

{magrittr}

Figure 10: a set of operators which make your code more readable

```r
library(magrittr)
```

Provides the following operators

- Pipe %>%
- Reassignment pipe %<>%
- T-Pipe %T>%

Motivation: make Tom eat an apple

Everyday language

Tom eats an apple

Subject - Verb - Complement

Programming language

`eat(Tom, apple)`

Verb - Subject - Complement

Pipes

⇝ get closer to everyday language in your code

⇝ clearly expressing a sequence of multiple operations

Pipe %>%

- when you read code, %>% is pronounced "then"
- the keybord shortcut for %>% is Ctrl + shift + M

Objective

- Helps writing `R` code which is easy to read (and thus, easy to understand)
- `x %>% f()` is equivalent to `f(x)`
- `x %>% f(y)` is equivalent to `f(x, y)`
- `x %>% f(y,.)` is équivalent to `f(y,x)`

Example

```
2^mean(log(seq_len(10), base = 2), na.rm = TRUE)
```

```
## [1] 4.528729
```

```
10 %>%
  seq_len() %>%
  log(base = 2) %>%
  mean(na.rm = TRUE) %>%
  {2^.}
```

Pipe %>%

- when you read code, %>% is pronounced "then"
- the keybord shortcut for %>% is Ctrl + shift + M

Objective

- Helps writing `R` code which is easy to read (and thus, easy to understand)
- `x %>% f()` is equivalent to `f(x)`
- `x %>% f(y)` is equivalent to `f(x, y)`
- `x %>% f(y,.)` is équivalent to `f(y,x)`

Example

```r
2^mean(log(seq_len(10), base = 2), na.rm = TRUE)
```

```
## [1] 4.528729
```

```r
10 %>%
  seq_len() %>%
  log(base = 2) %>%
  mean(na.rm = TRUE) %>%
  {2^.}
```

Pipe %>%

- when you read code, %>% is pronounced "then"
- the keybord shortcut for %>% is Ctrl + shift + M

Objective

- Helps writing R code which is easy to read (and thus, easy to understand)
- `x %>% f()` is equivalent to `f(x)`
- `x %>% f(y)` is equivalent to `f(x, y)`
- `x %>% f(y,.)` is équivalent to `f(y,x)`

Example

```
2^mean(log(seq_len(10), base = 2), na.rm = TRUE)
```

```
## [1] 4.528729
```

```
10 %>%
  seq_len() %>%
  log(base = 2) %>%
  mean(na.rm = TRUE) %>%
  {2^.}
```

Exercise

Consider

```
x <- c(0.109, 0.359, 0.63, 0.996, 0.515, 0.142, 0.017, 0.829, 0.907)
```

Compute the logarithm of `x`, return suitably lagged and iterated differences, compute the exponential function and round the result

1. In base `R`
2. Using %>%

(Re)assignment pipe %<>%

For affectation, `magrittr` provides the operator %<>% which allows to replace code like

```
mtcars <- mtcars%>% transform(cyl = cyl * 2)
```

by

```
mtcars %<>% transform(cyl = cyl * 2)
```

T-pipe %T>%

Problem with functions requiring early side effects along succession of %>%

- you might want to plot or print and object
- such function do not send back anything and break the pipe

Solution

- to overcome such an issue, use the "tee" pipe %T>%
- works like %>% except that it sends left side in place of right side of the expression
- "tee"because it looks like a pipe with a T shape

T-pipe %T>%: example without T

```
rnorm (100) %>%
  matrix(ncol = 2) %>%
  plot() %>%
  str()
```

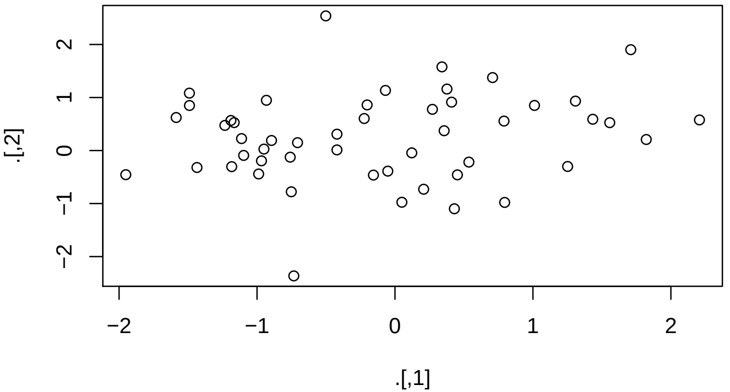


Figure 11: plot of bivariate Gaussian sample

```
## NULL
```

T-pipe %T>%: example with T

```
rnorm (100) %>%
  matrix(ncol = 2) %T>%
  plot() %>%
  str()
```

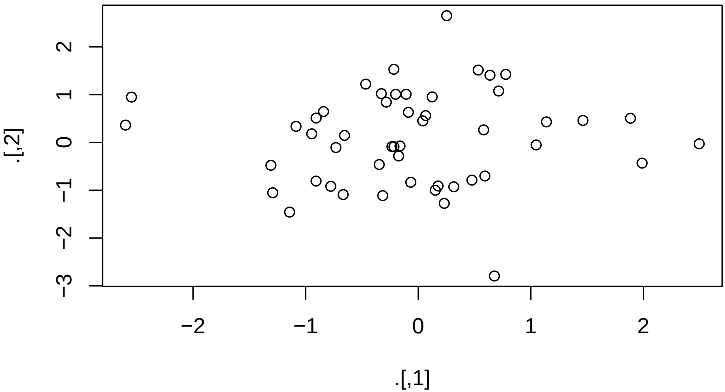


Figure 12: plot of bivariate Gaussian sample

```
## num [1:50, 1:2] -0.777 1.048 -0.216 1.463 -0.667 ...
```

Exposition Operator %$%

When working with functions that do not take data argumentbut still useful in a pipeline, e.g., when your data is first processed and then passed into the function.

Example

```
iris %>%
  subset(Sepal.Length > mean(Sepal.Length)) %$%
  cor(Sepal.Length, Sepal.Width)
```

```
## [1] 0.3361992
```

When not to use the pipe

Consider other solutions when

Pipes contain too many steps

Create *intermediate* objects with meaningful names

Multiple inputs or outputs are required

E.g., when several objects need to *combine* together

Complex dependance structures exists between your entries

Pipes are fundamentally *linear*: expressing complex relationships with them yield confusing code.

{purrr}

Figure 13: enhances R's functional programming (FP) toolkit

Map family of functions

Apply a function to each element of a vector: replace the [x]`apply` families (more coherent)

- `map()`, `map_if()` and `map_at()` *always return a list*
- `map_lgl()`, `map_int()`, `map_dbl()` and `map_chr()` return vectors of the corresponding type
- `map_dfr()` and `map_dfc()` return data frames created by row-binding and column-binding respectively

Examples

What is this piece of code doing?

```
1:10 %>%
  map(rnorm, n = 10) %>%
  map_dbl(mean)
```

```
##  [1] 1.236616 2.246661 2.938701 3.795700 4.977241 5.796827 7.166772
##  [8] 8.044998 8.704518 9.644171
```

split a data frame into pieces, fit a model to each piece, compute the summary, then extract the R2.

```
mtcars %>%
  split(.$cyl) %>% # from base R
  map(~ lm(mpg ~ wt, data = .)) %>%
  map(summary) %>%
  map_dbl("r.squared")
```

```
##         4         6         8
## 0.5086326 0.4645102 0.4229655
```

Examples

What is this piece of code doing?

```
1:10 %>%
  map(rnorm, n = 10) %>%
  map_dbl(mean)
```

```
##  [1] 1.236616 2.246661 2.938701 3.795700 4.977241 5.796827 7.166772
##  [8] 8.044998 8.704518 9.644171
```

split a data frame into pieces, fit a model to each piece, compute the summary, then extract the R2.

```
mtcars %>%
  split(.$cyl) %>% # from base R
  map(~ lm(mpg ~ wt, data = .)) %>%
  map(summary) %>%
  map_dbl("r.squared")
```

```
##         4         6         8
## 0.5086326 0.4645102 0.4229655
```

A more complicated example

```
iris %>%
  group_by(Species) %>%
  nest(.key = Data) %>%
  mutate(Model = purrr::map(Data,
                            ~ lm(data = .,
                                 Sepal.Length ~ Petal.Length))) %>%
  mutate(Summary = purrr::map(Model, summary)) %>%
  mutate(`R squared` = purrr::map_dbl(Summary, ~ .$r.squared))
```

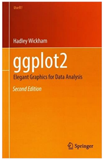
```
## # A tibble: 3 x 5
##   Species    Data              Model    Summary          `R squared`
##   <fct>      <list>            <list>   <list>                 <dbl>
## 1 setosa     <tibble [50 x 4]> <S3: lm> <S3: summary.lm>      0.0714
## 2 versicolor <tibble [50 x 4]> <S3: lm> <S3: summary.lm>      0.569
## 3 virginica  <tibble [50 x 4]> <S3: lm> <S3: summary.lm>      0.747
```

Outline

ggplot2

Figure 14: a system for declaratively creating graphics, based on The Grammar of Graphics

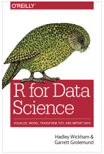
Fully documented (Wickham, 2016) http://ggplot2.tidyverse.org/



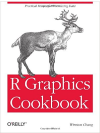
Learning ggplot2

R for data science (Wickham & Grolemund, 2016), http://r4ds.had.co.nz

See chapters *data visualisation* and *graphics for communication*



R for data science (Chang, 2012), http://www.cookbook-r.com/Graphs/

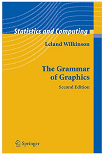


This course

A short introduction, mostly based on examples

ggplot2: grammar of graphics

Implements the grammar of graphics (Wilkinson, 2006)



Elements that composes a the grammar of `ggplot`

- a data set (*data*),
- a graphical projection/mapping (*aes*),
- a geometrical representation (*geom*),
- a statistical transformation (*stats*),
- a coordinate system (coord),
- some scales (*scale*),
- some groupings (*facet*).

Grammar of Graphics in ggplot: summary

```
ggplot(data = <DATA>) +
  <GEOM_FUNCTION>(mapping = aes(<MAPPINGS>),
                  stat = <STAT>, position = <POSITION>) +
  <COORDINATE_FUNCTION> +
  <FACET_FUNCTION>
```

⇝ any plot can be described by a combination of these 7 parameters.

ggplot2: standard steps

Supply data and specify mapping

with functions `ggplot()` and `aes()`

Create a layer

Combine data, mapping, a geometric object, a stat (statistical transformation) and a position adjustment

- by using `geom()` (overide the statistical transformation and position)
- by using `stat()` (specifying a statistical transformation with `stat`)
- add layers to the current ggplot object with the + operator

Adjustements

- the position (`position_`)
- the coordinate system (`coord_`)
- some annotations (`annotation_`)
- faceting (`facet_`)

Example: good old iris data set

```
as_tibble(iris)
```

```
## # A tibble: 150 x 5
##    Sepal.Length Sepal.Width Petal.Length Petal.Width Species
##           <dbl>       <dbl>        <dbl>       <dbl> <fct>
##  1         5.10        3.50         1.40       0.200 setosa
##  2         4.90        3.00         1.40       0.200 setosa
##  3         4.70        3.20         1.30       0.200 setosa
##  4         4.60        3.10         1.50       0.200 setosa
##  5         5.00        3.60         1.40       0.200 setosa
##  6         5.40        3.90         1.70       0.400 setosa
##  7         4.60        3.40         1.40       0.300 setosa
##  8         5.00        3.40         1.50       0.200 setosa
##  9         4.40        2.90         1.40       0.200 setosa
## 10         4.90        3.10         1.50       0.100 setosa
## # ... with 140 more rows
```

Initializing the plot object

Supply data and mapping

All layers use a common data set and common set of aesthetics

```
ggplot(data = iris, aes(x = Species, y = Sepal.Length))
```

Supply data

All layers use a common data set, but with specific aesthetics

```
ggplot(data = iris)
```

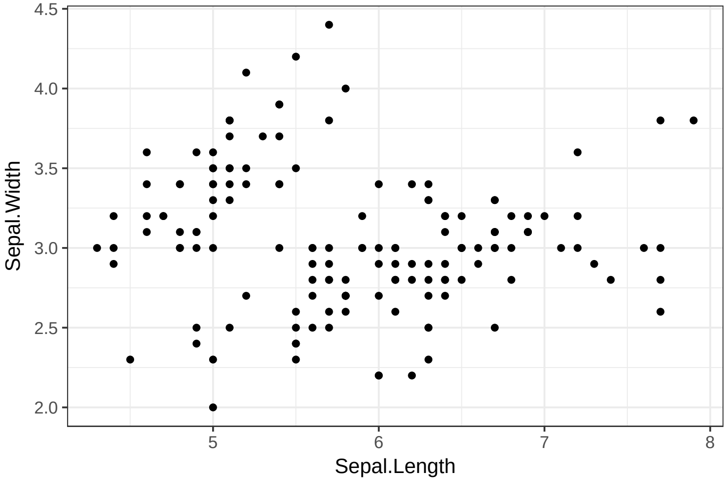
Simple initialization

Each layer use a specific data set

```
ggplot()
```

Add a layer: scatterplot

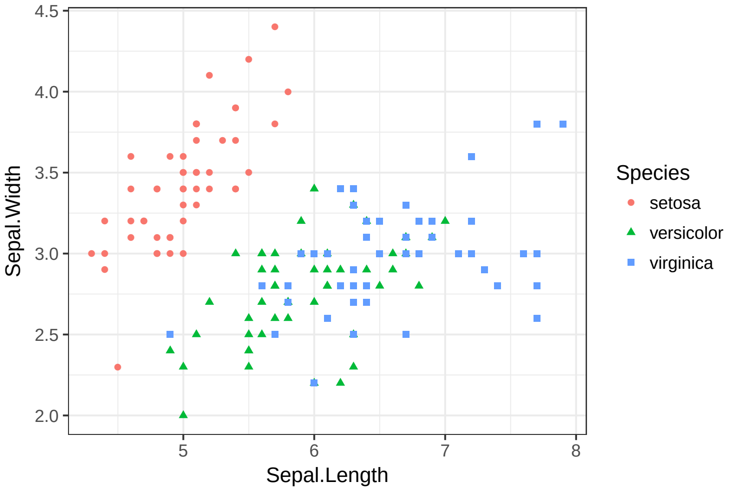
```
ggplot(iris) + geom_point(aes(x = Sepal.Length, y = Sepal.Width))
```



Add a layer: scatterplot + annotation

some aesthetic are optional

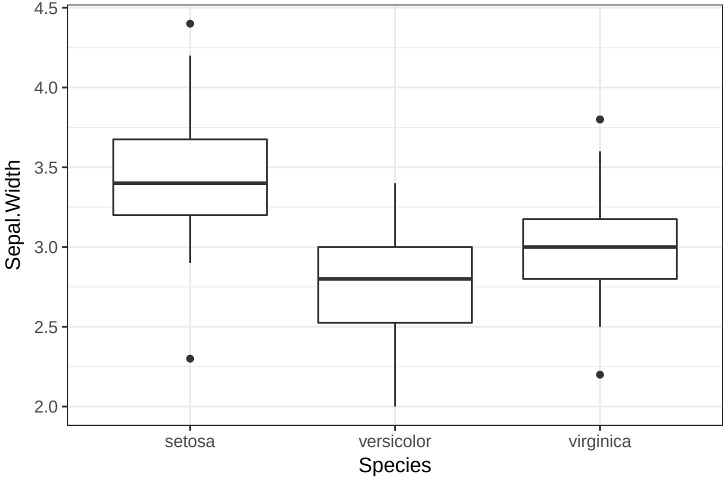
```
ggplot(iris) + geom_point(aes(x = Sepal.Length, y = Sepal.Width, color = Species, shape = Speci
```



Add a layer: boxplot

the aes depends on the geometry (here, a factor is expected for `x`)

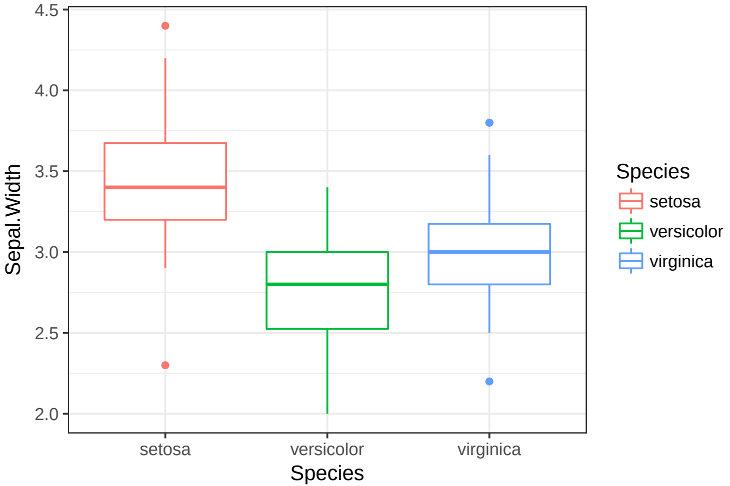
```
ggplot(iris) + geom_boxplot(aes(x = Species, y = Sepal.Width))
```



Add a layer: boxplot + annotation

the aes depends on the geometry (here, a factor is expected for `x`)

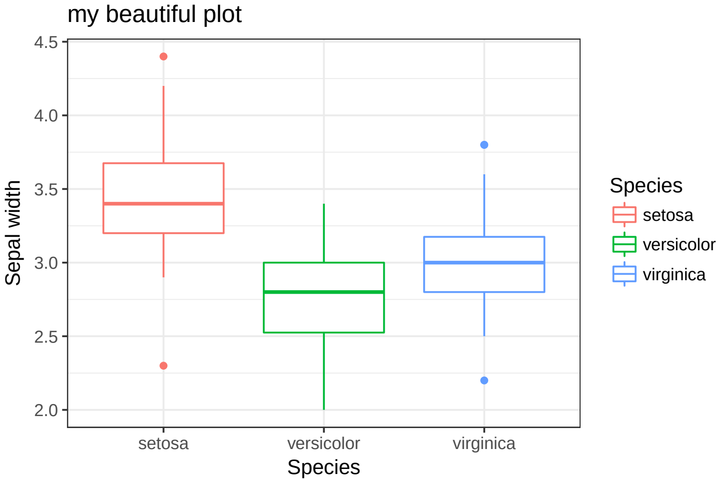
```
ggplot(iris) + geom_boxplot(aes(x = Species, y = Sepal.Width, color = Species))
```



Add a layer: boxplot + annotation (Cont'd)

the aes depends on the geometry (here, a factor is expected for `x`)

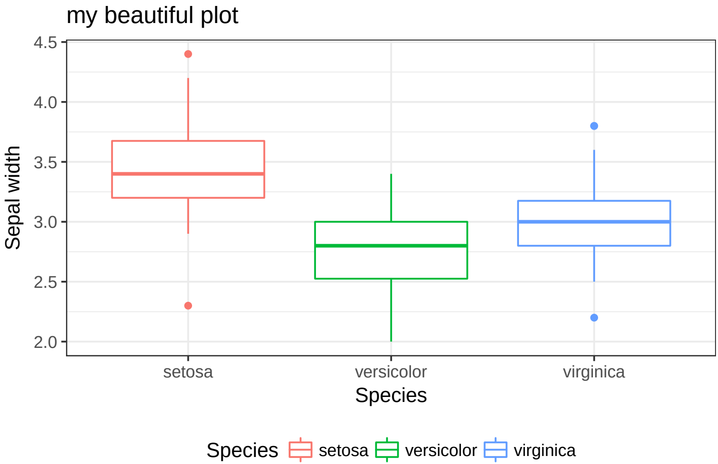
```
ggplot(iris) +
  geom_boxplot(aes(x = Species, y = Sepal.Width, color = Species)) +
  labs("species", y = "Sepal width", title = "my beautiful plot")
```



Add a layer: boxplot + annotation (Cont'd)

the aes depends on the geometry (here, a factor is expected for `x`)

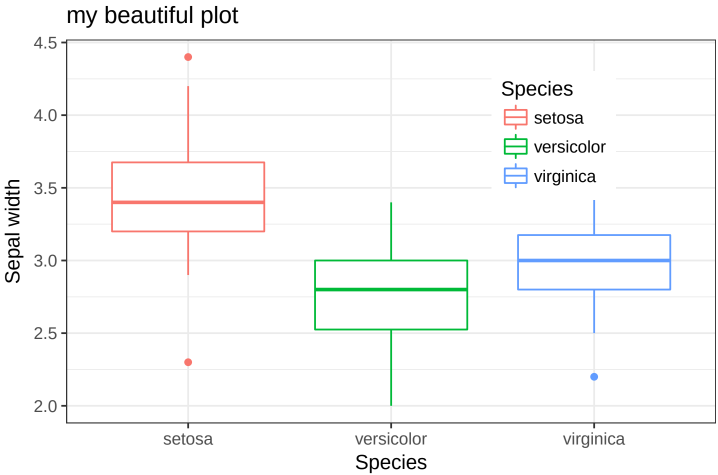
```
ggplot(iris) +
  geom_boxplot(aes(x = Species, y = Sepal.Width, color = Species)) +
  labs("species", y = "Sepal width", title = "my beautiful plot") +
  theme(legend.position = "bottom")
```



Add a layer: boxplot + annotation (Cont'd)

the aes depends on the geometry (here, a factor is expected for `x`)

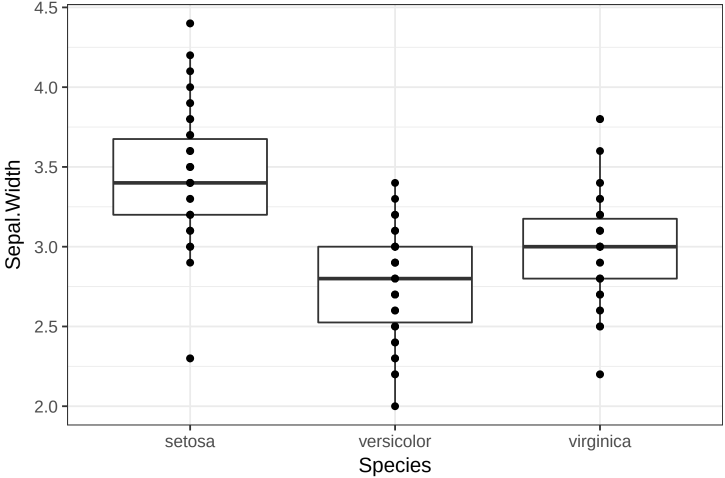
```r
ggplot(iris) +
  geom_boxplot(aes(x = Species, y = Sepal.Width, color = Species)) +
  labs("species", y = "Sepal width", title = "my beautiful plot") +
  theme(legend.position = c(.75, .75))
```



Add several layers: boxplot + points

Note how I changed the use of ggplot since aesthetic where common to both

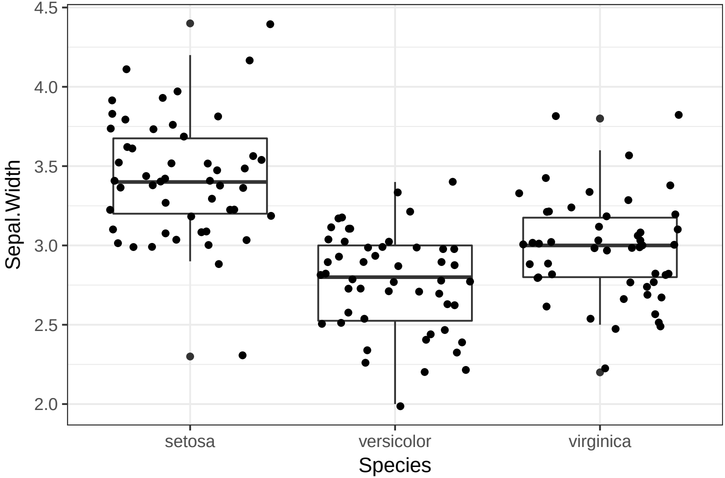
```
ggplot(iris, aes(x = Species, y = Sepal.Width)) + geom_boxplot() + geom_point()
```



Add several layers: boxplot + jitter

Note how I changed the use of `ggplot` since aesthetic where common to both

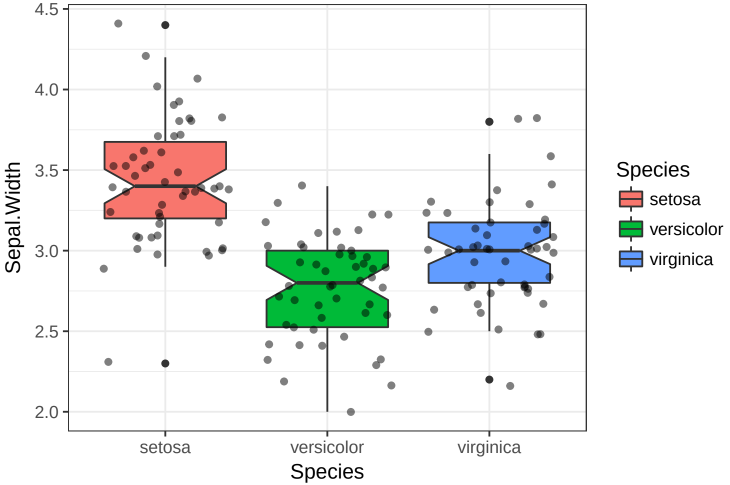
```
ggplot(iris, aes(x = Species, y = Sepal.Width)) + geom_boxplot() + geom_jitter()
```



Add several layers: boxplot + jitter

Note how I changed the use of ggplot since aesthetic where common to both

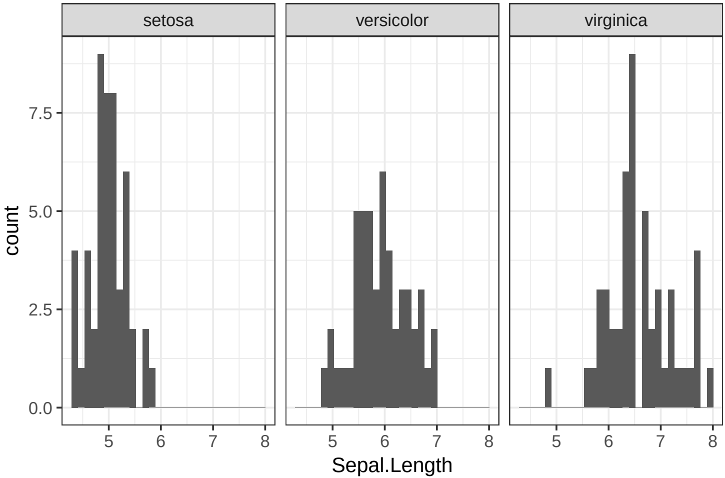
```
ggplot(iris, aes(x = Species, y = Sepal.Width)) +
  geom_boxplot(aes(fill = Species), notch = TRUE) +
  geom_jitter(alpha = .5)
```



Faceting

Note how I changed the use of `ggplot` since aesthetic where common to both

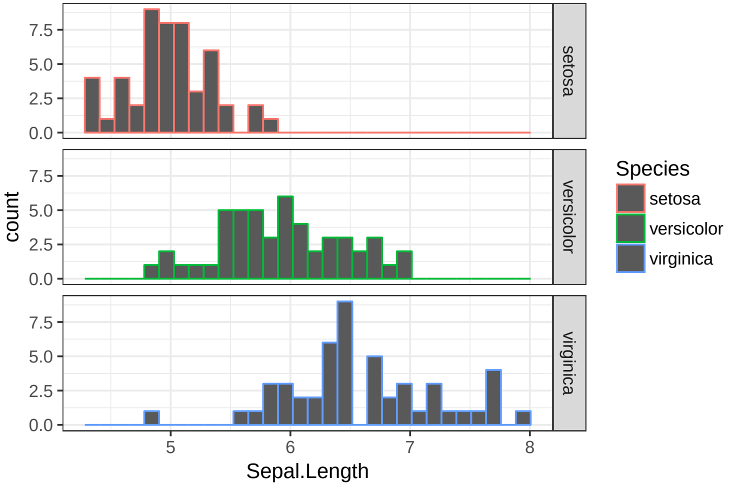
```
ggplot(iris) + geom_histogram(aes(x = Sepal.Length)) + facet_grid( . ~ Species)
```



Faceting (Cont'd)

Note how I changed the use of ggplot since aesthetic where common to both

```
ggplot(iris) + geom_histogram(aes(x = Sepal.Length, color = Species)) + facet_grid(Species ~ .)
```



Use ggplot2 in conjonction other packages of the tidyverse

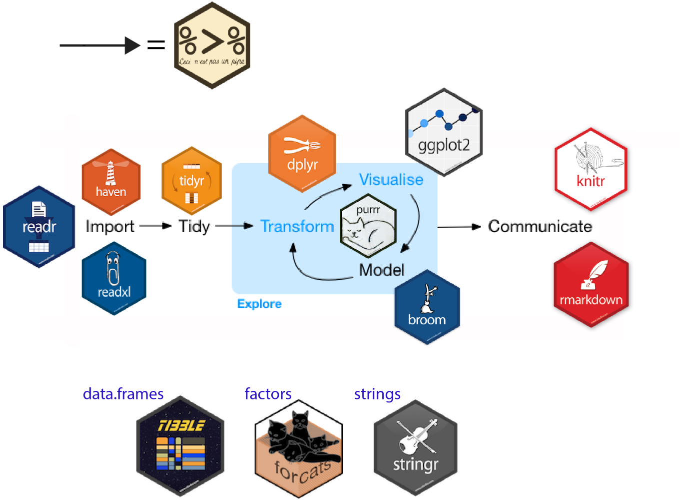
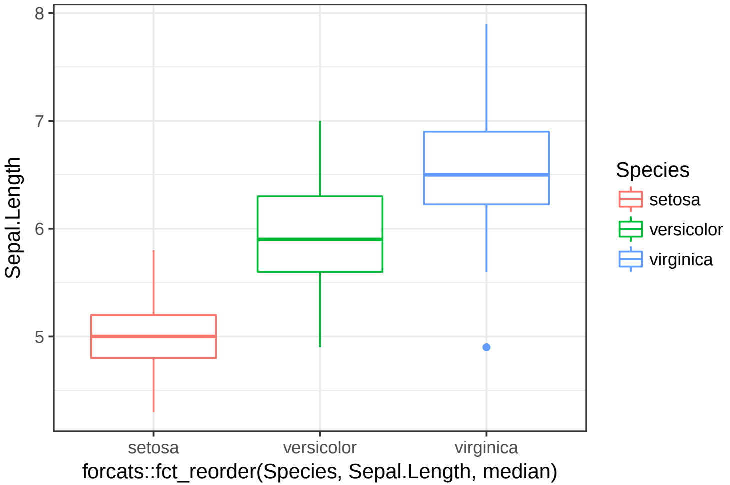


Figure 15: Rember the data process scheme?

Example: `forcats`

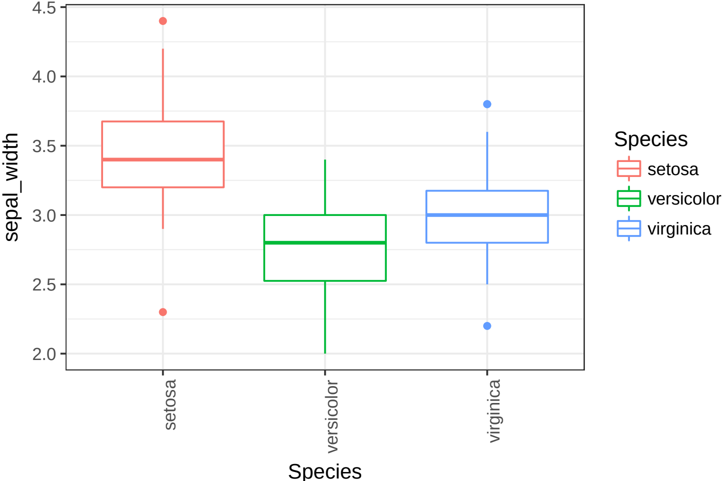
Automatically more readable graphs

```
ggplot(iris) +
  geom_boxplot(aes(
    x = forcats::fct_reorder(Species, Sepal.Length, median),
    y = Sepal.Length, color = Species))
```



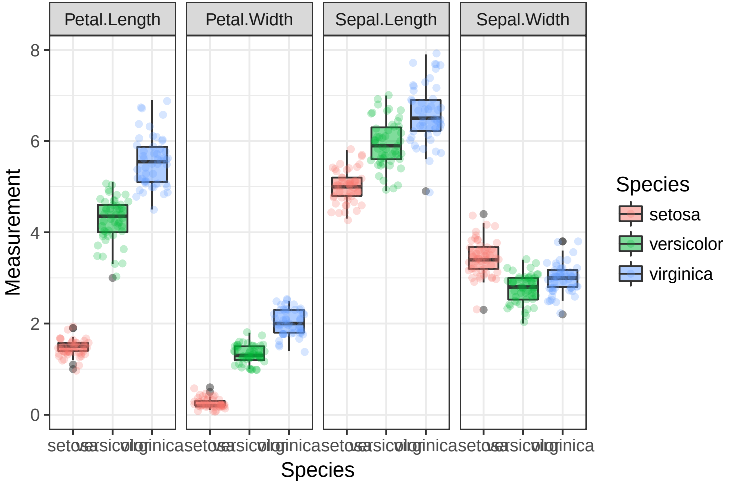
Example: dplyr + %>% for renaming before ploting

```
iris %>% rename(sepal_length = Sepal.Length,
                sepal_width = Sepal.Width,
                petal_length = Petal.Length,
                pepal_width = Petal.Width) %>%
  ggplot() + geom_boxplot(aes(x = Species, y = sepal_width, color = Species)) +
  theme(axis.text.x=element_text(angle=90,hjust=1))
```



Example: dplyr + %>% for gathering new data

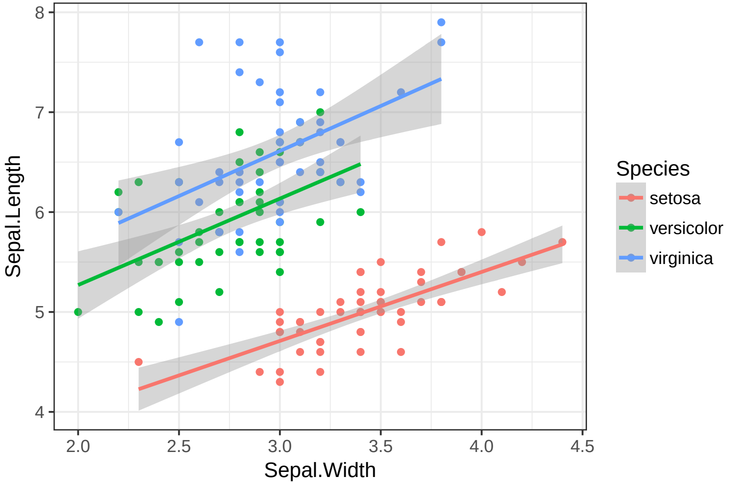
```
iris %>%
  gather(key = "Attribute", value = "Measurement", -Species) %>%
  ggplot(aes(x = Species, y = Measurement)) + geom_boxplot(aes(fill = Species), alpha = .5) +
  geom_jitter(aes(color = Species), alpha = 0.25) + facet_grid(. ~ Attribute)
```



Add a model layer

Adjust one linear model per species

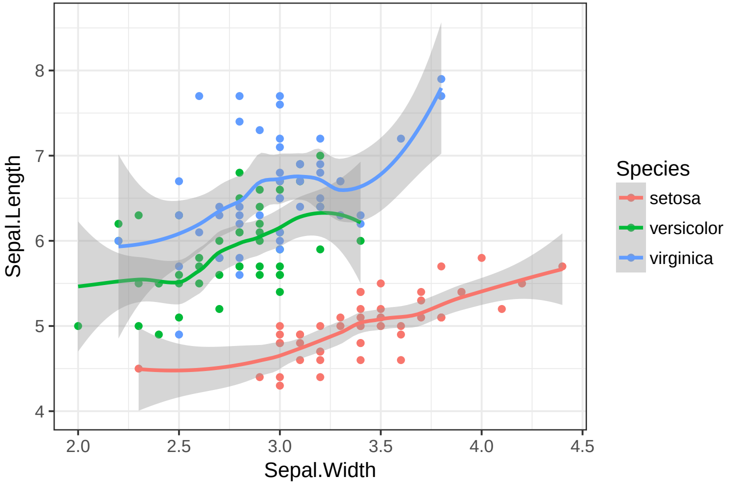
```
ggplot(iris, aes(x = Sepal.Width, y = Sepal.Length, colour = Species)) +
  geom_point() +  geom_smooth(method = lm)
```



Add a model layer (Cont'd)

Adjust one nonlinear model per species

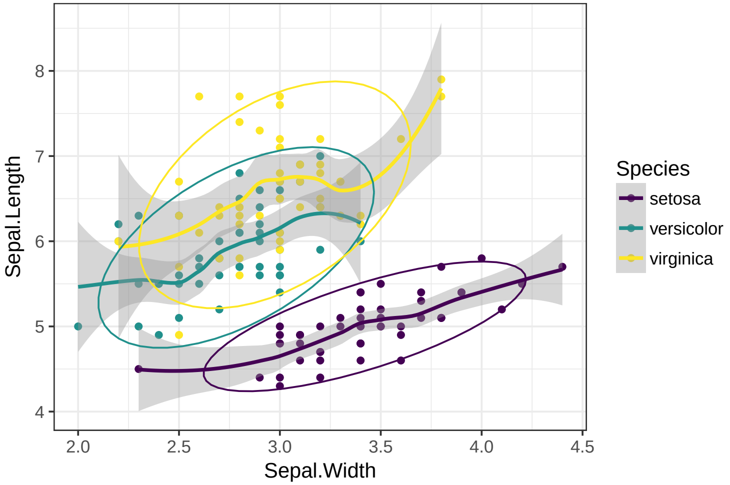
```
ggplot(iris, aes(x = Sepal.Width, y = Sepal.Length, color = Species)) +
  geom_point() +  geom_smooth(method = loess)
```



Add model + stat layers and colorblind pallete

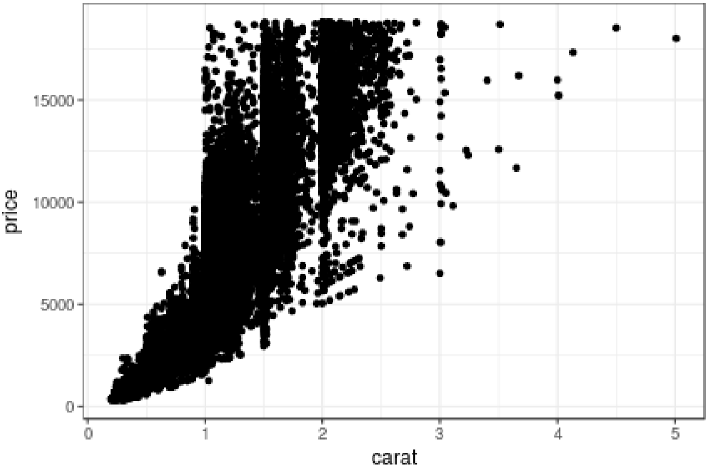
Adjust one nonlinear model per species

```
ggplot(iris, aes(x = Sepal.Width, y = Sepal.Length, color = Species)) +
  geom_point() +  geom_smooth(method = loess) +
  stat_ellipse() + viridis::scale_color_viridis(discrete = TRUE)
```



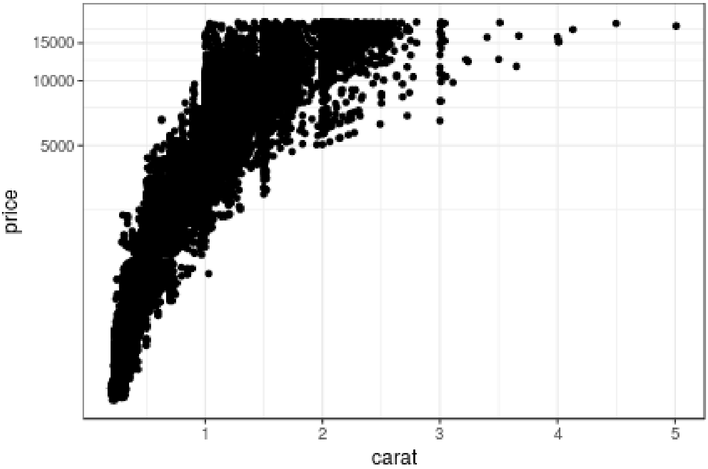
Transform coordinate: log-scales

```
ggplot(diamonds, aes(carat, price)) +
  geom_point()
```



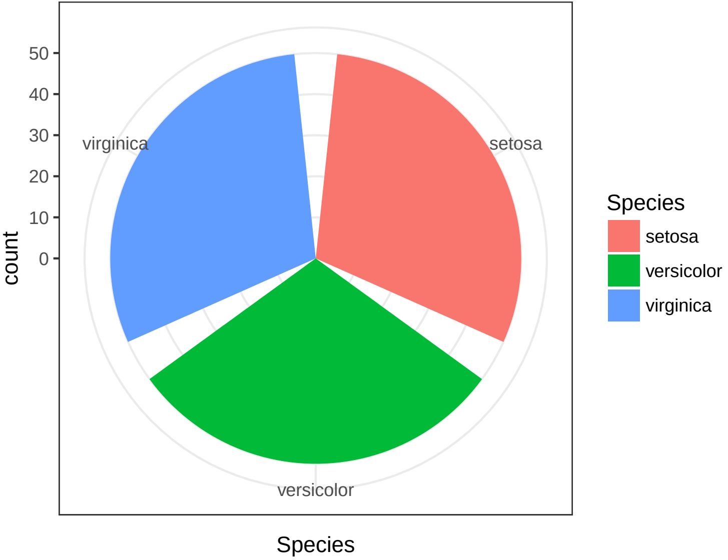
Transform coordinate: log-scales

```
ggplot(diamonds, aes(carat, price)) +
  geom_point() + coord_trans(x = "log10") + coord_trans(y = "log10")
```



Changing coordinate system: polar

```
ggplot(iris, mapping = aes(x = Species, fill = Species)) +
  geom_bar() + coord_polar() + theme_bw()
```

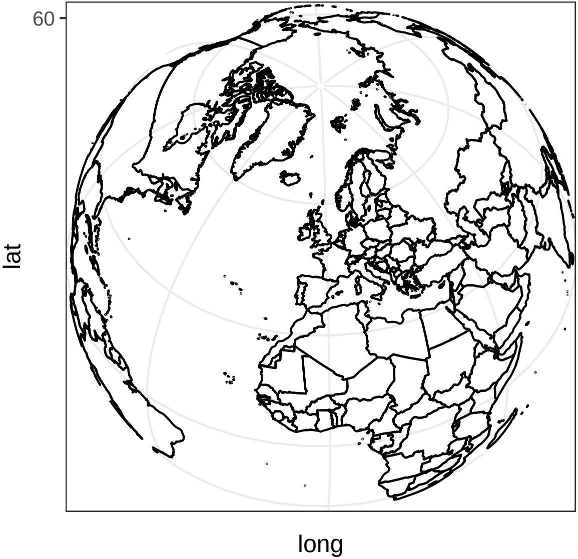


Changing coordinate system: maps I

```
# World map, using geom_path instead of geom_polygon
world <- map_data("world")
worldmap <- ggplot(world, aes(x = long, y = lat, group = group)) +
  geom_path() +
  scale_y_continuous(breaks = (-2:2) * 30) +
  scale_x_continuous(breaks = (-4:4) * 45)

# Orthographic projection centered on Paris
worldmap + coord_map("ortho",orientation = c(48, -2, 0))
```

Changing coordinate system: maps II



Exercice (thanks to Sophie Donnet) I

On s'intéresse à la base de données IMdb

```
install.packages("ggplot2movies")
```

```
library(ggplot2movies)
data(movies)
movies
```

```
## # A tibble: 58,788 x 24
##    title     year length budget rating votes    r1    r2    r3    r4    r5
##    <chr>    <int>  <int>  <int>  <dbl> <int> <dbl> <dbl> <dbl> <dbl> <dbl>
##  1 $         1971    121     NA   6.40   348  4.50  4.50  4.50  4.50 14.5
##  2 $1000 a~  1939     71     NA   6.00    20  0.   14.5   4.50 24.5  14.5
##  3 $21 a D~  1941      7     NA   8.20     5  0.    0.    0.    0.    0.
##  4 $40,000   1996     70     NA   8.20     6 14.5   0.    0.    0.    0.
##  5 $50,000~  1975     71     NA   3.40    17 24.5   4.50  0.   14.5  14.5
##  6 $pent     2000     91     NA   4.30    45  4.50  4.50  4.50 14.5  14.5
##  7 $windle   2002     93     NA   5.30   200  4.50  0.    4.50  4.50 24.5
##  8 '15'      2002     25     NA   6.70    24  4.50  4.50  4.50  4.50  4.50
##  9 '38       1987     97     NA   6.60    18  4.50  4.50  4.50  0.    0.
## 10 '49-'17   1917     61     NA   6.00    51  4.50  0.    4.50  4.50  4.50
## # ... with 58,778 more rows, and 13 more variables: r6 <dbl>, r7 <dbl>,
## #   r8 <dbl>, r9 <dbl>, r10 <dbl>, mpaa <chr>, Action <int>,
## #   Animation <int>, Comedy <int>, Drama <int>, Documentary <int>,
## #   Romance <int>, Short <int>
```

Questions

1. Vérifier que le jeu de données est bien de type `tibble`
2. Tracer le `rate` en fonction de l'année de sortie du film.
3. Créer grâce aux fonctions de `dplyr` et `tidyr` un sous jeu de données ne contenant les variables `title`, `year`, `length`, `rating` et durant moins de 300 minutes; les films devront être classés pas ordre décroissant de durée.
4. Mettre les points dans une couleur entre cyan et violet en fonction de la durée du film (utiliser `scale_colour_gradient`)
5. À partir du jeu de données complet, créer une variable "genre" à valeur dans ("Action", "Animation", "Comedy", "Drama", "Documentary", "Romance", "Short")
6. Créer maintenant un jeu de données contenant les films de moins de 300 minutes qui sont des drames, des romances, des films d'action ou des comédies.
7. On s'intéresse aux films dont on a le budget et qui ne sont par des courts-métrages, ni des documentaires ni de genre inconnu. Tracer les densités de probabilités des budgets par type de film
8. Ajuster un modèle linéaire entre $\log$ budget et le rating des films pour chaque genre de film.

References

Chang, W. (2012). *R graphics cookbook: Practical recipes for visualizing data*. " O'Reilly Media, Inc." Retrieved from http://www.cookbook-r.com/Graphs/

R Core Team. (2017). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Wickham, H. (2014). *Advanced r*. CRC Press. Retrieved from http://adv-r.had.co.nz/

Wickham, H. (2016). *Ggplot2: Elegant graphics for data analysis*. Springer. Retrieved from http://ggplot2.tidyverse.org/reference/

Wickham, H., & Grolemund, G. (2016). *R for data science: Import, tidy, transform, visualize, and model data*. " O'Reilly Media, Inc." Retrieved from http://r4ds.had.co.nz

Wilkinson, L. (2006). *The grammar of graphics*. Springer Science & Business Media.