

**Do you have a github account?  
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# Welcome!

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# Introduction to R & data

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# Outline

---

- Part I: Basics of R
- Lunch (~12:15)
- Part II: Modern R with tidyverse
- Final remarks (~17:00)

move the samples from the data  
\* {r}  
select the samples to keep  
keepsamples <- row.names(pheno)  
apply sample selection to counts  
counts.sub <- counts.sub[,keepsamples]  
pheno.sub <- pheno[keepsamples]  
mt.assay <- mt.assay[,keepsamples]  
rld.sub <- rld[,keepsamples]

# Quick intro: this is us! And who are you?

---

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# Introduction to R & data

---

## Part 1: Basics of R



# What is R?

---

- Widely used programming language for data analysis
- Based on statistical programming language **S** (1976)
- Developed by **Ross Ihaka & Robert Gentleman** (1995)
- Very active community, with many (often subject-specific) packages



## We will work in RStudio

---

- Integrated Development Environment for R
- Founded by JJ Allaire, available since 2010
- Bloody useful! Let's take a look: please open RStudio!

# Have you downloaded the course material?

---

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# R syntax & the RStudio console

---

# Variable assignment

---

>

# Variable assignment

---

```
> x <- 1
```

# Variable assignment

---

```
> x <- 1
```

```
> 1 -> x
```

```
> x = 1
```

```
> 1 = x
```

```
Error in 1 = x : invalid (do_set) left-hand side to assignment
```

# Base R

## Cheat Sheet

### Variable assignment

```
> x <- 6  
> hi <- "hello world"  
> x * 3  
[1] 18  
> y <- x + 2  
> log2(y)  
[1] 3
```

### Maths Functions

<code>log(x)</code>	Natural log.	<code>sum(x)</code>	Sum.
<code>exp(x)</code>	Exponential.	<code>mean(x)</code>	Mean.
<code>max(x)</code>	Largest element.	<code>median(x)</code>	Median.
<code>min(x)</code>	Smallest element.	<code>quantile(x)</code>	Percentage quantiles.
<code>round(x, n)</code>	Round to n decimal places.	<code>rank(x)</code>	Rank of elements.
<code>signif(x, n)</code>	Round to n significant figures.	<code>var(x)</code>	The variance.
<code>cor(x, y)</code>	Correlation.	<code>sd(x)</code>	The standard deviation.

### Variable Assignment

```
> a <- 'apple'  
> a  
[1] 'apple'
```

# A quick note on notes

---

- The console is for execution, not for storage
- Everything we do is on the slides!
- BUT: you can store, if you want, by copy-pasting to a text document
- Do you want to write notes in between?

```
> # write your notes in the console like this  
> # using a #hash sign.  
> # pressing enter will do nothing.  
> # go ahead and try!
```

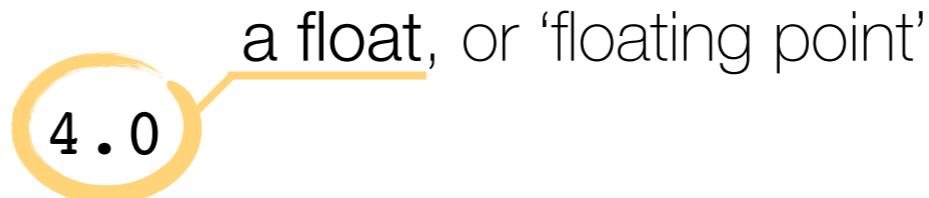
# Creating vectors

---

```
> 1:5  
[1] 1 2 3 4 5  
> seq(5)  
[1] 1 2 3 4 5  
> seq(2,4,by=0.5)  
[1] 2.0 2.5 3.0 3.5  
> rep(4,6)  
[1] 4 4 4 4 4 4  
> c(1,61,101)  
[1] 1 61 101  
> c(2:4,rep(8,3))  
[1] 2 3 4 8 8 8
```



vs.



# Vector functions

---

```
> p <- 1:5  
> mean(p)  
[1] 3  
> p * 2  
[1] 2 4 6 8 10  
> q <- 5:1  
> p * q  
[1] 5 8 9 8 5  
> table(p*q)  
5 8 9  
2 2 1
```

p * 2		
p	2	
1	2	2
2	2	4
3	2	6
4	2	8
5	2	10

p * q		
p	q	
1	5	5
2	4	8
3	3	9
4	2	8
5	1	5

# Exercise

---

1. Write a line of code that produces the following vector:

*(Note: there are multiple possible answers!)*

[ 1 ] 4 4 4 10 15 20 10 7 4

2. Divide the vector by 3. Round up to 1 decimal.

*(Hint: check the cheat sheet element ‘Maths Functions’.)*

# Exercise

---

1. Write a line of code that produces the following vector:

(Note: there are multiple possible answers!)

```
> c(rep(4,3),seq(10,20,by=5),seq(10,4,by=-3))  
[1] 4 4 4 10 15 20 10 7 4
```

2. Divide the vector by 3. Round up to 1 decimal.

(Hint: check the cheat sheet element ‘Maths Functions’.)

```
> v <- c(rep(4,3),seq(10,20,by=5),seq(10,4,by=-3))  
> round(v/3,1)  
[1] 1.3 1.3 1.3 3.3 5.0 6.7 3.3 2.3 1.3
```

# Another data type: logical

---

```
> T  
[1] TRUE  
> FALSE  
[1] FALSE  
> 1==1  
[1] TRUE  
> 3>=5  
[1] FALSE  
> 2!=4  
[1] TRUE
```

== is equal to  
!= is not  
>= larger than or equal to  
< smaller than

# Vectors and factors

```
> fc <- c("a", "b", "a", "c")
> fc
[1] "a" "b" "a" "c"
> fc <- factor(fc)
> fc
[1] a b a c
Levels: a b c
> fn <- 2:5
> fn
[1] 2 3 4 5
> fn <- factor(fn)
> fn
[1] 2 3 4 5
Levels: 2 3 4 5
> as.numeric(fn)
[1] 1 2 3 4
```

Note that vectors may consist of characters!

A factor is defined by its **levels**. Turning a factor into numeric specifies the order of the levels, but loses their content.

# Exercise

---

1. Generate a vector that contains numeric, logical, and character elements.
2. Turn it into a factor.
3. See what happens to the content when you convert this factor into numeric, logical, and character vectors.

*(Hint: check the cheat sheet element ‘Types’ for the functions.)*

# Exercise

---

1. Generate a vector that contains numeric, logical, and character elements.

```
> ft <- c(T,T,2,4,"apple","orange")
```

2. Turn it into a factor.

```
> ft <- factor(ft)
```

3. See what happens to the content when you convert this factor into numeric, logical, and character vectors.

(*Hint: check the cheat sheet element ‘Types’ for the functions.*)

```
> as.numeric(ft)
```

```
[1] 5 5 1 2 3 4
```

```
> as.logical(ft)
```

```
[1] TRUE TRUE NA NA NA NA
```

```
> as.character(ft)
```

```
[1] "TRUE"    "TRUE"    "2"      "4"      "apple"   "orange"
```

# But what if there *is no data*? Introducing: NA

```
> ft <- c(T,T,2,4,"apple","orange")  
> ft <- as.logical(ft)  
> ft  
[1] TRUE TRUE     NA     NA     NA     NA  
> factor(ft)  
[1] TRUE TRUE <NA> <NA> <NA> <NA>  
Levels: TRUE
```

NA = Not Available

Name	Age	Pet
Ann	33	Cat
Bob	25	<b>None</b>
Chloe	21	Iguana
Dan	45	<b>NA</b>

In other words:

We **know** that Bob has **no pets**.

We **do not know** if Dan has pets.

## Exercise: predict the answer

---

```
> NA == NA
```

Predict the results. Does the (real) answer make sense to you?

## Exercise: predict the answer

---

```
> NA == NA
```

```
[1] NA
```

Predict the results. Does the (real) answer make sense to you?

# NA != NULL

---

```
> is.na(NA)
```

```
[1] TRUE
```

```
> is.null(NULL)  
[1] TRUE
```

**NA** Information is **Not Available**

**NULL** Information **does not exist**

**"None"** Data entry specifying **"None"**

## Exercise: predict the answer

---

```
> is.na(NA)
```

```
[1] TRUE
```

```
> is.null(NULL)
```

```
[1] TRUE
```

Predict the results. Does the (real) answer make sense to you?

```
> is.null(NA)
```

```
> is.na(NULL)
```

# Exercise: try to predict the results!

---

```
> is.na(NA)
```

```
[1] TRUE
```

```
> is.null(NULL)
```

```
[1] TRUE
```

Predict the results. Does the (real) answer make sense to you?

```
> is.null(NA)
```

```
[1] FALSE
```

```
> is.na(NULL)
```

# Exercise: try to predict the results!

---

```
> is.na(NA)
```

```
[1] TRUE
```

```
> is.null(NULL)
```

```
[1] TRUE
```

Predict the results. Does the (real) answer make sense to you?

```
> is.null(NA)
```

```
[1] FALSE
```

```
> is.na(NULL)
```

```
[1] logical(0)
```

# Selecting vector elements by position

---

```
> m <- 8:4  
> m  
[1] 8 7 6 5 4  
> m[2]  
[1] 7  
> m[1:3]  
[1] 8 7 6  
> m[-(2:4)]  
[1] 8 4
```

# Selecting vector elements by value

---

```
> m <- 8:4  
  
> m  
[1] 8 7 6 5 4  
  
> m[m>5]  
[1] 8 7 6  
  
> m>5  
[1] TRUE TRUE TRUE FALSE FALSE  
  
> n <- 5:10  
  
> m[m %in% n]  
[1] 8 7 6 5  
  
> m[NA]  
[1] NA NA NA NA NA
```

m	m>5	result
8	TRUE	8
7	TRUE	7
6	TRUE	6
5	FALSE	
4	FALSE	

# Which bracket does what?

---

- [ ] **Indexing** vectors, lists, dataframes...
  - ( ) Passing **arguments** to functions
  - { } **Defining content** of loops, functions, etc.
- ```
> myvector[length(myvector)]
```

# Vectors, lists, and data frames

---

```
> v1 <- 4:6  
> v2 <- rep(3,3)
```

```
> c(v1,v2)  
[1] 4 5 6 3 3 3
```

```
> list(v1,v2)  
[[1]]  
[1] 4 5 6
```

```
[[2]]  
[1] 3 3 3
```

```
> data.frame(v1,v2)
```

| v1 | v2 |   |
|----|----|---|
| 1  | 4  | 3 |
| 2  | 5  | 3 |
| 3  | 6  | 3 |

| how many dimensions? | function   |
|----------------------|------------|
| vector               | 1          |
| list                 | any number |
| data frame           | 2          |

# Indexing lists

---

```
> v1 <- 4:6
> v2 <- rep(3,3)
> myList <- list(v1,v2)
> myList[1]
[[1]]
[1] 4 5 6
> myList[[1]]
[1] 4 5 6
> myList[[1]][2]
[1] 5
> myList[1][2]
[[1]]
NULL
```

# Indexing a data frame

---

```
> name <- c("Ann", "Bob", "Chloe", "Dan")  
> age <- c(33, 25, 21, 45)  
> df <- data.frame(name, age)  
> df
```

|   | name  | age |
|---|-------|-----|
| 1 | Ann   | 33  |
| 2 | Bob   | 25  |
| 3 | Chloe | 21  |
| 4 | Dan   | 45  |

# Indexing a data frame

```
> df$age  
[1] 33 25 21 45  
  
> df[,2]  
[1] 33 25 21 45  
  
> df[2,]  
    name age  
2    Bob  25  
  
> df[2,2]  
[1] 25
```

## Matrix subsetting

```
df[, 2]
```



```
df[2, ]
```



The diagram shows the text "row" on the left and "column" on the right, each with a yellow curved arrow pointing down to the index "df[2, 2]" below. To the right of the index is a 4x4 grid of colored squares: the first two columns are blue, the third is grey, and the fourth is yellow, representing the matrix element at row 2, column 2.



# Exercise

---

Return the names of everyone in your data frame under 30. Make good use of vectors as part of your index!

*Hint: this is how you extract a column from a dataframe: df\$column\_name*

# Exercise

---

Return the names of everyone in your data frame under 30. Make good use of vectors as part of your index!

*Hint: this is how you extract a column from a dataframe: df\$column\_name*

```
> df[df$age<30, "name"]
```

OR

```
> df[df$age<30, 1]
```

```
[1] Bob    Chloe
```

```
Levels: Ann Bob Chloe Dan
```

Question: what is the data type of your result?

# Let's breathe and recap!

---

What data types have you encountered so far?

`logical`

`numeric`

`integer`

`character`

`factor`

And what data collections have you encountered?

`vector` (one dimension)

`data frame` (two dimensions)

`list` (++ dimensions)

# Functions

---

What functions have you encountered so far?

```
> c()  
> rep()  
> round()  
> as.logical()  
> is.na()  
> table()  
...
```

And do you still know what they mean? And how to use them? **No?**

```
> ?table()  
> help.search("standard deviation")
```

(or use the Help window to the right of your console)

# Take a break!

---



# Ready?

---

- Writing your first script
- Programming with loops and functions
- Handling and processing a dataset

move the samples from the data  
\* {r}  
select the samples to keep  
keepsamples <- row.names(pheno)  
apply sample selection to counts  
counts.sub <- counts.sub[,keepsamples]  
pheno.sub <- pheno[keepsamples]  
mt.assay <- mt.assay[,keepsamples]  
rld.sub <- rld[,keepsamples]

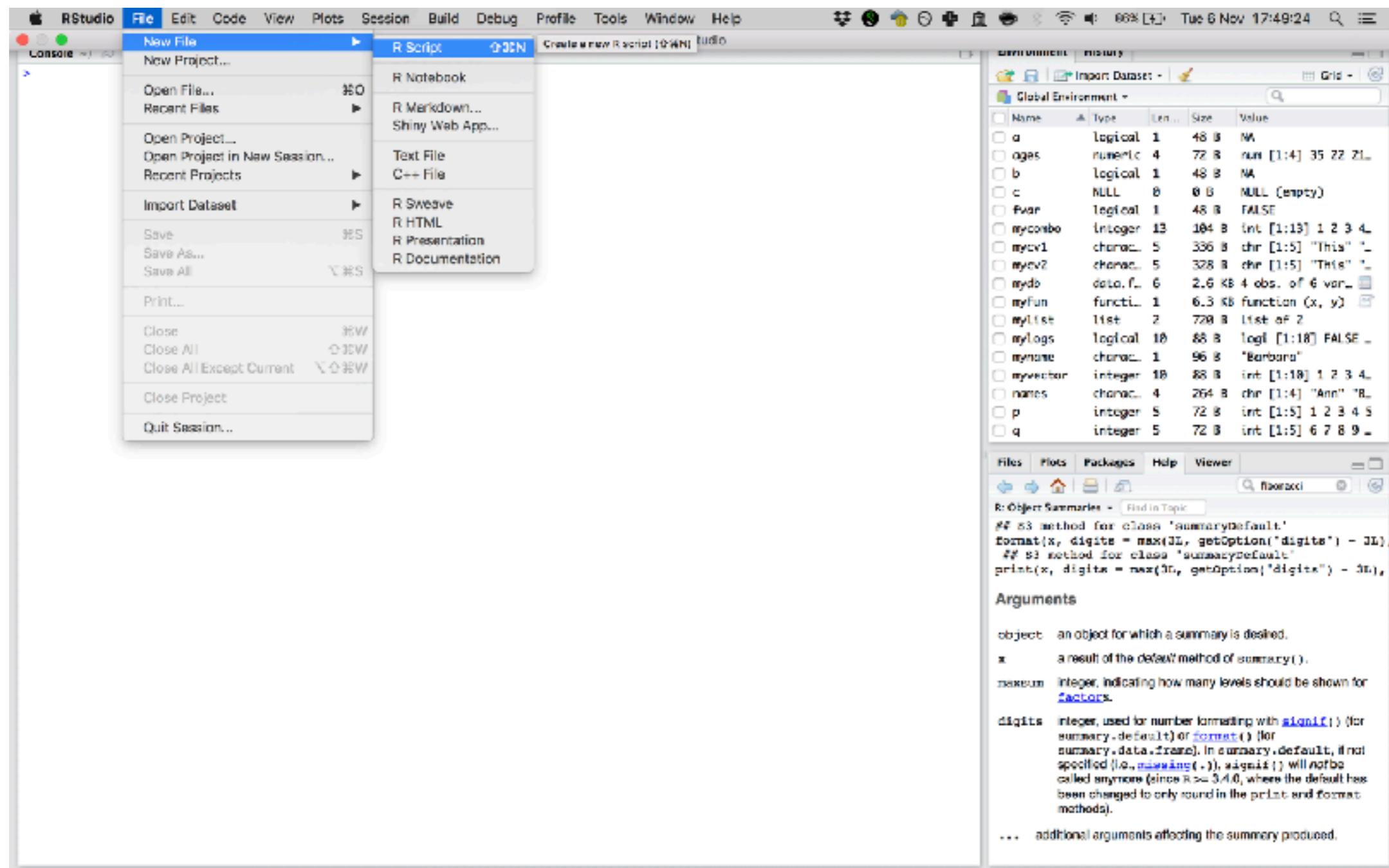
# Console and Scripts

---

|           |                  |                                         |
|-----------|------------------|-----------------------------------------|
| Console   | Code execution   | -                                       |
| Script    | Code             | Extension: .R<br>(example_script.R)     |
| Rmarkdown | Code + Narrative | Extension: .Rmd<br>(example_report.Rmd) |

# Ready to script?

RStudio > File > New File > R Script



# Console vs script on our slides

---

writing in the console

```
> x <- 1
```

```
> x
```

```
[1] 1
```

console output

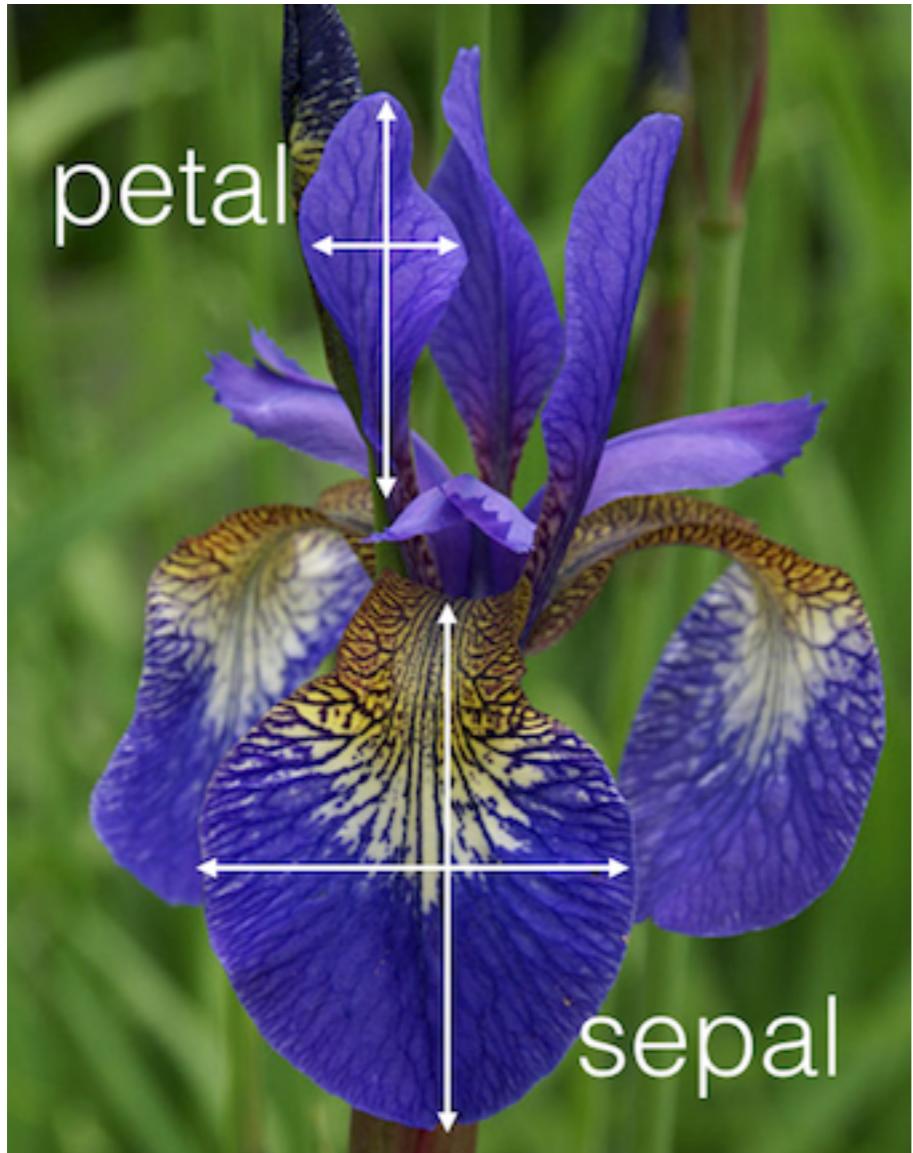
```
# Assigning the value 1 to x  
x <- 1
```

# indicates comment  
computer stops reading  
(but you should not!)

# Introducing a sample dataset

---

- Dataset: ‘iris’
- Standard dataset in R, measurements on 3 species of iris flowers



# Introducing a sample dataset

---

- Dataset: ‘iris’
- Standard dataset in R, measurements on 3 species of iris flowers

```
> 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  |

```
> summary(iris)
```

| Sepal.Length  | Sepal.Width   | Petal.Length  | Petal.Width   | Species       |
|---------------|---------------|---------------|---------------|---------------|
| Min. :4.300   | Min. :2.000   | Min. :1.000   | Min. :0.100   | setosa :50    |
| 1st Qu.:5.100 | 1st Qu.:2.800 | 1st Qu.:1.600 | 1st Qu.:0.300 | versicolor:50 |
| Median :5.800 | Median :3.000 | Median :4.350 | Median :1.300 | virginica :50 |
| Mean :5.843   | Mean :3.057   | Mean :3.758   | Mean :1.199   |               |
| 3rd Qu.:6.400 | 3rd Qu.:3.300 | 3rd Qu.:5.100 | 3rd Qu.:1.800 |               |
| Max. :7.900   | Max. :4.400   | Max. :6.900   | Max. :2.500   |               |

# Programming: for loop

---

```
# Iterate over 10 values
for(i in 1:10){
  print(i)
}
```

```
[1] 1
[1] 2
[1] 3
[1] 4
[1] 5
[1] 6
[1] 7
[1] 8
[1] 9
[1] 10
```

# Calculating averages: preparation

---

```
# what measurements exist in the iris db?  
measure <- colnames(iris)  
  
> measure  
[1] "Sepal.Length" "Sepal.Width"   "Petal.Length" "Petal.Width"  "Species"  
  
# remove "Species" from the list of names  
measure <- measure[measure!="Species"]  
  
# make a df with a single column: measurements  
iris_res <- data.frame(measure)  
  
# initiate a vector for averages  
avgs <- NULL
```

# Calculating averages in a for loop

---

```
# iterate over each measurement with a for-loop
for(m in measure){

}
```

# Calculating averages in a for loop

---

```
# iterate over each measurement with a for-loop
for(m in measure){
  # select the appropriate column

  # calculate the average for this column

  # put the average in the averages vector

}
```

# Calculating averages in a for loop

---

```
# iterate over each measurement with a for-loop
for(m in measure){
  # select the appropriate column
  column <- iris[,m]
  # calculate the average for this column

  # put the average in the averages vector
}
```

# Calculating averages in a for loop

---

```
# iterate over each measurement with a for-loop
for(m in measure){
  # select the appropriate column
  column <- iris[,m]
  # calculate the average for this column
  avg <- mean(column)
  # put the average in the averages vector
}
```

# Calculating averages in a for loop

---

```
# iterate over each measurement with a for-loop
for(m in measure){
  # select the appropriate column
  column <- iris[,m]
  # calculate the average for this column
  avg <- mean(column)
  # put the average in the averages vector
  avgs <- c(avgs,avg)
}

> avgs
[1] 5.843333 3.057333 3.758000 1.199333
```

# Calculating averages in a for loop

---

```
# add the averages as a column to the data frame
iris_res$average <- avgs

> iris_res
      measure   average
1 Sepal.Length 5.843333
2 Sepal.Width  3.057333
3 Petal.Length 3.758000
4 Petal.Width  1.199333
```

# Programming: functions

---

```
myFun <- function(x){  
  return(x)  
}
```

```
> myFun(1)  
[1] 1
```

# Programming: functions

---

```
myFun2 <- function(x) {  
  x <- x*20  
  return(x)  
}
```

```
> myFun2(1)  
[1] 20
```

# Programming: functions

---

```
myFun3 <- function(x,y){  
  z <- x*y  
  return(z)  
}
```

```
> myFun3(2,4)  
[1] 8
```

# Exercise: combine functions and for loops

---

- Open the script **programming\_exercise.R**
- You will see the for-loop (including comments) as we have just written
- You will then see the start of a function:

```
average_df <- function(df){  
  measure <- colnames(df)  
  measure <- measure[measure!="Species"]  
  avgs <- NULL  
  ### ENTER YOUR OWN CODE ###  
  return(avgs)  
}
```

- **Exercise:** place the for-loop in the function, and edit as necessary, so that the function now generates a list of averages.
- **TIP:** within the function, `iris` is renamed `df`!

# Exercise: combine functions and for loops

---

```
average_df <- function(df){  
  # determine measurement names and remove species  
  measure <- colnames(df)  
  measure <- measure[measure!="Species"]  
  # initialize the vector  
  avgs <- NULL  
  # iterate over each measurement with a for-loop  
  for(m in measure){  
    # select the appropriate column  
    column <- df[,m]  
    # calculate the average  
    avg <- mean(column)  
    # put the average in the averages vector  
    avgs <- c(avgs,avg)  
  }  
  # return the averages as a column  
  return(avgs)  
}  
# apply the function: add the averages as a column to the data frame  
iris_res$average <- average_df(iris)
```

# Programming: if statement

---

```
if(4>5){  
    print("math has changed!")  
} else{  
    print("all is well.")  
}
```

# Programming: if statement

---

```
if(4>5){  
    print("math has changed!")  
} else if(5>6){  
    print("this is not good either!")  
} else{  
    print("all is well.")  
}
```

# Exercise: add an if-statement to your function

---

- We want to build on our `average_df` function so it can do more calculations!
- To do this, we add a second argument, and include an if statement.
- First, copy-paste your function, and give it a new name. Consider changing some variable names, too (and make sure to change them all!).

```
stats_df <- function(df){  
  measure <- colnames(df)  
  measure <- measure[measure!="Species"]  
  results <- NULL  
  for(m in measure){  
    column <- df[,m]  
    results <- mean(column)  
    results <- c(results,res)  
  }  
  return(results)  
}
```

# Exercise: add an if-statement to your function

---

- Our function can calculate averages. We might want to add standard deviations (`sd()`), maximums (`max()`), and minimums (`min()`).
- Which line in the function do we need to expand on, to allow this?
- What additional information do we need?

```
stats_df <- function(df){  
  measure <- colnames(df)  
  measure <- measure[measure!="Species"]  
  results <- NULL  
  for(m in measure){  
    column <- df[,m]  
    results <- mean(column)  
    results <- c(results,res)  
  }  
  return(results)  
}
```

# Exercise: add an if-statement to your function

---

```
stats_df <- function(df,fnx){  
  measure <- colnames(df)  
  measure <- measure[measure!="Species"]  
  results <- NULL  
  for(m in measure){  
    column <- df[,m]  
    # perform different functions based on the input  
    if(fnx=="mean"){  
      res <- mean(column)  
    } else{  
      stop("no valid input received")  
    }  
    results <- c(results,res)  
  }  
  return(res)  
}
```

# Exercise: add an if-statement to your function

---

1. Add the if-statement below to your function! (Do you understand how it works?)

```
if(fnx=="mean") {  
  res <- mean(column)  
} else{  
  stop("no valid input received")  
}
```

2. Elaborate on the statement using `else if`, adding alternative functions. Consider standard deviation (`sd()`), maximum (`max()`), and minimum (`min()`).
3. Finally, call your new function to add columns to your `iris_res` dataframe!

# Exercise: add an if-statement to your function

---

```
stats_df <- function(df,fnx){  
  measure <- colnames(df)  
  measure <- measure[measure!="Species"]  
  results <- NULL  
  for(m in measure){  
    column <- df[,m]  
    if(fnx=="mean"){  
      res <- mean(column)  
    } else if(fnx=="sd"){  
      res <- sd(column)  
    } else{  
      stop("no valid input received")  
    }  
    results <- c(res,res)  
  }  
  return(res)  
}  
  
iris_res$standarddev <- stats_df(iris,"sd")
```

# Your result: a summary data frame

---

```
iris_res$standarddev <- stats_df(iris,"sd")
iris_res$largest <- stats_df(iris,"max")
iris_res$smallest <- stats_df(iris,"min")
```

```
> iris_res
```

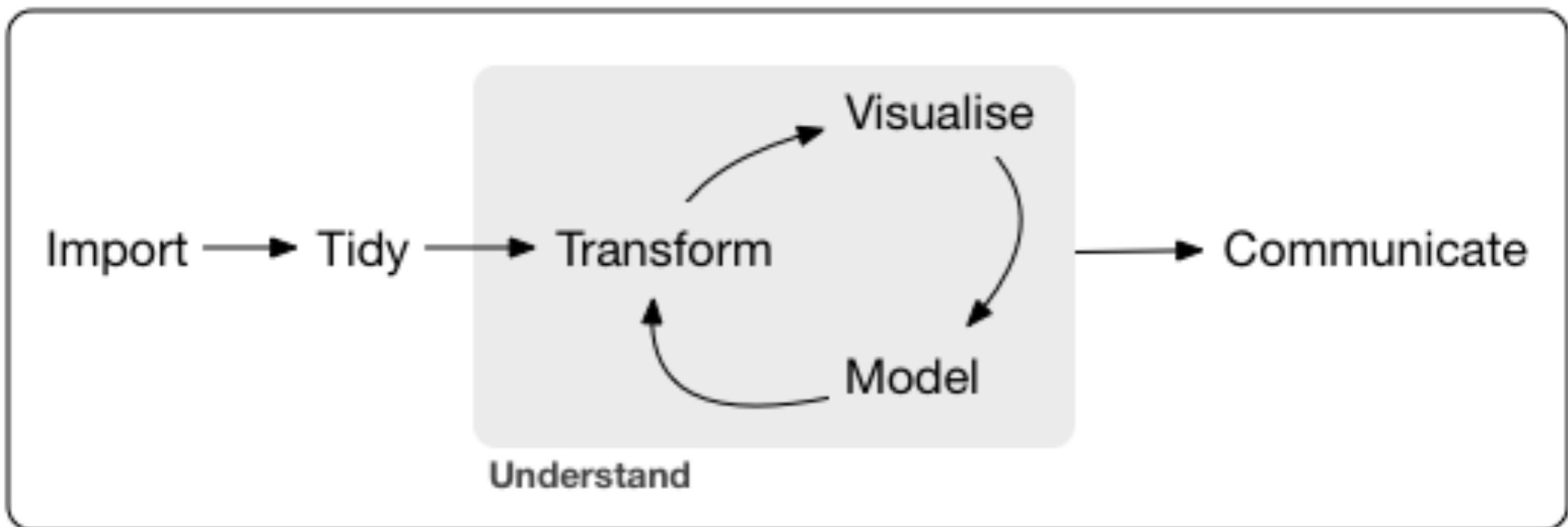
|   | measure      | average  | standarddev | largest | smallest |
|---|--------------|----------|-------------|---------|----------|
| 1 | Sepal.Length | 5.843333 | 0.8280661   | 7.9     | 4.3      |
| 2 | Sepal.Width  | 3.057333 | 0.4358663   | 4.4     | 2.0      |
| 3 | Petal.Length | 3.758000 | 1.7652982   | 6.9     | 1.0      |
| 4 | Petal.Width  | 1.199333 | 0.7622377   | 2.5     | 0.1      |

```
> summary(iris)
```

| Sepal.Length  | Sepal.Width   | Petal.Length  | Petal.Width   | Species    |
|---------------|---------------|---------------|---------------|------------|
| Min. :4.300   | Min. :2.000   | Min. :1.000   | Min. :0.100   | setosa     |
| 1st Qu.:5.100 | 1st Qu.:2.800 | 1st Qu.:1.600 | 1st Qu.:0.300 | versicolor |
| Median :5.800 | Median :3.000 | Median :4.350 | Median :1.300 | virginica  |
| Mean :5.843   | Mean :3.057   | Mean :3.758   | Mean :1.199   |            |
| 3rd Qu.:6.400 | 3rd Qu.:3.300 | 3rd Qu.:5.100 | 3rd Qu.:1.800 |            |
| Max. :7.900   | Max. :4.400   | Max. :6.900   | Max. :2.500   |            |

# Data science workflow: scripting is crucial

- Scripting combines commands to a comprehensive set of instructions.
- A script is code that can be **saved, reused, shared, published!**
- In short: a crucial step towards reproducible data analysis.



Program

*a single script for a single purpose!*

# Starting the script: write a header

---

```
## Date: 7 November 2018  
## Author: Barbara Vreede  
## This script was written as part of the R course  
## "Introduction to R & Data", at Utrecht University
```

# Load packages and dependencies

---

```
## Date: 7 November 2018
## Author: Barbara Vreede
## This script was written as part of the R course
## "Introduction to R & Data", at Utrecht University

# Load required packages
library(dplyr)
library(tidyr)
library(ggplot2)
```

# Custom functions

---

```
## Date: 7 November 2018
## Author: Barbara Vreede
## This script was written as part of the R course
## "Introduction to R & Data", at Utrecht University

# Load required packages
library(dplyr)
library(tidyr)
library(ggplot2)

# Functions
myFun <- function(var){
  var <- var*2*pi
  return(var)
}
```

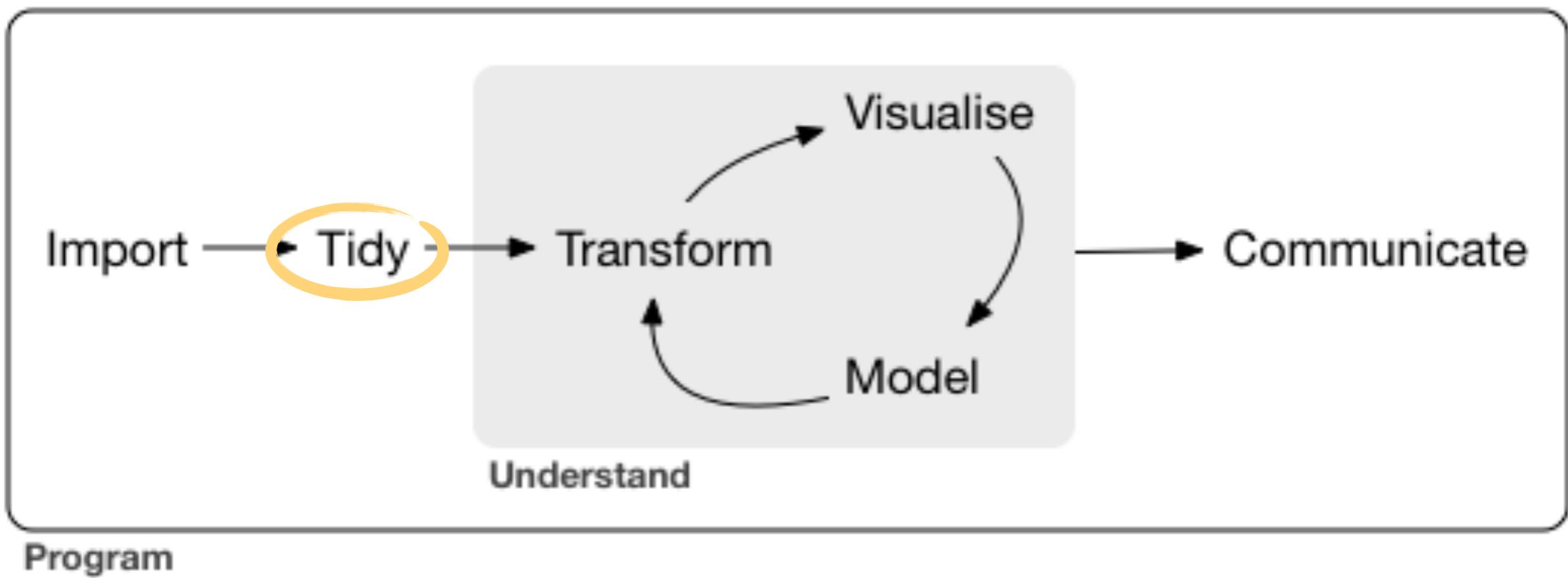
# Starting your script: header, packages, functions

```
## Date: 7 November 2018
## Author: Barbara Vreede
## This script was written as part of the R course
## "Introduction to R & Data", at Utrecht University
```

```
# Load required packages
library(dplyr)
library(tidyr)
library(ggplot2)
```

```
# Functions
myFun <- function(var){
  var <- var*2*pi
  return(var)
}
```

# Data science workflow



Tidy data ensures results that further processing can be done efficiently, and reproducibly.

Tidy data is easy to manipulate, model, and visualize.

# Tidy data

- Each **variable** is a column and contains **values**
- Each **observation** is a row
- Each type of **observational unit** forms a table

values in column names

| Patient | BP     | Med_A | BP_after_A | Med_B | BP_after_B |
|---------|--------|-------|------------|-------|------------|
| 122030  | 120_82 | 300   | 119_85     | NA    | NA         |
| 122021  | 131_91 | 200   | 132_85     | 85    | 125_90     |
| 124500  | 118_86 | 300   | 119_70     | NA    | NA         |
| 126098  | 99_67  |       |            | 100   | 110_71     |

multiple data points  
in a single cell

# Tidy data

**ID no longer unique per row**  
(but can still be used to collect  
all info on single patient)

| Patient | Systolic | Asystolic | Treatment |
|---------|----------|-----------|-----------|
| 122030  | 120      | 82        | None      |
| 122030  | 119      | 85        | A         |
| 122021  | 131      | 91        | None      |
| 122021  | 132      | 85        | A         |
| 122021  | 119      | 70        | B         |
| 124500  | 118      | 86        | None      |
| 124500  | 119      | 70        | A         |
| 126098  | 99       | 67        | None      |
| 126098  | 110      | 71        | B         |

**Time series (order) lost**  
(so make sure this is  
explicit)

To check before lunch: please load tidyverse

---

```
> library(tidyverse)
— Attaching packages ————— tidyverse 1.2.1 —
✓ ggplot2 3.1.0      ✓ purrr    0.3.0
✓ tibble   2.0.1      ✓ dplyr    0.7.8
✓ tidyrr   0.8.2      ✓ stringr  1.4.0
✓ readr    1.3.1      ✓forcats  0.3.0
— Conflicts ————— tidyverse_conflicts() —
✖ dplyr::filter() masks stats::filter()
✖ dplyr::lag()    masks stats::lag()
```

Enjoy your lunch!

---



# Introduction to R & data

---

## Part II: Modern R with tidyverse

## Outline part II

---

- Introduction to **tidyverse**, **rmarkdown**, and **tibble**.
- Load and save data with **readr**
- [break]
- Data visualisation with **ggplot**
- [break]
- Data transformation with **tidyr** and **dplyr**

```
row.names(pheno[pheno$sampleID %in% keepsamples,], na.rm = TRUE)
density(glnorm[, sname], na.rm = TRUE)
move the samples from the data
  {r}
select the samples to keep
keepsamples <- row.names(pheno[pheno$sampleID %in% keepsamples,], na.rm = TRUE)
apply sample selection to counts
counts.sub <- counts.sub[, keepsamples]
pheno.sub <- pheno[keepsamples, ]
assay <- nt.assay[, keepsamples]
rld.sub <- rld[, keepsamples]
```



Tidyverse

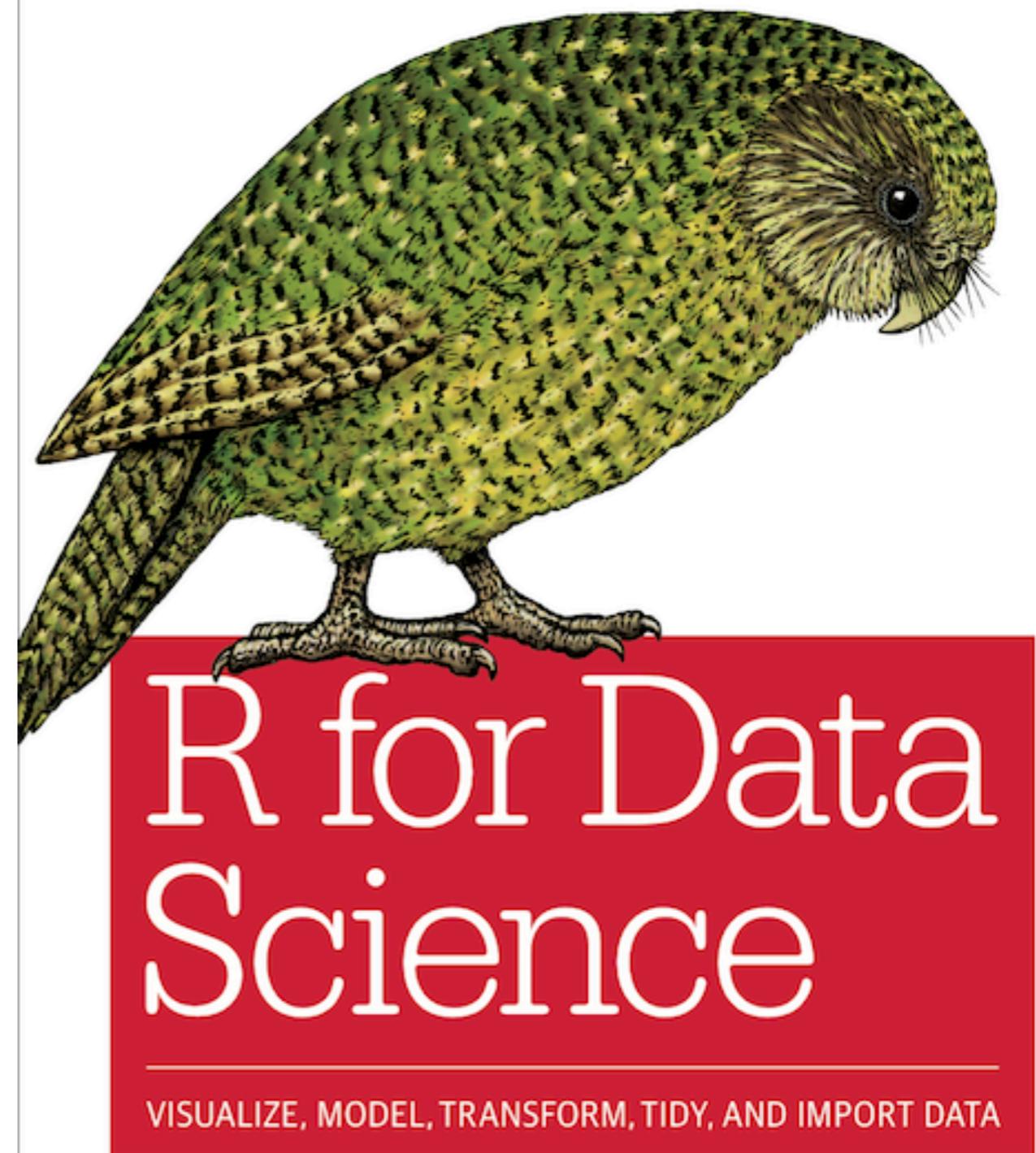
Modern R for data science

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

– **tidyverse.org (2018)**

# Learn tidyverse

- R for Data Science (book)  
Freely available on:  
[r4ds.had.co.nz/](http://r4ds.had.co.nz/)



Hadley Wickham &  
Garrett Grolemund

# Learn tidyverse

- R for Data Science (book)  
Freely available on:  
[r4ds.had.co.nz/](http://r4ds.had.co.nz/)
- ggplot2 (book)

Hadley Wickham

**ggplot2**

Elegant Graphics for Data Analysis



# Your afternoon roadmap

---

- A short explanation on screen (~15 minutes)
- Exercises in a document on your computer (~45 minutes)
  - 2-3 basic exercises
  - optional exercises, for further practice
  - reading exercises, for some extra insight into Tidyverse
- We will work with a new data set
- The exercises are presented in Rmarkdown format. We'll explain this later!

From code to  
document

---

Turn your analyses into high quality  
documents with Rmarkdown



# R Markdown

---

- **Combine code with narrative (R with markdown)**
- Turn your analyses into high quality documents, reports, presentations and dashboards.
- ... or your note book.
- Rmarkdown is different from a R script
- Rmarkdown files have file extension **.Rmd** (R scripts have extension **.R**)

# Console, Scripts and Rmarkdown

---

|           |                  |                                                |
|-----------|------------------|------------------------------------------------|
| Console   | Code execution   | -                                              |
| Script    | Code             | Extension: <b>.R</b><br>(example_script.R)     |
| Rmarkdown | Code + Narrative | Extension: <b>.Rmd</b><br>(example_report.Rmd) |

# Markdown

---

```
# title
```

```
Some text about your project
```

```
## Section
```

```
More text about your project
```

```
```{r}
max(iris$Petal.Length)
min(iris$Petal.Length)
```
```

# Rmarkdown: demo

---



# Exercise: open the exercise Rmarkdown

1. RStudio > File > Open Project > introduction-to-R-and-data-github.Rproj
2. From the ‘files’ menu (bottom right), select modernR\_exercises.Rmd
3. Update the header information with your name!

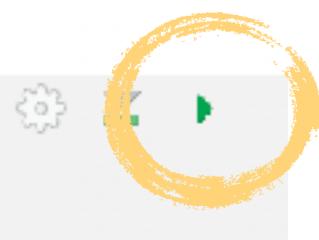
# Run the first code chunk!

---

```
## Technical requirements
```

This project depends on the `tidyverse` package. Load tidyverse into your work environment.

```
```{r}
library(tidyverse)
...``
```



```
> library(tidyverse)
```

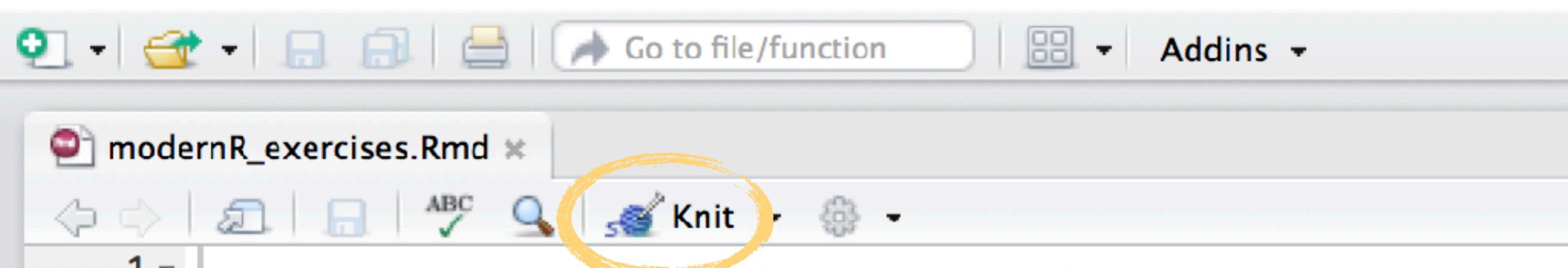
— Attaching packages ————— tidyverse 1.2.1 —

✓ ggplot2 3.1.0	✓ purrr 0.3.0
✓ tibble 2.0.1	✓ dplyr 0.7.8
✓ tidyverse 0.8.2	✓ stringr 1.4.0
✓ readr 1.3.1	✓forcats 0.3.0

— Conflicts ————— tidyverse\_conflicts() —

✖ dplyr::filter()	masks stats::filter()
✖ dplyr::lag()	masks stats::lag()

# All done? Time to knit!



The screenshot shows the RStudio interface with the 'modernR\_exercises.Rmd' file open. The 'Knit' button in the toolbar is highlighted with a yellow circle. The code in the document includes YAML front matter and a note about the workshop.

```
1 ---  
2 title: "Modern R with tidyverse"  
3 author: "[Insert your name]"  
4 output:  
5   html_document:  
6     toc: true  
7 ---  
8  
9 *This document is part of the workshop **Introduction to R & Data  
10  
11 # Introduction  
12  
13 In this document, we explore Crane migration, through the GPS dat  
data was kindly provided for this course by Sasha Pekarsky at the
```

# package: Tibble

---

Improved data frames



"Tibbles are data frames, but they tweak some older behaviours to make life a little easier."

– Hadley Wickham (creator of Tidyverse)

# Tibbles

---

```
> tibble(a = 1:26, b = letters)
# A tibble: 26 x 2
      a     b
  <int> <chr>
1     1     a
2     2     b
3     3     c
4     4     d
5     5     e
6     6     f
7     7     g
8     8     h
9     9     i
10    10    j
# ... with 16 more rows
```

# Tibbles: from data.frame to tibble

---

```
> 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
```

# Tibbles: from tibble to data.frame

---

```
> iris_tibble <- as_tibble(iris)
> as.data.frame(iris_tibble)
```

	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
7	4.6	3.4	1.4	0.3	setosa
8	5.0	3.4	1.5	0.2	setosa
9	4.4	2.9	1.4	0.2	setosa
10	4.9	3.1	1.5	0.1	setosa
11	5.4	3.7	1.5	0.2	setosa
12	4.8	3.4	1.6	0.2	setosa
13	4.8	3.0	1.4	0.1	setosa
14	4.3	3.0	1.1	0.1	setosa

## Load and save data

---

The basics of `readr`



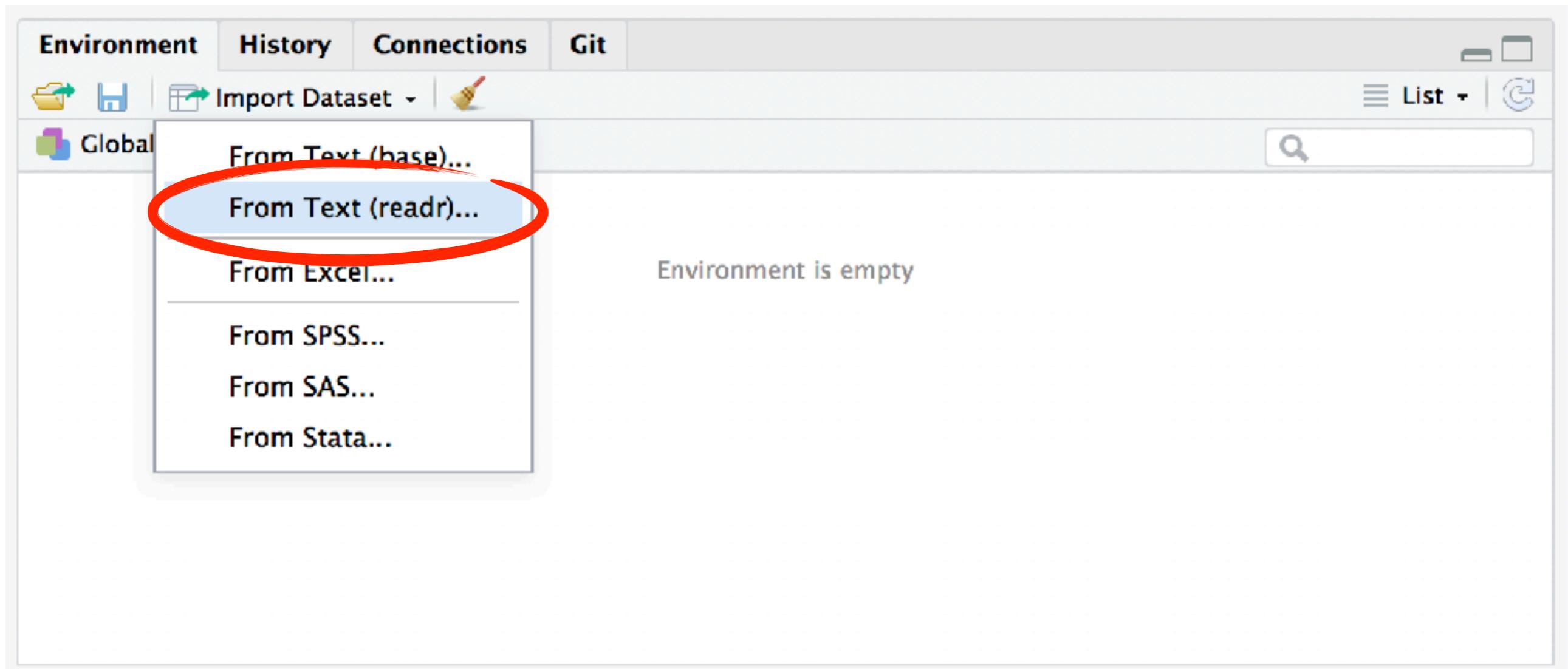
## Flat data files

---

- Most common format: Comma-separated values (CSV)
- Delimiter-separated values (also stored as CSV)
- Common delimiters:
  - comma ,
  - semicolon ;
  - tab \t

```
1 mpg;cyl;disp;hp;drat;wt;qsec;v
2 21;6;160;110;3.9;2.62;16.46;0;
3 21;6;160;110;3.9;2.875;17.02;0
4 22.8;4;108;93;3.85;2.32;18.61;
5 21.4;6;258;110;3.08;3.215;19.4
6 18.7;8;360;175;3.15;3.44;17.02
7 18.1;6;225;105;2.76;3.46;20.22
8 14.3;8;360;245;3.21;3.57;15.84
9 24.4;4;146.7;62;3.69;3.19;20;1
10 22.8;4;140.8;95;3.92;3.15;22.9
11 19.2;6;167.6;123;3.92;3.44;18.
12 17.8;6;167.6;123;3.92;3.44;18.
13 16.4;8;275.8;180;3.07;4.07;17.
14 17.3;8;275.8;180;3.07;3.73;17.
15 15.2;8;275.8;180;3.07;3.78;18;
16 10.4;8;472;205;2.93;5.25;17.98
17 10.4;8;460;215;3;5.424;17.82;0
18 14.7;8;440;230;3.23;5.345;17.4
19 32.4;4;78.7;66;4.08;2.2;19.47;
20 30.4;4;75.7;52;4.93;1.615;18.5
21 33.9;4;71.1;65;4.22;1.835;19.9
22 21.5;4;120.1;97;3.7;2.465;20.0
23 17.5;8;312;152;3.75;3.52;16.25
```

# Load data by using buttons



# Load data by using buttons

Import Text Data

File/Url:

~/surfdrive/Projects/presentations/workshops/introduction-to-R-and-data-github/data/iris.csv

Data Preview:

Sepal.Length (double) ▾	Sepal.Width (double) ▾	Petal.Length (double) ▾	Petal.Width (double) ▾	Species (character) ▾
5.1	3.5	1.4	0.2	setosa
4.9	3.0	1.4	0.2	setosa
4.7	3.2	1.3	0.2	setosa
4.6	3.1	1.5	0.2	setosa
5.0	3.6	1.4	0.2	setosa
5.4	3.9	1.7	0.4	setosa
4.6	3.4	1.4	0.3	setosa
5.0	3.4	1.5	0.2	setosa
4.4	2.9	1.4	0.2	setosa
4.9	3.1	1.5	0.1	setosa
5.4	3.7	1.5	0.2	setosa

Previewing first 50 entries.

Import Options:

Name: Iris  First Row as Names Delimiter: Comma  Escape: None  Skip: 0  Trim Spaces Quotes:  Comment: Default  Locale: Configure... NA: Default

Code Preview:

```
library(readr)
iris <- read_csv("~/surfdrive/Projects/presentations/workshops/introduction-to-R-and-data-github/data/iris.csv")
View(iris)
```

## Read flat files

---

```
> library(readr)  
> data_iris <- read_delim("data/iris.csv", delim=',')
```

## Read flat files

---

```
> library(readr)
> data_iris <- read_delim("data/iris.csv", delim=',')
Parsed with column specification:
cols(
  Sepal.Length = col_double(),
  Sepal.Width = col_double(),
  Petal.Length = col_double(),
  Petal.Width = col_double(),
  Species = col_character()
)
```

## Read flat files

---

```
> library(readr)
> data_iris <- read_csv("data/iris.csv")
Parsed with column specification:
cols(
  Sepal.Length = col_double(),
  Sepal.Width = col_double(),
  Petal.Length = col_double(),
  Petal.Width = col_double(),
  Species = col_character()
)
```

# Exercise dataset

---

- GPS data from 39 tagged individual cranes during fall migration of 2017
- Courtesy of Sasha Pekarsky at the Hebrew University of Jerusalem, Israel
- In the ‘data’ folder of your course materials.



# Exercises

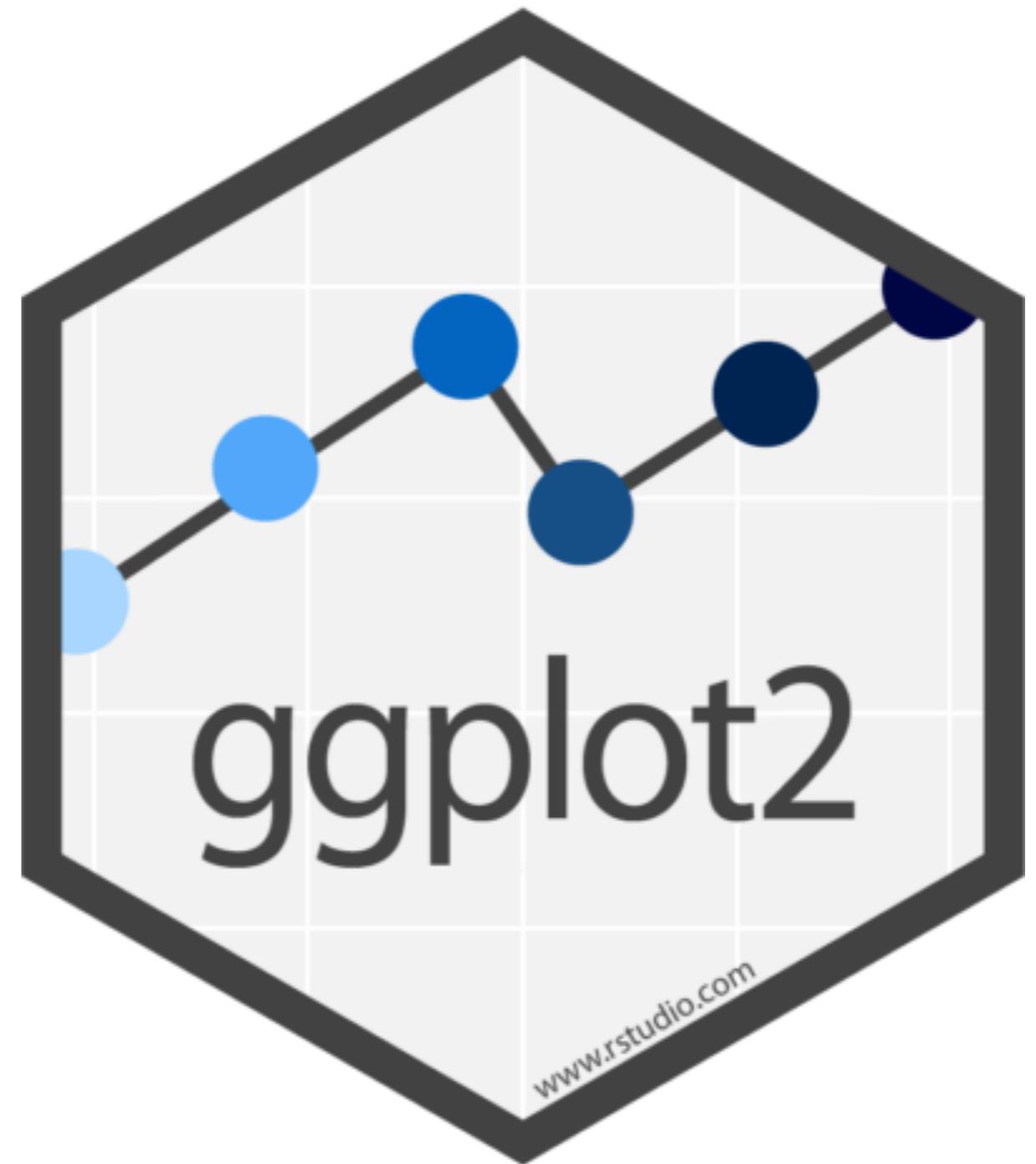
Please do basic exercises 1-I and 1-II.

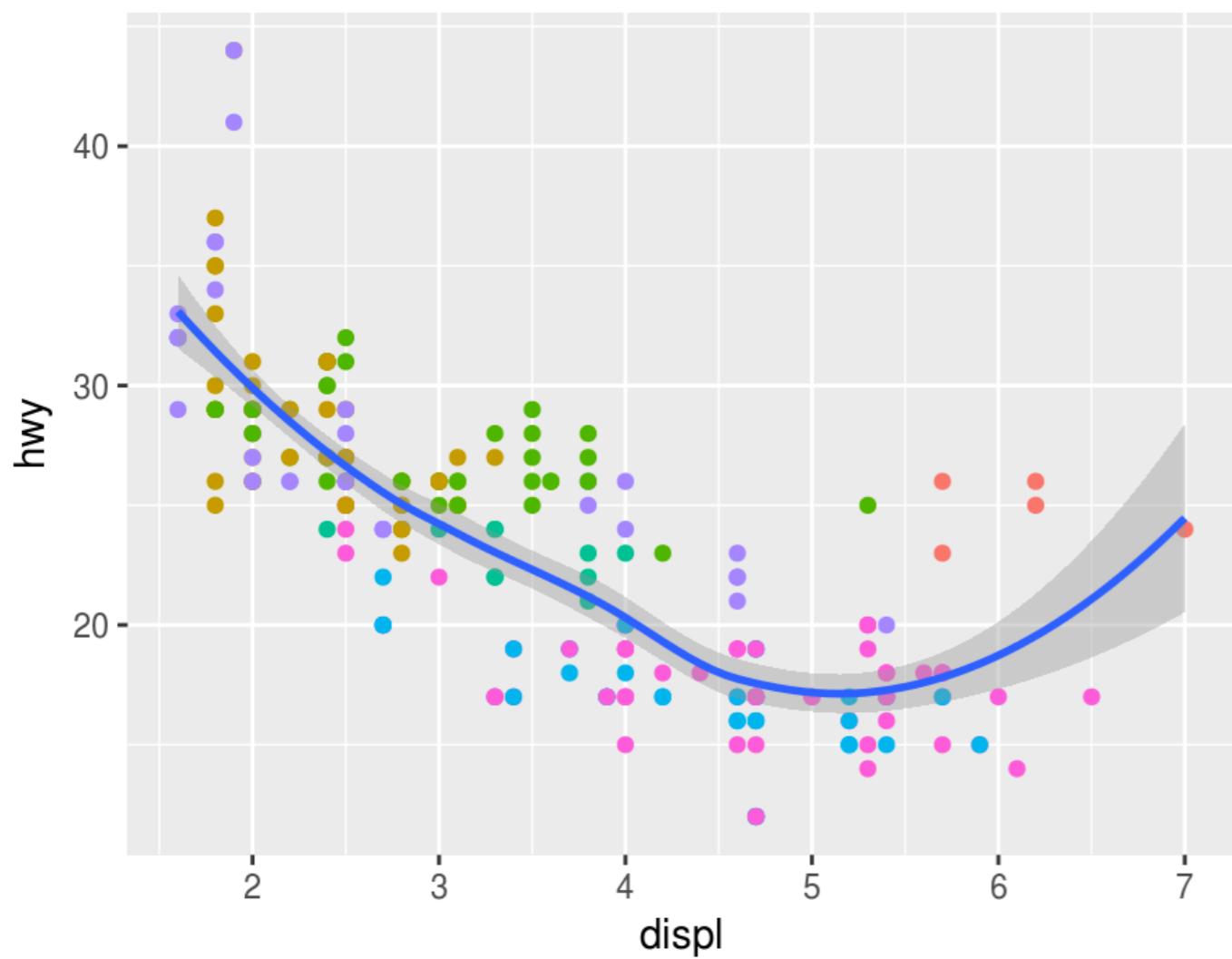
Time left? Opt for a reading exercise or optional exercise!

# Data visualisation

---

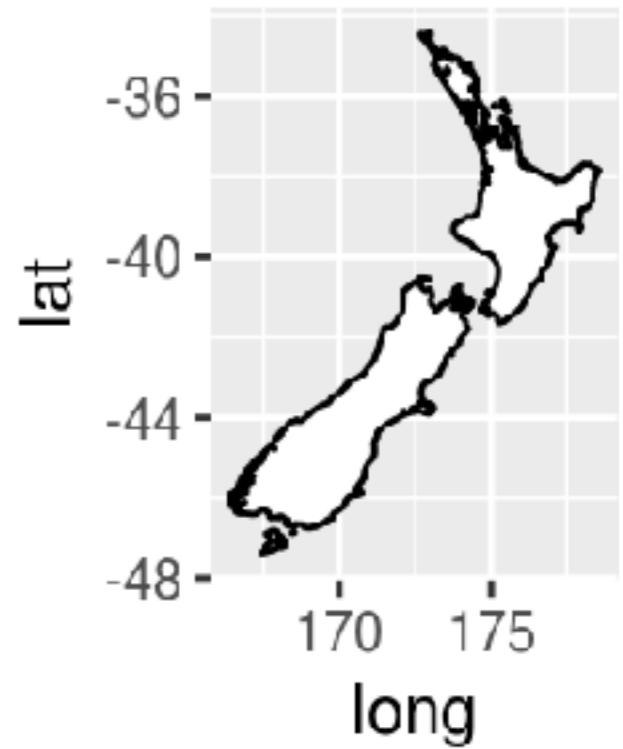
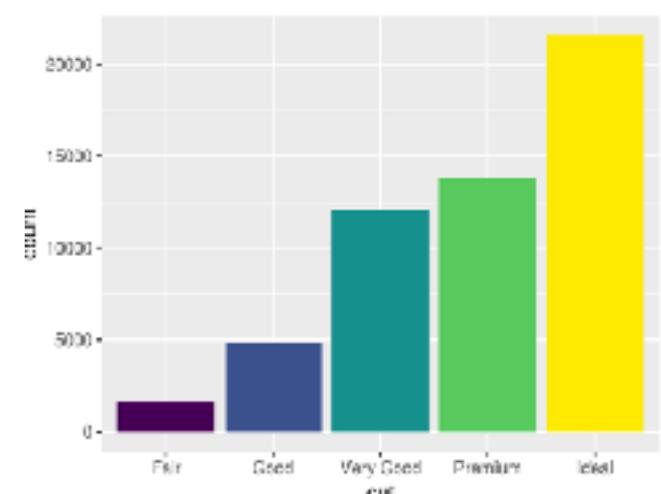
Create eye candy with ggplot2





class

- 2seater
- compact
- midsize
- minivan
- pickup
- subcompact
- suv



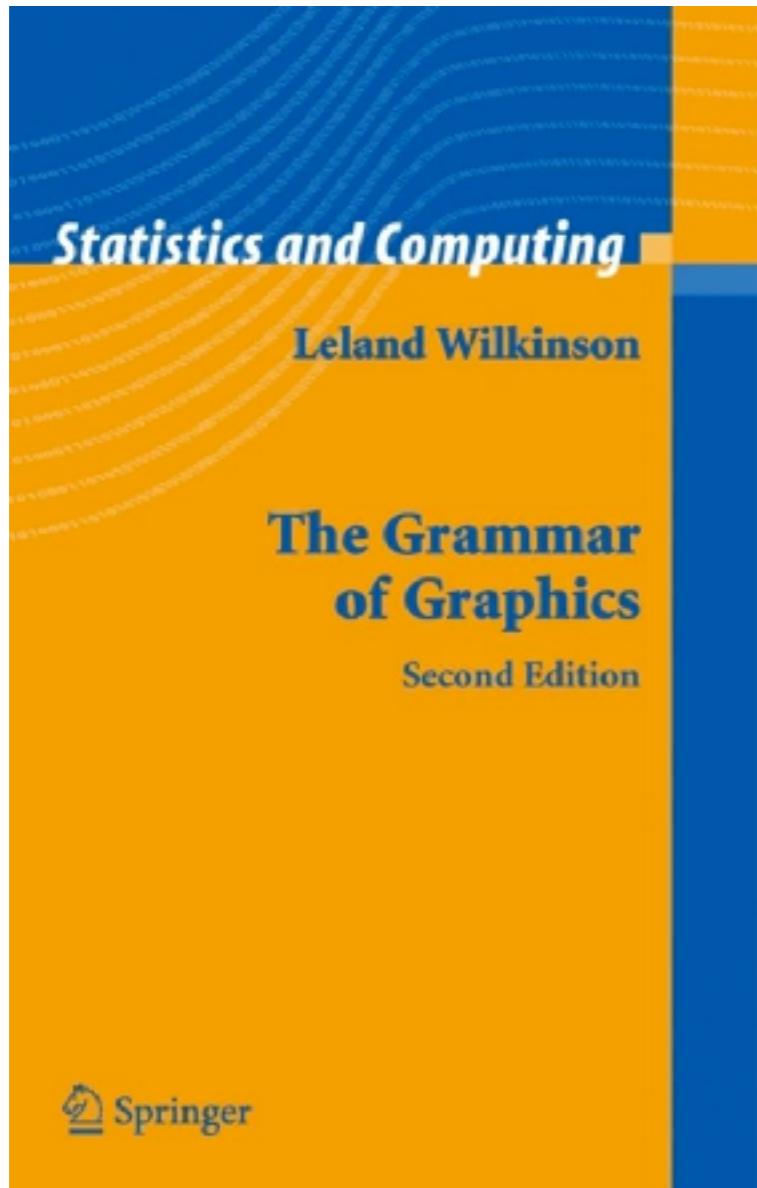
Examples of plots with R (and ggplot2)

# Data visualisation with ggplot2

---

- **ggplot2** is an extremely popular data visualisation package for R
- Simple syntax, easy to learn, nice plots
- Developed and maintained by Hadley Wickham
- Based on the book: The Grammar of Graphics (Wilkinson, 2005)

# The grammar of graphics



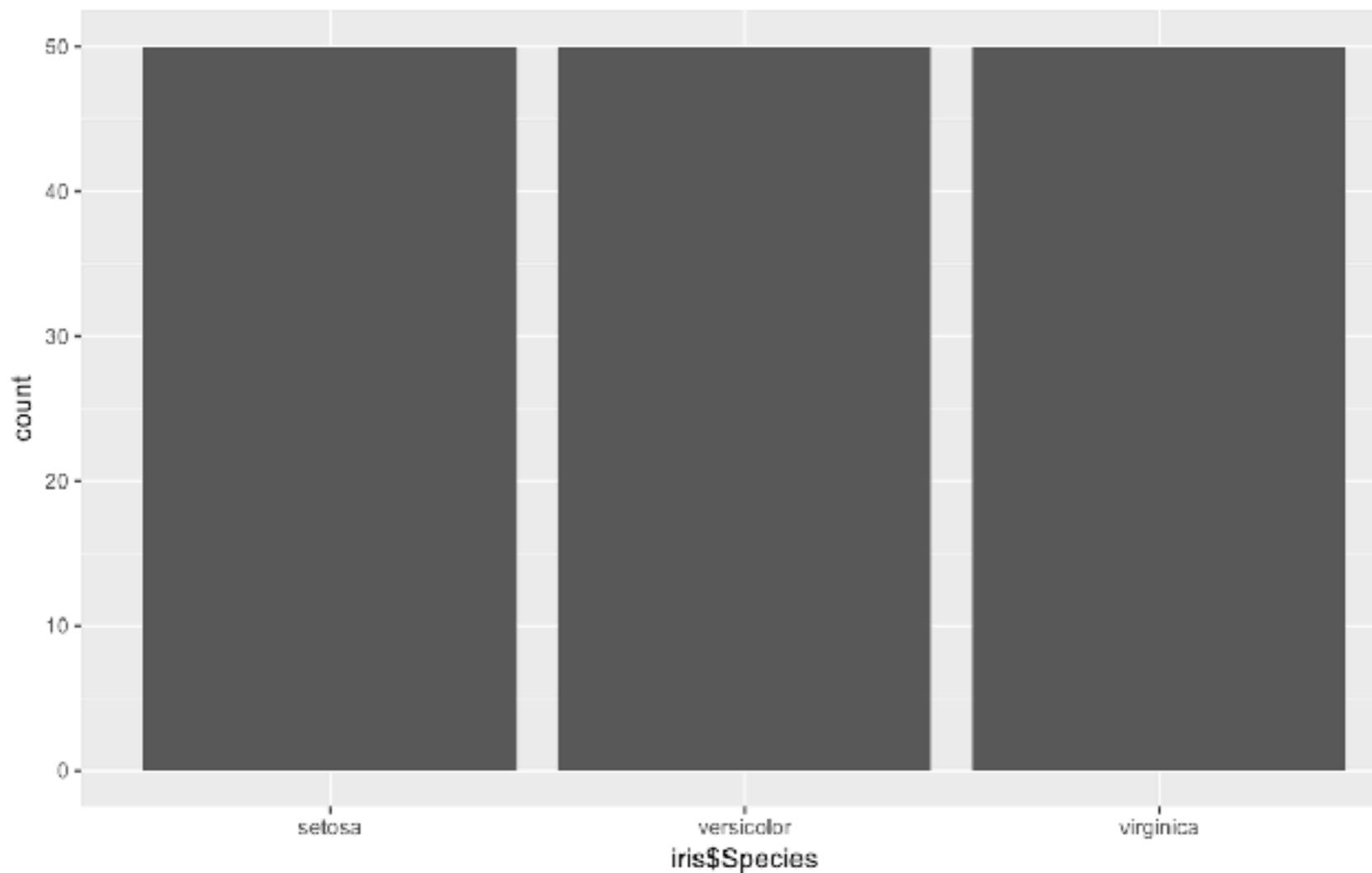
Data	The variables in a tibble or data.frame
Aesthetics	x- and y-axis, colour, size, alpha, shape
Geometries	point, line, bar, histogram

# Quick plotting

# Quick plots

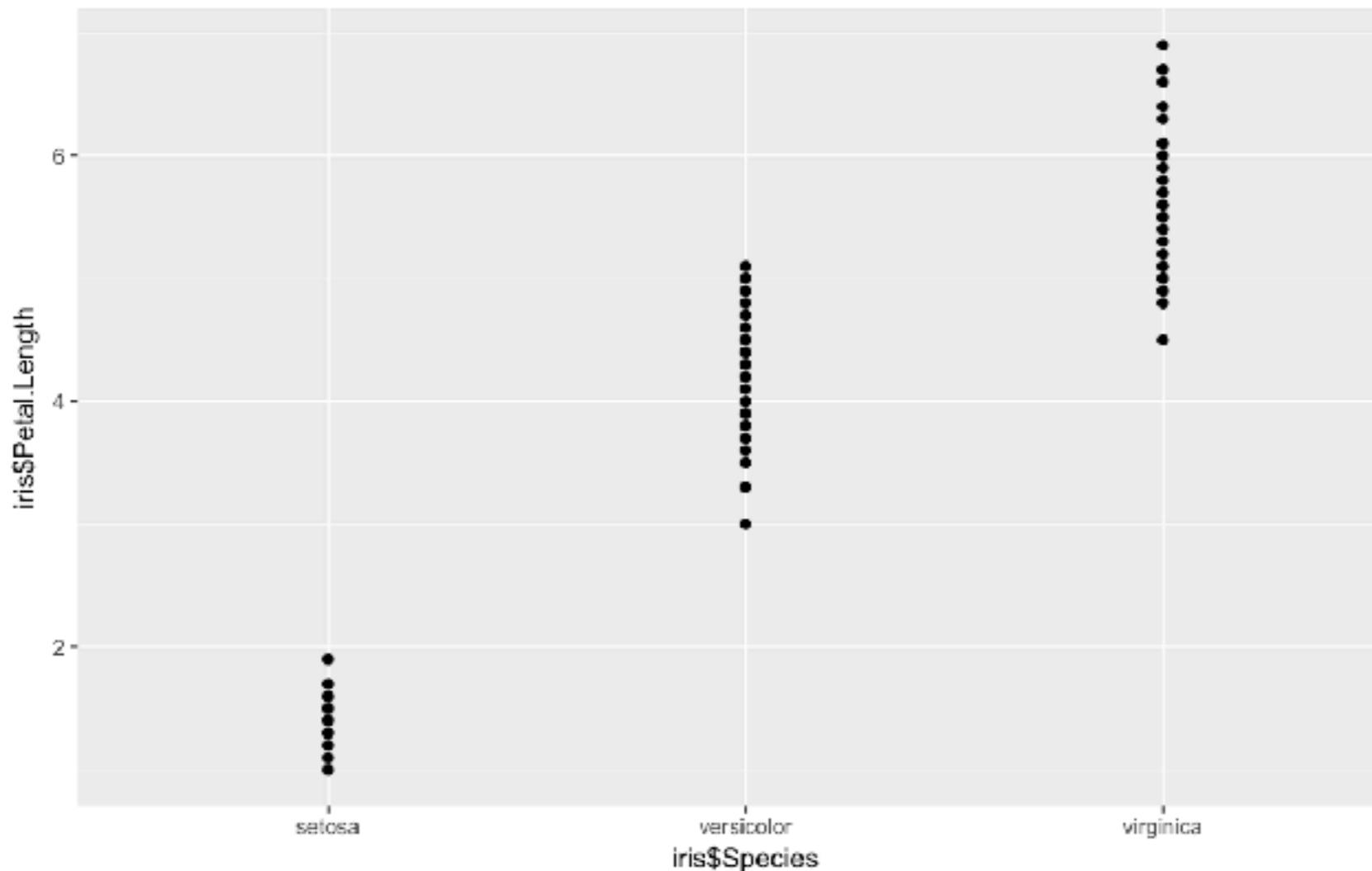
---

```
> qplot(Species, data = iris)
```



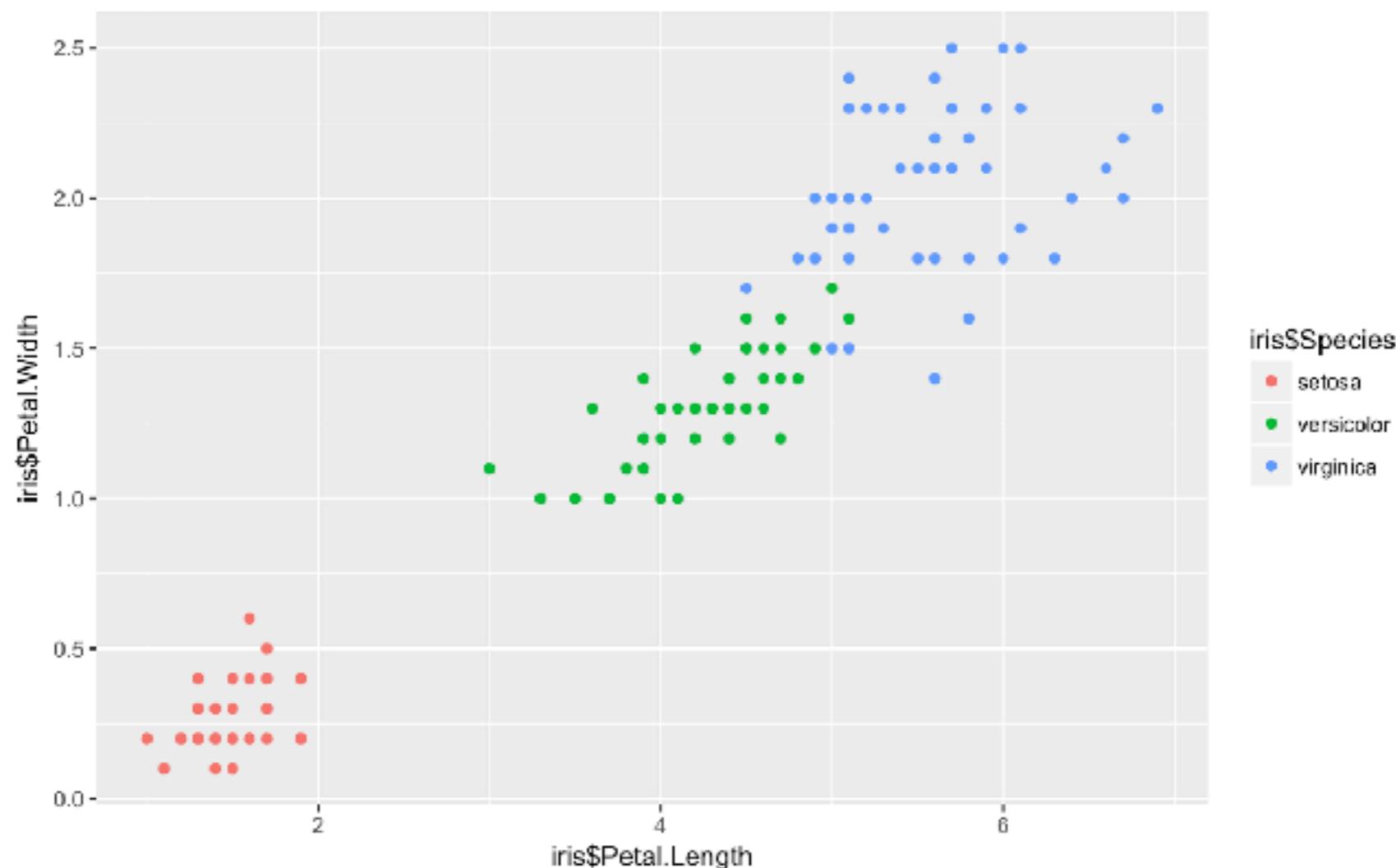
# Quick plots

```
> qplot(Species, data = iris)
> qplot(Species, Petal.Length, data = iris)
```



# Quick plots

```
> qplot(Species, data = iris)
> qplot(Species, Petal.Length, data = iris)
> qplot(Petal.Length, Petal.Width, data = iris, colour=Species)
```

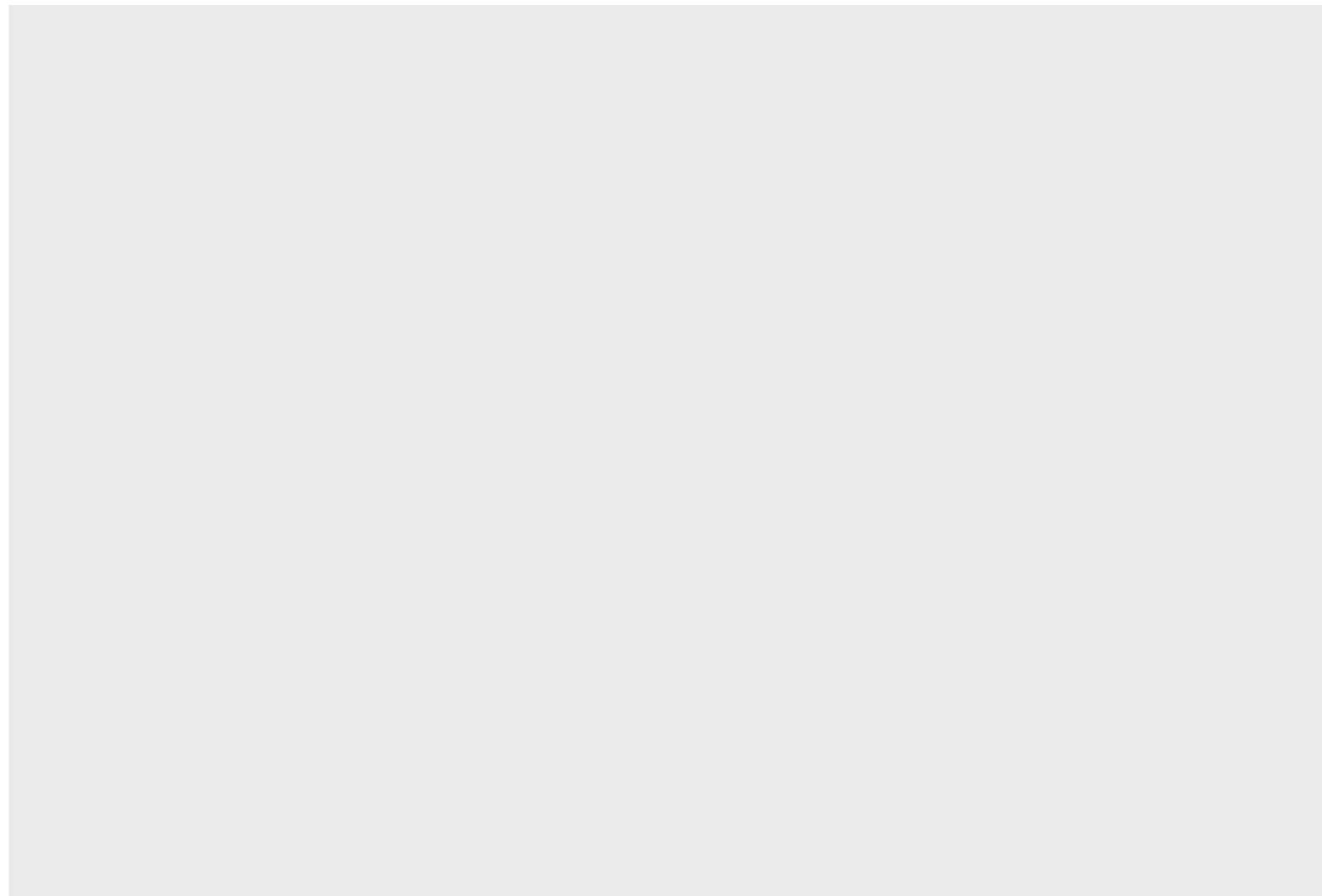


ggplot (grammar of graphics)

# ggplot: Data, aesthetics, geometrics

---

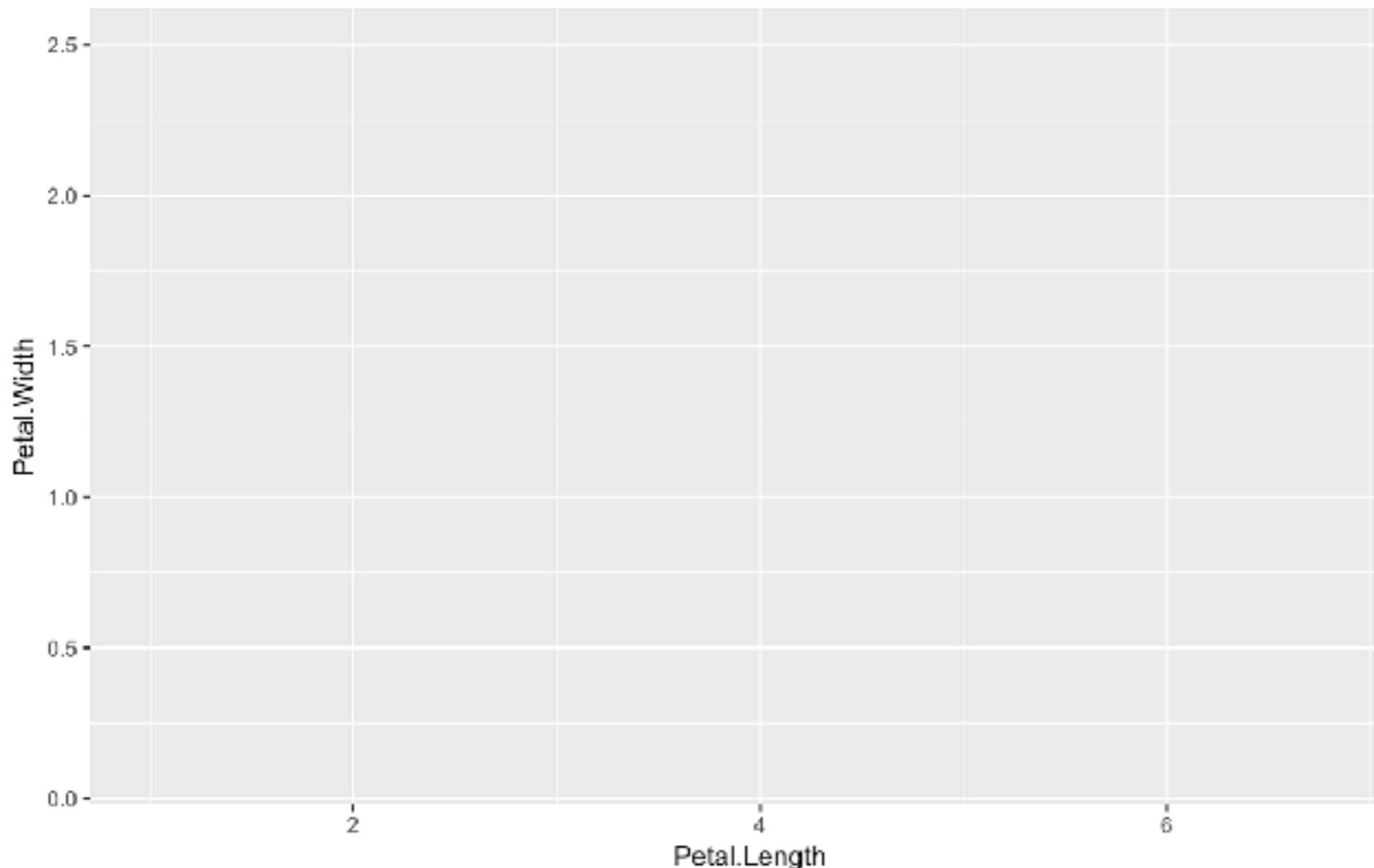
```
> ggplot(iris)
```



# ggplot: Data, aesthetics, geometrics

---

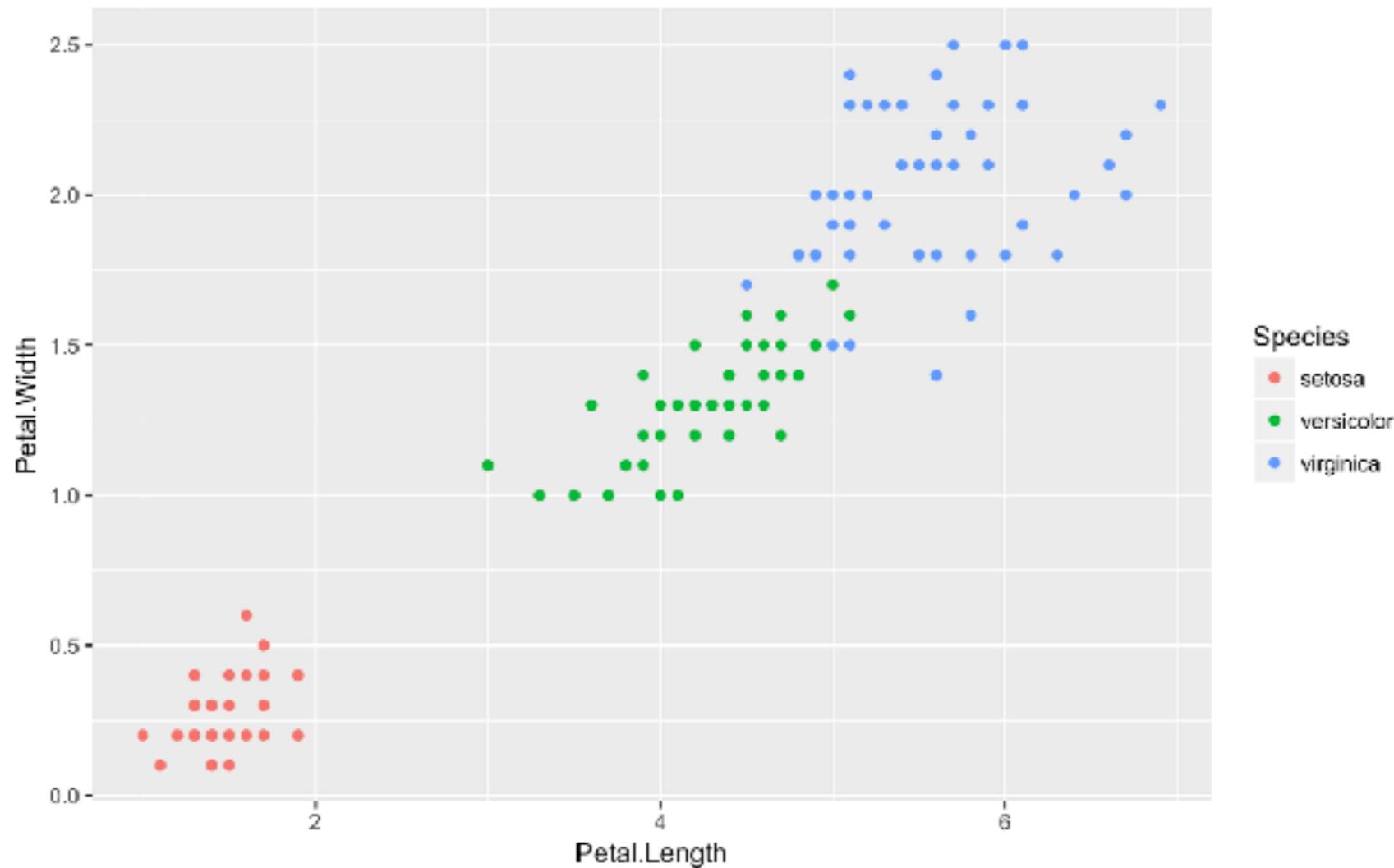
```
> ggplot(iris)  
> ggplot(iris, aes(x = Petal.Length, y = Petal.Width, colour=Species))
```



# ggplot: Data, aesthetics, geometrics

---

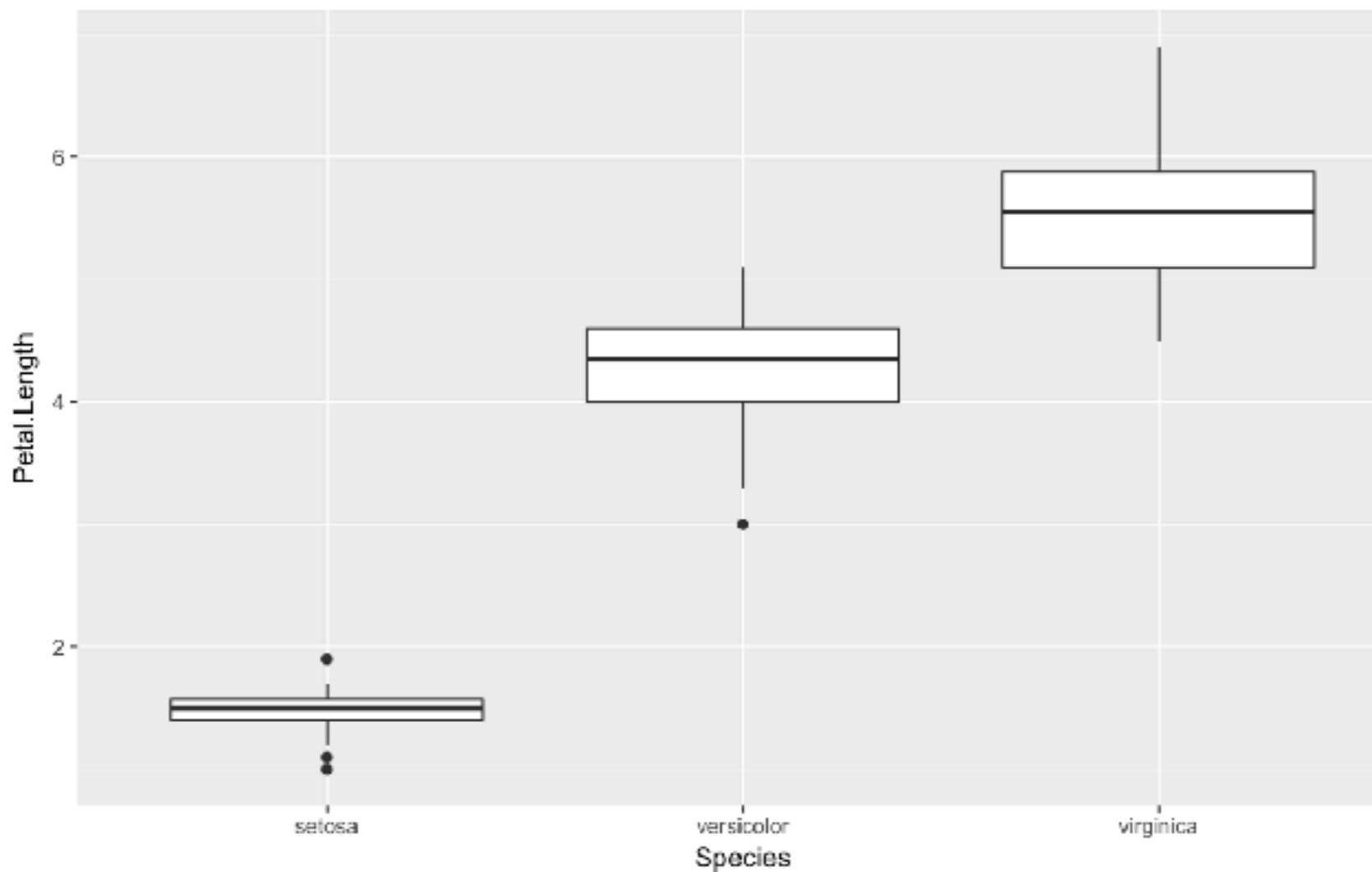
```
> ggplot(iris)  
> ggplot(iris, aes(x = Petal.Length, y = Petal.Width, colour=Species))  
> ggplot(iris, aes(x = Petal.Length, y = Petal.Width, colour=Species)) +  
  geom_point()
```



# ggplot: Multiple geometric layers

---

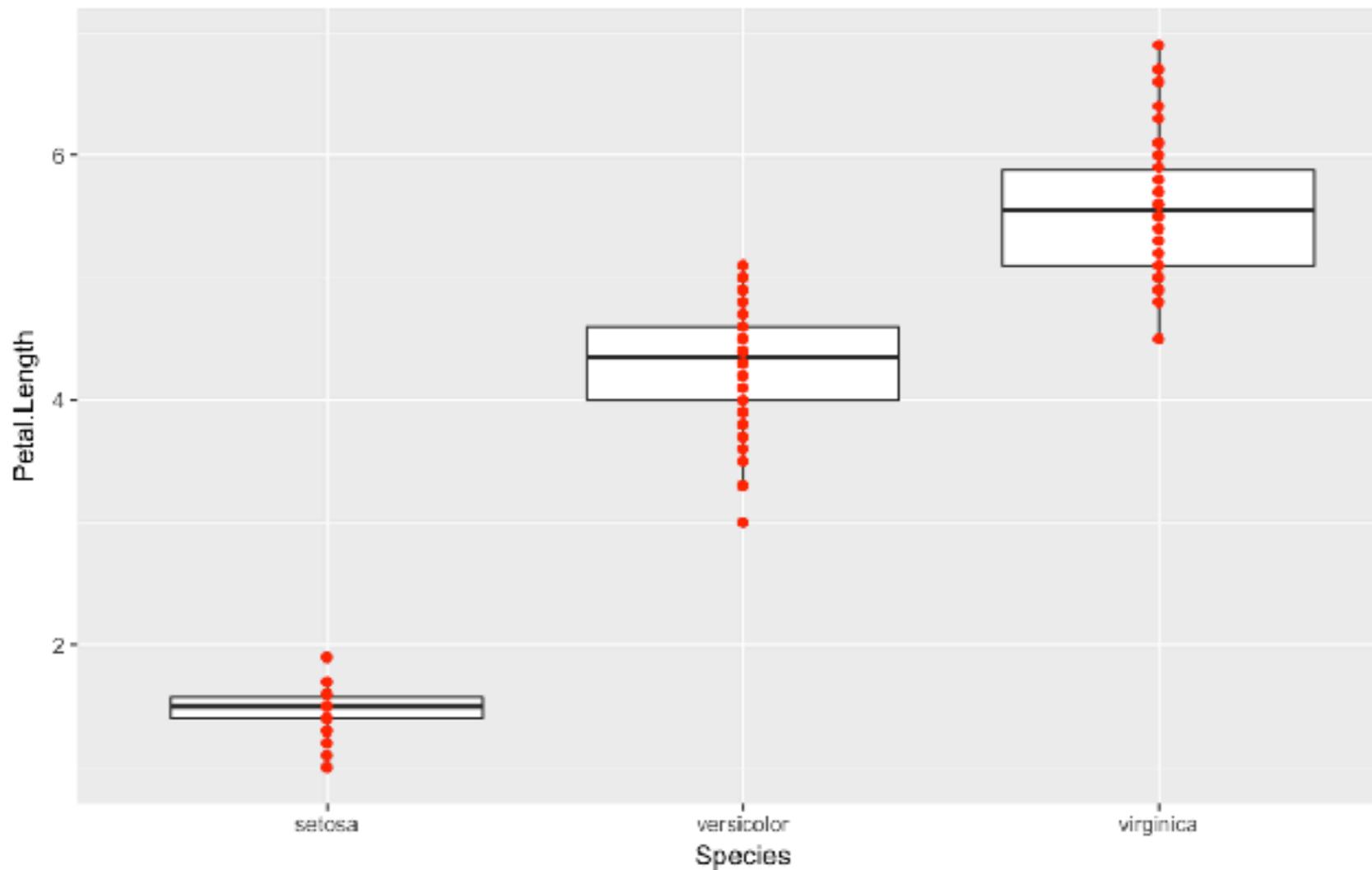
```
> ggplot(iris, aes(x = Species, y = Petal.Length)) +  
  geom_boxplot()
```



# ggplot: Multiple geometric layers

---

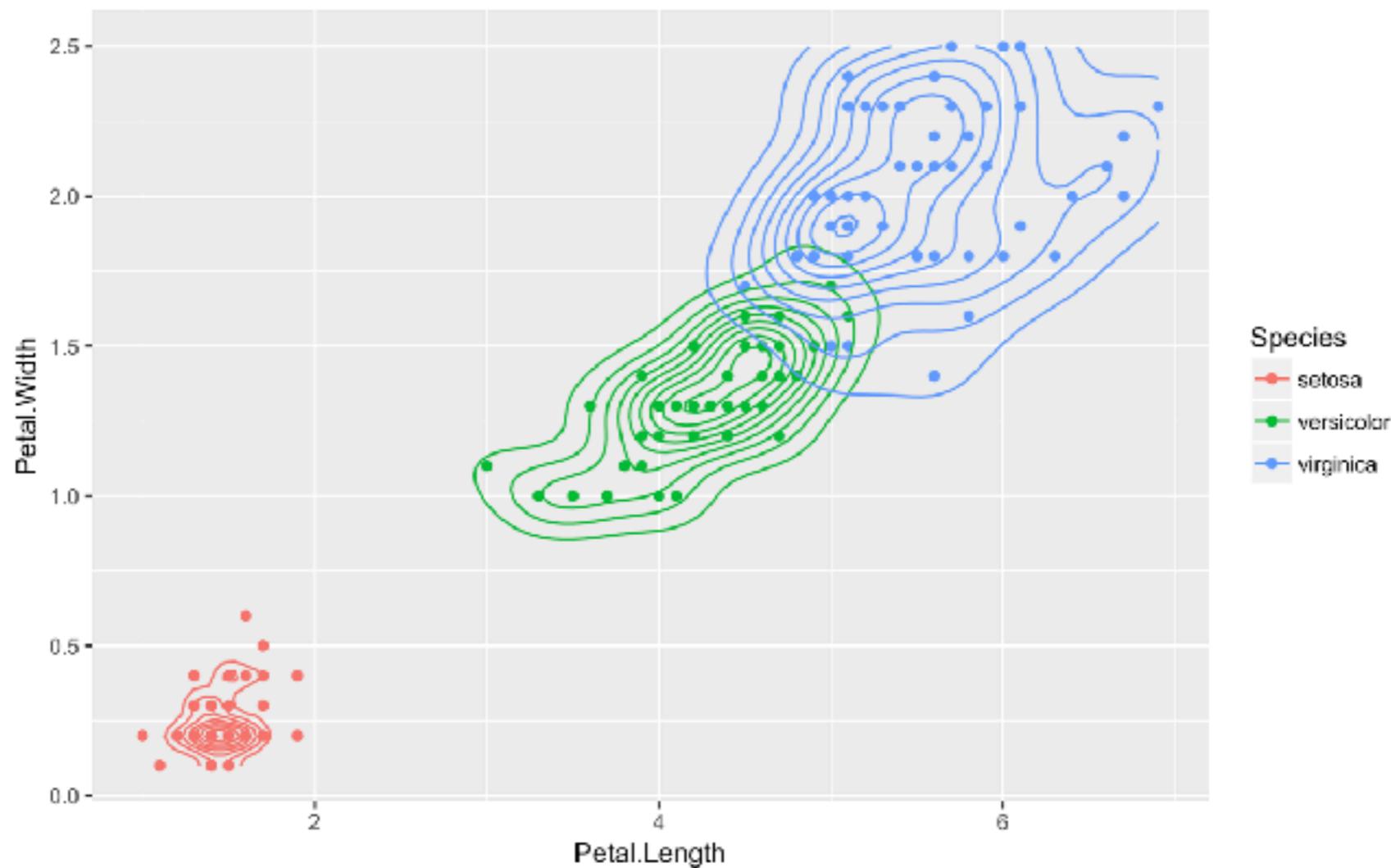
```
> ggplot(iris, aes(x = Species, y = Petal.Length)) +  
  geom_boxplot() +  
  geom_point(colour='red')
```



# ggplot: Statistical layers

---

```
> ggplot(iris, aes(x = Petal.Length, y = Petal.Width, colour=Species)) +  
  geom_point() +  
  stat_density_2d()
```



# Exercises

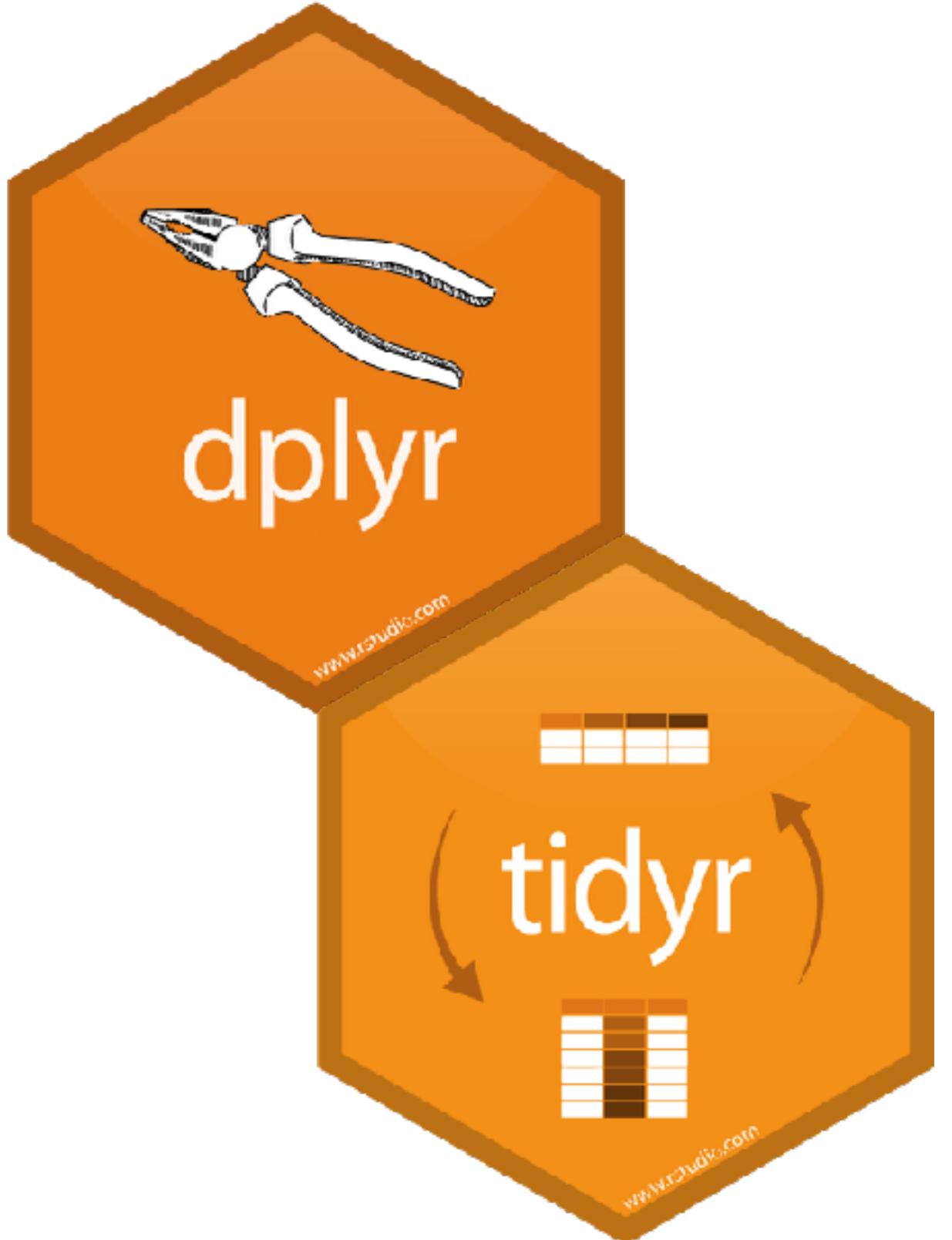
Please do basic exercises 2-I and 2-II.

Time left? Opt for a reading exercise or optional exercise!

# Data transformation

---

Explore the power of **dplyr** and **tidyr**



# Data Transformation with dplyr :: CHEAT SHEET



dplyr functions work with pipes and expect **tidy data**. In tidy data:



Each **variable** is in its own **column**



Each **observation**, or **case**, is in its own **row**



`x %>% f(y)` becomes `f(x, y)`

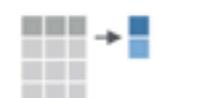
## Summarise Cases

These apply **summary functions** to columns to create a new table of summary statistics. Summary functions take vectors as input and return one value (see back).

### summary function



`summarise(.data, ...)`  
Compute table of summaries.  
`summarise(mtcars, avg = mean(mpg))`



`count(x, ..., wt = NULL, sort = FALSE)`  
Count number of rows in each group defined by the variables in ... Also `tally()`.  
`count(iris, Species)`

### VARIATIONS

`summarise_all()` - Apply funs to every column.  
`summarise_at()` - Apply funs to specific columns.  
`summarise_if()` - Apply funs to all cols of one type.

## Group Cases

Use `group_by()` to create a "grouped" copy of a table. dplyr functions will manipulate each "group" separately and then combine the results.



`mtcars %>%`  
`group_by(cyl) %>%`  
`summarise(avg = mean(mpg))`

`group_by(.data, ..., add = FALSE)`  
Returns copy of table grouped by ...  
`g_iris <- group_by(iris, Species)`

`ungroup(x, ...)`  
Returns ungrouped copy of table.  
`ungroup(g_iris)`

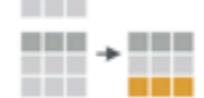
## Manipulate Cases

### EXTRACT CASES

Row functions return a subset of rows as a new table.



`filter(.data, ...)` Extract rows that meet logical criteria.  
`filter(iris, Sepal.Length > 7)`



`distinct(.data, ..., .keep_all = FALSE)` Remove rows with duplicate values.  
`distinct(iris, Species)`



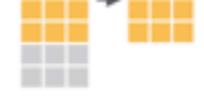
`sample_frac(tbl, size = 1, replace = FALSE, weight = NULL, .env = parent.frame())` Randomly select fraction of rows.  
`sample_frac(iris, 0.5, replace = TRUE)`



`sample_n(tbl, size, replace = FALSE, weight = NULL, .env = parent.frame())` Randomly select size rows.  
`sample_n(iris, 10, replace = TRUE)`



`slice(.data, ...)` Select rows by position.  
`slice(iris, 10:15)`



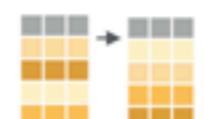
`top_n(x, n, wt)` Select and order top n entries (by group if grouped data).  
`top_n(iris, 5, Sepal.Width)`

### Logical and boolean operators to use with filter()

<      <=      is.na()      %in%      |      xor()  
>      >=      !is.na()      !      &

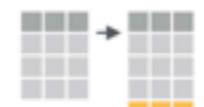
See `?base::logic` and `?Comparison` for help.

### ARRANGE CASES



`arrange(.data, ...)` Order rows by values of a column or columns (low to high), use with `desc()` to order from high to low.  
`arrange(mtcars, mpg)`  
`arrange(mtcars, desc(mpg))`

### ADD CASES



`add_row(.data, ..., .before = NULL, .after = NULL)`  
Add one or more rows to a table.  
`add_row(faithful, eruptions = 1, waiting = 1)`

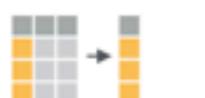
## Manipulate Variables

### EXTRACT VARIABLES

Column functions return a set of columns as a new vector or table.



`pull(.data, var = -1)` Extract column values as a vector. Choose by name or index.  
`pull(iris, Sepal.Length)`



`select(.data, ...)` Extract columns as a table. Also `select_if()`.  
`select(iris, Sepal.Length, Species)`

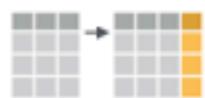
Use these helpers with `select()`, e.g. `select(iris, starts_with("Sepal"))`

`contains(match)`    `num_range(prefix, range)` ;, e.g. `mpg:cyl`  
`ends_with(match)`    `one_of(...)`    -, e.g., `-Species`  
`matches(match)`    `starts_with(match)`

### MAKE NEW VARIABLES

These apply **vectorized functions** to columns. Vectorized funs take vectors as input and return vectors of the same length as output (see back).

### vectorized function



`mutate(.data, ...)`  
Compute new column(s).  
`mutate(mtcars, gpm = 1/mpg)`



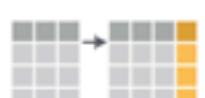
`transmute(.data, ...)`  
Compute new column(s), drop others.  
`transmute(mtcars, gpm = 1/mpg)`



`mutate_all(.tbl, .funs, ...)` Apply funs to every column. Use with `funs()`. Also `mutate_if()`.  
`mutate_all(faithful, funs(log(.), log2(.)))`  
`mutate_if(iris, is.numeric, funs(log(.)))`



`mutate_at(.tbl, .cols, .funs, ...)` Apply funs to specific columns. Use with `funs()`, `vars()` and the helper functions for `select()`.  
`mutate_at(iris, vars(-Species), funs(log(.)))`



`add_column(.data, ..., .before = NULL, .after = NULL)` Add new column(s). Also `add_count()`, `add_tally()`.  
`add_column(mtcars, new = 1:32)`



`rename(.data, ...)` Rename columns.  
`rename(iris, Length = Sepal.Length)`

`filter()`

## Subset Observations (Rows)



## Function: filter()

---

```
> filter(iris, Species=="virginica")
```

## Function: filter()

---

```
> filter(iris, Species=="virginica")
# A tibble: 50 x 5
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
        <dbl>       <dbl>       <dbl>       <dbl>   <fct>
1       6.30       3.30       6.00       2.50 virginica
2       5.80       2.70       5.10       1.90 virginica
3       7.10       3.00       5.90       2.10 virginica
4       6.30       2.90       5.60       1.80 virginica
5       6.50       3.00       5.80       2.20 virginica
6       7.60       3.00       6.60       2.10 virginica
7       4.90       2.50       4.50       1.70 virginica
8       7.30       2.90       6.30       1.80 virginica
9       6.70       2.50       5.80       1.80 virginica
10      7.20       3.60       6.10       2.50 virginica
# ... with 40 more rows
```

## Function: filter()

---

```
> filter(iris, Species=="virginica", Sepal.Length>= 7.5)
```

## Function: filter()

---

```
> filter(iris, Species=="virginica", Sepal.Length>= 7.5)
# A tibble: 6 x 5
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
        <dbl>       <dbl>      <dbl>       <dbl>   <fct>
1       7.60       3.00      6.60       2.10 virginica
2       7.70       3.80      6.70       2.20 virginica
3       7.70       2.60      6.90       2.30 virginica
4       7.70       2.80      6.70       2.00 virginica
5       7.90       3.80      6.40       2.00 virginica
6       7.70       3.00      6.10       2.30 virginica
```

## Function: filter()

---

```
> filter(iris, Species=="virginica", Sepal.Length>= 7.5)
# A tibble: 6 x 5
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
        <dbl>       <dbl>      <dbl>      <dbl>   <fct>
1       7.60       3.00      6.60      2.10 virginica
2       7.70       3.80      6.70      2.20 virginica
3       7.70       2.60      6.90      2.30 virginica
4       7.70       2.80      6.70      2.00 virginica
5       7.90       3.80      6.40      2.00 virginica
6       7.70       3.00      6.10      2.30 virginica
```

Same as:

```
> filter(iris, Species=="virginica" & Sepal.Length>= 7.5)
```

`select()`

## Subset Variables (Columns)



## Function: select()

---

```
> select(iris, Sepal.Length, Sepal.Width, Species)
```

## Function: select()

---

```
> select(iris, Sepal.Length, Sepal.Width, Species)
# A tibble: 150 x 3
  Sepal.Length Sepal.Width Species
        <dbl>       <dbl> <fct>
1         5.10       3.50 setosa
2         4.90       3.00 setosa
3         4.70       3.20 setosa
4         4.60       3.10 setosa
5         5.00       3.60 setosa
6         5.40       3.90 setosa
7         4.60       3.40 setosa
8         5.00       3.40 setosa
9         4.40       2.90 setosa
10        4.90       3.10 setosa
# ... with 140 more rows
```

## Function: select()

---

```
> select(iris, Sepal.Length, Sepal.Width, Species)  
> select(iris, starts_with("Sepal"), Species)
```

## Function: select()

---

```
> select(iris, Sepal.Length, Sepal.Width, Species)
> select(iris, starts_with("Sepal"), Species)
# A tibble: 150 x 3
  Sepal.Length Sepal.Width Species
        <dbl>      <dbl> <fct>
1         5.10      3.50 setosa
2         4.90      3.00 setosa
3         4.70      3.20 setosa
4         4.60      3.10 setosa
5         5.00      3.60 setosa
6         5.40      3.90 setosa
7         4.60      3.40 setosa
8         5.00      3.40 setosa
9         4.40      2.90 setosa
10        4.90      3.10 setosa
# ... with 140 more rows
```

## Function: select()

---

```
> select(iris, Sepal.Length, Sepal.Width, Species)
> select(iris, starts_with("Sepal"), Species)
> select(iris, -starts_with("Petal"))
```

## Function: select()

---

```
> select(iris, Sepal.Length, Sepal.Width, Species)
> select(iris, starts_with("Sepal"), Species)
> select(iris, -starts_with("Petal"))
# A tibble: 150 × 3
  Sepal.Length Sepal.Width Species
        <dbl>      <dbl> <fct>
1         5.10      3.50 setosa
2         4.90      3.00 setosa
3         4.70      3.20 setosa
4         4.60      3.10 setosa
5         5.00      3.60 setosa
6         5.40      3.90 setosa
7         4.60      3.40 setosa
8         5.00      3.40 setosa
9         4.40      2.90 setosa
10        4.90      3.10 setosa
# ... with 140 more rows
```

`mutate()`

## Make New Variables



## Function: mutate()

---

```
> mutate(iris,  
        petal_area = pi * Petal.Length/2 * Petal.Width/2)
```

## Function: mutate()

---

```
> mutate(iris,
        petal_area = pi * Petal.Length/2 * Petal.Width/2)
# A tibble: 150 x 6
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species petal_area
    <dbl>      <dbl>       <dbl>       <dbl>   <fct>     <dbl>
1       5.1       3.5        1.4        0.2 setosa    0.220
2       4.9       3.0        1.4        0.2 setosa    0.220
3       4.7       3.2        1.3        0.2 setosa    0.204
4       4.6       3.1        1.5        0.2 setosa    0.236
5       5.0       3.6        1.4        0.2 setosa    0.220
6       5.4       3.9        1.7        0.4 setosa    0.534
7       4.6       3.4        1.4        0.3 setosa    0.330
8       5.0       3.4        1.5        0.2 setosa    0.236
9       4.4       2.9        1.4        0.2 setosa    0.220
10      4.9       3.1        1.5        0.1 setosa    0.118
# ... with 140 more rows
```

## Function: mutate()

---

```
> mutate(iris,
  # compute the area of a single petal
  petal_area = pi * Petal.Length/2 * Petal.Width/2,
  # abbreviate the name of the species
  Species_abbr = substring(Species, 1, 3)
)
```

# Function: mutate()

---

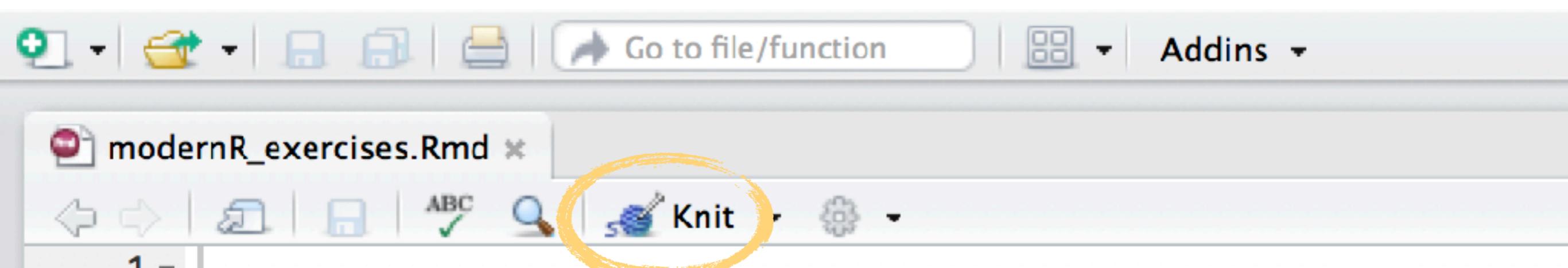
```
> mutate(iris,
  # compute the area of a single petal
  petal_area = pi * Petal.Length/2 * Petal.Width/2,
  # abbreviate the name of the species
  Species_abbr = substring(Species, 1, 3)
)
# A tibble: 150 x 7
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species petal_area Species_abbr
  <dbl>       <dbl>        <dbl>        <dbl>   <fct>      <dbl>    <chr>
1     5.1        3.5         1.4         0.2  setosa     0.220  set 
2     4.9        3.0         1.4         0.2  setosa     0.220  set 
3     4.7        3.2         1.3         0.2  setosa     0.204  set 
4     4.6        3.1         1.5         0.2  setosa     0.236  set 
5     5.0        3.6         1.4         0.2  setosa     0.220  set 
6     5.4        3.9         1.7         0.4  setosa     0.534  set 
7     4.6        3.4         1.4         0.3  setosa     0.330  set 
8     5.0        3.4         1.5         0.2  setosa     0.236  set 
9     4.4        2.9         1.4         0.2  setosa     0.220  set 
10    4.9        3.1         1.5         0.1  setosa     0.118  set 
# ... with 140 more rows
```

# Exercises

Please do basic exercises 3-I and 3-II.

Time left? Opt for a reading exercise or optional exercise!

# All done? Time to knit!



The screenshot shows the RStudio interface with the 'modernR\_exercises.Rmd' file open. The 'Knit' button in the toolbar is highlighted with a yellow circle. The code in the document includes YAML front matter and a note about the workshop.

```
1 ---  
2 title: "Modern R with tidyverse"  
3 author: "[Insert your name]"  
4 output:  
5   html_document:  
6     toc: true  
7 ---  
8  
9 *This document is part of the workshop **Introduction to R & Data  
10  
11 # Introduction  
12  
13 In this document, we explore Crane migration, through the GPS dat  
data was kindly provided for this course by Sasha Pekarsky at the
```

# Introduction to R & data

---

Before you leave...

# Other RDM workshops

---

- <https://www.uu.nl/en/research/research-data-management/tools-services/training-and-workshops>
- Learn to write your Data Management Plan (online course)
- Research Data Management basics
- Introduction to Python & Data (coming soon)
- Introduction to computational reproducibility (coming soon)

# R Cafe

---

- Monthly event for R programmers
- Join the R community
- Work on your project with the ability to ask questions
- Subscribe to the newsletter or follow RDM support website
- Check [https://github.com/  
UtrechtUniversity/R-data-cafe](https://github.com/UtrechtUniversity/R-data-cafe)
- Next edition: **Monday 25/2,  
15:00-17:00**



## Feedback is cool.

Please send your feedback, remarks, questions to us:

Barbara: [b.m.i.vreede@uu.nl](mailto:b.m.i.vreede@uu.nl)

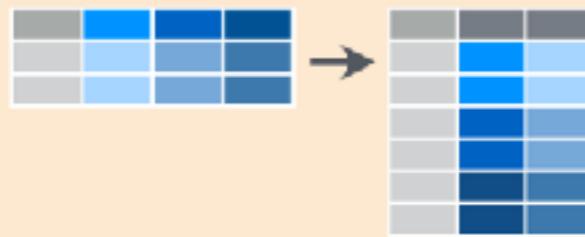
Jonathan: [j.debruin1@uu.nl](mailto:j.debruin1@uu.nl)

**Or generate an issue on github!**

[tinyurl.com/introRData](http://tinyurl.com/introRData)

```
useR <- function(){
  print("Good luck and see you!")
}
useR()
```

# gather() and spread()



`tidy::gather(cases, "year", "n", 2:4)`  
Gather columns into rows.



`tidy::spread(pollution, size, amount)`  
Spread rows into columns.

# Wide

# VS.

# Long

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

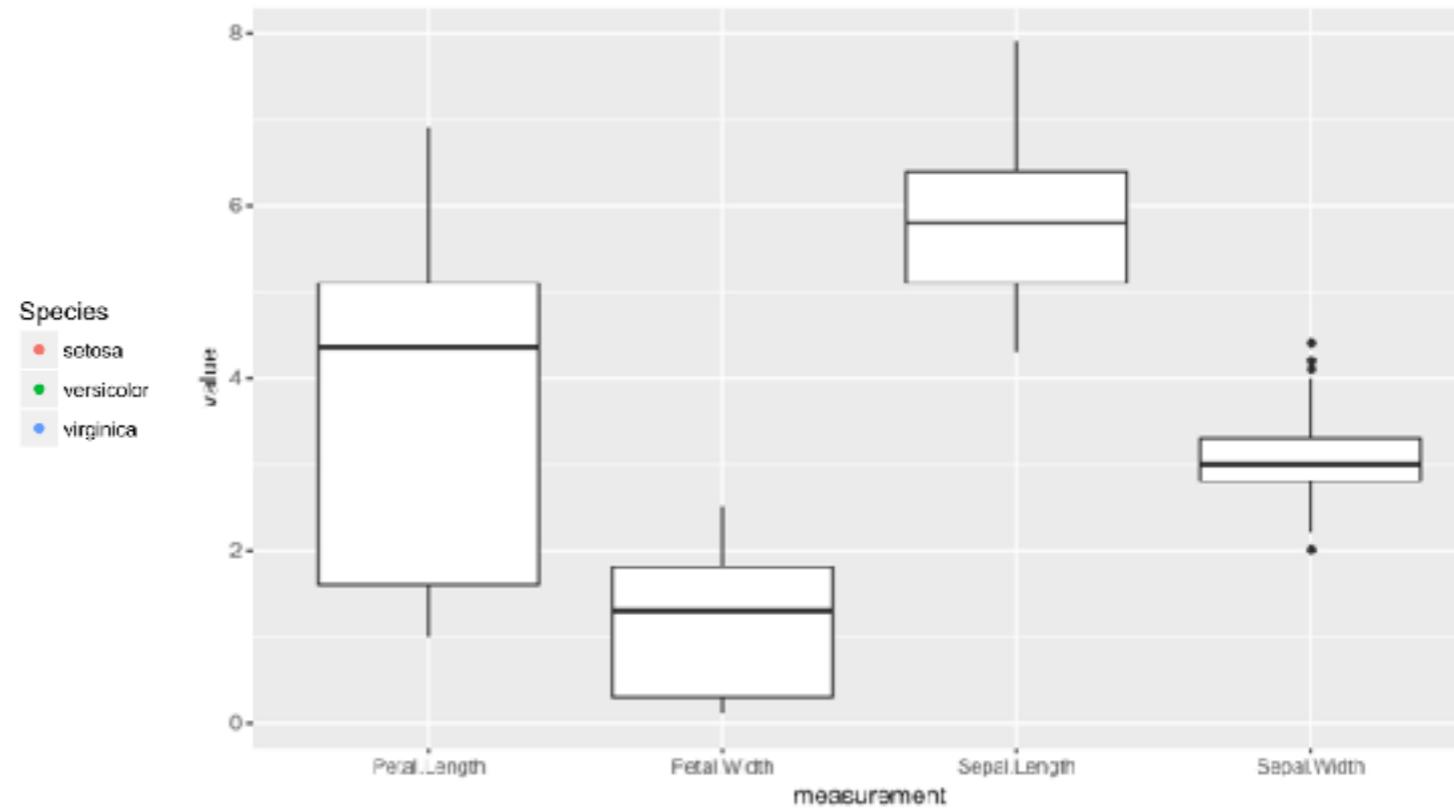
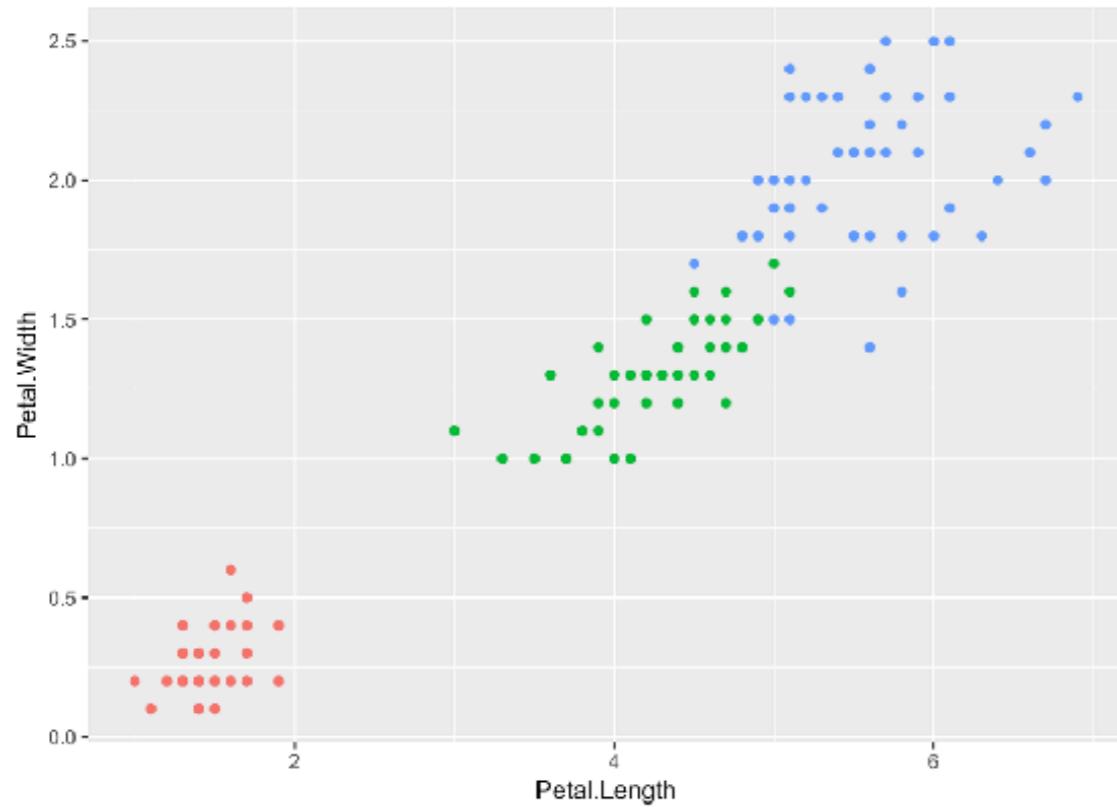
```
# A tibble: 600 x 4
  Species observation measurement value
  <chr>     <int>    <chr>      <dbl>
1 setosa      1 Sepal.Length 5.10
2 setosa      1 Sepal.Width  3.50
3 setosa      1 Petal.Length 1.40
4 setosa      1 Petal.Width  0.200
5 setosa      2 Sepal.Length 4.90
6 setosa      2 Sepal.Width  3.00
7 setosa      2 Petal.Length 1.40
8 setosa      2 Petal.Width  0.200
9 setosa      3 Sepal.Length 4.70
10 setosa     3 Sepal.Width  3.20
# ... with 590 more rows
```

- More information per row
  - Combines all measurements on a single individual
  - Necessary to plot matching measurements
- More information per column
  - No values as column headers (tidy)
  - Single observation in single row (tidy)
  - Necessary to plot large amounts of data in a single plot

# Wide

# VS.

# Long



- More information per row
- Combines all measurements on a single individual
- **Necessary to plot matching measurements**

- More information per column
- No values as column headers (tidy)
- Single observation in single row (tidy)
- **Necessary to plot large amounts of data in a single plot**

## Function: gather()

---

```
> iris_obs <- mutate(iris, observation = 1:n())
> iris_obs
```

# Function: gather()

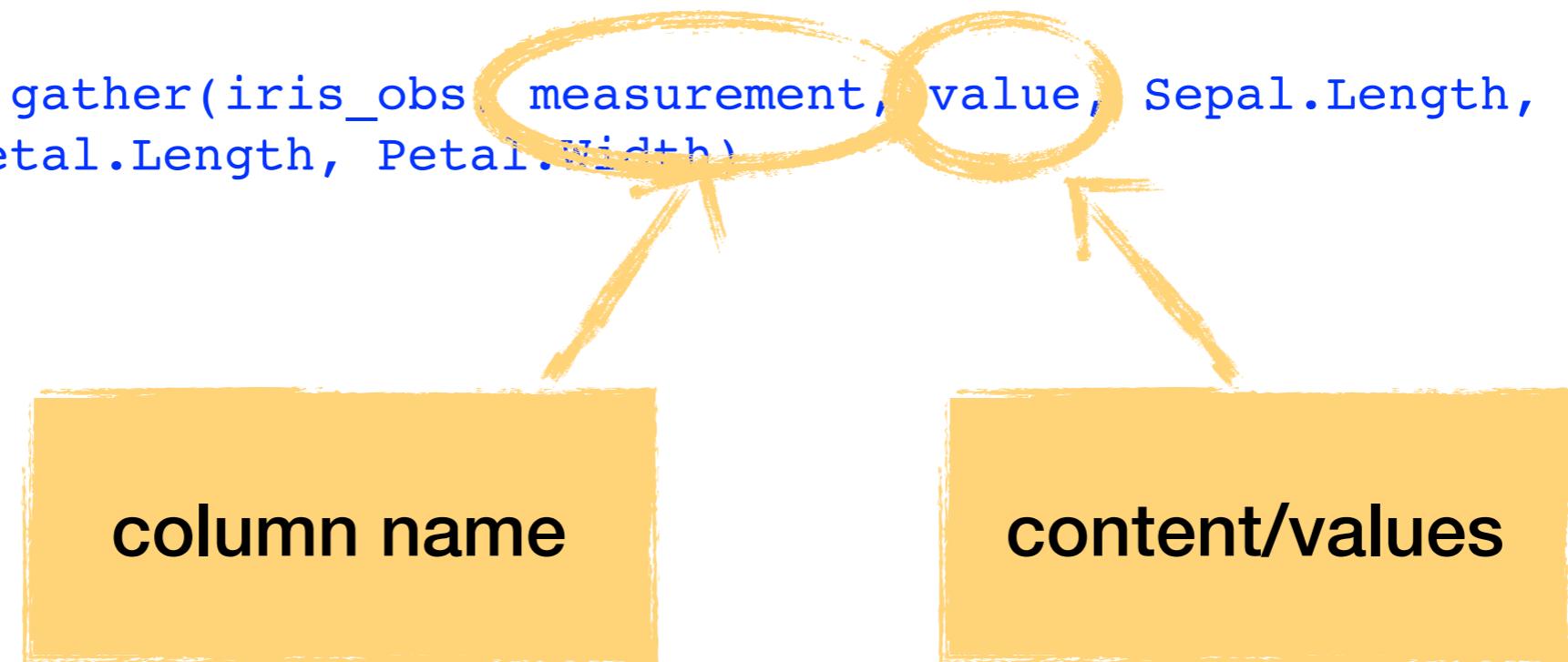
---

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

# Function: gather()

---

```
> iris_obs <- mutate(iris, observation = 1:n())
> iris_obs
> iris_long <- gather(iris_obs, measurement, value, Sepal.Length,
Sepal.Width, Petal.Length, Petal.Width)
> iris_long
```



# Function: gather()

---

```
> iris_obs <- mutate(iris, observation = 1:n())
> iris_obs
> iris_long <- gather(iris_obs, measurement, value, Sepal.Length,
Sepal.Width, Petal.Length, Petal.Width)
> iris_long
# A tibble: 600 x 4
  Species observation measurement  value
  <chr>        <int> <chr>      <dbl>
1 setosa          1 Sepal.Length 5.10 
2 setosa          1 Sepal.Width  3.50 
3 setosa          1 Petal.Length 1.40 
4 setosa          1 Petal.Width  0.200
5 setosa          2 Sepal.Length 4.90 
6 setosa          2 Sepal.Width  3.00 
7 setosa          2 Petal.Length 1.40 
8 setosa          2 Petal.Width  0.200
9 setosa          3 Sepal.Length 4.70 
```

## Function: spread()

---

```
> iris_wide <- spread(iris_long, measurement, value)
> iris_wide
```

# Function: spread()

---

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