An Introduction to R: Part I[1]

Mark Andrews
Psychology Department, Nottingham Trent University

@xmjandrews
mark.andrews@ntu.ac.uk
https://github.com/mark-andrews/u-herts-r-workshop

[1]These slides are not intended to be self-contained and comprehensive, but just aim to provide some of the workshop's content. Elaborations and explanations will be provided in the workshop itself.

What is R and why should you care

- R is a program for doing statistics and data analysis.
- R's advantages or selling points relative to other programs (e.g, SPSS, SAS, Stata, Minitab, Python, Matlab, Maple, Mathematica, Tableau, Excel, SQL, and many others) come down to three inter-related factors:
  - It is immensely powerful.
  - It is open-source.
  - It is very and increasingly widely used.

R: A power tool for data analysis

The range and depth of statistical analyses and general data analyses that can be accomplished with R is immense.

- Built into R are virtually the entire repertoire of widely known and used statistical methods.
- Also built in to R is an extensive graphics library.
- R has a vast set of add-on or contributed packages. There are presently 0 additional contributed packages.
- R is a programming language that is specialized to efficiently manipulate and perform calculations on data.
- The R programming language itself can be extended by interfacing with other programming languages like C, C++, Fortran, Python, and high performance computing or big data tools like Hadoop, Spark, SQL.

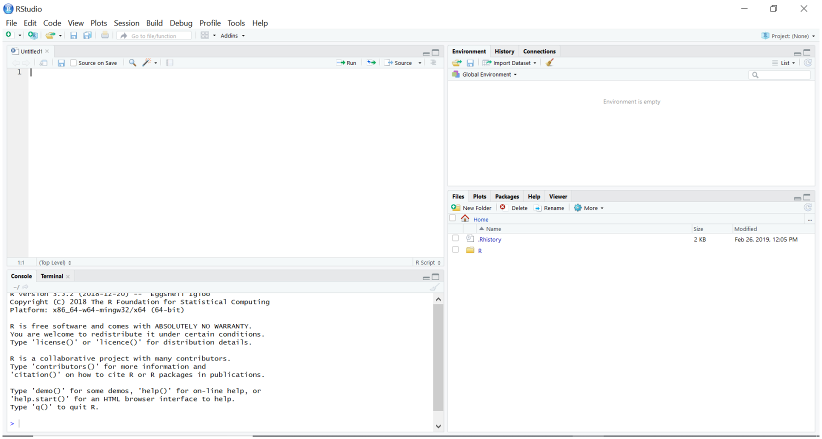
R: Open source software

- R is free and open source software, distributed according to the GNU public license.
- Likewise, virtually all of contributed R packages are likewise free and open source.
- In practical terms, this means that is freely available for everyone to use, now and forever, on more or less any device they choose.
- Open source software always has the potential to *go viral* and develop a large self-sustaining community of user/developers. This has arguably happened with R.

R: Popularity and widespread use

- When it comes to the computational implementation of modern statistical methods, R is the de facto standard. For example, the Journal of Statistical Software is overwhelmingly dominated by programs written in R.
- R is also currently very highly ranked according to many rankings of widely used programming languages of any kind. It ranked in the top 10 or top 20 most widely used programming languages.
- R is ranked as one of the top five most popular data science programs in jobs for data scientists, and in multiple surveys of data scientists, it is often ranked as the first or second mostly widely used data science tool.

A guided tour of RStudio



```
R version 3.5.2 (2018-12-20) -- "Eggshell Igloo"
Copyright (C) 2018 The R Foundation for Statistical Computing
Platform: x86_64-w64-mingw32/x64 (64-bit)

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> 
```

Introducing R commands

- A useful way to think about R, and not an inaccurate one either, is that it is simply a calculator.

```
> 2 + 2 # addition
#> [1] 4
> 3 - 5 # subtraction
#> [1] -2
> 3 * 2 # multiplication
#> [1] 6
> 4 / 3 # division
#> [1] 1.333333
> (2 + 2) ^ (3 / 3.5) # exponents and brackets
#> [1] 3.281341
```

Equality/inequality operations

- Testing for the equality or inequality of pairs of numbers, already starts to go beyond the usual capabilities of handheld calculator.

```
> 12 == (6 * 2)          # test for equality
#> [1] TRUE
> (3 * 4) != (18 - 7)    # test for inequality
#> [1] TRUE
> 3 < 10                 # less than
#> [1] TRUE
> (2 * 5) <= 10          # less than or equal
#> [1] TRUE
```

Logical values and logical operations

- In the previous step, the results are returned as either `TRUE` or `FALSE`. These are logical or *Boolean* values.
- Just as we can represent numbers and operations on numbers, so too can we have two logical values, `TRUE` and `FALSE` (always written in all uppercase), and Boolean operations (*and*, *or*, and *not*) on logical values.

```
> TRUE & FALSE  # logical and
#> [1] FALSE
> TRUE | TRUE   # logical or
#> [1] TRUE
> !TRUE         # logical not
#> [1] FALSE
> (TRUE | !TRUE) & !FALSE
#> [1] TRUE
```

Variables and assignment

- If we type the following at the command prompt and then press Enter, the result is displayed but not stored.

```
> (12/3.5)^2 + (1/2.5)^3 + (1 + 2 + 3)^0.33
#> [1] 13.6254
```

- We can, however, assign the value of the above calculation to a variable named `x`.

```
> x <- (12/3.5)^2 + (1/2.5)^3 + (1 + 2 + 3)^0.33
```

- Now, we can use `x` as is it were a number.

```
> x
#> [1] 13.6254
> x ^ 2
#> [1] 185.6516
> x * 3.6
#> [1] 49.05145
```

Assignment rules

- In general, the assignment rule is

```
name <- expression
```

The `expression` is any R code that returns some value.

- The `name` must consist of letters, numbers, dots, and underscores.

```
x123   # acceptable
.x
x_y_z
xXx_123
```

- It must begin with a letter or a dot that is not followed by a number.

```
_x   # not acceptable
.2x
x-y-z
```

- The recommendation is to use names that are meaningful, relatively short, without dots (using _ instead for punctuation), and primarily consisting of lowercase characters.

Vectors

- Vectors are one dimensional sequences of values.
- For example, if we want to create a vector of the first 6 primes numbers, we could do the following.

```
> primes <- c(2, 3, 5, 7, 11, 13)
```

- We can now perform operations (arithmetic, logical, etc) on the `primes` vector.

```
> primes + 1
#> [1]  3  4  6  8 12 14
> primes / 2
#> [1] 1.0 1.5 2.5 3.5 5.5 6.5
> primes == 3
#> [1] FALSE  TRUE FALSE FALSE FALSE FALSE
> primes >= 7
#> [1] FALSE FALSE FALSE  TRUE  TRUE  TRUE
```

Indexing vectors

- For any vector, we can refer to individual elements using indexing operations.

```
> primes[1]
#> [1] 2
> primes[5]
#> [1] 11
```

- If we want to refer to sets of elements, rather than just individual elements, we can use vectors (made with the `c()` function) inside the indexing square brackets.

```
> primes[c(3, 5, 2)]
#> [1]  5 11  3
```

- If we use a negative valued index, we can refer to or all elements *except* one.

```
> primes[-1]
#> [1]  3  5  7 11 13
> primes[-2]
#> [1]  2  5  7 11 13
```

Vector types

- A vector be a sequence of numbers, logical values, or characters.

```
> nation <- c('ireland', 'england', 'scotland', 'wales')
```

- We can index this vector as we did with a vector of numbers.

```
> nation[1]
#> [1] "ireland"
> nation[2:3]
#> [1] "england"  "scotland"
> nation == 'ireland'
#> [1]  TRUE FALSE FALSE FALSE
```

- The `class` function in R will identify the data type of the vector.

```
> class(primes)
#> [1] "numeric"
> class(nation)
#> [1] "character"
> class(nation == 'ireland')
#> [1] "logical"
```

Data frames

- Data frames are rectangular data structures; they have certain number of columns, and each column has the same number of rows. Each column is in fact a vector.
- Usually, data frames are created when read in the contents of a data file, but we can produce them on the command line with the `data.frame()`.

```
> Df <- data.frame(name = c('billy', 'joe', 'bob'),
+                  age = c(21, 29, 23))
> Df
#>    name age
#> 1 billy  21
#> 2   joe  29
#> 3   bob  23
```

Indexing data frames

- We can refer to elements of a data frame in different ways.
- The simplest is to use double indices, one for the rows, one for the columns.

```
> Df[3, 2] # row 3, col 2
#> [1] 23
> Df[c(1, 3), 2] # rows 1 and 3, col 2
#> [1] 21 23
> Df[1,] # row 1, all cols
#>    name age
#> 1 billy  21
> Df[, 2] # all rows, col 2
#> [1] 21 29 23
```

Indexing data frames (contined)

- We could also refer to the column by name. To do so, we could use the following `$` notation.

```
> Df$age
#> [1] 21 29 23
```

- An alternative syntax that accompishes the same thing is to use *double* square brackets as follows.

```
> Df[['age']]
#> [1] 21 29 23
```

- A *single* square brackets, we would obtain the following.

```
> Df['age']
#>   age
#> 1  21
#> 2  29
#> 3  23
```

Functions

- In functions, we put data in, calculations or done to or using this data, and new data, perhaps just a single value, is then returned.
- There are probably hundreds of thousands of functions in R.
- For example,

```
> length(primes)
#> [1] 6
> sum(primes)
#> [1] 41
> mean(primes)
#> [1] 6.833333
> median(primes)
#> [1] 6
> sd(primes)
#> [1] 4.400758
> var(primes)
#> [1] 19.36667
```

Custom functions

- R makes it easy to create new functions.

```
> my_mean <- function(x){ sum(x)/length(x)}
```

- This `my_mean` takes a vector as input and divides its sum by the number of elements in it. It then returns this values. The `x` is a placeholder for whatever variable we input into the function.
- We would use it just as we would use `mean`.

```
> my_mean(primes)
#> [1] 6.833333
```

Writing R scripts

- Scripts are files where we write R commands, which can be then saved for later use.
- You can bring up RStudio's script editor with Ctrl+Shift+N, or go to the File/ New File/ R script, or click on the New icon on the left of the taskbar below the menu and choose R script.
- In a script, you can have as many lines of code as you wish, and there can be as many blank lines as you wish.

```
1  composites <- c(4, 6, 8, 9, 10, 12)
2
3  composites_plus_one <- composites + 1
4
5  composites_minus_one <- composites - 1
```

- If you place the cursor on line 1, you can then click the Run icon, or press the Ctrl+Enter keys.

Writing R scripts (continued)

One reason why writings in scripts is very practically valuable, even if you don't wish to save the scripts, is when you are write long and complex commands.

```r
Df <- data.frame(name = c('jane', 'joe', 'billy'),
                 age = c(23, 27, 24),
                 sex = c('female', 'male', 'male'),
                 occupation = c('tinker', 'tailor', 'spy')
)
```

We can execute this command as if it were on a single line by placing the cursor anywhere on any line and pressing Ctrl+Enter.

Code comments

- An almost universal feature of programming language is the option to write *comments* in the code files.
- A comment allows you write to notes or comments around the code that is then skipped over when the script or the code lines are being executed.
- In R, anything following the # symbol on any line is treated as a comment.

```r
# Here is a data frame with four variables.
# The variables are name, age, sex, occupation.
Df <- data.frame(name = c('jane', 'joe', 'billy'),
                 # This line is a comment too.
                 age = c(23, 27, 24), # Another comment.
                 sex = c('female','male', 'male'),
                 occupation = c('tinker', 'tailor', 'spy')
)
```

Packages

- There are presently 0 contributed packages in R.
- The easiest way to install a package is to click the Install button on the top left of the *Packages* window in the lower right pane.
- You can also install a package or packages with the `install.packages` command.

```
> install.packages("dplyr")
> install.packages(c("dplyr", "tidyr", "ggplot2"))
```

- Having installed a package, it must be loaded to be used. This can be done by clicking the tick box before the package name in the *Packages* window, or use the `library` command.

```
> library("tidyverse")
```

Reading in data

- R allows you to import data from a very large variety of data file types, including from other statistics programs like SPSS, Stata, SAS, Minitab, and so on, and common file formats like `.xlsx` and `.csv`.
- When learning R initially, the easiest way to import data is using the Import Dataset button in the Environment window.
- If we use the *From Text (readr)...* option, it runs the `read_csv` R command, which we can run ourselves on the command line, or write in a script.

```
> library(readr)
> blp_df <- read_csv("data/blp-trials-short.txt")
```

Viewing data

- The easiest way to view a data frames is to type its name.

```
> blp_df
#> # A tibble: 1,000 x 7
#>    participant lex   spell    resp     rt prev.rt rt.raw
#>          <dbl> <chr> <chr>    <chr> <dbl>   <dbl>  <dbl>
#>  1          20 N     staud    N       977     511    977
#>  2           9 N     dinbuss  N       565     765    565
#>  3          47 N     snilling N       562     496    562
#>  4         103 N     gancens  N       572     656    572
#>  5          45 W     filled   W       659     981    659
#>  6          73 W     journals W       538    1505    538
#>  7          24 W     apache   W       626     546    626
#>  8          11 W     flake    W       566     717    566
#>  9          32 W     reliefs  W       922    1471    922
#> 10          96 N     sarves   N       555     806    555
#> # ... with 990 more rows
```

Viewing data (continued)

- Another option to view a data frame is to `glimpse` it.

```
> glimpse(blp_df)
#> Observations: 1,000
#> Variables: 7
#> $ participant <dbl> 20, 9, 47, 103, 45, 73, 24, 11, 32, 96, 8
#> $ lex         <chr> "N", "N", "N", "N", "W", "W", "W", "W", "
#> $ spell       <chr> "staud", "dinbuss", "snilling", "gancens"
#> $ resp        <chr> "N", "N", "N", "N", "W", "W", "W", "W", "
#> $ rt          <dbl> 977, 565, 562, 572, 659, 538, 626, 566, 9
#> $ prev.rt     <dbl> 511, 765, 496, 656, 981, 1505, 546, 717,
#> $ rt.raw      <dbl> 977, 565, 562, 572, 659, 538, 626, 566, 9
```

Summarizing data with summary

- An easy way to summarize a data frame is with summary.

```
> summary(blp_df)
#>   participant          lex                 spell                 r
#>  Min.   :  1.00   Length:1000        Length:1000        Lengt
#>  1st Qu.: 20.00   Class :character   Class :character   Class
#>  Median : 47.00   Mode  :character   Mode  :character   Mode
#>  Mean   : 49.46
#>  3rd Qu.: 75.00
#>  Max.   :105.00
#>
#>        rt              prev.rt           rt.raw
#>  Min.   : 361.0   Min.   :   0.0   Min.   : 335.0
#>  1st Qu.: 514.0   1st Qu.: 510.0   1st Qu.: 518.0
#>  Median : 588.0   Median : 594.0   Median : 605.0
#>  Mean   : 637.8   Mean   : 660.1   Mean   : 707.9
#>  3rd Qu.: 708.2   3rd Qu.: 712.0   3rd Qu.: 754.0
#>  Max.   :1750.0   Max.   :2413.0   Max.   :9925.0
#>  NA's   :176      NA's   :3
```

Data wrangling tools in R

- There are many tools in R for doing data wrangling. Here, we will focus of a core set of inter-related `tidyverse` tools.
- We'll begin with commands available in the `dplyr` package, particularly its so-called *verbs* such as the following.
  - select
  - rename
  - slice
  - filter
  - mutate
  - arrange
  - group_by
  - summarize
- All of these tools are can be combined together using the %>% pipe operator

Selecting variables with `select`

- The `dplyr` command `select` allows us to select variables from a data frame we want.

```
> select(blp_df, participant, lex, resp, rt)
#> # A tibble: 1,000 x 4
#>    participant lex   resp     rt
#>          <dbl> <chr> <chr> <dbl>
#>  1          20 N     N       977
#>  2           9 N     N       565
#>  3          47 N     N       562
#>  4         103 N     N       572
#>  5          45 W     W       659
#>  6          73 W     W       538
#>  7          24 W     W       626
#>  8          11 W     W       566
#>  9          32 W     W       922
#> 10          96 N     N       555
#> # ... with 990 more rows
```

Selecting variables with `select`

- We can select a range of variables by specifying the first and last variables in the range with a `:` between them as follows.

```
> select(blp_df, spell:prev.rt)
#> # A tibble: 1,000 x 4
#>    spell    resp     rt prev.rt
#>    <chr>    <chr> <dbl>   <dbl>
#>  1 staud    N       977     511
#>  2 dinbuss  N       565     765
#>  3 snilling N       562     496
#>  4 gancens  N       572     656
#>  5 filled   W       659     981
#>  6 journals W       538    1505
#>  7 apache   W       626     546
#>  8 flake    W       566     717
#>  9 reliefs  W       922    1471
#> 10 sarves   N       555     806
#> # ... with 990 more rows
```

Selecting variables with `select`

- We can also select a range of variables using indices as in the following example.

```
> select(blp_df, 2:5) # columns 2 to 5
#> # A tibble: 1,000 x 4
#>    lex   spell    resp     rt
#>    <chr> <chr>    <chr> <dbl>
#>  1 N     staud    N       977
#>  2 N     dinbuss  N       565
#>  3 N     snilling N       562
#>  4 N     gancens  N       572
#>  5 W     filled   W       659
#>  6 W     journals W       538
#>  7 W     apache   W       626
#>  8 W     flake    W       566
#>  9 W     reliefs  W       922
#> 10 N     sarves   N       555
#> # ... with 990 more rows
```

Selecting variables with `select`

- We can select variables according to the character or characters that they begin with.

```
> select(blp_df, starts_with('p'))
#> # A tibble: 1,000 x 2
#>    participant prev.rt
#>          <dbl>   <dbl>
#>  1          20     511
#>  2           9     765
#>  3          47     496
#>  4         103     656
#>  5          45     981
#>  6          73    1505
#>  7          24     546
#>  8          11     717
#>  9          32    1471
#> 10          96     806
#> # ... with 990 more rows
```

Selecting variables with `select`

- We can select variables by the characters they end with.

```
> select(blp_df, ends_with('t'))
#> # A tibble: 1,000 x 3
#>    participant    rt prev.rt
#>          <dbl> <dbl>   <dbl>
#>  1          20   977     511
#>  2           9   565     765
#>  3          47   562     496
#>  4         103   572     656
#>  5          45   659     981
#>  6          73   538    1505
#>  7          24   626     546
#>  8          11   566     717
#>  9          32   922    1471
#> 10          96   555     806
#> # ... with 990 more rows
```

Selecting variables with `select`

- We can select variables that contain a certain set of characters in any position.

```
> select(blp_df, contains('rt'))
#> # A tibble: 1,000 x 4
#>    participant    rt prev.rt rt.raw
#>          <dbl> <dbl>   <dbl>  <dbl>
#>  1          20   977     511    977
#>  2           9   565     765    565
#>  3          47   562     496    562
#>  4         103   572     656    572
#>  5          45   659     981    659
#>  6          73   538    1505    538
#>  7          24   626     546    626
#>  8          11   566     717    566
#>  9          32   922    1471    922
#> 10          96   555     806    555
#> # ... with 990 more rows
```

Selecting variables with `select`

- We can select variables using *regular expressions*.
- For example, the regular expression `^rt|rt$` will match the `rt` if it begins or ends a string.

```
> select(blp_df, matches('^rt|rt$'))
#> # A tibble: 1,000 x 3
#>       rt prev.rt rt.raw
#>    <dbl>   <dbl>  <dbl>
#>  1   977     511    977
#>  2   565     765    565
#>  3   562     496    562
#>  4   572     656    572
#>  5   659     981    659
#>  6   538    1505    538
#>  7   626     546    626
#>  8   566     717    566
#>  9   922    1471    922
#> 10   555     806    555
#> # ... with 990 more rows
```

Removing variables with `select`

- We can use `select` to *remove* variables as well as select them. To remove a variable, we precede its name with a minus sign.

```
> select(blp_df, -participant) # remove `participant`
#> # A tibble: 1,000 x 6
#>    lex   spell    resp     rt prev.rt rt.raw
#>    <chr> <chr>    <chr> <dbl>   <dbl>  <dbl>
#>  1 N     staud    N       977     511    977
#>  2 N     dinbuss  N       565     765    565
#>  3 N     snilling N       562     496    562
#>  4 N     gancens  N       572     656    572
#>  5 W     filled   W       659     981    659
#>  6 W     journals W       538    1505    538
#>  7 W     apache   W       626     546    626
#>  8 W     flake    W       566     717    566
#>  9 W     reliefs  W       922    1471    922
#> 10 N     sarves   N       555     806    555
#> # ... with 990 more rows
```

Removing variables with `select`

- To remove variables indexed 2 to 6, we would do the following.

```
> select(blp_df, -(2:6))
#> # A tibble: 1,000 x 2
#>    participant rt.raw
#>          <dbl>  <dbl>
#>  1          20    977
#>  2           9    565
#>  3          47    562
#>  4         103    572
#>  5          45    659
#>  6          73    538
#>  7          24    626
#>  8          11    566
#>  9          32    922
#> 10          96    555
#> # ... with 990 more rows
```

Reording variables with `select` and `everything()`

- We can rearrange variables by selecting some and then using `everything()` for the others.

```
> select(blp_df, spell, participant, resp, everything())
#> # A tibble: 1,000 x 7
#>    spell    participant resp  lex      rt prev.rt rt.raw
#>    <chr>          <dbl> <chr> <chr> <dbl>   <dbl>  <dbl>
#>  1 staud             20 N     N       977     511    977
#>  2 dinbuss            9 N     N       565     765    565
#>  3 snilling          47 N     N       562     496    562
#>  4 gancens          103 N     N       572     656    572
#>  5 filled            45 W     W       659     981    659
#>  6 journals          73 W     W       538    1505    538
#>  7 apache            24 W     W       626     546    626
#>  8 flake             11 W     W       566     717    566
#>  9 reliefs           32 W     W       922    1471    922
#> 10 sarves            96 N     N       555     806    555
#> # ... with 990 more rows
```

Renaming with `rename`

- When we select individual variables with `select`, we can rename them too.

```
> select(blp_df, subject=participant, reaction_time=rt)
#> # A tibble: 1,000 x 2
#>    subject reaction_time
#>      <dbl>         <dbl>
#>  1      20           977
#>  2       9           565
#>  3      47           562
#>  4     103           572
#>  5      45           659
#>  6      73           538
#>  7      24           626
#>  8      11           566
#>  9      32           922
#> 10      96           555
#> # ... with 990 more rows
```

- But this just return the selected variables.

Renaming with `rename`

- If we want to rename some variables, and get a data frame with all variables, including the renamed ones, we should use `rename`.

```
> rename(blp_df, subject=participant, reaction_time=rt)
#> # A tibble: 1,000 x 7
#>    subject lex   spell    resp  reaction_time prev.rt rt.raw
#>      <dbl> <chr> <chr>    <chr>         <dbl>   <dbl>  <dbl>
#>  1      20 N     staud    N               977     511    977
#>  2       9 N     dinbuss  N               565     765    565
#>  3      47 N     snilling N               562     496    562
#>  4     103 N     gancens  N               572     656    572
#>  5      45 W     filled   W               659     981    659
#>  6      73 W     journals W               538    1505    538
#>  7      24 W     apache   W               626     546    626
#>  8      11 W     flake    W               566     717    566
#>  9      32 W     reliefs  W               922    1471    922
#> 10      96 N     sarves   N               555     806    555
#> # ... with 990 more rows
```

Selecting observations with `slice`

- To select rows 10, 20, 50, 100, 500:

```
> slice(blp_df, c(10, 20, 50, 100, 500))
#> # A tibble: 5 x 7
#>   participant lex   spell  resp     rt prev.rt rt.raw
#>         <dbl> <chr> <chr>  <chr> <dbl>   <dbl>  <dbl>
#> 1          96 N     sarves N       555     806    555
#> 2          46 W     mirage W       778     571    778
#> 3          72 N     gright N       430     675    430
#> 4           3 W     gleam  W       361     370    361
#> 5          92 W     coaxes W       699     990    699
```

Selecting observations with `slice`

- To select rows 10 to 100 inclusive:

```
> slice(blp_df, 10:100)
#> # A tibble: 91 x 7
#>    participant lex   spell     resp     rt prev.rt rt.raw
#>          <dbl> <chr> <chr>     <chr> <dbl>   <dbl>  <dbl>
#>  1          96 N     sarves    N       555     806    555
#>  2          82 W     deceits   W       657     728    657
#>  3          37 W     nothings  N        NA     552    712
#>  4          52 N     chuespies N       427     539    427
#>  5          96 N     mowny     N      1352    1020   1352
#>  6          96 N     cranned   N       907     573    907
#>  7          89 N     flud      N       742     834    742
#>  8           3 N     bromble   N       523     502    523
#>  9           7 N     trubbles  N       782     458    782
#> 10          35 N     playfound N       643     663    643
#> # ... with 81 more rows
```

Selecting observations with `slice`

A useful `dplyr` function that can be used in `slice` and elsewhere is `n()`, which gives the number of observations in the data frame.

```
> slice(blp_df, 600:n())
#> # A tibble: 401 x 7
#>    participant lex   spell      resp      rt prev.rt rt.raw
#>          <dbl> <chr> <chr>      <chr> <dbl>   <dbl>  <dbl>
#>  1          16 W     earthworms W       767     659    767
#>  2          50 W     markers    W       664     852    664
#>  3          35 N     spoton     N       522     721    522
#>  4          88 W     tawny      N        NA     535    856
#>  5          51 N     gember     N       562     598    562
#>  6          63 W     classed    W       706     429    706
#>  7          63 N     clallers   N       401     495    401
#>  8           8 W     pauper     W       734    1126    734
#>  9           2 W     badges     W       485     498    485
#> 10          97 N     foarded    N       802     464    802
#> # ... with 391 more rows
```

Dropping observations with `slice`

- We can drop the first 10 observations as follows.

```
> slice(blp_df, -(1:10))
#> # A tibble: 990 x 7
#>    participant lex   spell     resp     rt prev.rt rt.raw
#>          <dbl> <chr> <chr>     <chr> <dbl>   <dbl>  <dbl>
#>  1          82 W     deceits   W       657     728    657
#>  2          37 W     nothings  N        NA     552    712
#>  3          52 N     chuespies N       427     539    427
#>  4          96 N     mowny     N      1352    1020   1352
#>  5          96 N     cranned   N       907     573    907
#>  6          89 N     flud      N       742     834    742
#>  7           3 N     bromble   N       523     502    523
#>  8           7 N     trubbles  N       782     458    782
#>  9          35 N     playfound N       643     663    643
#> 10          46 W     mirage    W       778     571    778
#> # ... with 980 more rows
```

Selecting observations with `filter`

- The `filter` command is a powerful means to filter (i.e., to filter in, not filter out) observations according to their values.
- For example, we can select all the observations where the `lex` variable is `N`.

```
> filter(blp_df, lex == 'N')
#> # A tibble: 502 x 7
#>    participant lex   spell     resp     rt prev.rt rt.raw
#>          <dbl> <chr> <chr>     <chr> <dbl>   <dbl>  <dbl>
#>  1          20 N     staud     N       977     511    977
#>  2           9 N     dinbuss   N       565     765    565
#>  3          47 N     snilling  N       562     496    562
#>  4         103 N     gancens   N       572     656    572
#>  5          96 N     sarves    N       555     806    555
#>  6          52 N     chuespies N       427     539    427
#>  7          96 N     mowny     N      1352    1020   1352
#>  8          96 N     cranned   N       907     573    907
#>  9          89 N     flud      N       742     834    742
#> 10           3 N     bromble   N       523     502    523
#> # ... with 492 more rows
```

Selecting observations with `filter`

- We can filter by multiple conditions by listing each one with commas between them.

```
> filter(blp_df, lex == 'N', resp=='W')
#> # A tibble: 35 x 7
#>    participant lex   spell    resp     rt prev.rt rt.raw
#>          <dbl> <chr> <chr>    <chr> <dbl>   <dbl>  <dbl>
#>  1          73 N     bunding  W        NA     978   1279
#>  2          63 N     gallays  W        NA     589    923
#>  3          50 N     droper   W        NA     741    573
#>  4           6 N     flooder  W        NA     524    557
#>  5          73 N     khantum  W        NA     623   1355
#>  6          81 N     seaped   W        NA     765    691
#>  7          43 N     gafers   W        NA     556    812
#>  8         101 N     winchers W        NA     632    852
#>  9          81 N     flaged   W        NA     674    609
#> 10          11 N     frocker  W        NA     653    665
#> # ... with 25 more rows
```

Selecting observations with `filter`

- We can make a *disjunction* of conditions for filtering using the logical-or symbol `|`.
- For example, here we select observations where `rt.raw` is less than 500 *or* greater than 1000.

```
> filter(blp_df, rt.raw < 500 | rt.raw > 1000)
#> # A tibble: 296 x 7
#>    participant lex   spell      resp     rt prev.rt rt.raw
#>          <dbl> <chr> <chr>      <chr> <dbl>   <dbl>  <dbl>
#>  1          52 N     chuespies  N       427     539    427
#>  2          96 N     mowny      N      1352    1020   1352
#>  3          28 W     stelae     N        NA     678    497
#>  4          85 W     forewarned N        NA     525    350
#>  5          24 W     owl        W       470     535    470
#>  6          97 W     soda       W       436     447    436
#>  7          81 N     fugate     N       425     403    425
#>  8         105 N     pamps      N        NA     884   1494
#>  9          27 W     outgrowth  N        NA     633   1014
#> 10          82 W     kitty      W       431     476    431
#> # ... with 286 more rows
```

Selecting observations with `filter`

- here we filter observations where values of `rt.raw` is *in* the set on integers 500 to 510.

```
> filter(blp_df, rt.raw %in% 500:510)
#> # A tibble: 26 x 7
#>    participant lex   spell       resp     rt prev.rt rt.raw
#>          <dbl> <chr> <chr>       <chr> <dbl>   <dbl>  <dbl>
#>  1          44 W     subscribed  W       509     475    509
#>  2          89 W     snatcher    W       506    1004    506
#>  3           2 N     tronculling N       508     490    508
#>  4          43 N     trabnate    N       510     542    510
#>  5          75 N     dousleens   N       508     924    508
#>  6          94 W     strangeness W       508     522    508
#>  7          68 W     greed       W       505     653    505
#>  8          32 N     krifo       N       508     607    508
#>  9           2 W     tweaks      W       508     474    508
#> 10          85 N     waffs       N       506     471    506
#> # ... with 16 more rows
```

Selecting observations with `filter`

In general, we may filter the observations by creating complex Boolean conditionals

```
> filter(blp_df,
+        lex == 'W',
+        str_length(spell) < 5 & (resp != lex | rt.raw > 900))
#> # A tibble: 14 x 7
#>    participant lex   spell resp     rt prev.rt rt.raw
#>          <dbl> <chr> <chr> <chr> <dbl>   <dbl>  <dbl>
#>  1          21 W     bosk  N        NA     608   1532
#>  2          68 W     wily  N        NA     723    636
#>  3          30 W     sew   N        NA     473    524
#>  4          34 W     jibs  N        NA     781    756
#>  5          85 W     rote  N        NA     505    458
#>  6          13 W     oofs  N        NA     560    654
#>  7          72 W     awed  N        NA    1203   1801
#>  8          14 W     yids  N        NA     625    620
#>  9          68 W     oho   N        NA     633    630
#> 10         103 W     carl  N        NA    1046   1042
#> 11          46 W     brae  N        NA     644    720
```

Changing variables and values using `mutate`

- The `mutate` commnd is a very powerful tool in the `dplyr` toolbox.
- As an example, we can create a new variable `acc` that takes the value of `TRUE` whenever `lex` and `resp` have the same value as follows.

```
> mutate(blp_df, acc = lex == resp)
#> # A tibble: 1,000 x 8
#>    participant lex   spell    resp     rt prev.rt rt.raw acc
#>          <dbl> <chr> <chr>    <chr> <dbl>   <dbl>  <dbl> <lgl
#>  1          20 N     staud    N       977     511    977 TRUE
#>  2           9 N     dinbuss  N       565     765    565 TRUE
#>  3          47 N     snilling N       562     496    562 TRUE
#>  4         103 N     gancens  N       572     656    572 TRUE
#>  5          45 W     filled   W       659     981    659 TRUE
#>  6          73 W     journals W       538    1505    538 TRUE
#>  7          24 W     apache   W       626     546    626 TRUE
#>  8          11 W     flake    W       566     717    566 TRUE
#>  9          32 W     reliefs  W       922    1471    922 TRUE
#> 10          96 N     sarves   N       555     806    555 TRUE
#> # ... with 990 more rows
```

Changing variables and values using `mutate`

- We can also create multiple new variable at the same time as in the following example.

```
> mutate(blp_df,
+        acc = lex == resp,
+        fast = rt.raw < mean(rt.raw, na.rm=TRUE))
#> # A tibble: 1,000 x 9
#>    participant lex   spell    resp     rt prev.rt rt.raw acc
#>          <dbl> <chr> <chr>    <chr> <dbl>   <dbl>  <dbl> <lgl
#>  1          20 N     staud    N       977     511    977 TRUE
#>  2           9 N     dinbuss  N       565     765    565 TRUE
#>  3          47 N     snilling N       562     496    562 TRUE
#>  4         103 N     gancens  N       572     656    572 TRUE
#>  5          45 W     filled   W       659     981    659 TRUE
#>  6          73 W     journals W       538    1505    538 TRUE
#>  7          24 W     apache   W       626     546    626 TRUE
#>  8          11 W     flake    W       566     717    566 TRUE
#>  9          32 W     reliefs  W       922    1471    922 TRUE
#> 10          96 N     sarves   N       555     806    555 TRUE
#> # ... with 990 more rows
```

Sorting with `arrange`

- Sorting observations in a data frame is easily accomplished with `arrange`.

```
> arrange(blp_df, participant, spell) # sort by `participant`, t
#> # A tibble: 1,000 x 7
#>    participant lex   spell     resp     rt prev.rt rt.raw
#>          <dbl> <chr> <chr>     <chr> <dbl>   <dbl>  <dbl>
#>  1           1 W     abyss     W       629     683    629
#>  2           1 N     baisees   N       524     574    524
#>  3           1 W     carport   W       779     605    779
#>  4           1 N     cellies   N       792     652    792
#>  5           1 W     chafing   W       601     720    601
#>  6           1 N     dametails N       694     635    694
#>  7           1 N     foother   N       789     566    789
#>  8           1 W     gantries  W       644     581    644
#>  9           1 N     hogtush   N       679     568    679
#> 10           1 N     lisedess  N       679     619    679
#> # ... with 990 more rows
```

Sorting with arrange

- We can sort by the reverse order of any variable by using the `desc`.

```
> arrange(blp_df, participant, desc(spell))
#> # A tibble: 1,000 x 7
#>    participant lex   spell     resp     rt prev.rt rt.raw
#>          <dbl> <chr> <chr>     <chr> <dbl>   <dbl>  <dbl>
#>  1           1 N     wintes    N       545     629    545
#>  2           1 N     treeps    N       607     610    607
#>  3           1 W     squashes  W       494     491    494
#>  4           1 N     sinkhicks N       536     519    536
#>  5           1 W     shafting  W       553     571    553
#>  6           1 W     month     W       500     498    500
#>  7           1 N     lisedess  N       679     619    679
#>  8           1 N     hogtush   N       679     568    679
#>  9           1 W     gantries  W       644     581    644
#> 10           1 N     foother   N       789     566    789
#> # ... with 990 more rows
```

Summarizing with summarize

- The summarize (or summarise) function allows us to calculate summary statistics.

```
> summarize(blp_df,
+           mean_rt = mean(rt, na.rm = T),
+           median_rt = median(rt, na.rm = T),
+           sd_rt.raw = sd(rt.raw, na.rm = T)
+ )
#> # A tibble: 1 x 3
#>   mean_rt median_rt sd_rt.raw
#>     <dbl>     <dbl>     <dbl>
#> 1    638.       588      474.
```

Summarizing with `summarize` and `group_by`

- Combined with `group_by`, `summarize` allows us to calculate summary statistics by group

```
> summarize(group_by(blp_df, lex),
+           mean_rt = mean(rt, na.rm = T),
+           median_rt = median(rt, na.rm = T),
+           sd_rt.raw = sd(rt.raw, na.rm = T)
+ )
#> # A tibble: 2 x 4
#>   lex   mean_rt median_rt sd_rt.raw
#>   <chr>   <dbl>     <dbl>     <dbl>
#> 1 N        638.       585      307.
#> 2 W        637.       588      597.
```

The %>% operator

- The %>% operator in R is known as the *pipe*.
- In RStudio, the keyboard shortcut Ctrl+Shift+M types %>%.
- To understand pipes, let us begin with a simple example of nested functions.

```
> primes <- c(2, 3, 5, 7, 11, 13, 17, 19, 23, 29)
```

```
> sum(primes) # The sum of `primes`
#> [1] 129
```

```
> sqrt(sum(primes)) # The sqrt of the sum
#> [1] 11.35782
```

```
> log(sqrt(sum(primes))) # The log of the sqrt of the sum
#> [1] 2.429906
```

The %>% operator

- The %>% allows us to rewrite nested functions as *pipelines*.
- This

```
> log(sqrt(sum(primes))) # The log of the sqrt of the sum
#> [1] 2.429906
```

is equivalent to this

```
> primes %>% sum() %>% sqrt() %>% log()
#> [1] 2.429906
```

Using %>% with dplyr

- When used with `dplyr` verbs, the %>% provides a mini-language for data wrangling.

```
> blp_df %>%
+   mutate(accuracy = resp == lex,
+          stimulus = recode(lex, 'W'='word', 'N'='nonword')
+   ) %>%
+   select(stimulus, item=spell, accuracy, speed=rt.raw) %>%
+   arrange(speed) %>%
+   head(5)
#> # A tibble: 5 x 4
#>   stimulus item       accuracy speed
#>   <chr>    <chr>      <lgl>    <dbl>
#> 1 word     hopeless   FALSE      335
#> 2 word     tutored    FALSE      348
#> 3 word     forewarned FALSE      350
#> 4 word     gleam      TRUE       361
#> 5 word     looks      TRUE       365
```

Combining data frames with `bind`

- A *bind* operation is a simple operation that either vertically stack data frames that share common variables, or horizontally stack data frames that have the same number of observations.

To illustrate, we will create three small data frames.

```
> Df_1 <- tibble(x = c(1, 2, 3),
+                y = c(2, 7, 1),
+                z = c(0, 2, 7))
>
> Df_2 <- tibble(y = c(5, 7),
+                z = c(6, 7),
+                x = c(1, 2))
>
> Df_3 <- tibble(a = c(5, 6, 1),
+                b = c('a', 'b', 'c'),
+                c = c(T, T, F))
```

Combining data frames with `bind`

- The `Df_1` and `Df_2` data frames share common variable names. They can be vertically stacked using a `bind_rows` operation.

```
> bind_rows(Df_1, Df_2)
#> # A tibble: 5 x 3
#>       x     y     z
#>   <dbl> <dbl> <dbl>
#> 1     1     2     0
#> 2     2     7     2
#> 3     3     1     7
#> 4     1     5     6
#> 5     2     7     7
```

Combining data frames with **bind**

- The Df_1 and Df_3 data frames have the same number of observations and so can be stacked side by side with a bind_cols operation.

```
> bind_cols(Df_1, Df_3)
#> # A tibble: 3 x 6
#>       x     y     z     a b     c
#>   <dbl> <dbl> <dbl> <dbl> <chr> <lgl>
#> 1     1     2     0     5 a     TRUE
#> 2     2     7     2     6 b     TRUE
#> 3     3     1     7     1 c     FALSE
```

Combining data frames with `join`

- A *join* operation is a common operation in relational databases using SQL.
- The `blp_df` has a variable `spell` that gives the identity of the stimulus. In a separate file, `blp-stimuli.csv` file, we have three additional variables for these stimuli.

```
> stimuli <- read_csv('data/blp_stimuli.csv')
> stimuli
#> # A tibble: 55,865 x 4
#>    spell   old20   bnc subtlex
#>    <chr>   <dbl> <dbl>   <dbl>
#>  1 a/c      1.95    14       0
#>  2 aas      1.55     9       1
#>  3 aback    1.85   327      15
#>  4 abaft    2        8       2
#>  5 aband    1.95     0       0
#>  6 abase    1.7      6       2
#>  7 abased   1.75     6       0
#>  8 abashed  1.85    57       0
#>  9 abate    1.75    69       5
```

Combining data frames with `join`

- We can join these two data frames with `inner_join`.

```
> inner_join(blp_df, stimuli)
#> # A tibble: 1,000 x 10
#>    participant lex   spell   resp     rt prev.rt rt.raw old20
#>          <dbl> <chr> <chr>   <chr> <dbl>   <dbl>  <dbl> <dbl>
#>  1          20 N     staud   N       977     511    977  1.85
#>  2           9 N     dinbuss N       565     765    565  2.9
#>  3          47 N     snilli~ N       562     496    562  1.8
#>  4         103 N     gancens N       572     656    572  2.3
#>  5          45 W     filled  W       659     981    659  1.45
#>  6          73 W     journa~ W       538    1505    538  2.7
#>  7          24 W     apache  W       626     546    626  2.45
#>  8          11 W     flake   W       566     717    566  1.5
#>  9          32 W     reliefs W       922    1471    922  2.25
#> 10          96 N     sarves  N       555     806    555  1.65
#> # ... with 990 more rows
```

Reshaping data with `tidyr`*'s* `gather` *and* `spread`

- Consider the following data frame, which is in a *wide* format.

```
> (recall_df <- read_csv('data/repeated_measured_a.csv'))
#> # A tibble: 5 x 4
#>   Subject   Neg   Neu   Pos
#>   <chr>   <dbl> <dbl> <dbl>
#> 1 Faye       26    12    42
#> 2 Jason      29     8    35
#> 3 Jim        32    15    45
#> 4 Ron        22    10    38
#> 5 Victor     30    13    40
```

Reshaping data with tidyr's gather and spread

- We can convert it to a *long* format as follows:

```
> library(tidyr)
> gather(recall_df, key=condition, value=score, Neg:Pos)
#> # A tibble: 15 x 3
#>    Subject condition score
#>    <chr>   <chr>     <dbl>
#>  1 Faye    Neg          26
#>  2 Jason   Neg          29
#>  3 Jim     Neg          32
#>  4 Ron     Neg          22
#>  5 Victor  Neg          30
#>  6 Faye    Neu          12
#>  7 Jason   Neu           8
#>  8 Jim     Neu          15
#>  9 Ron     Neu          10
#> 10 Victor  Neu          13
#> 11 Faye    Pos          42
#> 12 Jason   Pos          35
#> 13 Jim     Pos          45
```

Reshaping data with `tidyr`'s `gather` and `spread`

- The inverse of a `gather` is a `spread`. To do this, we supply the `key` and `value` variables, as defined in the `gather` operation.

```
> recall_long_df <- gather(recall_df, key=condition, value=score
```

```
> spread(recall_long_df, key=condition, value=score)
#> # A tibble: 5 x 4
#>   Subject   Neg   Neu   Pos
#>   <chr>   <dbl> <dbl> <dbl>
#> 1 Faye       26    12    42
#> 2 Jason      29     8    35
#> 3 Jim        32    15    45
#> 4 Ron        22    10    38
#> 5 Victor     30    13    40
```

Plots and data visualiztion

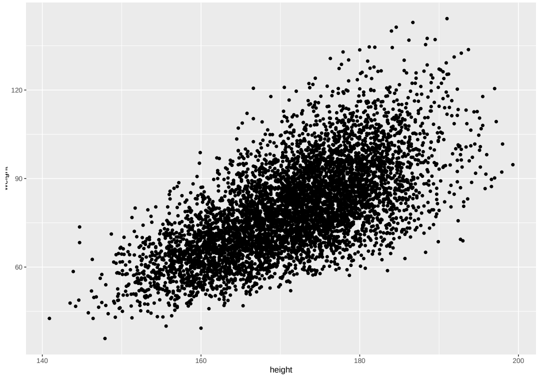
- The best way to data visualization in R is with `ggplot2`.

```
> library(ggplot2)
```

- `ggplot2` is package whose main function is `ggplot`.
- `ggplot` is a *layered* plotting system where we map variables to aesthetic properties of a graphic and then add layers.

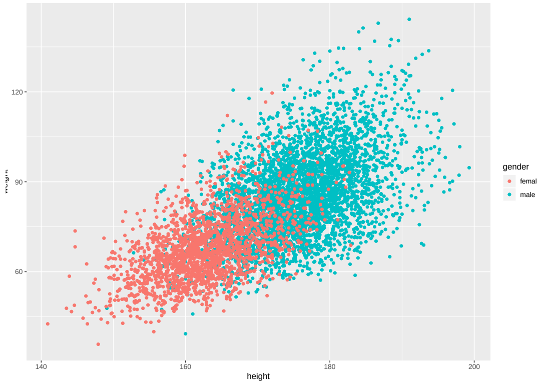
Scatterplot

```
> weight_df <- read_csv('data/weight.csv')
>
> ggplot(weight_df,
+        aes(x = height, y = weight)
+ ) + geom_point()
```



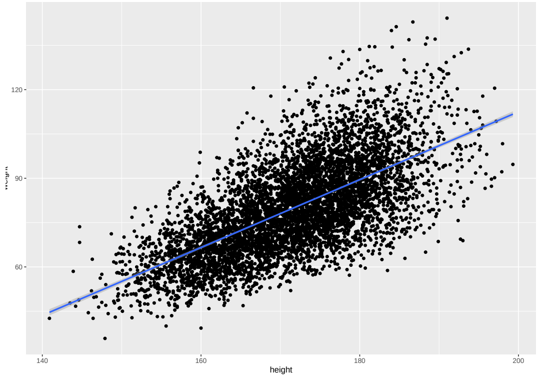
Scatterplot with `gender` indicated by colour

```
> ggplot(weight_df,
+        aes(x = height, y = weight, col = gender)
+ ) + geom_point()
```



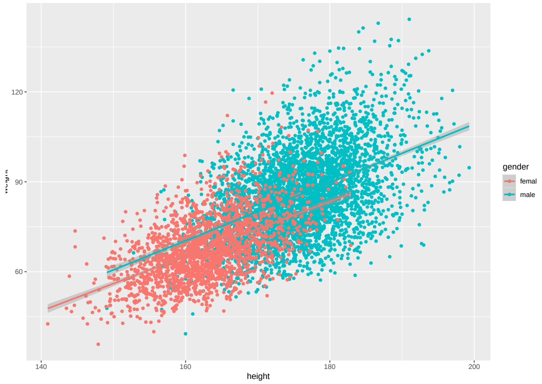
Scatterplot with line of best fit

```
> ggplot(weight_df,
+        aes(x = height, y = weight)
+ ) + geom_point() +
+   stat_smooth(method = 'lm')
```



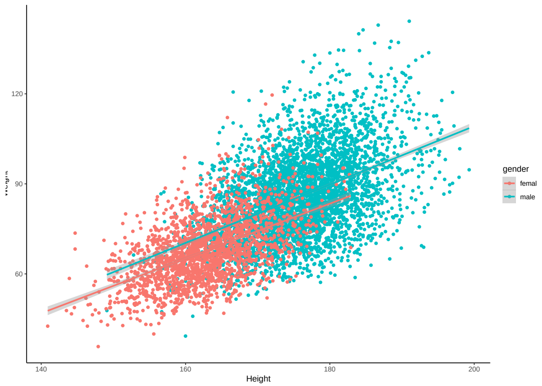
Scatterplot with line of best fit, for each value of `gender`

```
> ggplot(weight_df,
+        aes(x = height, y = weight, col = gender)
+ ) + geom_point() + stat_smooth(method = 'lm')
```



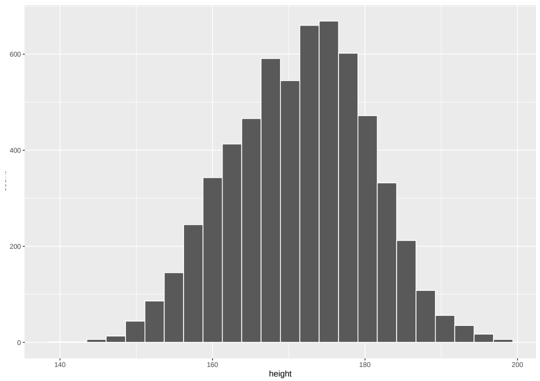
Changing style of a plot

```
> ggplot(weight_df,
+        aes(x = height, y = weight, col = gender)
+ ) + geom_point() + stat_smooth(method = 'lm') +
+   xlab('Height') +
+   ylab('Weight') +
+   theme_classic()
```



Histograms

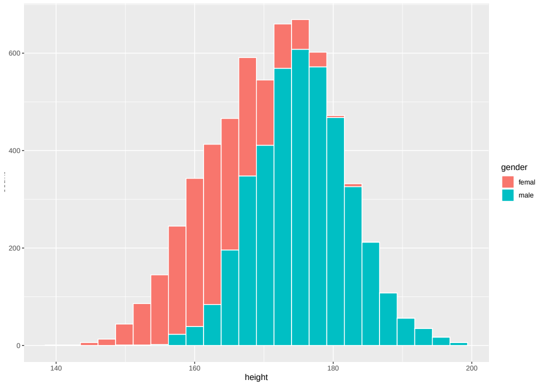
```
> ggplot(weight_df,
+        aes(x = height)
+ ) + geom_histogram(col = 'white', binwidth = 2.54)
```



Histograms

- A *stacked* histogram

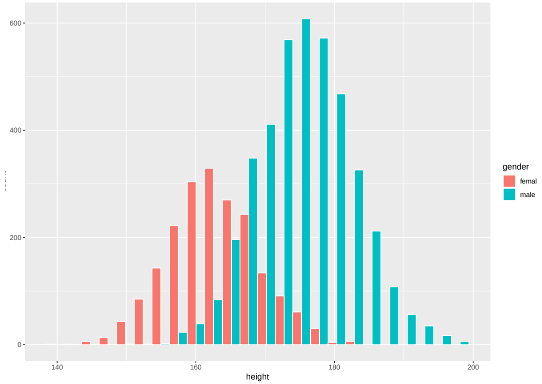
```
> ggplot(weight_df,
+        aes(x = height, fill = gender)
+ ) + geom_histogram(col = 'white', binwidth = 2.54)
```



Histograms

- A *dodged* histogram

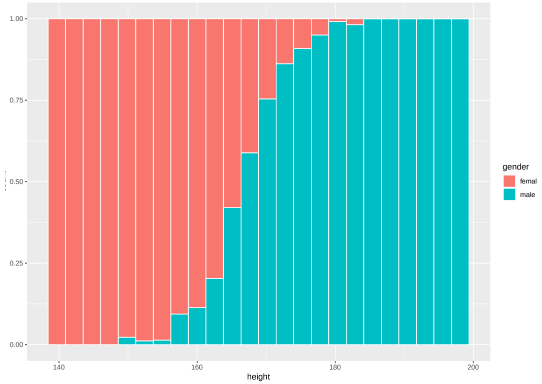
```
> ggplot(weight_df,
+        aes(x = height, fill = gender)
+ ) + geom_histogram(col = 'white', binwidth = 2.54,
+                    position = 'dodge')
```



Histograms

- A *filled* histogram

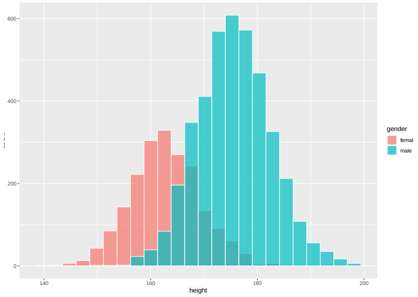
```
> ggplot(weight_df,
+        aes(x = height, fill = gender)
+ ) + geom_histogram(col = 'white', binwidth = 2.54,
+                    position = 'fill')
```



Histograms

- A *identity* histogram

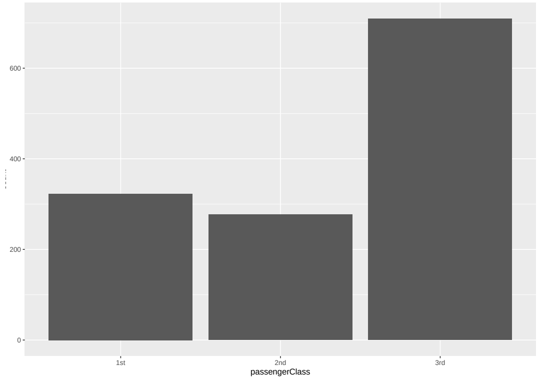
```
> ggplot(weight_df,
+        aes(x = height, fill = gender)
+ ) + geom_histogram(col = 'white', binwidth = 2.54,
+                    position = 'identity', alpha = 0.7)
```



Barplots

- *Barplots* are used for categorical variables.

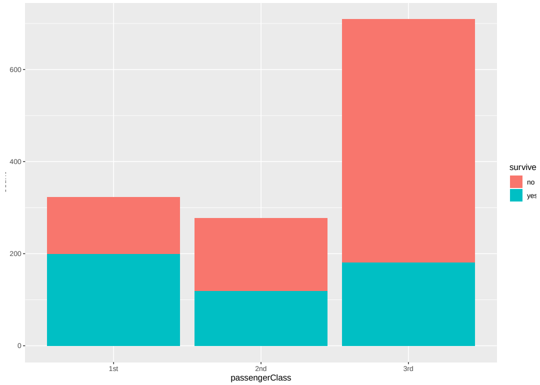
```
> titanic_df <- read_csv('data/TitanicSurvival.csv') %>% select(
> ggplot(titanic_df,
+        mapping = aes(x = passengerClass)
+ ) + geom_bar()
```



Barplots

- A *stacked* bar plot

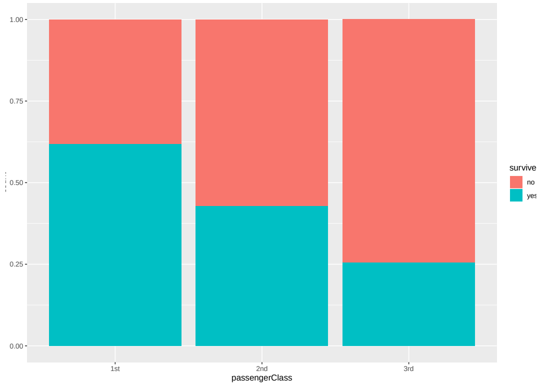
```
> ggplot(titanic_df,
+        mapping = aes(x = passengerClass, fill=survived)
+ ) + geom_bar()
```



Barplots

- A *filled* bar plot

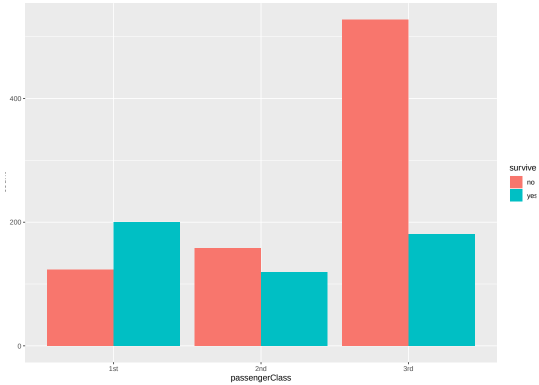
```
> ggplot(titanic_df,
+         mapping = aes(x = passengerClass, fill=survived)
+ ) + geom_bar(position = 'fill')
```



Barplots

- A *dodged* bar plot

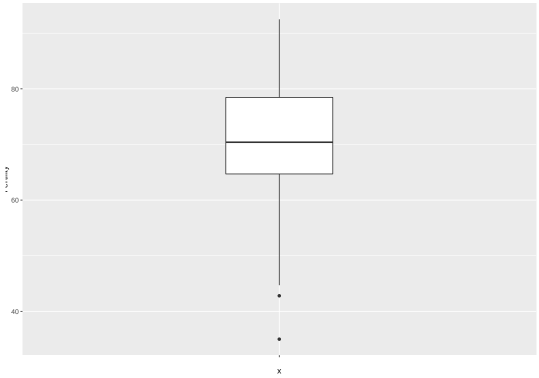
```
> ggplot(titanic_df,
+         mapping = aes(x = passengerClass, fill=survived)
+ ) + geom_bar(position = 'dodge')
```



Boxplots

- We can draw Tukey box plots with `geom_boxplot`.

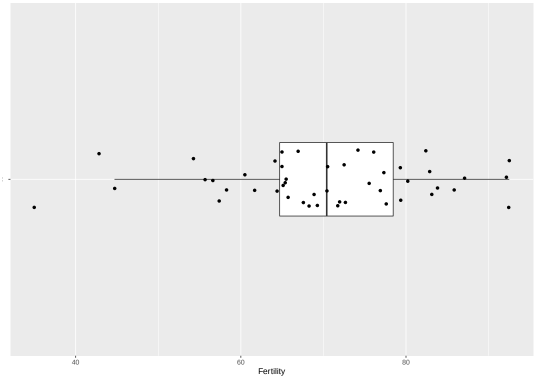
```
> swiss_df <- read_csv('data/swiss.csv')
> ggplot(swiss_df,
+        mapping = aes(x = '', y = Fertility)
+ ) + geom_boxplot(width = 0.25)
```



Boxplots

- We can *jitter* etc.

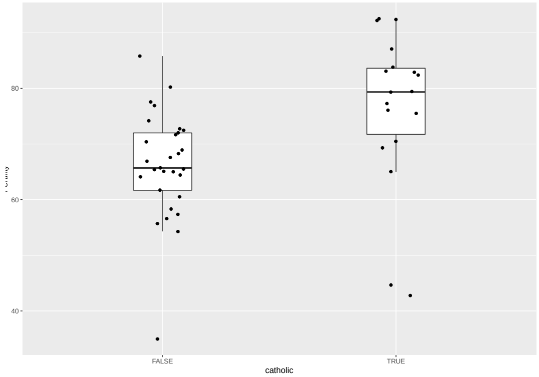
```
> ggplot(swiss_df,
+        mapping = aes(x = '', y = Fertility)
+ ) + geom_boxplot(width = 0.25, outlier.shape = NA) +
+   geom_jitter(width = 0.1) +
+   coord_flip()
```



Boxplots

- We can have more than one boxplot.

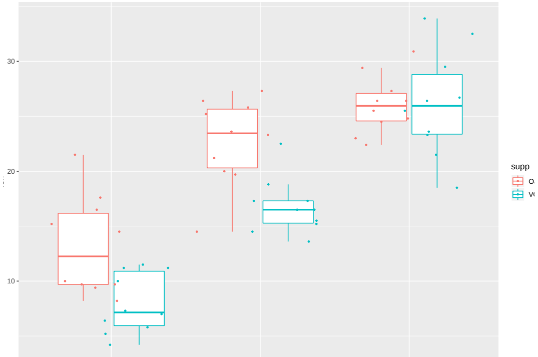
```
> ggplot(swiss_df,
+         mapping = aes(x = catholic, y = Fertility, )
+ ) + geom_boxplot(width = 0.25, outlier.shape = NA) +
+   geom_jitter(width = 0.1)
```



Boxplots

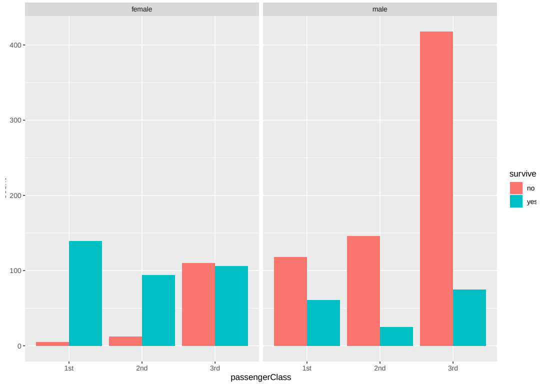
- We can group by multiple variables at once.

```
> toothgrowth_df <- read_csv('data/toothgrowth.csv')
> toothgrowth_df %>%
+   ggplot(mapping = aes(x = dose, y = len, colour = supp)
+          ) + geom_boxplot(outlier.shape = NA, varwidth = T) +
+              geom_jitter(position = position_jitterdodge(0.5),
+                          size = 0.75) +
+   scale_x_discrete(limits=c('low', 'medium' ,'high'))
```



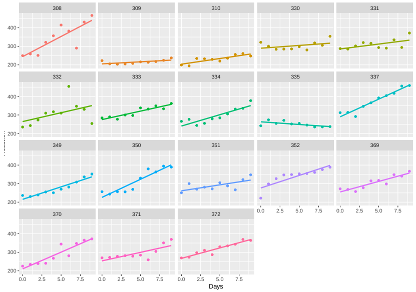
Facet plots

```
> ggplot(titanic_df,
+        mapping = aes(x = passengerClass, fill = survived)
+ ) + geom_bar(position = 'dodge') +
+   facet_wrap(~sex)
```



Facet plots

```
> sleepstudy_df <- read_csv("data/sleepstudy.csv",
+                           col_types = cols(Subject = col_characte
+ )
>
> ggplot(sleepstudy_df,
+        mapping = aes(x = Days, y = Reaction, colour = Subject)
+ ) + geom_point() +
+   geom_smooth(method = 'lm', se = F) +
+   facet_wrap(~Subject) +
+   theme(legend.position = 'none')
```


Days