Introduction to R, RStudio

Data Science Team

Introduction

In this class, we will be using the R language (https://www.r-project.org) heavily in class notes, examples and lab exercises. R is free and you can install it like any other program on your computer.

1. Go to the CRAN (https://cloud.r-project.org/) website and download it for your Mac or PC. (We assume no one is using Linux; if you are that advanced, then you already know what to do!)

2. Install the free version of the RStudio (https://www.rstudio.com/products/rstudio/download/) Desktop Software.

3. Go through our install instructions (http://web.stanford.edu/class/stats101/install.html) to install the background libraries this course uses.

RStudio makes it very easy to learn and use R, providing a number of useful features that many find indispensable.

About the R language, briefly

If you are used to traditional computing languages, you will find R different in many ways. The basic ideas behind R date back four decades and have a strong flavor of exploration: one can grapple with data, understand its structure, visualize it, summarize it etc. Therefore, a common way people use R is by typing a command and immediately see the results. (Of course, scripts can also be written and fed to R for batch execution.)

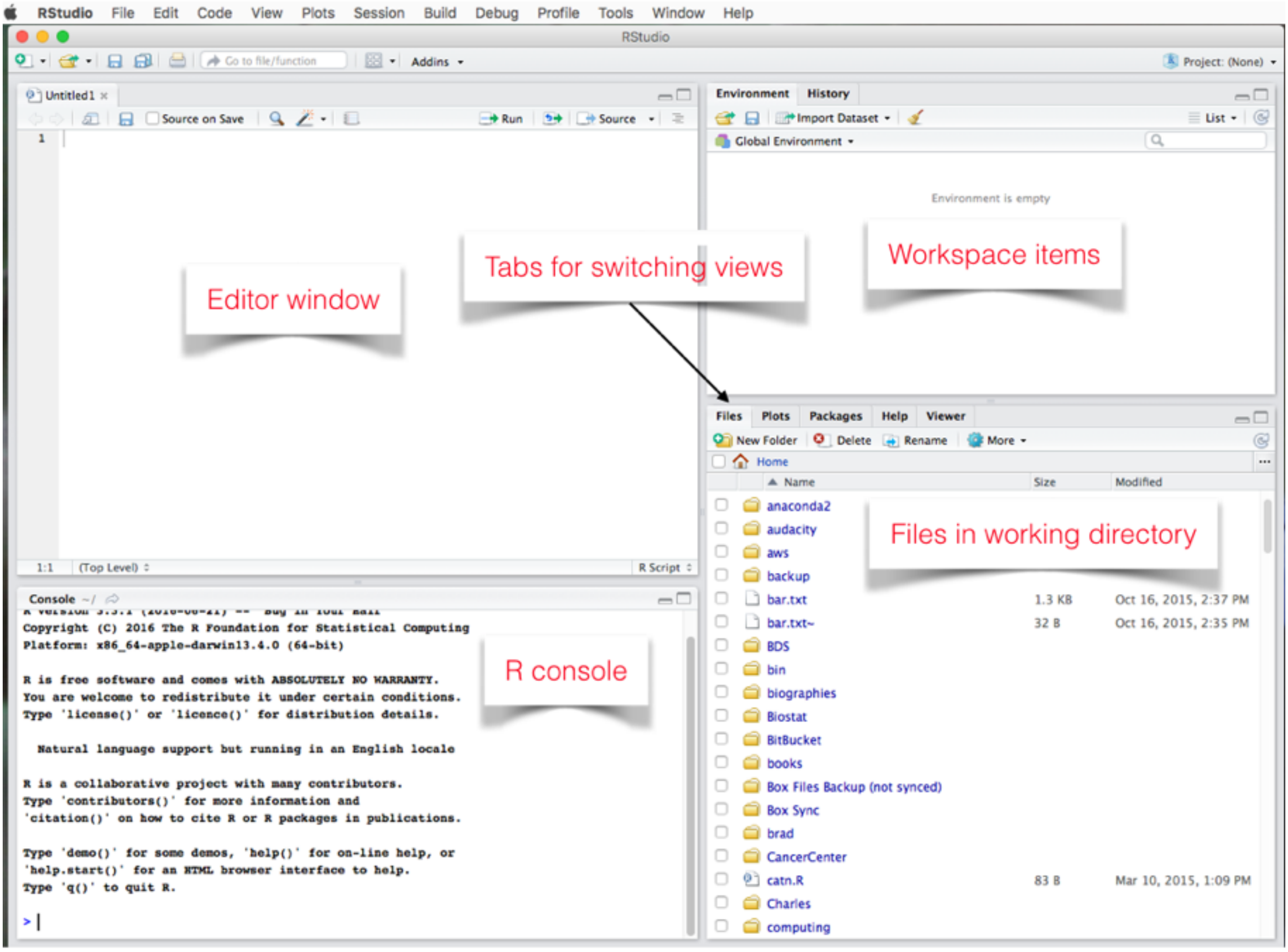
The core of R itself is reasonably small, but over time, it has also become a vehicle for researchers to disseminate new tools and methodologies via packages. That is one reason for R's popularity: there are thousands of packages (10,300+ as of this writing, not to mention over 1,000 for genomic analysis that are part of BioConductor) that extend R in many useful ways.

The CRAN (https://cloud.r-project.org) website is something you will consult frequently for both the software, documentation and packages others have developed.

RStudio

We can only cover some important aspects of RStudio here. There are a number of resources online, including Youtube videos that you can consult outside of class.

When you start RStudio, you will get a view similar to what is shown below with perhaps slight differences.

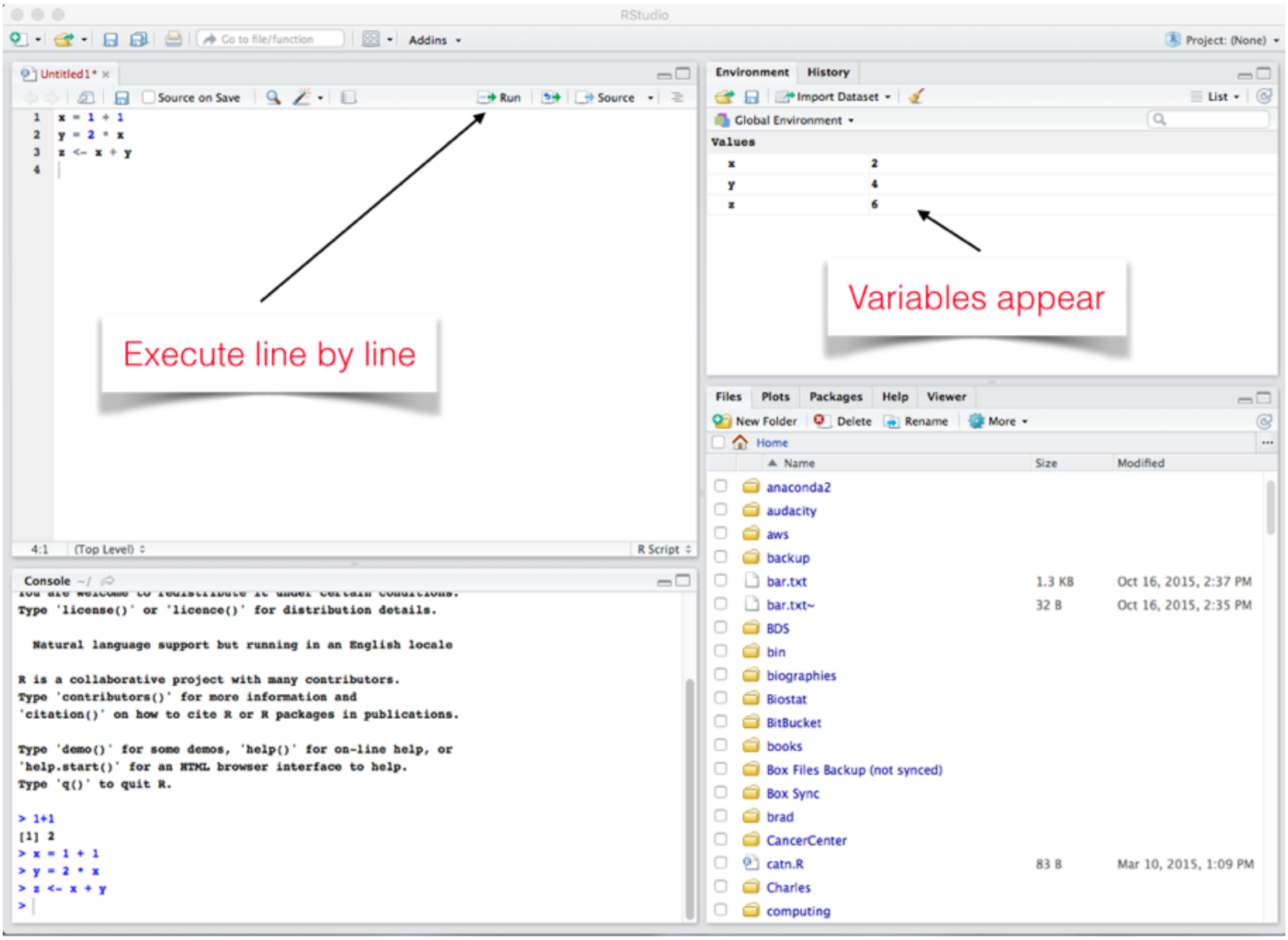


One can type commands directly into the console window and see results. For example, go ahead and type `1+1` to use R as a calculator and see the result. However, one often wants to write a sequence of commands, execute them and possibly save the commands to run them again another time. That's what the editor window is for. You can type a series of commands into the editor window and RStudio will offer to save them when you quit, and bring them back when you restart RStudio.

If you type

```
x = 1 + 1
y = 2 * x
z <- (x + y)
```

into the editor window, you can press the `Run` arrow shown and execute each line in the R console, one by one. The figure below shows this and as new variables are created, the workspace panel displays them.

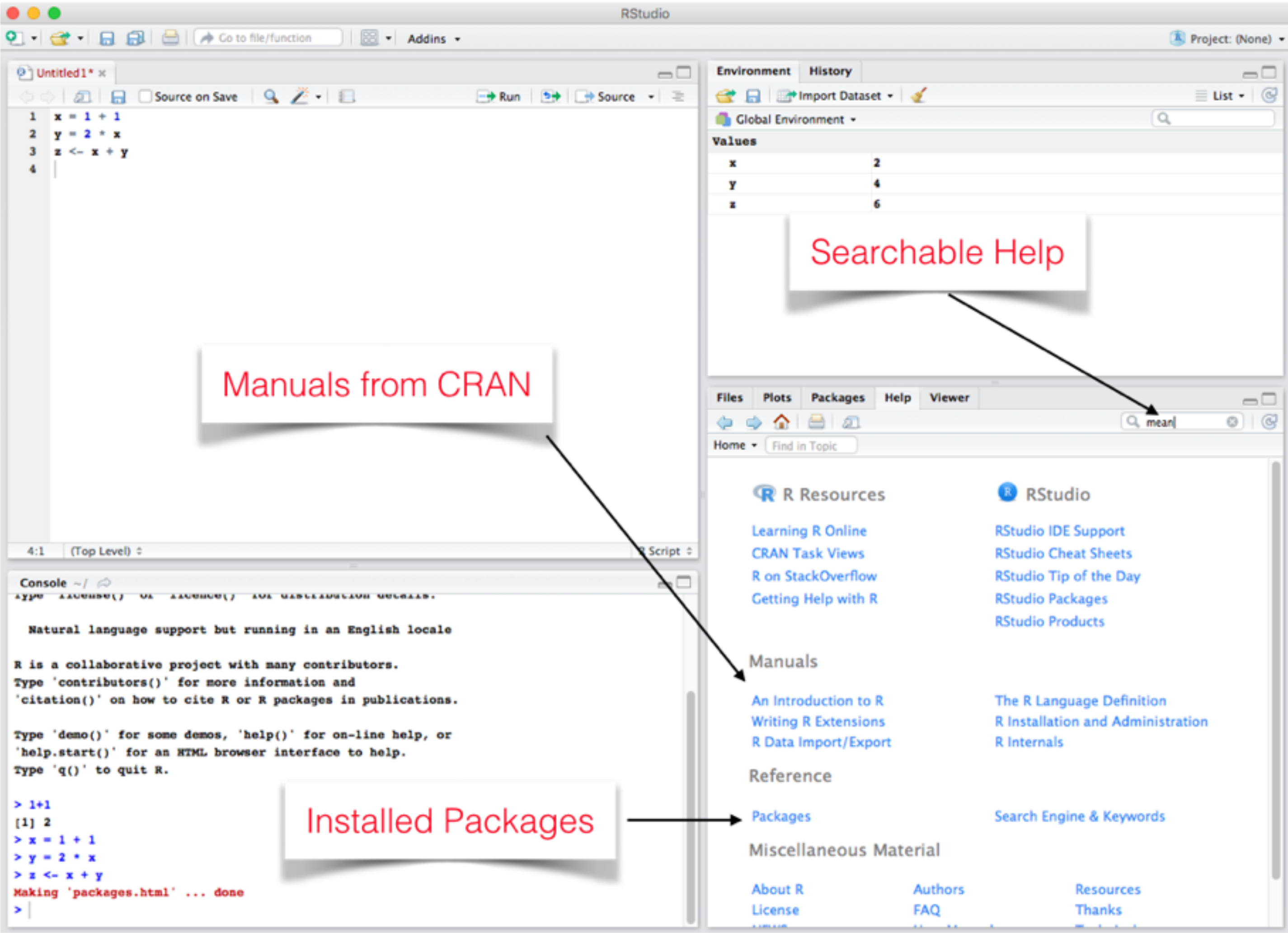


Should I use = or <- for assignment?

In R, both = and <- can be used for assigning a value to variables. The various instructors in this class have personal preferences and so you will see both used.

Help

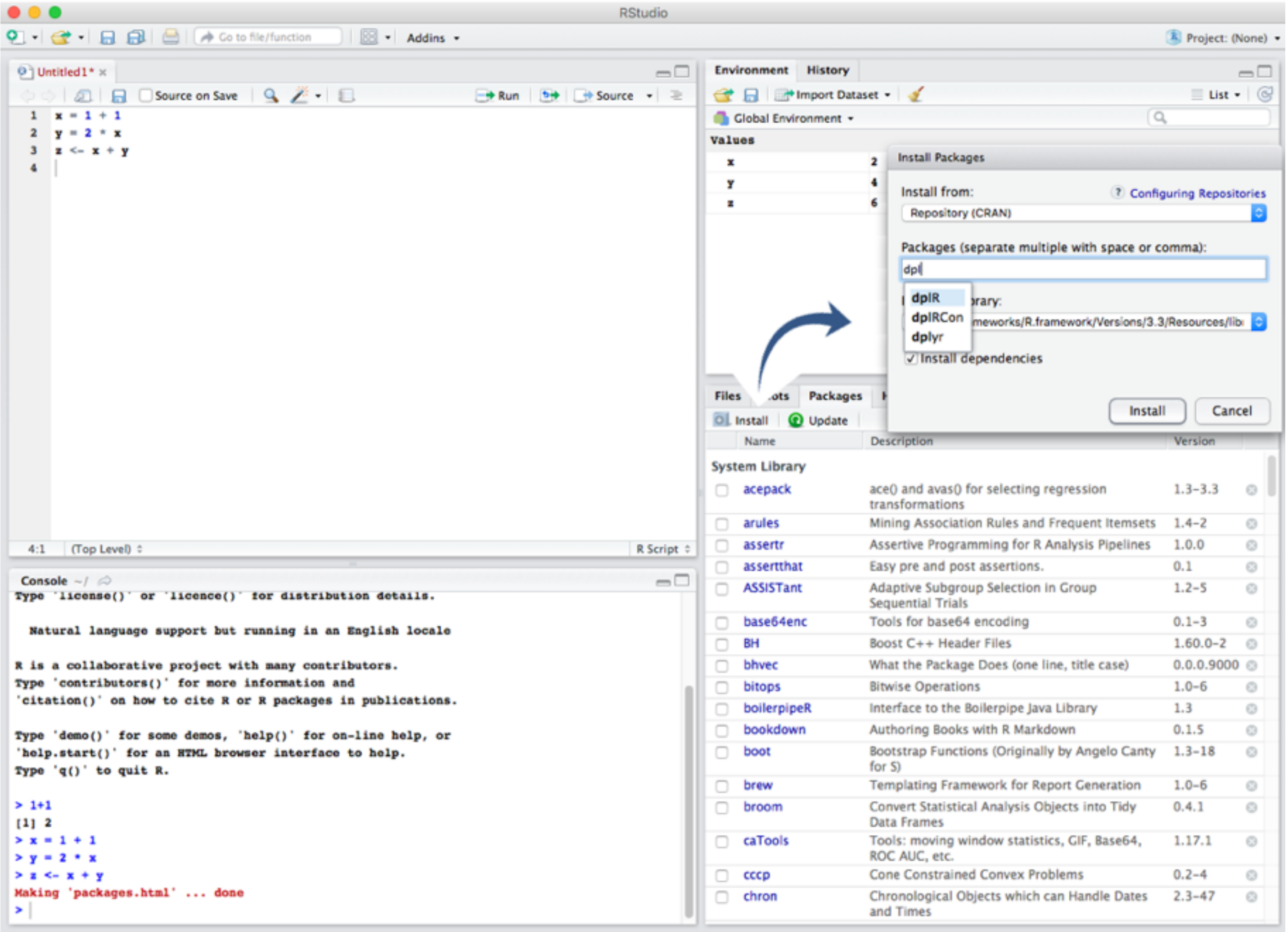
A lot of help is available in RStudio in the help tab that you should feel free to investigate. We merely point out a few.



When anyone installs R, there is a set of recommended packages that is always installed. So your *installed packages* will reflect that. As we proceed, you will have to install many packages and that list will, of course, grow.

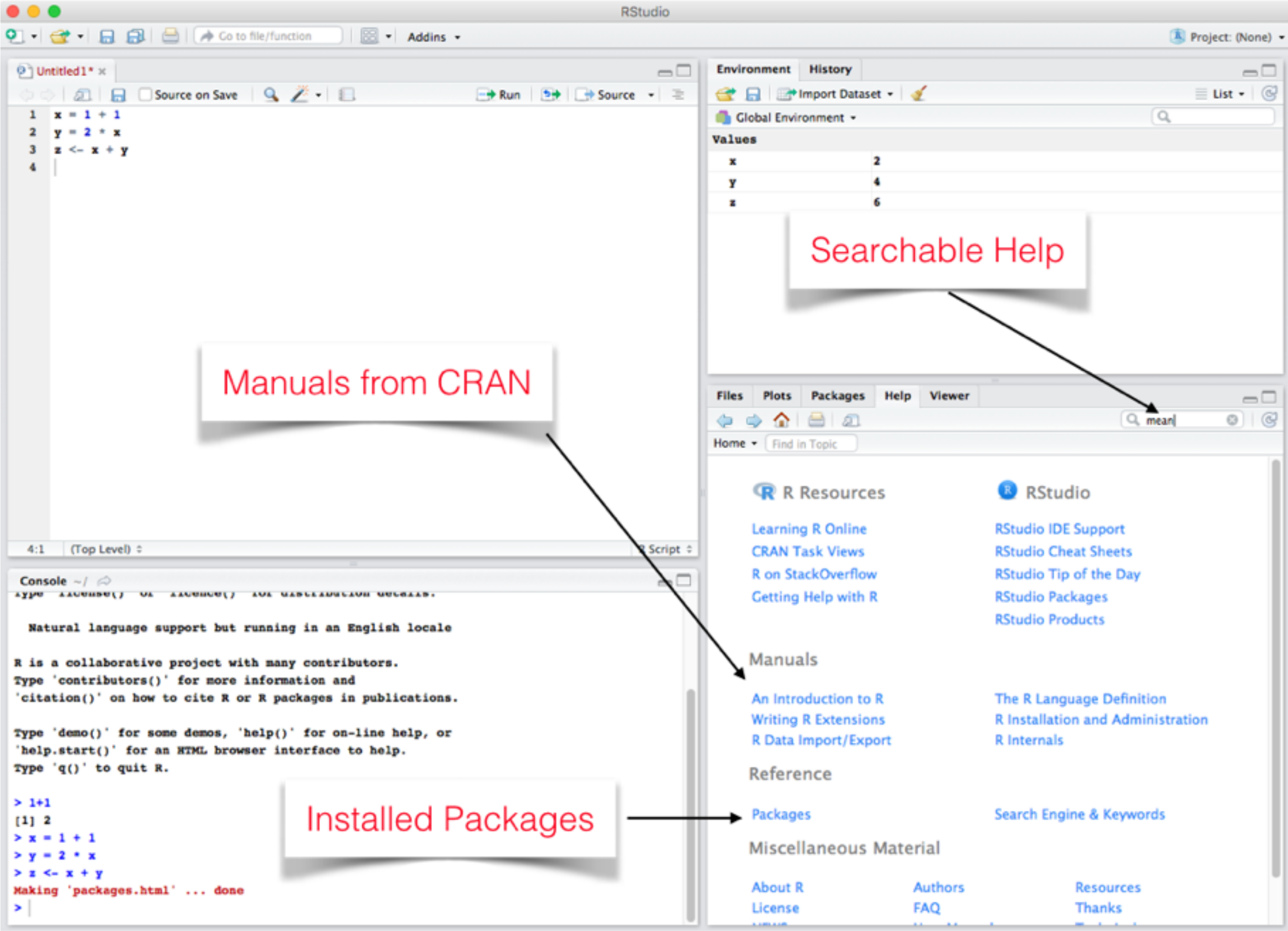
Installing Packages

There are world-wide R package repositories or Comprehensive R Archive Network (CRAN) sites that allow packages to be downloaded and installed. You almost never have to directly work with them since RStudio makes it easy to install the packages as shown in the figure below, where we have clicked on the **Packages** tab and clicked on the *Install* button. Note how as you type the name of a package, you get auto-completion. (In fact, RStudio provides auto-completion even as you type R commands, showing you various options you can use for the commands!)

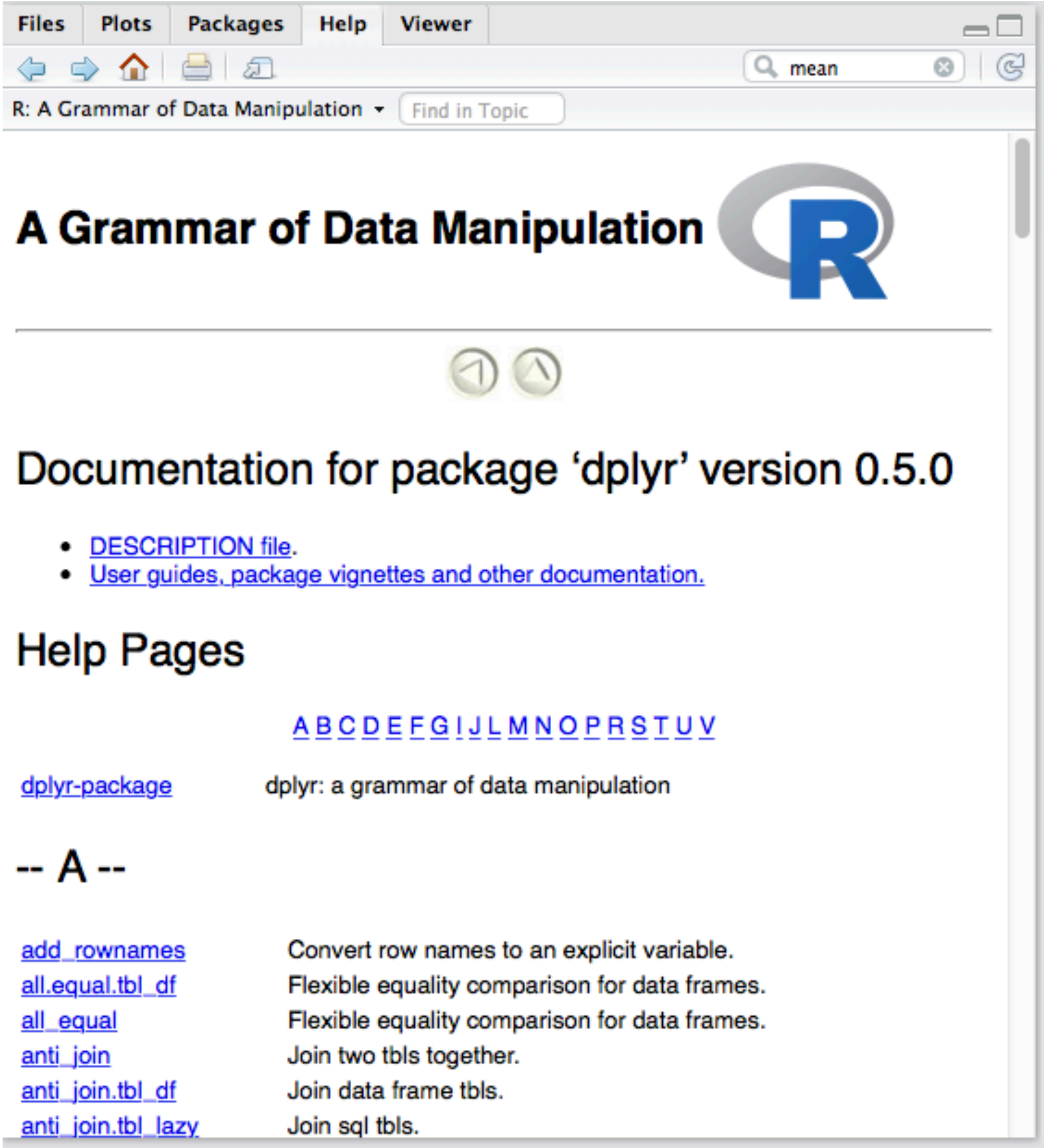


Activity

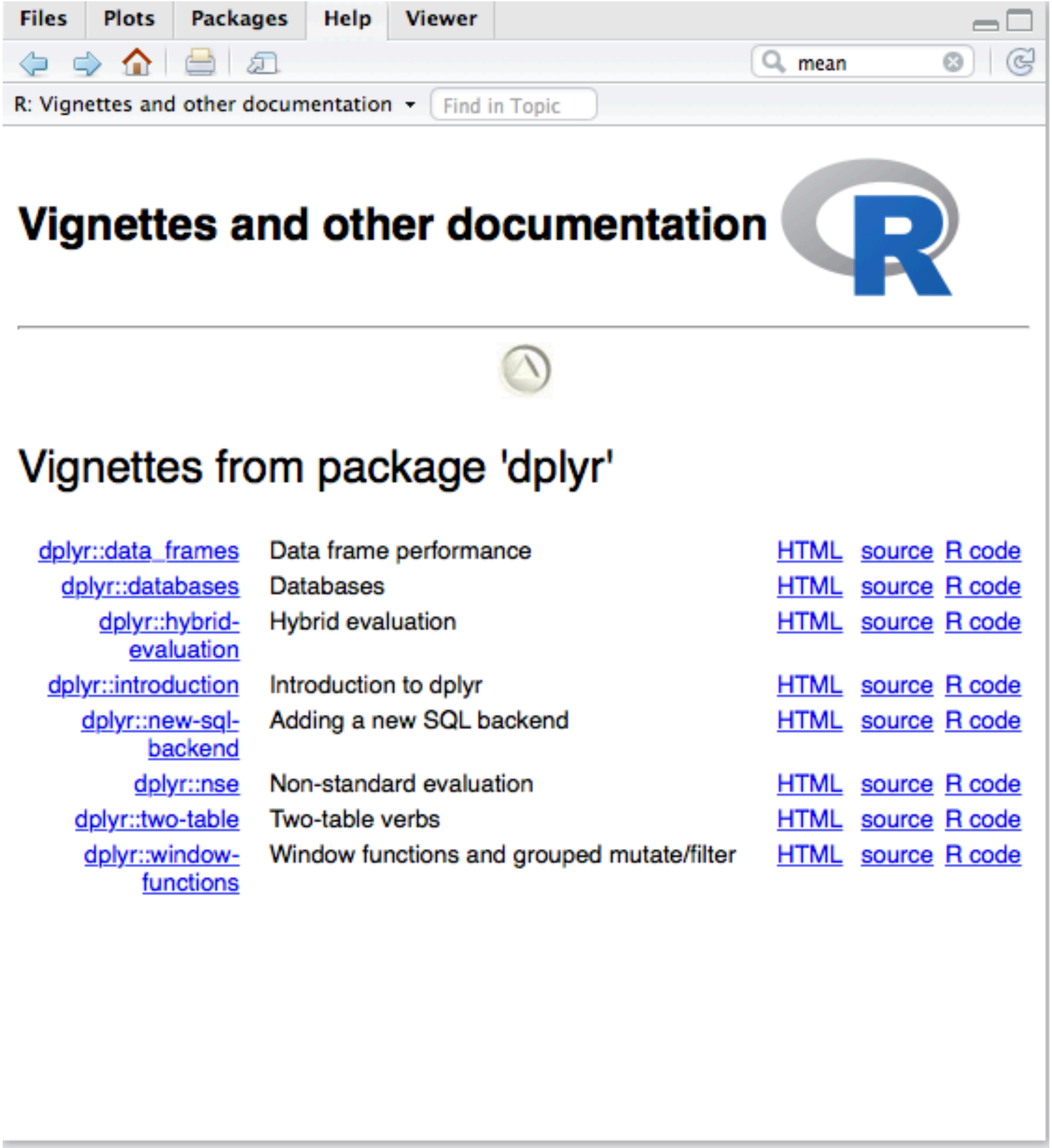
`dplyr` should appear on the lower right (install the package it if not). Press all the buttons necessary to make the install happen. After you have done the installation, go back to the **Help** tab where you can click on the *Installed Packages* link shown in the figure below.



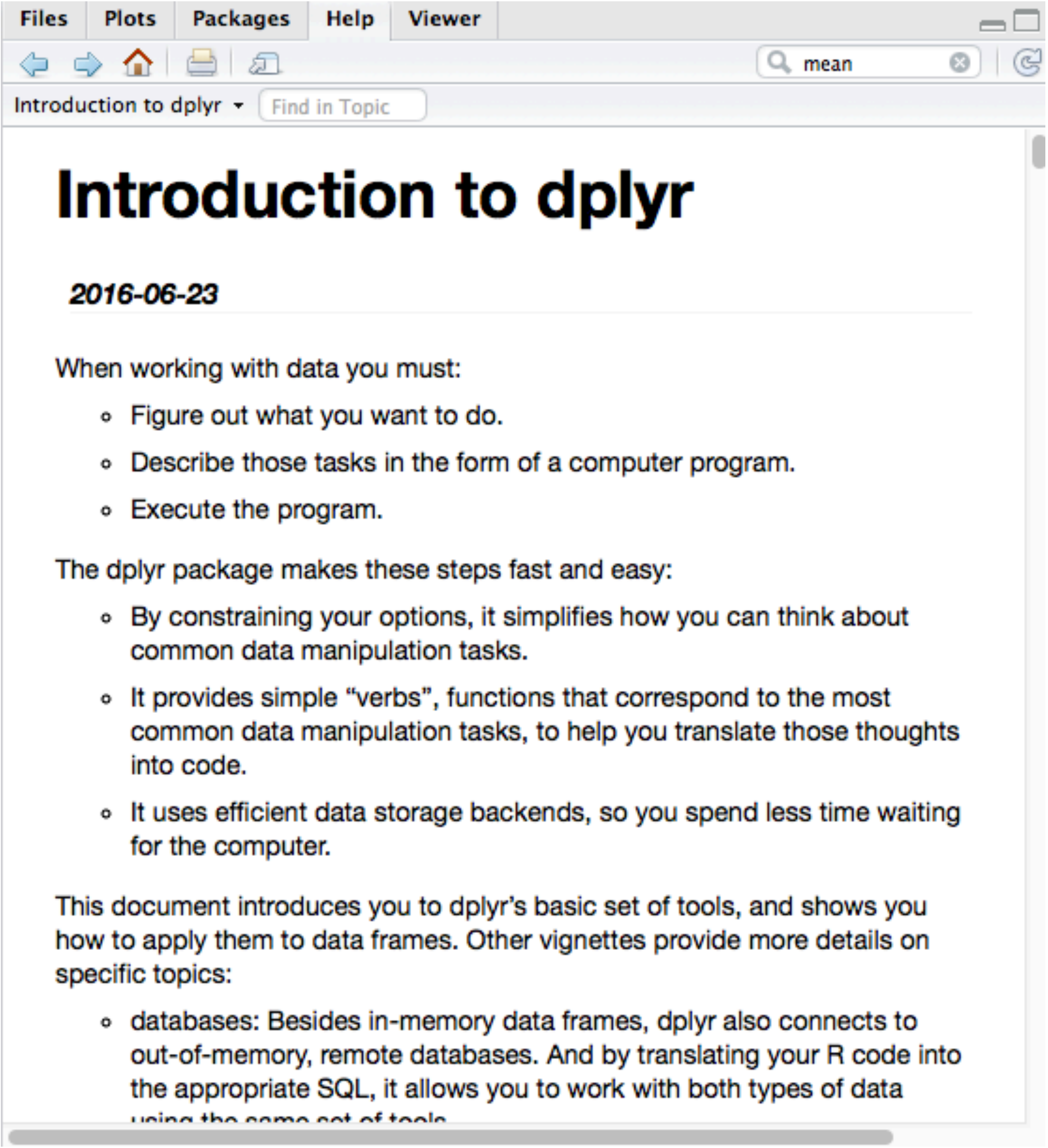
Navigate to the `dplyr` link and click on it so that you get to the help on the `dplyr` package. Two kinds of help are displayed: *Documentation* and *Help Pages*.



The *Help Pages* document facilities that the package `dplyr` in detail. The *Documentation* is often more useful, because they can contain user guides and *vignettes* that are very useful for people learning about the package. So click on the *User guides…*



Click on the *Introduction to dplyr* vignette to see the vignette.



Vignettes, when present, are indispenable in learning about a package. Not all packages provide vignettes, however!

Activity (to be done outside class)

This needs to be done only once for the entire course.

```
source('https://www.stanford.edu/class/stats101/INSTALL.R')
```

A transcript of what happens is shown below. In the case below, the packages were already mostly installed and so there was not much activity. But a typical fresh install will take anywhere from 5 to 10 minutes. A good time for a cuppa.

Workspace

As you use RStudio more, you will find yourself creating variables (like `x`, `y`, `z` above, except far more valuable) and it is desirable to save them. When you quit RStudio, you will be given a choice of saving your workspace. It is worth doing so if you have important things created.

RStudio also a notion of projects and so you can keep project workspaces separate. Each such project can be designated a working folder so that `x` from one workspace does not clobber `x` from another. You can explore these options via the *File* menu.

Later, we will see facilities to selectively save and restore some specified objects in our workspace, but not all of them.

The R Language, in some detail

Instead of giving a deep dive into R, we focus on details that we expect to be of immediate use, filling in others as needed.

Like other computer languages, R has ways of naming things in the language. Above, we used `x` as a name for the value 1 and `y` for the value 2. The names have to follow some rules. It is sufficient to be aware that they must start with an alphabetic character and can contain periods and underscores. Also, for obvious reasons, space is not permitted. (It is common to see names for variables such as `male.cholesterol` or `male_cholesterol`!)

Nomenclature: R users tend to use the word *objects* to refer to R variables, functions, datasets, etc.

In R, all the action occurs via *functions*. You can think of functions as code that takes some inputs and produces some output. Even something as simple as

```
1 + 2
```

```
## [1] 3
```

is computed via functions. The rich set of functions in R and the thousands of R packages make it a very powerful tool for data science.

There are various types of data structures in R.

Vectors and Indexing

R can handle both numeric and non-numeric data. Non-numeric data occurs commonly in the real world and sometimes needs to be cleaned up and converted to numeric values.

```
x <- c(1.0, 2)
x
```

```
## [1] 1 2
```

```
typeof(x)
```

```
## [1] "double"
```

```
y <- c("abc", "d", "e", 'fgh')
y
```

```
## [1] "abc" "d"   "e"   "fgh"
```

```
typeof(y)
```

```
## [1] "character"
```

```
y %in% letters
```

```
## [1] FALSE  TRUE  TRUE FALSE
```

```
sum(y %in% letters)
```

```
## [1] 2
```

What is `sum(y %in% letters)` and what does it represent?

```
z <- 1:5
z
```

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

```
typeof(z)
```

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

```
w <- c(TRUE, FALSE, TRUE, TRUE)
w
```

```
## [1]  TRUE FALSE  TRUE  TRUE
```

```
typeof(w)
```

```
## [1] "logical"
```

```
sum(w)
```

```
## [1] 3
```

The `c` stands for the *combine* function and it creates a vector of two numbers for `x` and a vector of four strings for `y`. Note how both single and double quotes may be used (useful when we have quotes within strings). For `z` we use a shortcut `1:5` for creating a sequence of integers from 1 to 5. And finally, `w` is a logical vector; R recognizes the symbols `TRUE` and `FALSE` as special symbols; you cannot have a variable named `TRUE` for example! (The `typeof` function is useful to understand basic underlying types.)

Character data can be treated differently in R, depending on the context. An important notion is that of a *factor*, which is basically a way of stating that variable has categorical semantics. Declaring a variable as factor causes R to treat it in differently in certain contexts, particularly model fitting. To create a factor, one uses the `factor` function.

```
gender <- factor(c("Male", "Female", "Female", "Male"))
gender
```

```
## [1] Male   Female Female Male
## Levels: Female Male
```

Factors always print in a special way; above, there are two categories or `Levels` for `gender` namely `Female` and `Male` . The variable `gender` itself has four values the first and last being `Male` . The unique categories represented by a factor variable can be queried using the `levels` function:

```
levels(gender)
```

```
## [1] "Female" "Male"
```

```
sum(gender == "male")
```

```
## [1] 0
```

```
sum(gender == "Male")
```

```
## [1] 2
```

```
table(gender)
```

```
## gender
## Female   Male
##      2      2
```

By default, the categories appear in *lexicographic* order but can be forced to be any other order.

Indexing

Often, one needs to access a part, or a subset or a slice of a vector. This is done by specifying indices indexing construct

```
## The first element; indexing begins from 1
x[1]
```

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

```
## The third element of y
y[3]
```

```
## [1] "e"
```

```
## The second to fourth element of z
z[2:4]
```

```
## [1] 2 3 4
```

```
## The first and last element of y
y[c(1, length(y))]
```

```
## [1] "abc" "fgh"
```

```
## The first and last gender
gender[c(1, length(gender))]
```

```
## [1] Male Male
## Levels: Female Male
```

Note the use of the function `length` that returns the length of `y` (4 for us).

Nothing stops one from combining types.

```
## Combine x and y into one
c(x, y)
```

```
## [1] "1"   "2"   "abc" "d"   "e"   "fgh"
```

Note, however, that the last combine operation silently coerces everything to strings. This is because vectors contain *homogeneous* elements. That seems limiting, because sometimes you may have both types of data and you don't want to be converting things back and forth.

Lists

Lists are versatile data structures that can grow or shrink and contain heterogeneous data. They are constructed using the `list` function:

```
aList <- list(1, 2, list(1, 2, "abc"))
aList
```

```
## [[1]]
## [1] 1
##
## [[2]]
## [1] 2
##
## [[3]]
## [[3]][[1]]
## [1] 1
##
## [[3]][[2]]
## [1] 2
##
## [[3]][[3]]
## [1] "abc"
```

Note how a list prints differently. Individual elements of the list, unlike the vectors above, are accessed using the double bracket notation, suggested by the printing. Note also that there is no coercion of types.

```
## The second element
aList[[2]]
```

```
## [1] 2
```

```
## The third element, which is itself a list!
aList[[3]]
```

```
## [[1]]
## [1] 1
##
## [[2]]
## [1] 2
##
## [[3]]
## [1] "abc"
```

```
## The second element of the third element
aList[[3]][[2]]
```

```
## [1] 2
```

With lists, the single bracket indexing behaves differently from double bracket indexing.

```
aList[[2]]
```

```
## [1] 2
```

```
aList[2]
```

```
## [[1]]
## [1] 2
```

The difference is clear from the way each is printed: the former is just the second element of the list whereas the latter is another list whose second element is from the original list.

The rule is simple: single bracket indexing returns the same type of object.

```
typeof(aList[[2]])
```

```
## [1] "double"
```

```
typeof(aList[2])
```

```
## [1] "list"
```

Negative indexing is a convenient way to drop some elements from a vector.

```
## Drop the first element of x
x[-1]
```

```
## [1] 2
```

```
## Drop the last element of y
y[-length(y)]
```

```
## [1] "abc" "d"   "e"
```

```
## Drop the first and last element of aList
aList[c(-1, -length(aList))]
```

```
## [[1]]
## [1] 2
```

Mixing of negative and non-negative indices is not permitted.

```
## This results in an error
y[c(-1, 3:4)]
```

```
## Error in y[c(-1, 3:4)]: only 0's may be mixed with negative subscripts
```

R also allows logical indexing:

```
## Select y elements where w is TRUE
y[w]
```

```
## [1] "abc" "e"   "fgh"
```

will select the first, third and fourth elements and drop the rest. Selecting elements based on conditions is very useful and we will see further examples.

Missing and null values

R has a notion of a missing value that can be used to indicate data is missing for some cases, an all too real phenomenon. It is denoted by `NA` .

```
miss1 <- c(1.0, NA, 2.0)
2 * miss1
```

```
## [1]  2 NA  4
```

Notice how the last operation did the appropriate thing with the missing value. It is extremely convenient to be able to use missing values as you would any other object in R. But numerical computations will have to provide hints on how to handle the missing values. For example, the `mean` function computes the average of a set of numbers.

```
## No hint to process missing values
mean(miss1)
```

```
## [1] NA
```

```
## Remove missing values before processing
mean(miss1, na.rm = TRUE)
```

```
## [1] 1.5
```

Another value `NULL` is used to indicate *nothing is present*. Note that it is semantically different from a missing value.

```
NULL
```

```
## NULL
```

```
## Combine nothing
c()
```

```
## NULL
```

One can check for missing-ness or nullity using the `is` family of functions.

```
is.null(c())
```

```
## [1] TRUE
```

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

```
## [1] FALSE
```

```
## This should produce a warning
is.na(c())
```

```
## Warning in is.na(c()): is.na() applied to non-(list or vector) of type
## 'NULL'
```

```
## logical(0)
```

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

```
## [1] TRUE
```

There are many others: `is.numeric`, `is.list`, `is.vector`, etc.

Arithmetic and logical operations

The standard operations are all available: `+`, `-`, `*` (multiplication), `/` division. In R, when you perform arithmetic on vectors, the operations happen on all elements.

```
## Add two vectors
1:3 + 2:4
```

```
## [1] 3 5 7
```

```
## Multiply a vector by 2
2 * 1:3
```

```
## [1] 2 4 6
```

```
## Better to have parenthesis
2 * (1:3)
```

```
## [1] 2 4 6
```

```
## Divide
c(2, 4, 6) / c(2, 4, 6)
```

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

```
## Halve
c(2, 4, 6) / 2
```

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

```
## R recycles shorter vector to match length
c(2, 4, 6, 8) / c(1, 2)
```

```
## [1] 2 2 6 4
```

```
## Above is same as
c(2, 4, 6, 8) / c(1, 2, 1, 2)
```

```
## [1] 2 2 6 4
```

```
## Warning, but not error below
c(2, 4, 6) / c(1, 2)
```

```
## Warning in c(2, 4, 6)/c(1, 2): longer object length is not a multiple of
## shorter object length
```

```
## [1] 2 2 6
```

The last operation shows how R tries to make two vectors conform in length and provides a warning. *Good code avoids relying on such behaviors as they can cause unpredictable errors.* **When you see this warning, try to find its source – probably a bug!**

The usual comparison operators are available: `==` for equality, `!=` for not equal to, `>=` for greater than or equal to, etc.

```
xx <- 1:3
xx == xx
```

```
## [1] TRUE TRUE TRUE
```

```
## 1 is expanded to match length of xx
xx > 1
```

```
## [1] FALSE  TRUE  TRUE
```

Comparison operators can be used to select subsets of vectors. Some examples with the understanding that `a %% 2` returns the reminder upon division of a by 2.

```
xx <- 1:10
## Pick all numbers >= 5
xx[ xx >= 5]
```

```
## [1]  5  6  7  8  9 10
```

```
## Pick even numbers from 1 to 10
xx[ xx %% 2 == 0]
```

```
## [1]  2  4  6  8 10
```

```
## Pick odd numbers from 1 to 10
xx[ xx %% 2 != 0]
```

```
## [1] 1 3 5 7 9
```

Coercion

We saw above that some functions, can silently coerce the results to something meaningful. In many case, such coercions can be useful.

How many even numbers between 1 and 10?

```
xx <- 1:10
xx %% 2 == 0
```

```
##  [1] FALSE  TRUE FALSE  TRUE FALSE  TRUE FALSE  TRUE FALSE  TRUE
```

```
sum(xx %% 2 == 0)
```

```
## [1] 5
```

Here `xx %% 2 == 0` is a list of 10 logical values with `TRUE` wherever we have an even number. The function `sum` converts `TRUE` values to 1 and `FALSE` values to 0 and results to provide the answer.

R usually coerces the results where possible to the type that can accomodate the result. If it cannot, it signals an error.

There are many explicit coercion functions such as `as.numeric` , `as.integer` , as `as.list` .

```r
xx <- 1:5
as.integer(xx %% 2 == 0)
```

```
## [1] 0 1 0 1 0
```

```r
as.character(xx)
```

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

```r
as.list(xx)
```

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

Although we have not discussed dates and times, the function `as.Date` will convert a character string to a date object. It needs a hint as to the date format and assumes an international format (more below) for dates by default.

```r
## February date is wrong, just to illustrate
as.Date(c("2016-06-15", "2016-02-30"))
```

```
## [1] "2016-06-15" NA
```

```r
as.Date("9/27/2016", format = "%m/%d/%Y")
```

```
## [1] "2016-09-27"
```

```r
Sys.timezone()
```

```
## [1] "America/Los_Angeles"
```

The last function returns the current time zone. (Using zone information automatically takes daylight savings time in arithmetic!)

Coercion functions are useful when processing external data for computational work.

Dates and Times

Dates and times occur often in data and R is well-equipped to handle them. There are functions in base R (`strptime` , coercion functions `as.Date` , `as.POSIXlt`) that can convert from strings to date-time objects and vice-versa. These often require a format string that specifies how the way the date is formatted, something that can vary all the time. The exact details of the format string (`%m` for month, `%d` for day, `%Y` for year including century, etc.) are described in the documentation for the `strptime` function.

For this class, we recommend the package `lubridate` as it offers many convenient functions for arithmetic with dates. The vignette for the package is a good introduction, and we merely provide a few quick examples.

```
library(lubridate)
```

```
##
## Attaching package: 'lubridate'
```

```
## The following object is masked from 'package:base':
##
##     date
```

```
ymd(c("20160927", "20160230"))
```

```
## Warning: 1 failed to parse.
```

```
## [1] "2016-09-27" NA
```

```
mdy(c("6/12/16", "2/9/16"))
```

```
## [1] "2016-06-12" "2016-02-09"
```

```
dmy(c("1/9/2016", "26/9/16"))
```

```
## [1] "2016-09-01" "2016-09-26"
```

```
parse_date_time("9/27/2016 10:30:00",
                orders = "%m/%d/%y %H:%M:%S",
                tz = Sys.timezone())
```

```
## [1] "2016-09-27 10:30:00 PDT"
```

The format string used by `lubridate` is described in detail in the documentation/help for the function `parse_date_time`.

Naming

R allows one to add *names* to objects.

```
named_x <- c(a = 1.02, b = 2, 3)
named_x
```

```
##    a    b
## 1.02 2.00 3.00
```

Above, only two of the three elements were named. This makes the third element have an empty name. The function `names` allows one to retrieve the names of an object.

```
names(named_x)
```

```
## [1] "a" "b" ""
```

The naming facility allows one to access elements of vectors using names rather than indices.

```
## Equivalent to named_x[2]
named_x["b"]
```

```
## b
## 2
```

```
## Equivalent to named_x[1:2]
named_x[c("a", "b")]
```

```
##    a    b
## 1.02 2.00
```

Naming is an extremely useful tool in writing readable code. One might worry about a performance penalty but it is negligible in most cases and the gains in readability far outweigh any inefficiencies.

Naming works for lists too.

```
named_list <- list(x = x, y = y, zed = z)
named_list[c("x", "zed")]
```

```
## $x
## [1] 1 2
##
## $zed
## [1] 1 2 3 4 5
```

With lists, the individual *elements* can also be accessed using the *dollar* (`$`) notation.

```
named_list$zed
```

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

Much of R code and functions exploit naming; many functions return more than one value and they are often stuffed into a named vector or list.

```
aSummary <- summary(1:10)
aSummary
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##    1.00    3.25    5.50    5.50    7.75   10.00
```

```
names(aSummary)
```

```
## [1] "Min."    "1st Qu." "Median"  "Mean"    "3rd Qu." "Max."
```

```
typeof(aSummary)
```

```
## [1] "double"
```

```
aSummary["Median"]
```

```
## Median 
##    5.5
```

Matrices

The function `matrix` can be used for creating matrices which are two-dimensional arrays.

```
## Create a 3 by 2 matrix.
m <- matrix(1:6, nrow = 3)
m
```

```
##      [,1] [,2]
## [1,]    1    4
## [2,]    2    5
## [3,]    3    6
```

Another way is to use existing vectors to *bind* into a matrix.

```r
xx <- 1:3
yy <- 4:6
## Bind by columns
m2 <- cbind(xx, yy)
## Bind by rows
rbind(xx, yy)
```

```
##    [,1] [,2] [,3]
## xx    1    2    3
## yy    4    5    6
```

The matrix `m2` has the same content as `m` above, but the columns have names `xx` and `yy` which can be used in subsetting indexing again.

```r
## Access element in row 1, column 2
m[1, 2]
```

```
## [1] 4
```

```r
## Access second column
m[ , 2]
```

```
## [1] 4 5 6
```

```r
## Do the same with matrix m2
m2[, "yy"]
```

```
## [1] 4 5 6
```

```r
## Access the third row of m
m[3, ]
```

```
## [1] 3 6
```

Datasets

R comes with many datasets built in. These are part of the `datasets` package that is always loaded in R. For example, the `mtcars` dataset is a well-known dataset from Motor Trend magazine, documenting fuel consumption and vehicle characteristics for a number of vehicles. At the R console, typing `mtcars` will print the entire dataset.

You can find help on datasets as usual using the *Help* tab in RStudio, clicking on the `Packages` link and navigating to the `datasets` package.

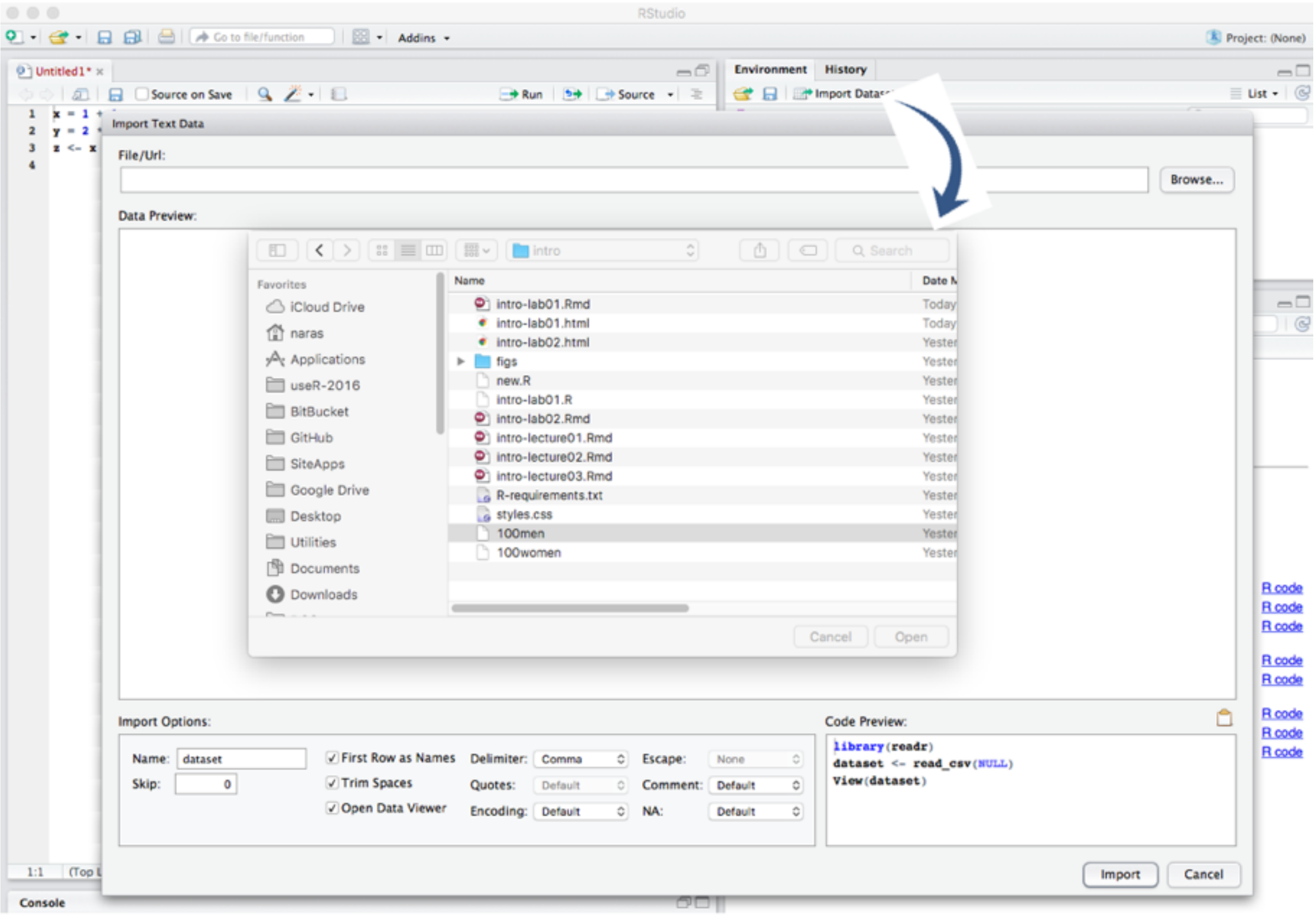
Import data

To do any real work, one has to load data from an external source. RStudio makes it easy to import data.

Consider the data set that will be used in Lab 2, which is the 100m times for men and women. We will illustrate importing this data set, step by step.

Step 1

From the *Import Dataset* menu, select *From CSV* to get a dialog as shown below and navigate to the folder containing the `100men` file.

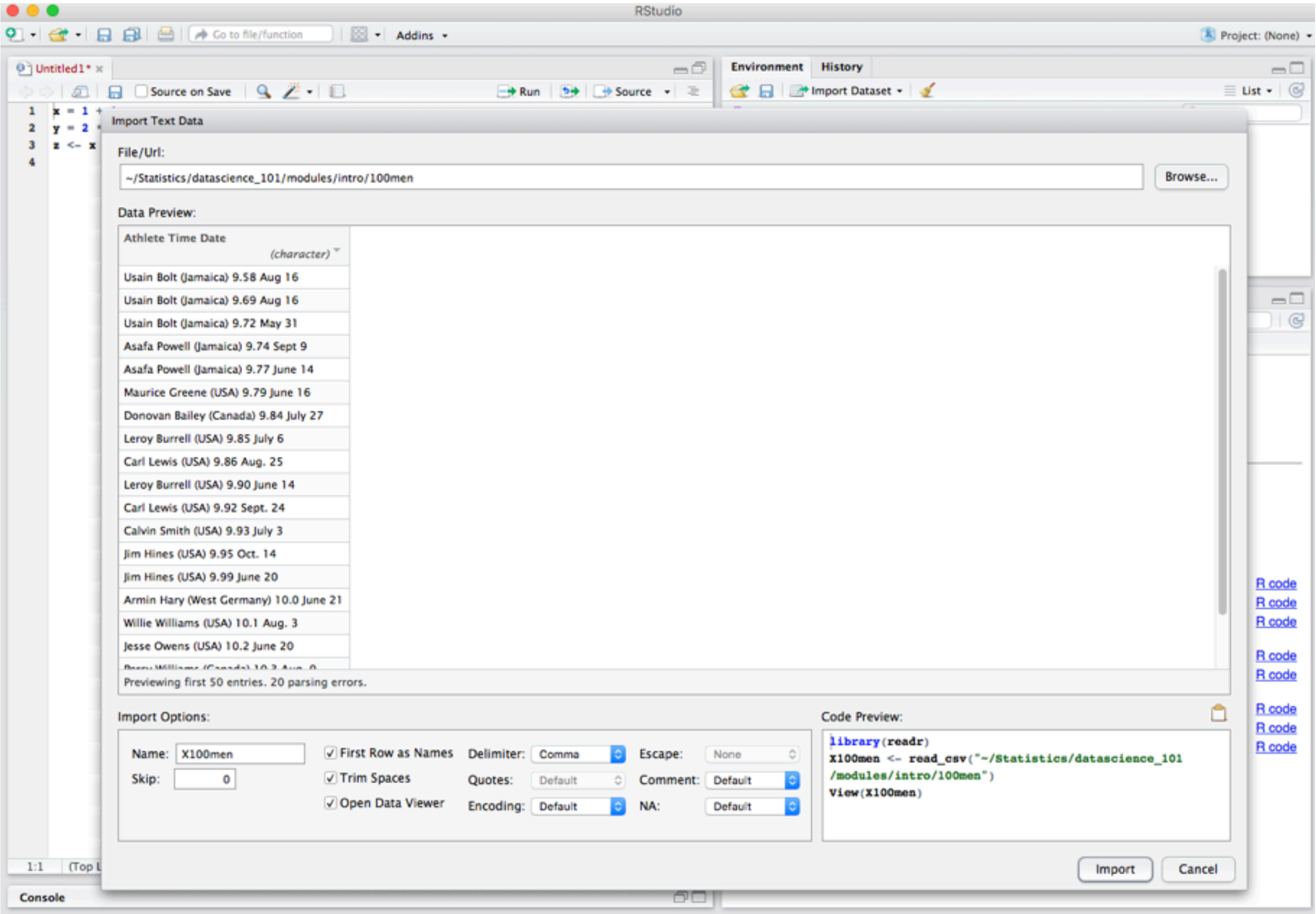


Note that the import dialog has a number of options and on the right buttom it shows a preview of the code that will be used to import the data. If one cut and pasted the code into the R console, the result would be the same as what one would get via the dialogs.

RStudio also take care to name the variable that will hold data according R conventions using `X100men` !

Step 2

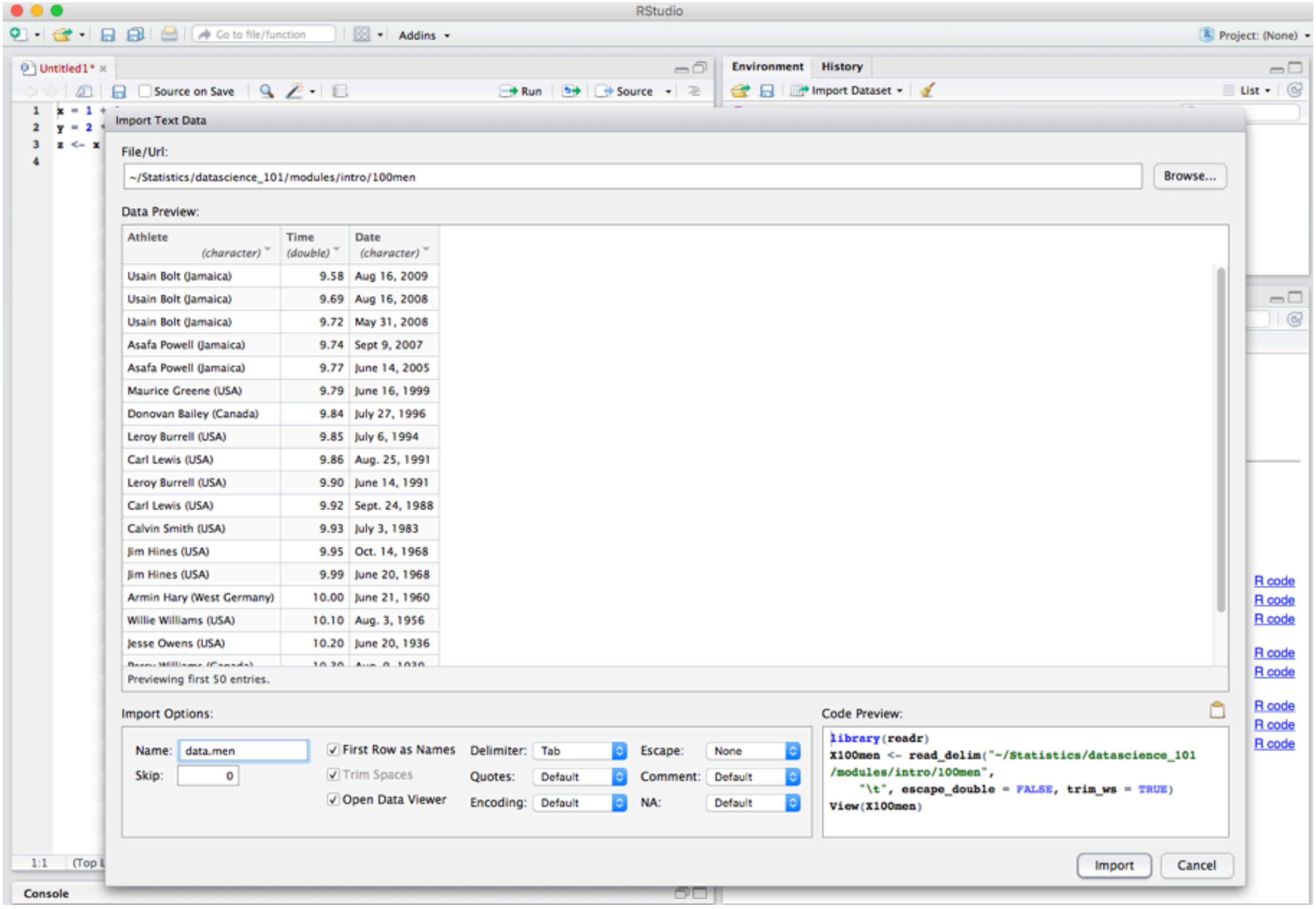
When you open the file, RStudio shows a preview of the data in the viewer window.



This is of course not what we want since a cursory inspection shows that the data appears to contain three columns. So obviously, we have specified something wrong.

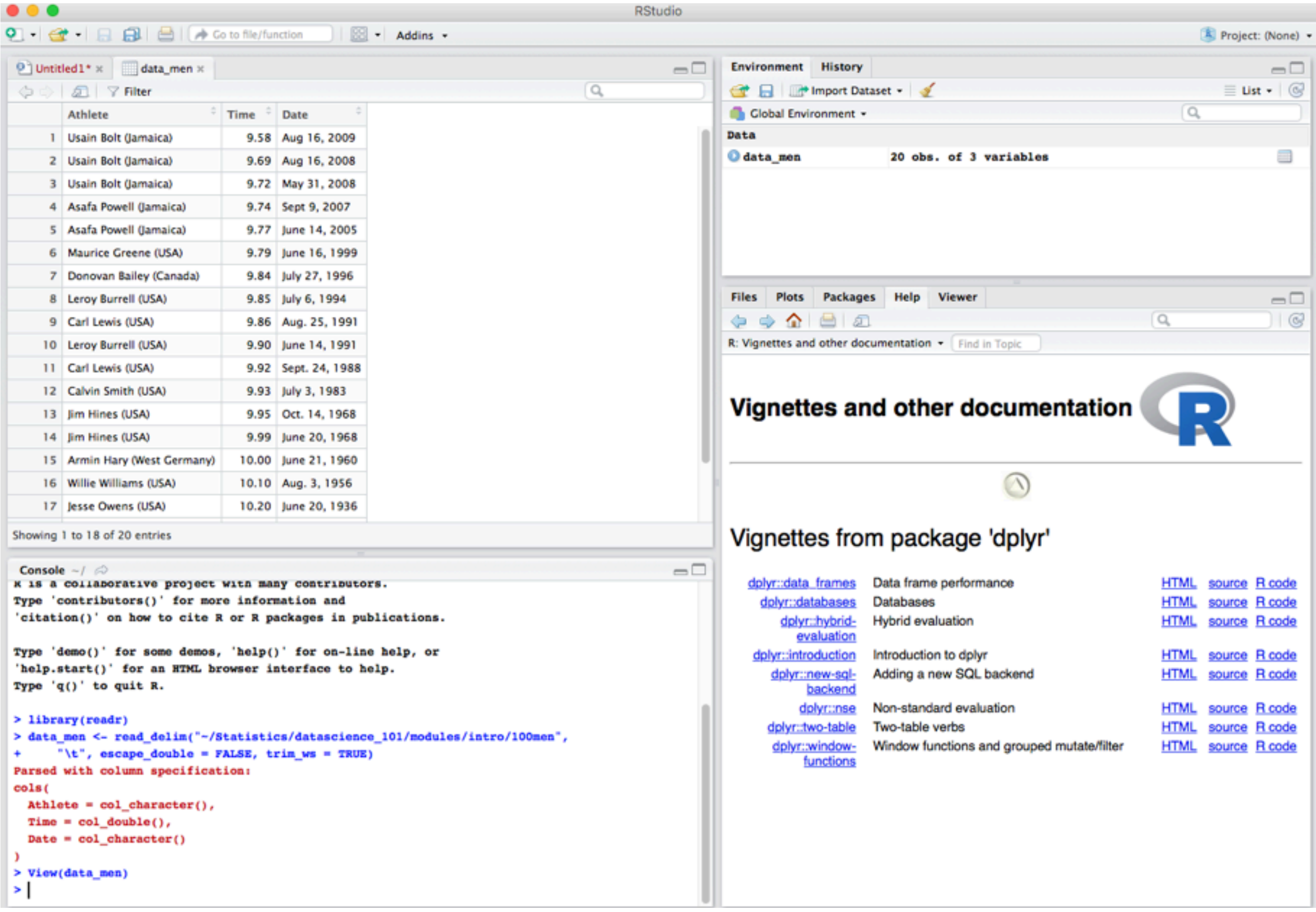
Step 3

In the *Import Options* panel, change the delimeter to `Tab` and while we are at it, change the name to `data.men`. Notice how the code preview reflects changes made to these options.



Step 4

Press the *Import* button to get the data into R.



The result of the import is a variable called `data.men` that contains the data. Data formatted this way (either tab-delimeted, or comma-separated, or spread-sheet like) is so common that R has a abstraction for it: the *data frame*. You will have more opportunity to learn about data frames in the data parts of the course.

Avoiding dialogs

As one becomes more and more familiar with R, direct code becomes preferable to the slower interactive dialogs. This is one reason that RStudio gives you the code preview, to aid in your learning process. So, to get the same effect as the above dialog process did, one could have pasted the RStudio code into an R console to get the same result.

```
library(readr)
data.men <- read_delim("100men", "\t", escape_double = FALSE, trim_ws = TRUE)
```

```
## Parsed with column specification:
## cols(
##   Athlete = col_character(),
##   Nation = col_character(),
##   Time = col_double(),
##   Date = col_date(format = "")
## )
```

That would create the same data set.

With more complex structures like data frames, the function `str` (for structure) is a good way to examine them.

```
str(data.men)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    20 obs. of  4 variables:
##  $ Athlete: chr  "Usain Bolt" "Usain Bolt" "Usain Bolt" "Asafa Powell" ...
##  $ Nation : chr  "Jamaica" "Jamaica" "Jamaica" "Jamaica" ...
##  $ Time   : num  9.58 9.69 9.72 9.74 9.77 9.79 9.84 9.85 9.86 9.9 ...
##  $ Date   : Date, format: "2009-08-16" "2008-08-16" ...
##  - attr(*, "spec")=List of 2
##   ..$ cols   :List of 4
##   .. ..$ Athlete: list()
##   .. .. ..- attr(*, "class")= chr  "collector_character" "collector"
##   .. ..$ Nation : list()
##   .. .. ..- attr(*, "class")= chr  "collector_character" "collector"
##   .. ..$ Time   : list()
##   .. .. ..- attr(*, "class")= chr  "collector_double" "collector"
##   .. ..$ Date   :List of 1
##   .. .. ..$ format: chr ""
##   .. .. ..- attr(*, "class")= chr  "collector_date" "collector"
##   ..$ default: list()
##   .. ..- attr(*, "class")= chr  "collector_guess" "collector"
##   ..- attr(*, "class")= chr "col_spec"
```

We see that the data consists of 20 observations on 3 variables: `Athlete` , `Time` , `Date` . The second is numeric while the others are character.

More on data import

RStudio provides ways to import data directly from spreadsheets like Excel, etc. You can explore these options on your own.

RStudio makes use of some packages to import data, notably the `readr` package. Strictly speaking these packages are not necessary for the job, but such packages include improvements that make them attractive. For example, a vanilla installation of R provides functions like `read.csv` and `read.delim` (analogous to `read_csv` , `read_delim`) that can also be used. However, by default, these functions perform some conversions, treating character variables as factors, for example. That can be troublesome (and computationally expensive) when dealing with large data sets. In this class, some instructors may use these vanilla R functions with various options to control the behavior.

Graphs and Plots

Graphing/plotting are among the great strengths of R. There are two main main approaches that are common in building graphs and plots.

1. Using basic functions provided by R itself via the `graphics` package which has a number of standard facilities. A quick way to familiarize yourself with base graphics is to type the command `demo(graphics)` at the R console to see its capabilities.

2. Using a package like `ggplot2` , which requires a more nuanced understanding of a graphics object. You will have to install this package. `ggplot2` implements a grammar of graphics and so takes a bit more work to use, but is quite powerful.

Both approaches allow for step-by-step building up of complex plots, and creating PDFs or images that can be included in other documents. Although `ggplot2` is becoming more popular, many packages may not use `ggplot2` for plotting. Furthermore, some special plots created by packages may use one of base graphics or `ggplot2` and so there isn't a ready made equivalent in the other, although it can be constructed with extra work. So you will see both bae graphics and `ggplot2` used in this course.

For ease of use, `ggplot2` provides a function called `qplot` that can emulate the base graphics `plot` function capabilities. This offers a quick way to begin using `ggplot2`, initially.

Description	Base Graphics	`ggplot2`
Plot `y` versus `x` using points	`plot(x, y)`	`qplot(x, y)`
Plot `y` versus `x` using lines	`plot(x, y, type = "l")`	`qplot(x, y, geom = "line")`
Plot `y` versus `x` using both points and lines	`plot(x, y, type = "b")`	`qplot(x, y, geom = c("point", "line"))`
Boxplot of `x`	`boxplot(x)`	`qplot(x, geom = "boxplot")`
Side-by-side boxplot of `x` and `y`	`boxplot(x, y)`	`qplot(x, y, geom = "boxplot")`
Histogram of `x`	`hist(x)`	`qplot(x, geom = "histogram")`

Examples

It is a good idea to try out the functions using the `example` function. At the R console type,

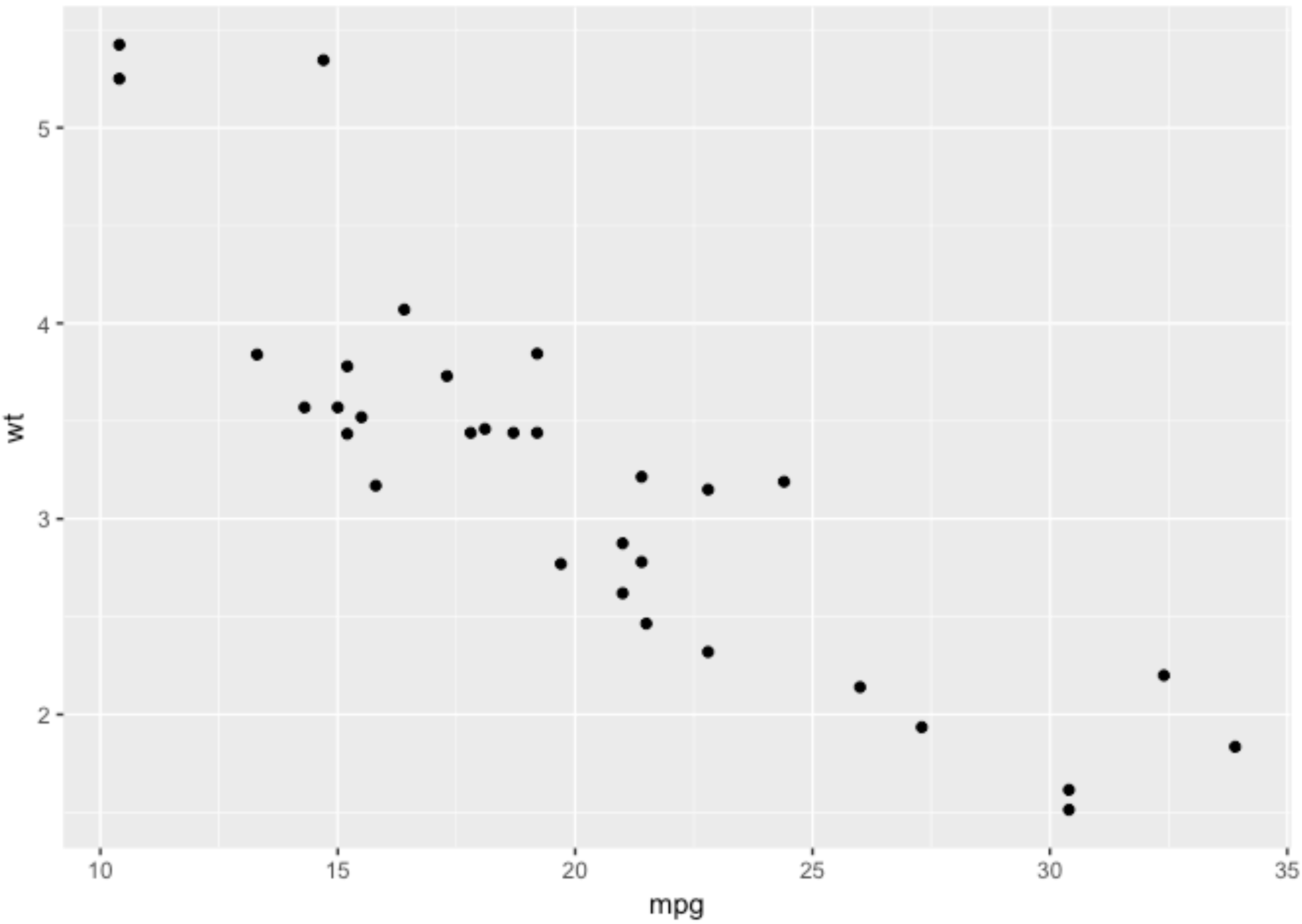
```
example(plot)
```

to see the `plot` examples.

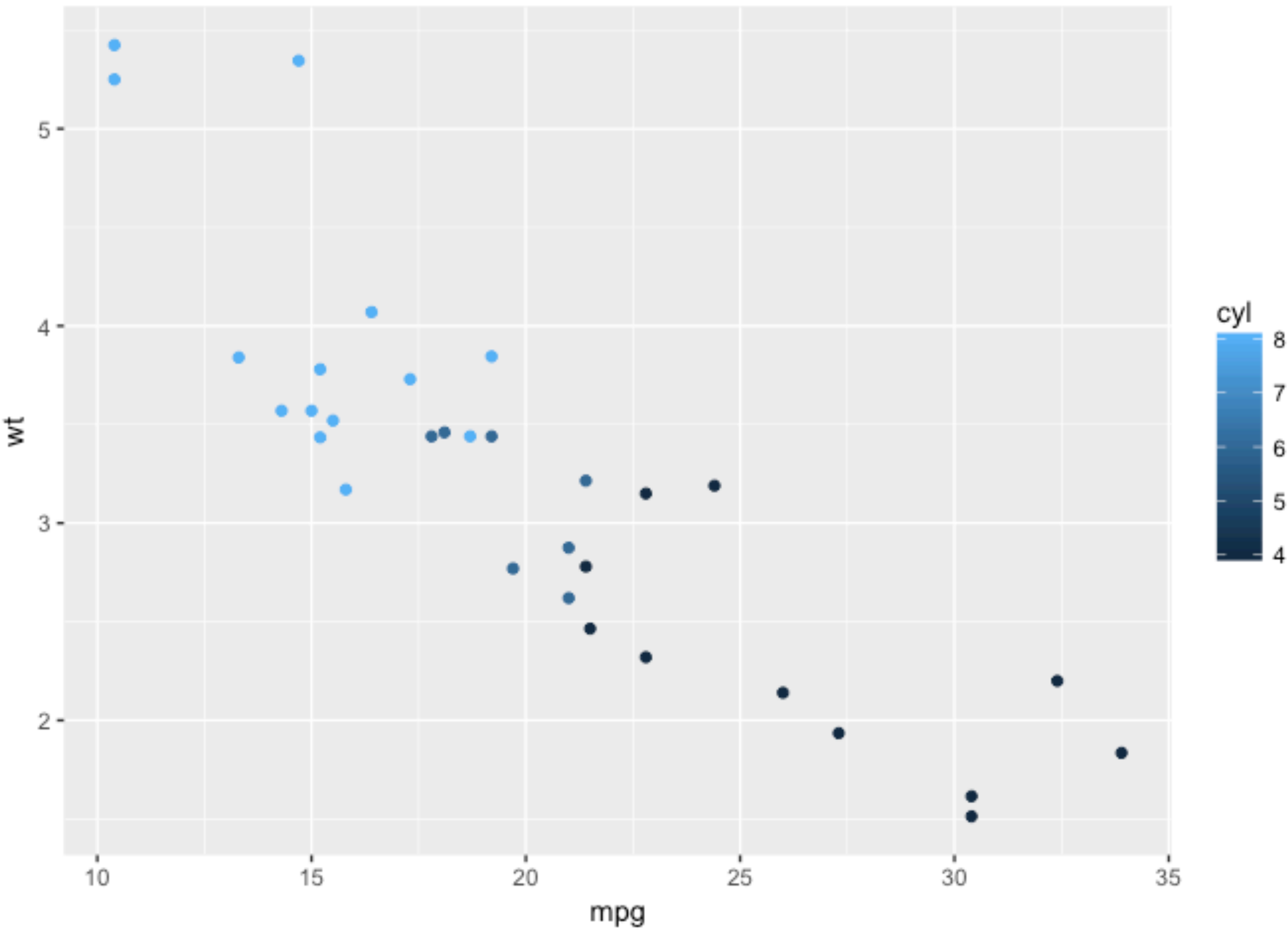
For `ggplot2`, you will have to load the library first and then use `example`.

```
library(ggplot2)
example(qplot)
```

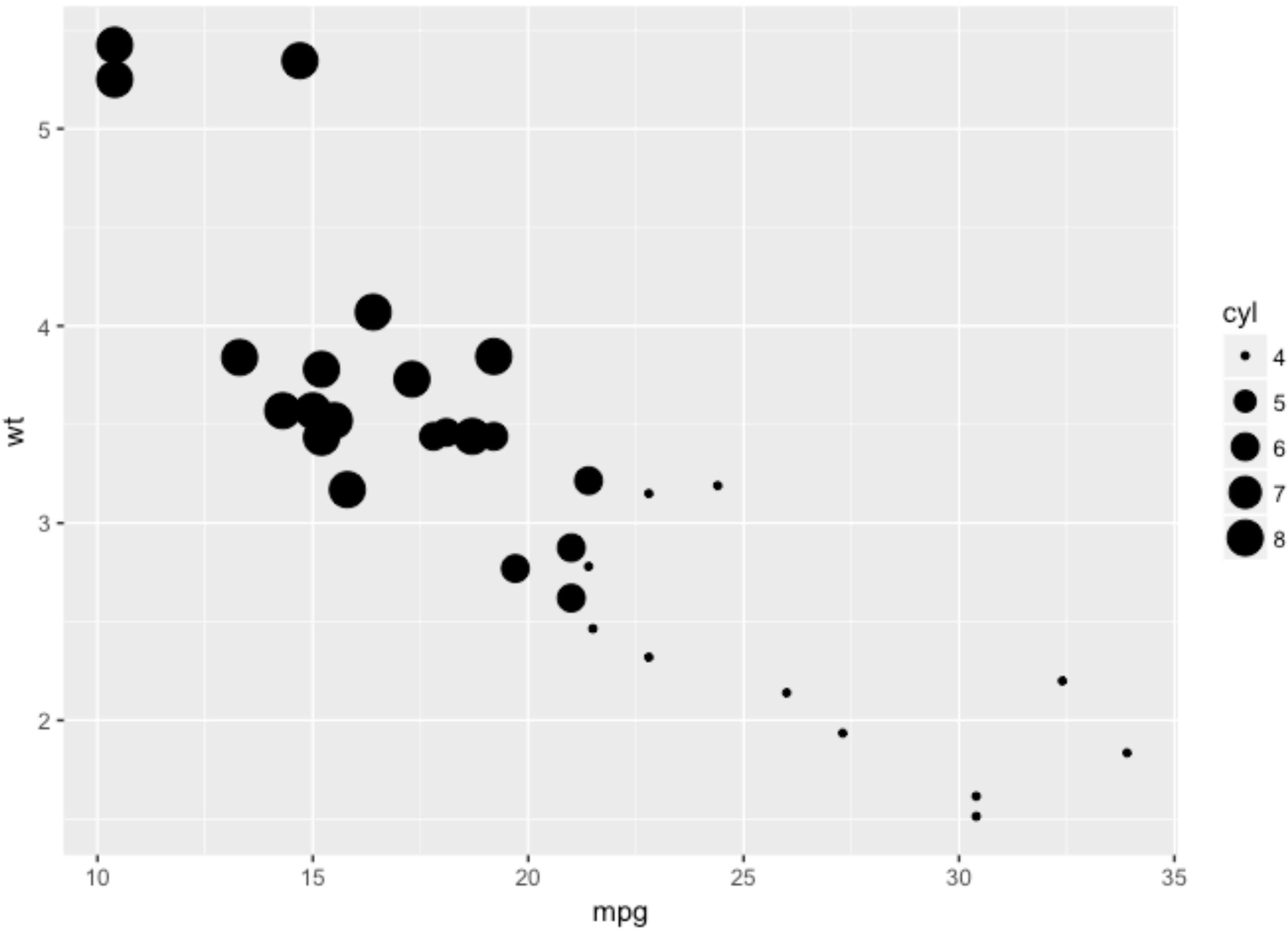
```
##
## qplot> # Use data from data.frame
## qplot> qplot(mpg, wt, data = mtcars)
```



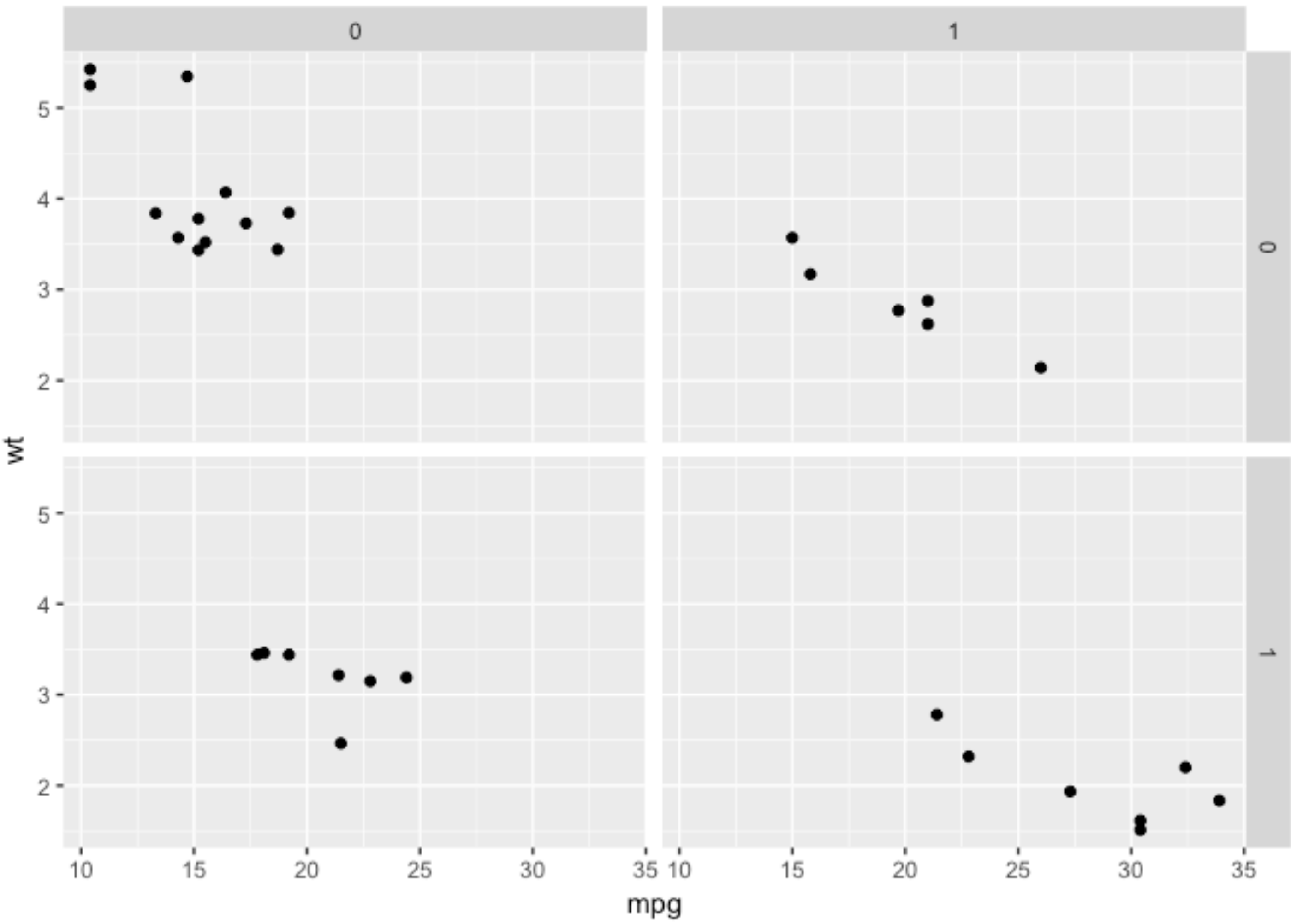

```
##
## qplot> qplot(mpg, wt, data = mtcars, colour = cyl)
```




```
##
## qplot> qplot(mpg, wt, data = mtcars, size = cyl)
```




```
##
## qplot> qplot(mpg, wt, data = mtcars, facets = vs ~ am)
```


0
1
0
1
wt
5
4
3
2
10
15
20
25
30
35
mpg

```
##
## qplot> ## No test:
## qplot> ##D qplot(1:10, rnorm(10), colour = runif(10))
## qplot> ##D qplot(1:10, letters[1:10])
## qplot> ##D mod <- lm(mpg ~ wt, data = mtcars)
## qplot> ##D qplot(resid(mod), fitted(mod))
## qplot> ##D
## qplot> ##D f <- function() {
## qplot> ##D    a <- 1:10
## qplot> ##D    b <- a ^ 2
## qplot> ##D    qplot(a, b)
## qplot> ##D }
## qplot> ##D f()
## qplot> ##D
## qplot> ##D # To set aesthetics, wrap in I()
## qplot> ##D qplot(mpg, wt, data = mtcars, colour = I("red"))
## qplot> ##D
## qplot> ##D # qplot will attempt to guess what geom you want depending on the inp
ut
## qplot> ##D # both x and y supplied = scatterplot
## qplot> ##D qplot(mpg, wt, data = mtcars)
## qplot> ##D # just x supplied = histogram
## qplot> ##D qplot(mpg, data = mtcars)
## qplot> ##D # just y supplied = scatterplot, with x = seq_along(y)
## qplot> ##D qplot(y = mpg, data = mtcars)
## qplot> ##D
## qplot> ##D # Use different geoms
## qplot> ##D qplot(mpg, wt, data = mtcars, geom = "path")
## qplot> ##D qplot(factor(cyl), wt, data = mtcars, geom = c("boxplot", "jitter"))
## qplot> ##D qplot(mpg, data = mtcars, geom = "dotplot")
## qplot> ## End(No test)
## qplot>
## qplot>
## qplot>
```