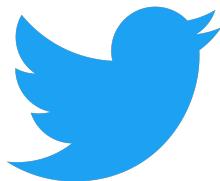


Introduction to

Introduction to



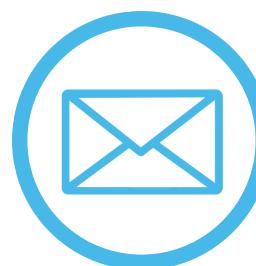
[A]R[RRRRRR]



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<http://www.blue-granite.com/blog>



Our Day...



You can expect to learn:

- The syntax of the R language and basic data types
- One way to ingest data from commonly used sources in business
- One way to prepare data for analytics
- Basic modeling techniques

Before we begin:

1. Make sure you have R installed
2. Make sure you have RStudio installed
3. Clone this GitHub repository:

<https://github.com/joshuafennessy/LearnRInADay>

R and RStudio

R is....

- a **functional** programming language specifically geared towards analytics
- Open Source - covered under the GNU General Public License
- Free (as in beer)*
- Cross-platform
- Delivered by **The Comprehensive R Archive Network (CRAN)**, who provide base R and additional mirrors for a large collection of add-on packages

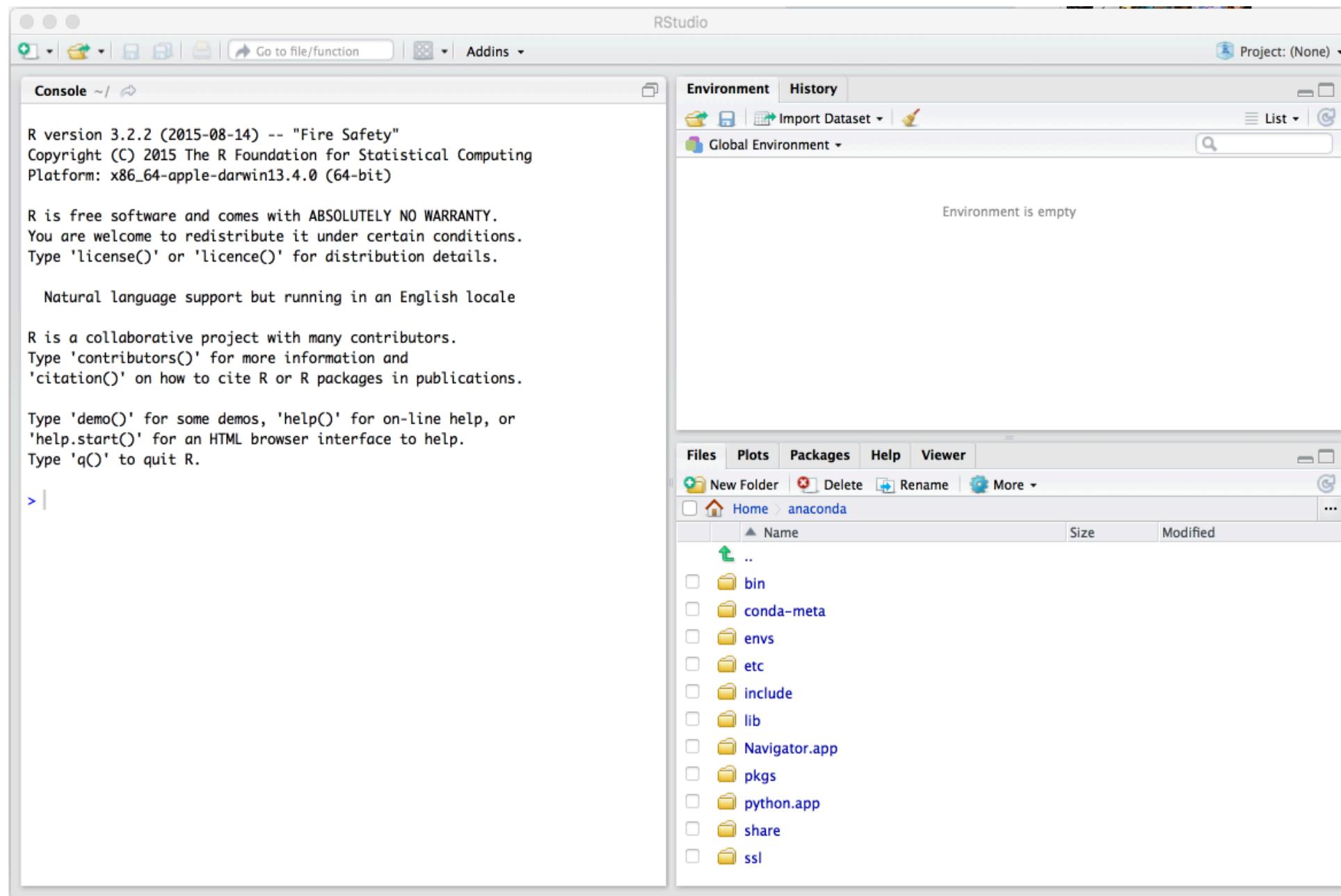
<http://www.cran.r-project.org>

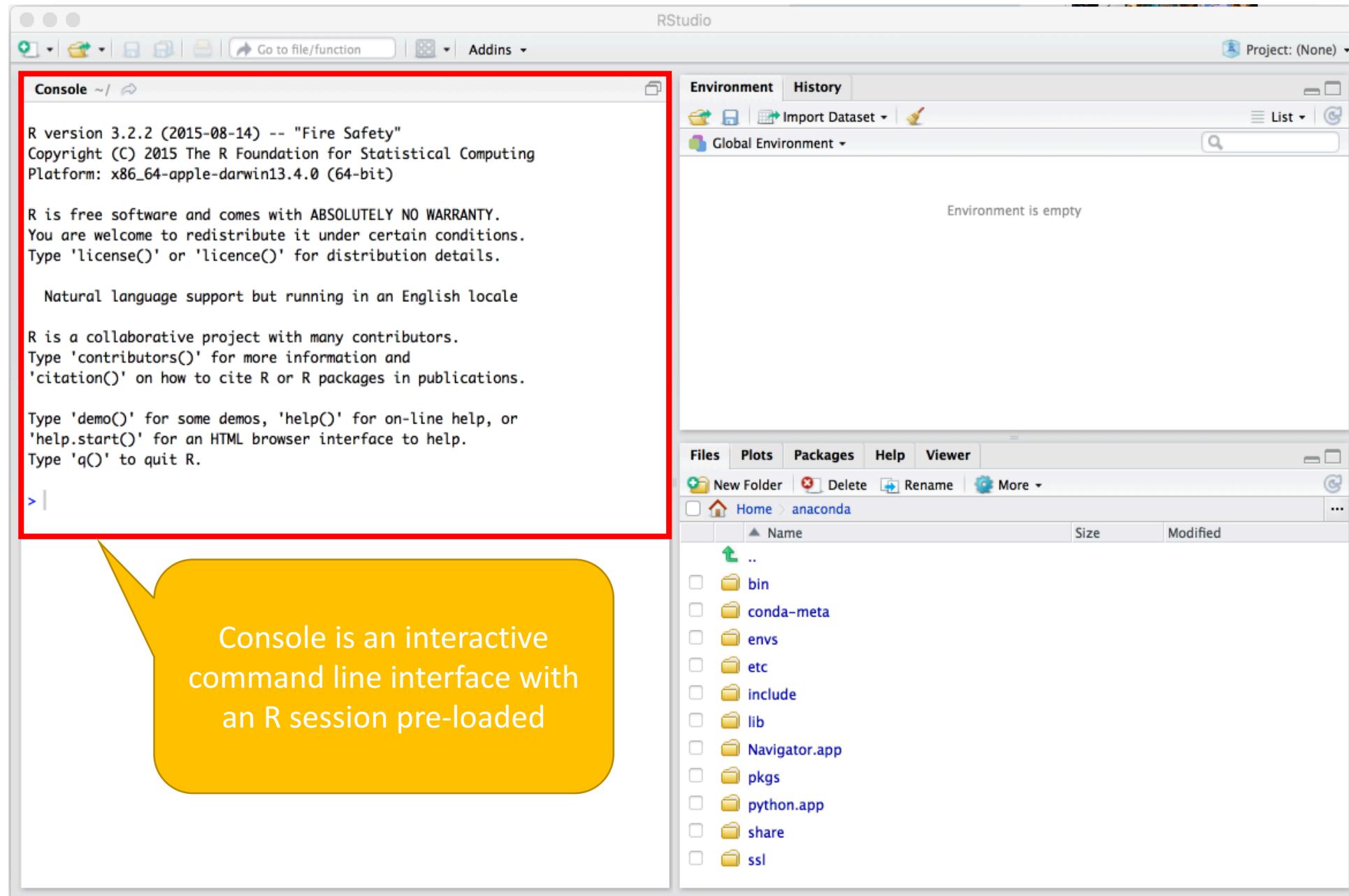
You might choose to get R from Microsoft...

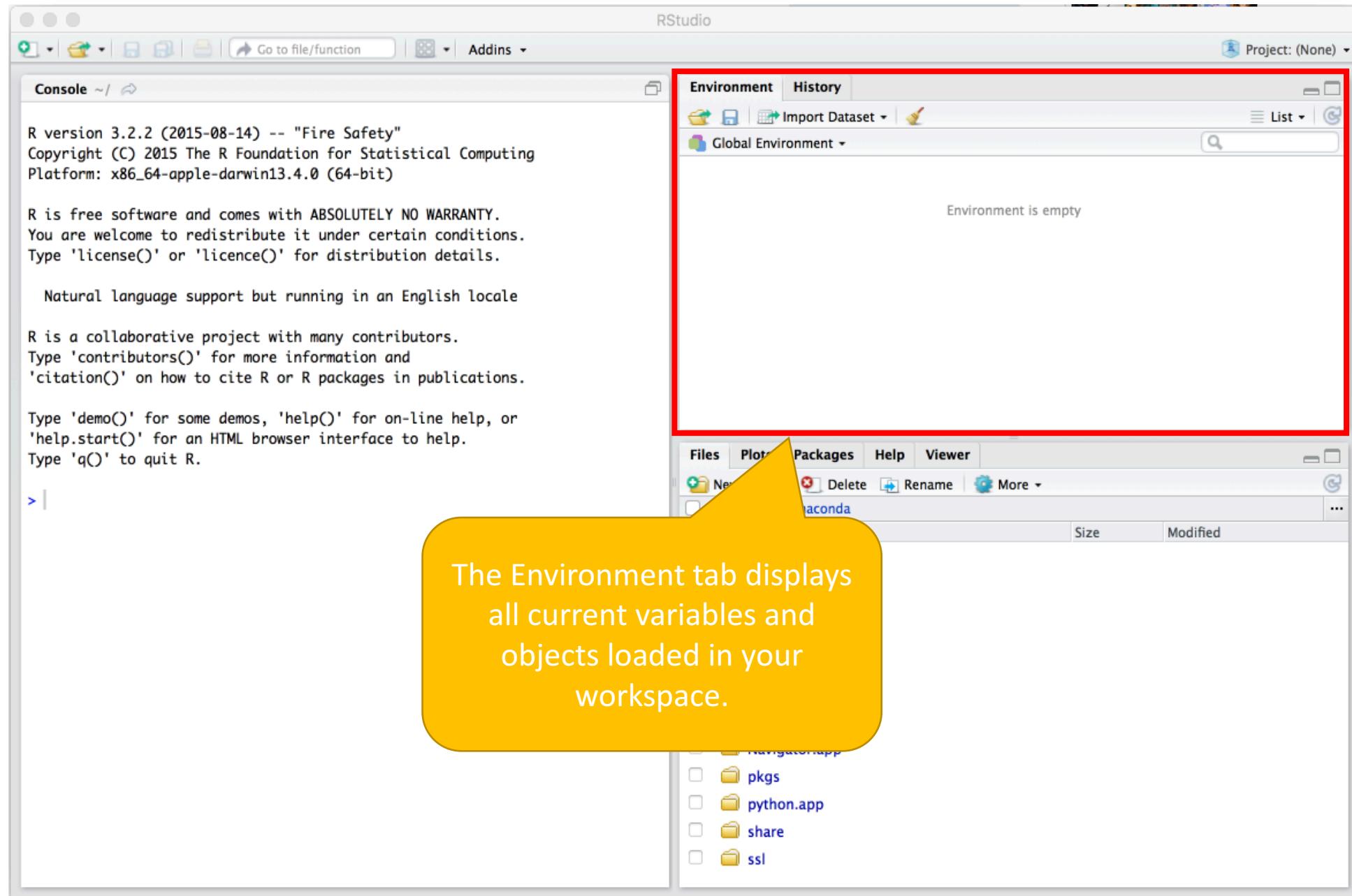
- Fully CRAN compatible
- Performance improvements through the use of multi-core processing
- Static CRAN repository based on the date downloaded
- Included checkpoint package to simplify code sharing and package versioning
- Additional bundled packages that provide additional features to R and aren't included with base R.

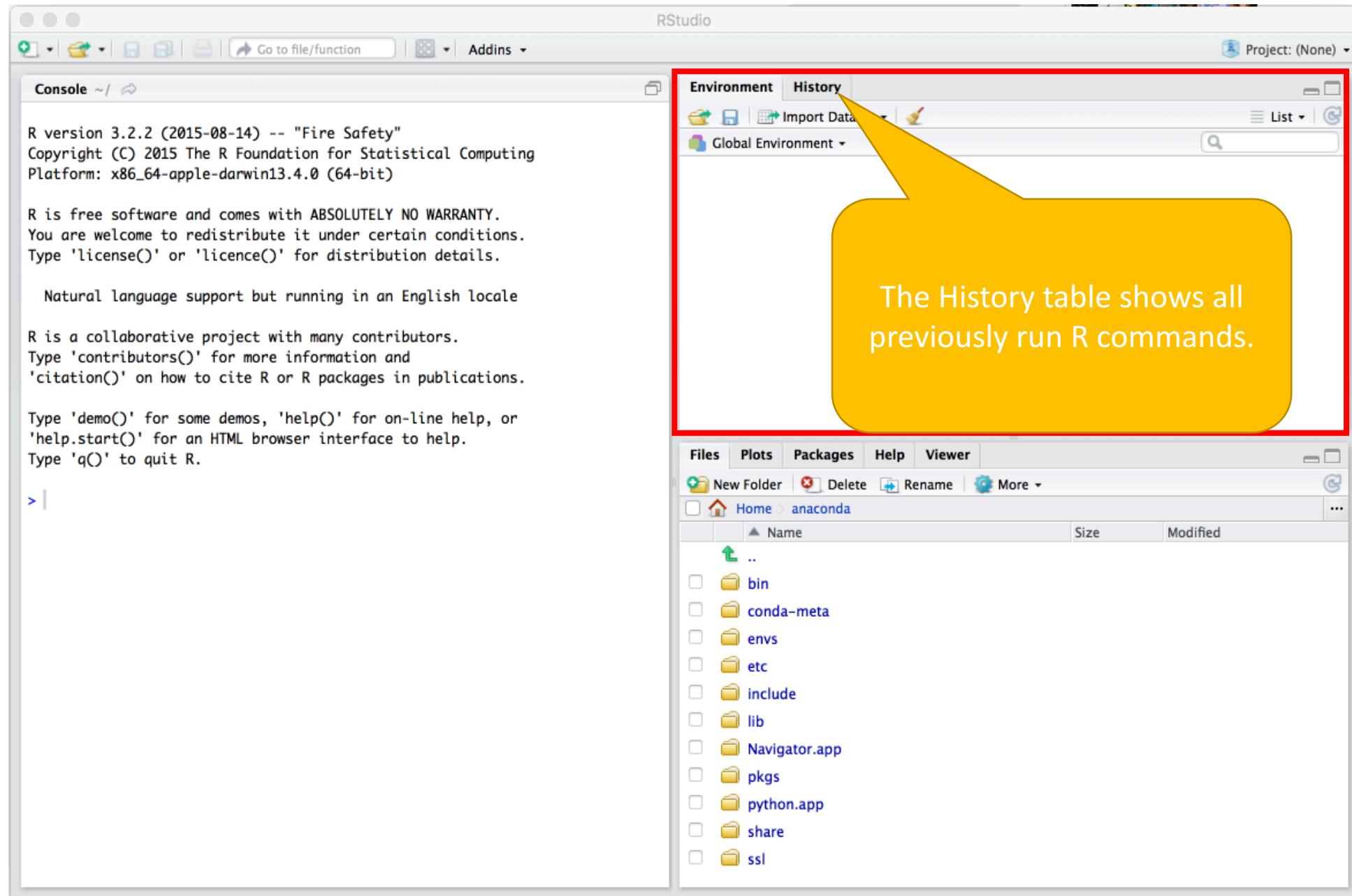
We typically develop R in...

- Rstudio (<http://www.rstudio.com>)
- Installed as a client application (Windows/Mac/*nix) with Free (as in beer) and Enterprise versions available
- Also installed as a server, allowing you to access RStudio in a browser.









RStudio

Console ~/

```
R version 3.2.2 (2015-08-14) -- "Fire Safety"
Copyright (C) 2015 The R Foundation for Statistical Computing
Platform: x86_64-apple-darwin13.4.0 (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.

Natural language support but running in an English locale

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
Type 'q()' to quit

> |
```

This pane shows content in the current working directory. Other tabs will be explained later on

Environment History

Import Dataset

Global Environment

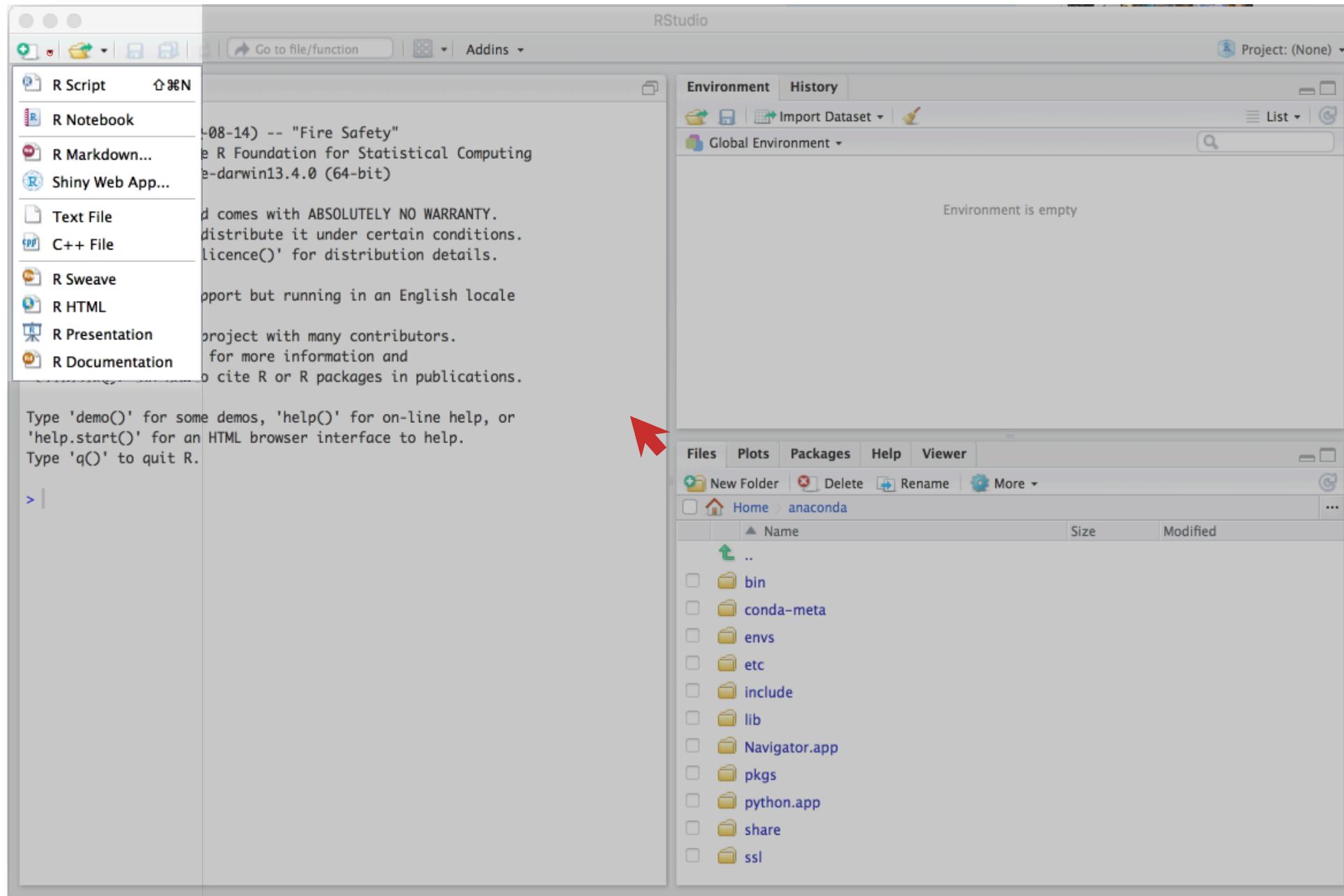
Environment is empty

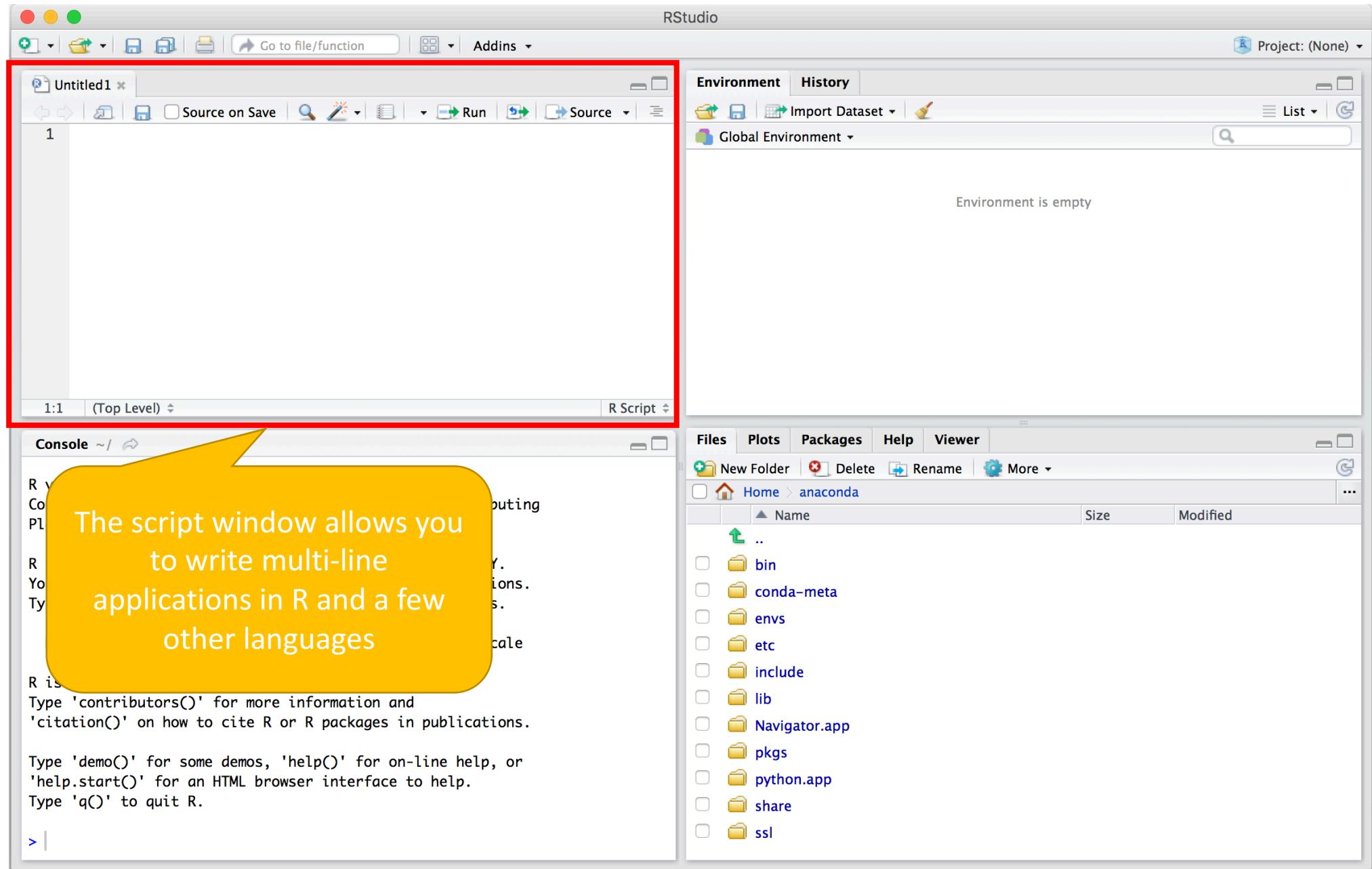
Files Plots Packages Help Viewer

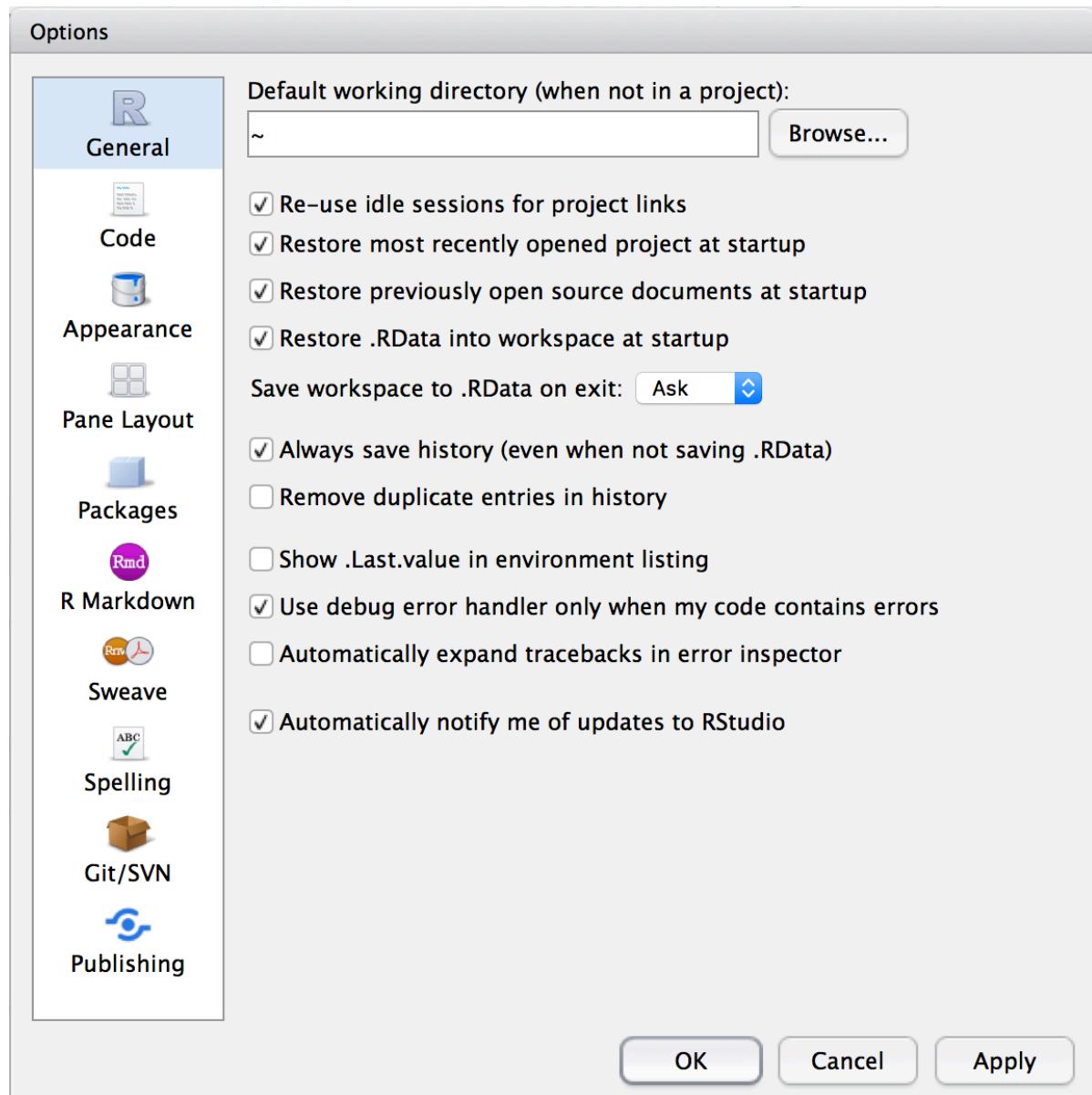
New Folder Delete Rename More

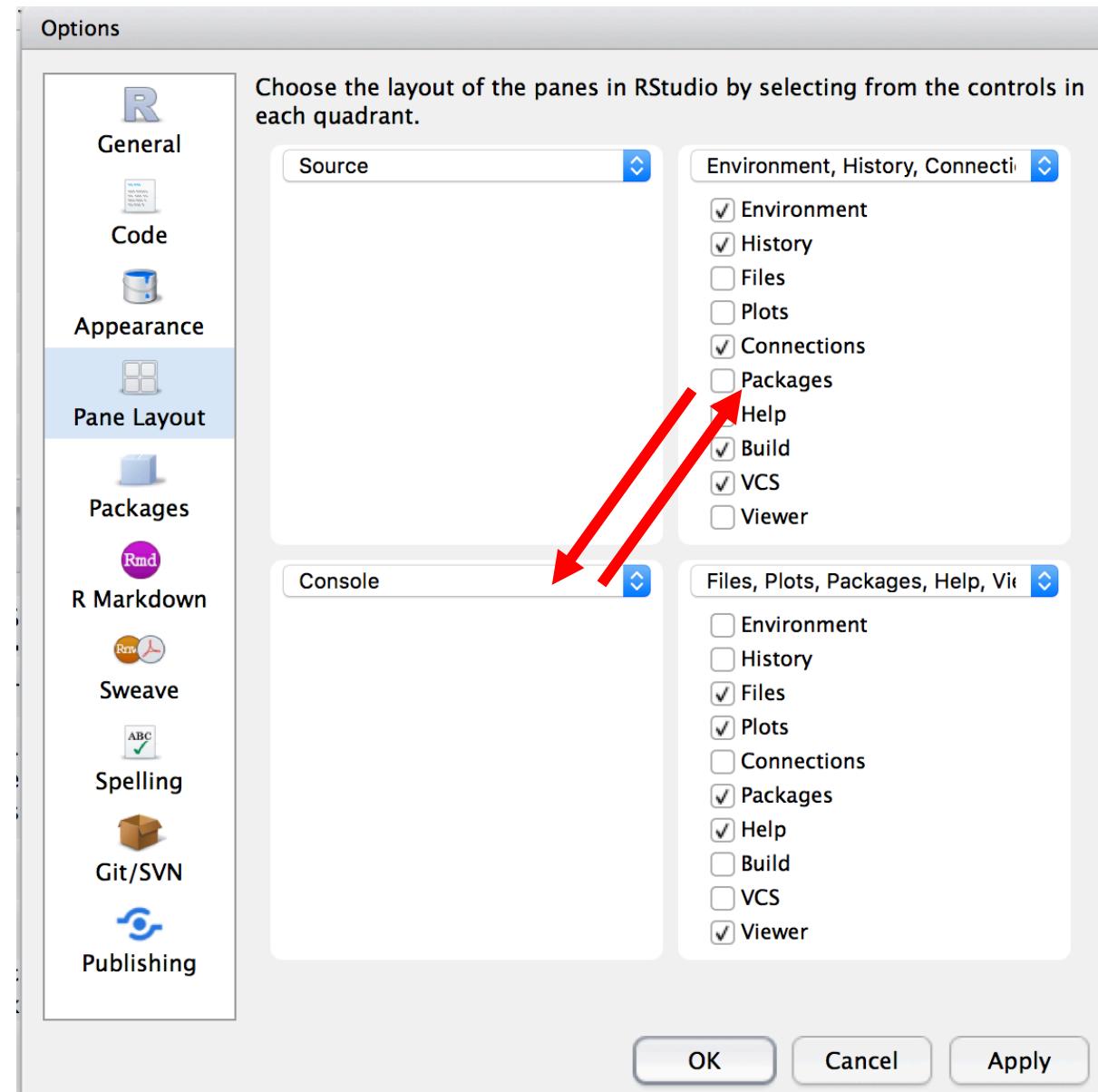
Home > anaconda

	Name	Size	Modified
<input type="checkbox"/>	..		
<input type="checkbox"/>	bin		
<input type="checkbox"/>	conda-meta		
<input type="checkbox"/>	envs		
<input type="checkbox"/>	etc		
<input type="checkbox"/>	include		
<input type="checkbox"/>	lib		
<input type="checkbox"/>	Navigator.app		
<input type="checkbox"/>	pkgs		
<input type="checkbox"/>	python.app		
<input type="checkbox"/>	share		
<input type="checkbox"/>	ssl		









Options



General



Code



Appearance



Pane Layout



Packages



R Markdown



Sweave



Spelling



Git/SVN



Publishing

Choose the layout of the panes in RStudio by selecting from the controls in each quadrant.

Source

Console

Environment, History, Connections

Files, Plots, Packages, Help, Viewer

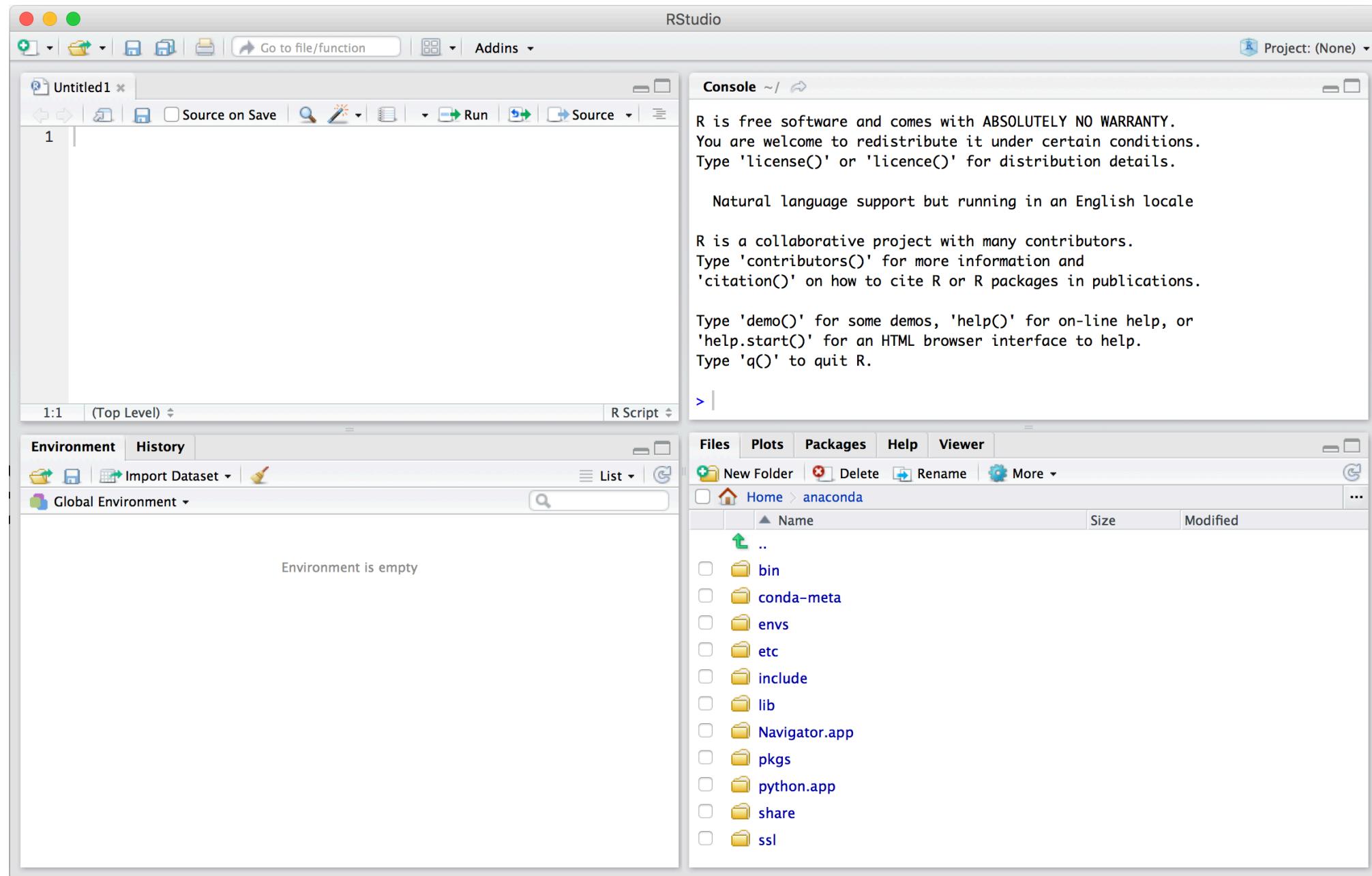
- Environment
- History
- Files
- Plots
- Connections
- Packages
- Help
- Build
- VCS
- Viewer

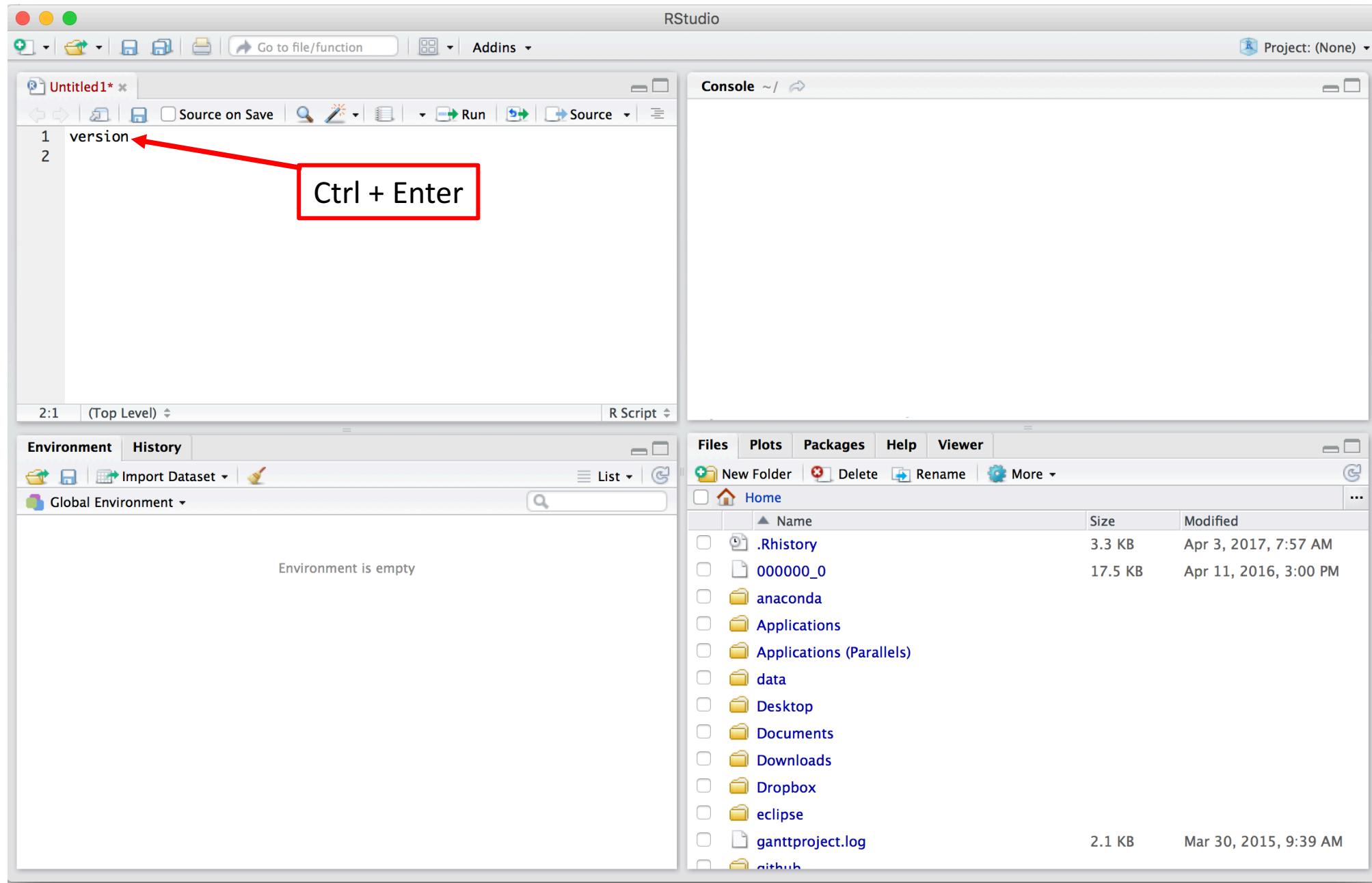
- Environment
- History
- Files
- Plots
- Connections
- Packages
- Help
- Build
- VCS
- Viewer

OK

Cancel

Apply





```
***** COMMODORE 64 BASIC V2 *****  
64K RAM SYSTEM 38911 BASIC BYTES FREE  
READY.  
PRINT "HELLO WORLD!"  
HELLO WORLD!  
READY.
```

R Basics

```
> 1 + 1
```

You can enter commands in
the console

```
> 1 + 1  
[1] 2
```

Enter commands in the console

Results will appear after the command

```
> 1 + 1
```

```
[1] 2
```

```
> print("Hello World")
```

Enter commands in the console

Results will appear after the command

Functions are called with parenthesis

```
> 1 + 1
```

```
[1] 2
```

```
> print("Hello World")
```

```
[1] "Hello World"
```

Enter commands in the console

Results will appear after the command

Functions are called with parenthesis

Functions accept zero to many parameters

```
> x <- 2
```

Variables don't require declaration. Assign with the <- operator.

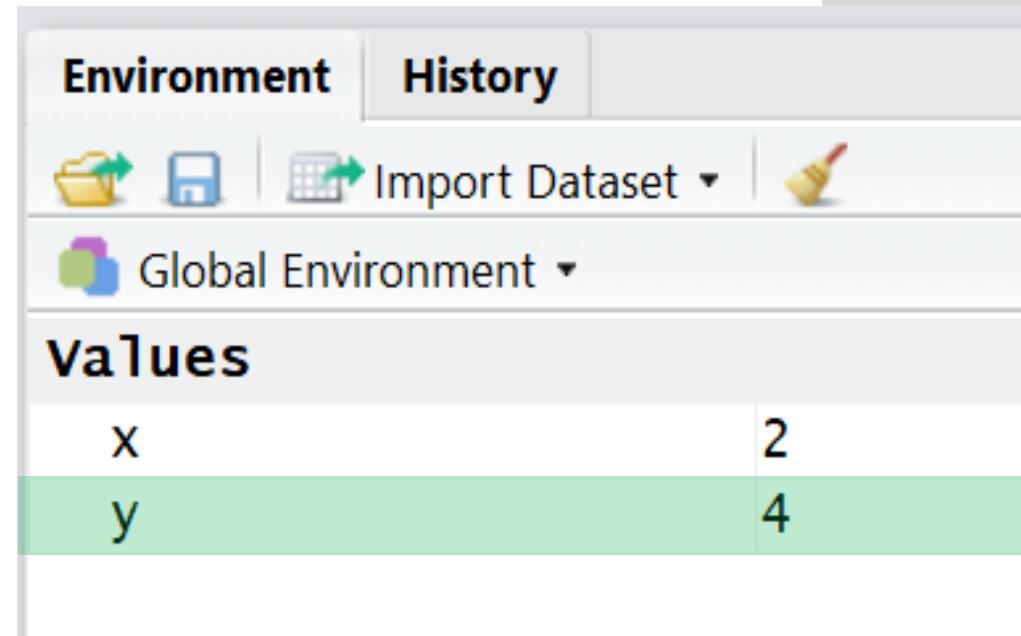
```
> x <- 2  
> y <- x * x
```

Variables don't require declaration. Assign with the `<-` operator.

Variables can be used in future operations.

```
> x <- 2  
> y <- x * x
```

Variables don't require declaration. Assign with the `<-` operator.



The screenshot shows the RStudio interface with the 'Environment' tab selected. The 'Values' section displays two variables: 'x' with the value '2' and 'y' with the value '4'. The row for 'y' is highlighted with a green background.

Values	
x	2
y	4

Variables can be used in operations.

```
> x <- 2  
> y <- x * x
```

Variables don't require declaration. Assign with the `<-` operator.

```
> (y <- x * x * x)
```

Variables can be used in future operations.

Variables can be overwritten

```
> x <- 2  
> y <- x * x
```

Variables don't require declaration. Assign with the `<-` operator.

```
> (y <- x * x * x)  
[1] 8
```

Variables can be used in future operations.

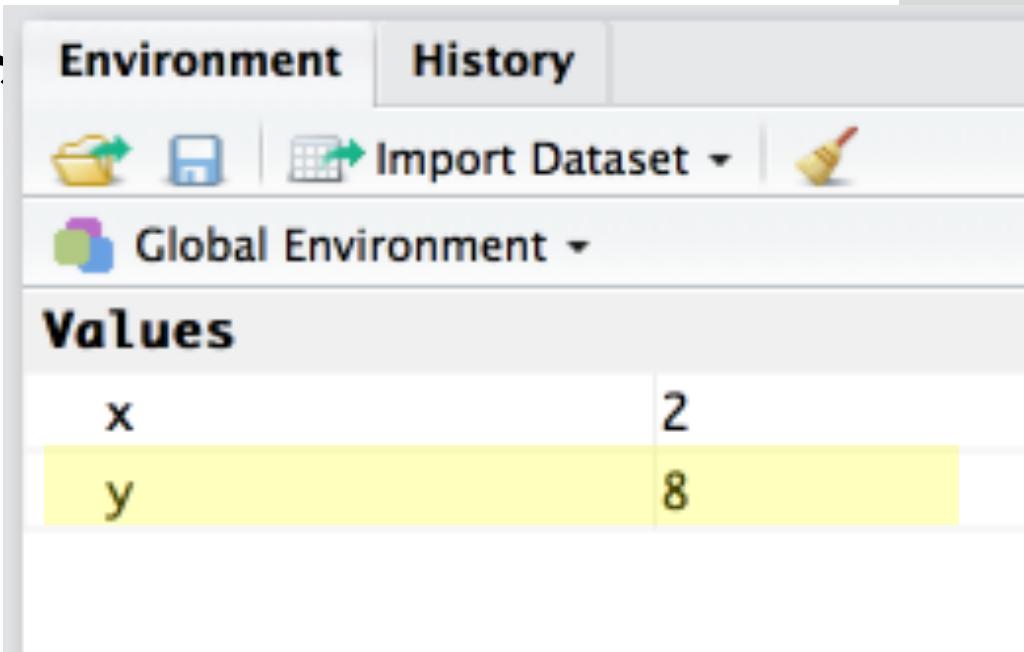
Variables can be overwritten

Wrapping commands in parenthesis forces console output

```
> x <- 2  
> y <- x * x
```

Variables don't require declaration. Assign with the `<-` operator.

```
> (y <- x  
[1] 8
```



The screenshot shows the RStudio interface with the 'Environment' tab selected. The 'Global Environment' dropdown is open. A table titled 'Values' lists two variables: 'x' with value 2 and 'y' with value 8. The row for 'y' is highlighted with a yellow background.

Values	
x	2
y	8

Variables can be used in future operations.

Mapping commands in parenthesis forces console put

```
> x <- 1  
> typeof(x)
```

Data types in R are inferred by the data

```
> x <- 1  
> typeof(x)  
[1] "double"
```

Data types in R are inferred by the data

Numbers are inferred as doubles

```
> x <- 1  
> typeof(x)  
[1] "double"
```

Data types in R are inferred by the data

```
> x <- 1  
> typeof(integer(x))
```

Numbers are inferred as doubles

You can manually coerce data types as needed

```
> x <- 1  
> typeof(x)  
[1] "double"
```

Data types in R are inferred by the data

```
> x <- 1  
> typeof(integer(x))  
[1] "integer"
```

Numbers are inferred as doubles

You can manually coerce data types as needed

Why do this? Integers require less memory than doubles. Or maybe you want to express a number as a character string.

Everything in R is an object.

```
> x <- 1  
> class(x)
```

Everything in R is an object.

```
> x <- 1  
> class(x)  
[1] "numeric"
```

The class function shows what your object is inherited from.

```
> x <- 1  
> class(x)  
[1] "numeric"  
  
> is.numeric(x)
```

Everything in R is stored as an object.

The class function shows what your object is inherited from.

You can also test for classes before performing an operation.

```
> x <- 1  
> class(x)  
[1] "numeric"
```

Everything in R is an object.

The class function shows what your object is inherited from.

```
> is.numeric(x)  
[1] TRUE
```

You can also test for classes before performing an operation.

This is useful for certain types of arithmetic or models

```
> (myvec <- c(1,2,3))
```

The first kind of set is called a **vector**. It's like an array in other languages. It's a set of values, all of the same data type.

```
> (myvec <- c(1,2,3))  
[1] 1 2 3
```

The first kind of set is called a **vector**. It's like an array in other languages. It's a set of values, all of the same data type.

Vectors are created with the **c()** function.

```
> (myvec <- c(1,2,3))  
[1] 1 2 3
```

The first kind of set is called a vector. It's like an array in other languages. It's a set of values, all of the same data type.

```
> str(myvec)
```

Vectors are created with the `c()` function.

The `str()` function shows an object's structure

```
> (myvec <- c(1,2,3))  
[1] 1 2 3
```

The first kind of set is called a **vector**. It's like an array in other languages. It's a set of values, all of the same data type.

```
> str(myvec)  
num [1:3] 1 2 3
```

Vectors are created with the `c()` function.

The `str()` function shows an object's structure

myvec has one row and three columns; stored as numeric

```
> v2 <- c("a", "b", "c")
> str(v2)
```

Here is another vector, but this one has character values.

```
> v2 <- c("a", "b", "c")
> str(v2)
chr [1:3] "a" "b" "c"
```

Here is another vector, but this one has character values.

Like before, `str()` shows the structure of the vector. This time it's stored as characters.

```
> summary(myvec)
```

Summary() is another useful function that will display basic summary information about your object

```
> summary(myvec)
Min. 1st Qu. Median ...
1.0   1.5     2.0 ...
```

Summary() is another useful function that will display basic summary information about your object

Because **myvec** is numeric, summary stats are calculated

```
> summary(myvec)
Min. 1st Qu. Median ...
1.0   1.5     2.0 ...
```

```
> summary(v2)
```

Summary() is another useful function that will display basic summary information about your object

Because **myvec** is numeric, summary stats are calculated

But what about v2, our character vector?

```
> summary(myvec)
```

```
Min. 1st Qu. Median ...  
1.0   1.5     2.0 ...
```

```
> summary(v2)
```

Length	Class	Mode
3	character	character

Summary() is another useful function that will display basic summary information about your object

Because myvec is numeric, summary stats are calculated

But what about v2, our character vector?

Summary shows a different set of information for a character vector

CHALLENGE

Creating a vector

Remember that a vector contains values of the same data type.

What will happen with this vector?

```
> quiz <- c(1, "2", 3)
```

R will raise an error

Vector of numerics

Vector of characters

```
> quiz <- c(1,"2",3)
```

Remember that a vector contains values that are all the same data type.

```
> str(quiz)
```

Reminder: use the `str()` function to examine the structure.

```
> quiz <- c(1,"2",3)
```

Remember that a vector contains values that are all the same data type.

```
> str(quiz)
chr [1:3] "1" "2" "3"
```

Reminder: use the `str()` function to examine the structure.

R will coerce all values in a vector to a common type, in this case, character

```
> lgvec <-  
  sample(1:1000, 100)
```

Sometimes you'll need to select certain values from a vector. Consider this vector with 100 random values.

```
> lgvec <-  
  sample(1:1000, 100)
```

```
> lgvec[75]  
[1] 96
```

Sometimes you'll need to select certain values from a vector. Consider this vector with 100 random values.

Single values can be extracted using an index.

```
> lgvec <-  
  sample(1:1000, 100)
```

Sometimes you'll need to select certain values from a vector. Consider this vector with 100 random values.

```
> lgvec[75]  
[1] 96
```

Single values can be extracted using an index.

```
> lgvec[1:10]  
[1] 642 756 263 463 ...
```

You can also select a range of values. In this example I'm asking for the first 10 values from the vector.

```
> 1gvec > 500
```

Another way to filter is by using a logical condition.

```
> 1gvec > 500  
[1] TRUE TRUE FALSE FA.  
[11] TRUE FALSE FALSE .
```

Another way to filter is by using a logical condition.

This will return a vector containing the response to the condition for each value

```
> 1gvec > 500  
[1] TRUE TRUE FALSE FA.  
[11] TRUE FALSE FALSE .  
  
> gt500 <- 1gvec > 500  
> 1gvec[gt500]
```

Another thing you can do with vector is to filter based on a condition.

This will return a vector containing the response to the condition for each value

So, if you save the result of the condition into an object, you can filter the original integer vector using the logical vector.

```
> lgvec > 500  
[1] TRUE TRUE FALSE FA.  
[11] TRUE FALSE FALSE .  
  
> gt500 <- lgvec > 500  
> lgvec[gt500]  
[1] 642 756 579 536 790  
[16] 525 765 598 577 ...
```

Another thing you can do with vector is to filter based on a condition.

This will return a vector containing the response to the condition for each value

So, if you save the result of the condition into an object, you can filter the original integer vector using the logical vector.

CHALLENGE

Filtering Vectors

Using Igvec (our vector with 100 random integers) return only the even numbers;
Or only the odd numbers, you decide.

-- HINT: R has a mod operator
> 9 %% 3
[1] 0

```
> onlyEven  
<- lgvec %% 2 == 0)
```

Starting with `lgvec`, we first need to build a logical vector containing results of the conditional statement.

```
> onlyEven  
<- lgvec %% 2 == 0)
```

Starting with `lgvec`, we first need to build a logical vector containing results of the conditional statement

```
> lgvec[onlyEven]
```

Now, we simply need to filter `lgvec` by the new logical vector, `onlyEven`

```
> onlyEven  
<- lgvec %% 2 == 0)
```

Starting with `lgvec`, we first need to build a logical vector containing results of the conditional statement

```
> lgvec[onlyEven]
```

Now, we simply need to filter `lgvec` by the new logical vector, `onlyEven`

```
> lgvec[!onlyEven]
```

Did you want to return odd numbers? Easy enough with vector operations

A list is a set of **objects** with varying data types.

```
> l1 <-  
  list(1, "a", 4))
```

A list is a set of objects with varying data types.

```
> l1 <-  
  list(1, "a", 4))
```

[1]
[[1]]

[1] 1

When you create this list, the output you'll see is the value of each list item.

[1]
[[2]]

[1] "a"

[1]
[[3]]

[1] 4

```
> l1 <-  
  list(1, "a", 4))
```

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

This is a **list slice** in
position 1

```
[[2]]  
[1] "a"
```

This is the first value
in slice 2

```
[[3]]  
[1] 4
```

A list is a set of objects with
varying data types.

When you create this list,
the output you'll see is the
value of each list item.

Since a list can contain
different object types, it's
organized differently than a
vector

```
> 11[2]
```

You can select a list slice by using single square brackets.

```
> l1[2]  
[[2]]  
[1] "a"
```

You can select a list slice by using single square brackets

This will return the entire slice.

```
> l1[2]
```

```
[[2]]
```

```
[1] "a"
```

```
> l1[[2]]
```

```
[1] "a"
```

You can select a list slice by using single square brackets

This will return the entire list slice

To select only the value, use two square brackets

```
> typeof(11[2])
```

Let's look at that another way.

```
> typeof(l1[2])  
[1] "list"
```

Let's look at that another way

With single brackets, a list is returned

```
> typeof(l1[2])  
[1] "list"
```

Let's look at that another way

```
> typeof(l1[[2]])  
[1] "character"
```

With single brackets, a list is returned

But with double brackets a string type is returned – the type of the value in slice 2

Now for the big reveal...

```
> v1 <- c("a", "b", "c")
> v2 <- c(1, 2, 3)
> name <- "Josh"
```

Now for the big reveal...

```
> l1 <-  
  list(v1,v2,name)  
[[1]]  
[1] "a"  "b"  "c"  
[[2]]  
[1] 1 2 3  
[[3]]  
[1] "Josh"
```

Lists can contain vectors AND single values. You can mix many types of objects in a list.

CHALLENGE

List Selection

Given list **l1**, return the first item of the second slice. Then return the third item of the first slice.

- Remember single brackets
- vs double brackets
- > l1[[1]] -- returns the object
- > l1[1] - returns a list

```
> vec2 <- 11[[2]]
```

First, remember that the second slice is a numeric vector. Use square brackets to isolate it

```
> vec2 <- 11[[2]]  
> vec2[1]  
[1] 1
```

First, remember that the second slice is a numeric vector. Use square brackets to isolate it

Then, select the first value from the vector object

```
> vec2 <- l1[[2]]  
> vec2[1]  
[1] 1
```

First, remember that the second slice is a numeric vector. Use square brackets to isolate it

```
> l1[[1]][3]  
[1] "c"
```

Then, select the first value from the vector object

Because R is a functional language, you can also shortcut the reference

```
> names(11)  
NULL
```

In the real world, we don't often reference data by index. We name things.

```
> names(11)
```

```
NULL
```

```
> names_11 <-  
  c("letters",  
    "numbers",  
    "me")
```

In the real world, we don't often reference data by index. We name things

To name slices in a list, start by creating a chr vector with the name of each item

```
> names(11) <- names_11
```

Now, pass the new vector of item names, **names_l1**, into the **names()** function

```
> names(l1) <- names_l1  
> l1  
$letters  
[1] "a" "b" "c"  
  
$numbers  
[1] 1 2 3  
  
$me  
[1] "Josh"
```

Now, pass the new vector of item names, `names_l1`, into the `names()` function

Now when you return `l1`, each slice is named using the `$` notation

```
> l1$letters  
[1] "a" "b" "c"
```

Now you can select an object by referencing the name using the "\$" notation

```
> l1$letters  
[1] "a" "b" "c"
```

Now you can select an object by referencing the name using the "\$" notation

```
>str(l1)  
>summary(l1)
```

Have you tried looking at the list structure or summary yet? Give it a shot.

Take a look at this database table. Does it remind you of anything?

	Stock Item Key	Stock Item	Color
1	0	Unknown	N/A
2	1	Void fill 400 L bag (White) 400L	N/A
3	2	Void fill 300 L bag (White) 300L	N/A
4	3	Void fill 200 L bag (White) 200L	N/A
5	4	Void fill 100 L bag (White) 100L	N/A
6	5	Air cushion machine (Blue)	N/A
7	6	Air cushion film 200mmx200mm 325m	N/A
8	7	Air cushion film 200mmx100mm 325m	N/A
9	8	Large replacement blades 18mm	N/A

Take a look at this database table. Does it remind you of anything?

	Stock Item Key	Stock Item	Color
1	0	Unknown	N/A
2	1	Void fill 400 L bag (White) 400L	N/A
3	2	Void fill 300 L bag (White) 300L	N/A
4	3	Void fill 200 L bag (White) 200L	N/A
5	4	Void fill 100 L bag (White) 100L	N/A
6	5	Air cushion machine (Blue)	N/A
7	6	Air cushion film 200mmx200mm 325m	N/A
8	7	Air cushion film 200mmx100mm 325m	N/A
9	8	Large replacement blades 18mm	N/A

The columns kind of look like a vector...

Take a look at this database table. Does it remind you of anything?

	Stock Item Key	Stock Item	Color
1	0	Unknown	N/A
2	1	Void fill 400 L bag (White) 400L	N/A
3	2	Void fill 300 L bag (White) 300L	N/A
4	3	Void fill 200 L bag (White) 200L	N/A
5	4	Void fill 100 L bag (White) 100L	N/A
6	5	Air cushion machine (Blue)	N/A
7	6	Air cushion film 200mmx200mm 325m	N/A
8	7	Air cushion film 200mmx100mm 325m	N/A
9	8	Large replacement blades 18mm	N/A

The columns kind of look like a vector...

A row kind of looks like a list...

Take a look at this database table. Does it remind you of anything?

	Stock Item Key	Stock Item	Color
1	0	Unknown	N/A
2	1	Void fill 400 L bag (White) 400L	N/A
3	2	Void fill 300 L bag (White) 300L	N/A
4	3	Void fill 200 L bag (White) 200L	N/A
5	4	Void fill 100 L bag (White) 100L	N/A
6	5	Air cushion machine (Blue)	N/A
7	6	Air cushion film 200mmx200mm 325m	N/A
8	7	Air cushion film 200mmx100mm 325m	N/A
9	8	Large replacement blades 18mm	N/A

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

The columns kind of look like a vector...

A row kind of looks like a list...

The collection of all rows looks like a list of vectors with named slices...

```
> (d1 <-  
    data.frame(11))  
  letters numbers   me  
1          a         1 Josh  
2          b         2 Josh  
3          c         3 Josh
```

In R, this is called a data.frame, and it's the most important set object you'll use at work.

```
> typeof(d1)  
[1] "list"
```

Under the covers, a
data.frame is stored as a list

```
> typeof(d1)
```

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

```
> class(d1)
```

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

Under the covers, a
data.frame is stored as a list

But it inherits from the
data.frame class, so you'll
get extra functionality on top
of everything you know
about working with a list

```
> typeof(d1)
[1] "list"

> class(d1)
[1] "data.frame"

> str(d1)
> summary(d1)
```

Under the covers, a **data.frame** is stored as a list

But it inherits from the **data.frame** class, so you'll get extra functionality on top of everything you know about working with a list

We'll spend the rest of the course working mostly with **data.frames**. For now, look at the **str()** and **summary()** to get acquainted.

```
> d1[3, ]
```

You can select a single row
of a dataframe

You can select a single row
of a dataframe

```
> d1[3, ]
```

Or, you can select a range of
rows

```
> d1[1:3, ]
```

```
> d1[3, ]
```

You can select a single row
of a data.frame

```
> d1[1:3, ]
```

Or, you can select a range of
rows

```
> d1[1, 1:2]
```

Likewise, you can select
columns along with (or
without rows. Single
columns or ranges are
supported.

```
> d1[3, ]
```

You can select a single row
of a data.frame

```
> d1[1:3, ]
```

Or, you can select a range of
rows

```
> d1[1,1:2]
```

Likewise, you can select
columns along with (or
without rows. Single
columns or ranges are
supported.

```
> d1$field1[1, ]
```

Just like a list, you can
reference column names
with the "\$" notation

Congratulations!

You survived the introduction.



A winner is you!



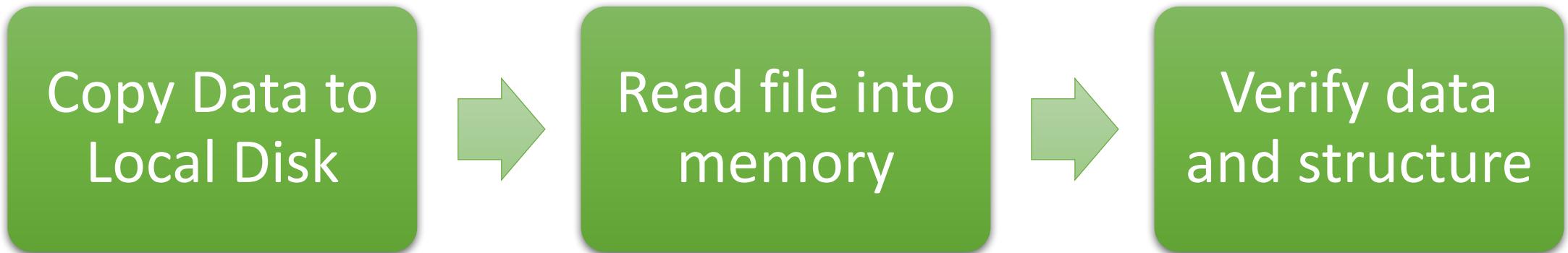
Acquiring Data with R

R can read data from many sources

In this workshop, we'll cover three major types you'll probabaly encounter at work

- CSV
- Excel
- Database

Loading data from files has three main steps





Breaking into secret NYC Taxi servers

Well, maybe we'll just download the CSV file of the open data they provide

```
> getwd()  
[1] "C:/Users/Josh/Documents"
```

R includes functions to manipulate directories and files on local disk

getwd() returns the current working directory

```
> getwd()  
[1] "C:/Users/Josh/Documents"
```

R includes functions to manipulate directories and files on local disk

```
> setwd(tempdir())
```

getwd() returns the current working directory

setwd() allows you to change your working directory -- tempdir() creates a new temp directory

This line sets your current working directory to a new temp directory

```
> getwd()  
[1] "C:/Users/Josh/Documents"
```

```
> setwd(tempdir())
```

```
> getwd()  
[1] "C:/Users/AppData/Local/Temp..."
```

setwd() allows you to change your working directory -- tempdir() creates a new temp directory

This line sets your current working directory to a new temp directory

Your current working directory is now in your system's temp folder

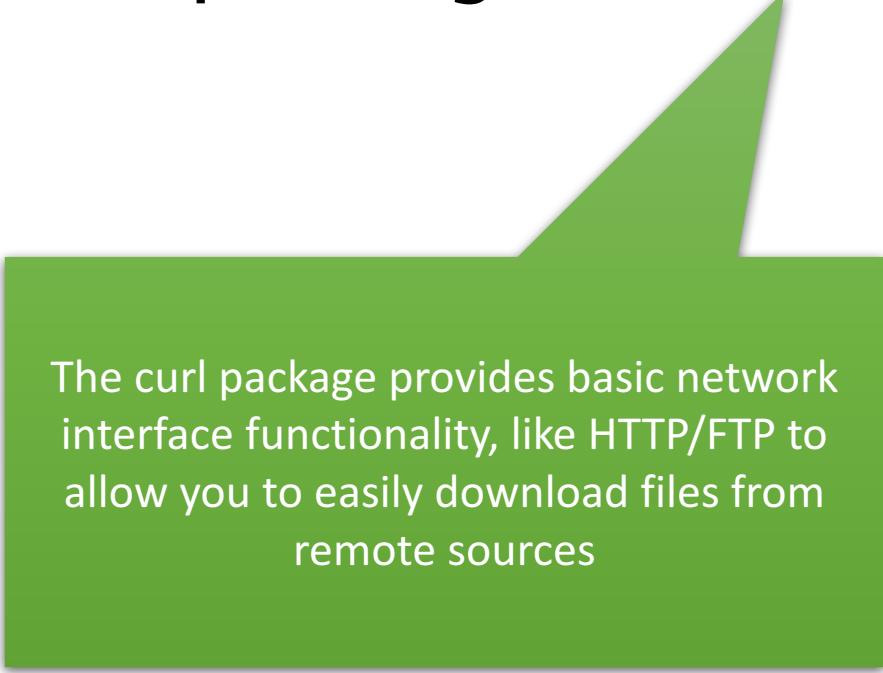
```
-- check if a directory exists  
> dir.exists()
```

```
-- create a new directory  
> dir.create()
```

```
-- build a file path string  
> file.path()  
> file.path(getwd(),  
           "newfile.txt")
```

There are additional functions that help with manipulating directories and files on disk

```
> install.packages("curl")
```



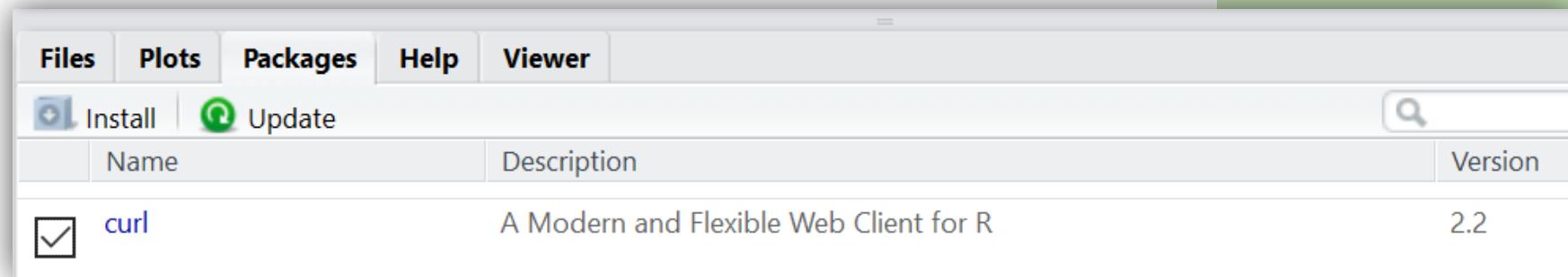
The curl package provides basic network interface functionality, like HTTP/FTP to allow you to easily download files from remote sources

R Packages are developed by the open source community.

Packages first must be installed.

```
> install.packages("curl")
```

```
> library("curl")
```



R Packages are developed by the open source community

Packages first must be installed

ed, load the using the library

```
> install.packages("curl")  
  
> library("curl")  
  
> curl_download(  
    fileToDownload,  
    destfile="file")
```

R Packages are developed by the open source community

Packages first must be installed

Once installed, load the package(s) using the library function

The curl package includes a curl_download() function to download files

Your turn - Download a zipped CSV

1. Create a new Rscript to be used for the workshop
2. Ensure the **curl** package is installed and loaded
3. Set your working directory to a new temp directory
4. Download the file using **curl_download()**
5. BONUS - Unzip the file with the **unzip()** function

https://bgmrstrainingfiles.blob.core.windows.net/lab-data/NYC_sample.zip

Solution - Download a CSV

```
1 install.packages("curl")
2 library("curl")
3
4 Setwd(tempdir())
5 fileurl <- "https://bgmrstrainingfiles.blob.core.windows.net/lab-data/NYC_sample.zip"
6
7 curl_download(fileurl, destfile="NYC_Sample.zip")
8
9
10
```

Explore a file: read the first 3 lines

```
print(readLines(file('NYC_Sample.csv'), n=3))
```

```
[1] "vendorid,tpep_pickup_datetime,tpep_dropoff_datetime,passenger_count,trip_distance,pickup_longitude,fwd_flag,dropoff_longitude,dropoff_latitude,payment_type,fare_amount,extra,mta_tax,improvement_surcharge"  
[2] "1,2016-01-29 09:29:04,2016-01-29 09:39:46,1,1.40,-73.994697570800781,40.725814819335938,1,N,-0.05,1,0,0.3,10.3"  
[3] "1,2016-01-29 09:29:09,2016-01-29 09:37:48,1,2.60,-73.974021911621094,40.746917724609375,1,N,-5,0,0.5,1,0,0.3,12.3"
```

R and CSV files

R prefers "clean" CSV files:

Headers

No-quoted strings

Standard separators

Well formatted line endings

Fill a data frame

Base R

```
target_df <- read.csv('file.csv')
```

Dates read as strings

Slow performance

No feedback

Fill a data frame

A better option

```
install.packages('readr')
library(readr)

target_df <- read_csv(file='file.csv')
```

Your turn – Load the taxi data with *readr*

1. Ensure the **readr** package is installed and loaded
2. Fill a *data.frame*, **nyc_taxi**, using **read_csv()**
3. BONUS - Answer the following questions about **nyc_taxi** using **str()** and **summary()**

How many variables are in **nyc_taxi**?

what is the data type of the **tpep_dropoff_datetime** variable?

what was the largest **tip_amount**?

Solution – Load the taxi data

```
1 install.packages("readr")
2 library("readr")
3
4 nyc_taxi <- read_csv("NYC_Sample.csv")
5
6 ##examine the data.frame structure and data
7 str(nyc_taxi)
8 summary(nyc_taxi)
9
10 ##show first few rows
11 head(nyc_taxi)
12
```



Identifying Holidays

Which happen to be stored in an Excel file

Consuming Excel files

Excel files can be a challenge:

Data in arbitrary locations

	A	B	C	D	E
1					
2	Kids				
3	Name	Age			
4	Sam	8			
5	James	6			
6	Tiffany	11	Parents		
7	Jack	13	Name	Age	
8			Josh	37	
9			Ned	26	
10			Staci	25	
11			Monica	31	
12					
13					

Multiple Sheets

29
30
31
◀ ▶ Store 17 Sales Store 182 Sales Store 24 Sales Store 48 Sales West Region Forecast Jim's Baseball Card Collection

Consuming Excel files

Readxl package

```
install.packages("readxl")
library("readxl")
```

Consuming Excel files

Readxl package

```
##read one sheet of a file
read_excel("file.xlsx", sheet = "sheet 1")
read_excel("file.xlsx",
           sheet = "Sheet 1",
           range="C25:G75")
```

Consuming Excel files

Readxl package

```
##read multiple sheets  
excel_sheets("file.xlsx") #returns a list  
  
lapply(excel_sheets("file.xlsx"),  
       read_excel,  
       path = "file.xlsx")
```

Your turn – Load the holidays with readXL

1. Ensure the **readXL** package is installed and loaded
2. Fill a *data.frame*, **holidays**, using **read_excel()**
3. BONUS - Answer the following questions about **holidays**

How many observations are in **holidays**?

which `holidayname` is in the 13th row?

what **date** is exactly in the middle of the **data.frame**?

Solution – Load the taxi data

```
1 install.packages("readxl")
2 library("readxl")
3
4 holidays <- read_excel("holidays.xlsx")
5
6 ##examine the data.frame structure and data
7 str(holidays)
8 summary(holidays)
9
10 ##peek at the 13th row
11 holidays[13,]
12
```



WET

Tuesday

COOLER

SNOW

MIX

MONTREAL

SHOWERS

NEW YORK

Don't check the weather

Actually, do check it, it might come in handy for our analysis

Connecting to a database

In order to build business ready R applications,
we'll need to be able to connect to a database.



Connecting to a database

RODBC package

```
install.packages("RODBC")
library("RODBC")
```

NOTE ** You may have to install/update unixODBC on Mac or Linux systems

Connecting to a database

Step 1: Make a connection

Using a DSN (System or User)

```
dsn <- "MyDatabaseConnection"  
openChannel <-  
    odbcConnect(dsn=, uid=, pwd=)
```

Using an explicit connection string

```
conStr <- "driver=;server=;database;uid=;pwd="  
openChannel <-  
    odbcDriverConnect(connection=conStr)
```

Connecting to a database

Step 2: Check connection info

Use the channel object created in the connection step

```
odbcGetInfo(openChannel)
```

DBMS_Name	DBMS_Ver
"MySQL"	"5.6.26.0"
Driver_ODBC_Ver	Data_Source_Name
"03.80"	"03.80"
Driver_Name	Driver_Ver
"libmyodbc5w.so"	"05.03.0008"
ODBC_Ver	Server_Name
"03.52.0000" "jf.mysql.database.azure.com via TCP/IP"	

Connecting to a database

Step 3: List tables found in the database

Use the channel object created in the connection step

```
sqlTables(openChannel)
```

	TABLE_CAT	TABLE_SCHEMA	TABLE_NAME	TABLE_TYPE	REMARKS
1	weather		dailyrecords	TABLE	

Connecting to a database

Step 4: Examine table schema

Use the channel object created in the connection step

```
sqlColumns(channel = openChannel,  
           sqtable = "dailyrecords",  
           schema = "weather")
```

TABLE_CAT	TABLE_SCHEMA	TABLE_NAME	COLUMN_NAME	DATA_TYPE	TYPE_NAME	COLUMN_SIZE	BUFFER_LENGTH	DECIMAL_DIGITS
1	<NA>	dailyrecords	id	12	varchar	20	20	NA
2	<NA>	dailyrecords	yyyymmdd	4	integer	10	4	0
3	<NA>	dailyrecords	prcp	3	decimal	12	14	9
4	<NA>	dailyrecords	tmax	3	decimal	6	8	2
5	<NA>	dailyrecords	tmin	3	decimal	6	8	2
				NUM_PREC_RADIX	NULLABLE	REMARKS	COLUMN_DEF	SQL_DATA_TYPE
								SQL_DATETIME_SUB
1	NA	1	<NA>	12		NA		20
2	10	1	<NA>	4		NA		NA
3	10	1	<NA>	3		NA		NA
4	10	1	<NA>	3		NA		NA
5	10	1	<NA>	3		NA		NA
				CHAR_OCTET_LENGTH			ORDINAL_POSITION	
					IS_NULLABLE			
1	YES							
2	YES							
3	YES							
4	YES							
5	YES							

Connecting to a database

Step 5: Read data

Use the channel object created in the connection step

```
sqlFetch(channel = openChannel,  
          sqtable = "[tablename]",  
          schema = "[schema]")
```

Connecting to a database

Additional Functionality

Use the channel object created in the connection step

```
sqlSave() #creates a new table (if not exists)  
          #and appends rows
```

```
sqlUpdate() #updates existing rows in a table
```

```
sqlClear() #removes all rows (TRUNCATE)
```

```
sqlDrop() #drops a table
```

Your turn – Load the holidays data with RODBC

Option 1 – SQL Server

Server: jfdw.database.windows.net

Database: weather

Username: weatherReader

Password: Weather1

1. Ensure the **RODBC** package is installed and loaded
2. Fill a *data.frame*, **weather**,
3. BONUS Questions

How many days had precipitation?

what was the average temp on July 4?

what day had the lowest temp?

Option 2 – MySQL

Server: jf.mysql.database.azure.com

Schema: weather

Username: weatherReader@jf

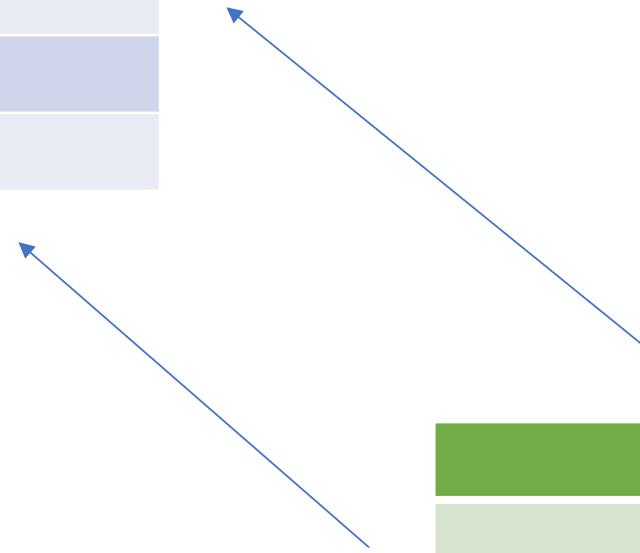
Password: Weather1

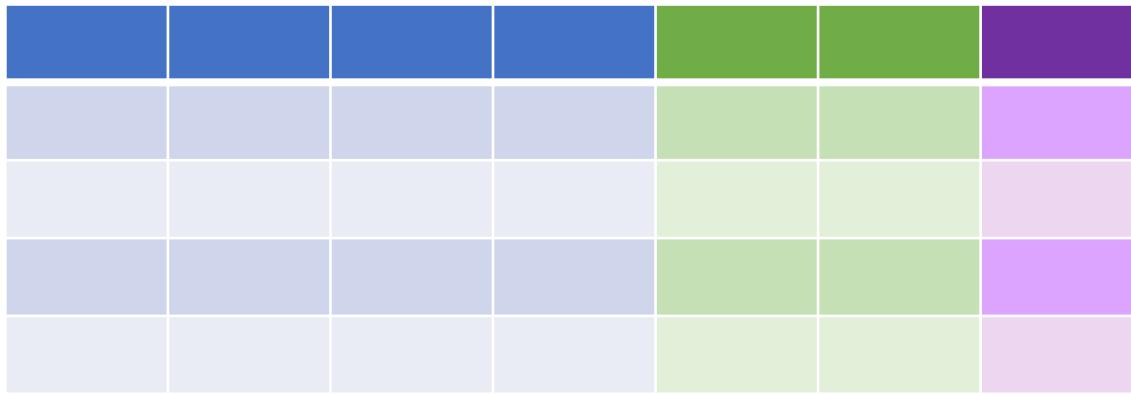
Data Cleansing and Transformation



After data is loaded...

You'll probably have multiple data.frames





The multitool of R Development - dplyr



```
install.packages("dplyr")
library("dplyr")

df <- filter(df, variable1 >= 100)
```

The multitool of R Development - dplyr



```
install.packages("dplyr")
library("dplyr")

df <- filter(df, variable1 >= 100)
```

dplyr function

data.frame (or tibble)

Function arguments

Making hard tasks easier to perform...



```
install.packages("dplyr")
library("dplyr")

df <- select(
  filter(df, variable1 >= 100),
  variable1:variable5)
```

... and read



```
install.packages("dplyr")
library("dplyr")

df <- filter(df, variable1 >= 100) %>%
      select(variable1:variable5)
```



Common tasks

If you want to....

Use the *dplyr* function

Return a subset of rows	<code>filter()</code>
Return a subset of columns	<code>select()</code>
Reorder rows	<code>arrange()</code>
Rename an existing column	<code>rename()</code>
Create a new column	<code>mutate()</code>
Replace an existing column	<code>transmute()</code>
Merge columns of two tables	<code>left_join()</code> , <code>right_join()</code> , <code>inner_join()</code> , <code>full_join()</code>
Find all rows of one table matching rows in another (or vice versa)	<code>semi_join()</code> , <code>anti_join()</code>



dplyr::rename()

Rename one column

```
install.packages("dplyr")
library("dplyr")

df <- rename(df, new_name = old_name)
```



dplyr::rename()

Rename more than one column

```
install.packages("dplyr")
library("dplyr")

df <- rename(df,
              new_name = old_name,
              next_new = next_old)
```



Your turn – rename some columns

1. Here's a softball. Use dplyr to rename the following columns.

- tpep_dropoff_datetime to dropoff_time
- tpep_pickup_datetime to pickup_time



dplyr::select()

Select specific columns

```
install.packages("dplyr")
library("dplyr")

df <- select(df, f1, f2, f3, f4, f5)
```



dplyr::select()

Select a range of columns

```
install.packages("dplyr")
library("dplyr")

df <- select(df, f1:f5)
```



dplyr::select()

Select all columns except

```
install.packages("dplyr")
library("dplyr")

df <- select(df, -c(f6, f7, f8))
```



dplyr::select()

Mix it up...

```
install.packages("dplyr")
library("dplyr")

df <- select(df, f1:f6, -(f4))
```



dplyr::select()

Use a vector to select

```
install.packages("dplyr")
library(dplyr)

colnames <- c("f1", "f2", "f3")
df <- select(df, .dots = colnames)
```

dplyr::select()



vendorid	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	trip_distance		
Min. : 1.000	Min. : 2016-01-01 00:00:03	Min. : 2016-01-01 00:00:11	Min. : 0.00	Min. : 0.0		
1st Qu.: 1.000	1st Qu.: 2016-02-17 20:40:37	1st Qu.: 2016-02-17 20:54:03	1st Qu.: 1.00	1st Qu.: 1.0		
Median : 2.000	Median : 2016-04-01 17:24:37	Median : 2016-04-01 17:41:41	Median : 1.00	Median : 1.7		
Mean : 1.531	Mean : 2016-04-01 12:58:44	Mean : 2016-04-01 13:14:36	Mean : 1.66	Mean : 4.4		
3rd Qu.: 2.000	3rd Qu.: 2016-05-15 08:52:33	3rd Qu.: 2016-05-15 09:07:12	3rd Qu.: 2.00	3rd Qu.: 3.2		
Max. : 2.000	Max. : 2016-06-30 23:59:52	Max. : 2016-07-01 21:48:41	Max. : 9.00	Max. : 1587540.0		
pickup_longitude	pickup_latitude	ratecodeid	store_and_fwd_flag	dropoff_longitude	dropoff_latitude	payment_type
Min. :-121.93	Min. : 0.00	Min. : 1.000	Length:1388631	Min. :-121.93	Min. : 0.00	Min. : 1.000
1st Qu.: -73.99	1st Qu.: 40.74	1st Qu.: 1.000	Class :character	1st Qu.: -73.99	1st Qu.: 40.73	1st Qu.: 1.000
Median : -73.98	Median : 40.75	Median : 1.000	Mode :character	Median : -73.98	Median : 40.75	Median : 1.000
Mean : -72.93	Mean : 40.18	Mean : 1.052		Mean : -73.00	Mean : 40.21	Mean : 1.343
3rd Qu.: -73.97	3rd Qu.: 40.77	3rd Qu.: 1.000		3rd Qu.: -73.96	3rd Qu.: 40.77	3rd Qu.: 2.000
Max. : 0.00	Max. : 48.51	Max. : 99.000		Max. : 0.00	Max. : 44.62	Max. : 4.000
fare_amount	extra	mta_tax	improvement_surcharge	tip_amount	tolls_amount	
Min. :-198.00	Min. :-16.6100	Min. :-1.0000	Min. :-14.320	Min. :-10.5000	Min. :-0.3000	
1st Qu.: 6.50	1st Qu.: 0.0000	1st Qu.: 0.5000	1st Qu.: 0.000	1st Qu.: 0.0000	1st Qu.: 0.3000	
Median : 9.50	Median : 0.0000	Median : 0.5000	Median : 1.330	Median : 0.0000	Median : 0.3000	
Mean : 12.88	Mean : 0.3323	Mean : 0.4975	Mean : 1.801	Mean : 0.3195	Mean : 0.2997	
3rd Qu.: 14.50	3rd Qu.: 0.5000	3rd Qu.: 0.5000	3rd Qu.: 2.360	3rd Qu.: 0.0000	3rd Qu.: 0.3000	
Max. : 3013.50	Max. : 51.0000	Max. : 17.4100	Max. : 399.990	Max. : 905.6200	Max. : 0.7600	
total_amount						
Min. :-208.80						
1st Qu.: 8.75						
Median : 11.80						
Mean : 16.13						
3rd Qu.: 17.80						
Max. : 3014.30						

Your turn – clean up columns with select()

1. Ensure the dplyr packages in installed and loaded
2. Using dplyr, devise three (3) ways to remove the following columns from nyc_taxi
 - vendorid
 - Ratecodeid
 - Store_and_fwd_flag
 - Payment_type



dplyr::filter()

Select rows based on a single condition

```
install.packages("dplyr")
library("dplyr")

df <- filter(sales, total_price >= 100.00)
```



dplyr::filter()

Select rows based on multiple conditions

```
install.packages("dplyr")
library("dplyr")

df <- filter(sales,
             total_price >= 100.00,
             store_name = "Grand Rapids")
```



dplyr::filter()

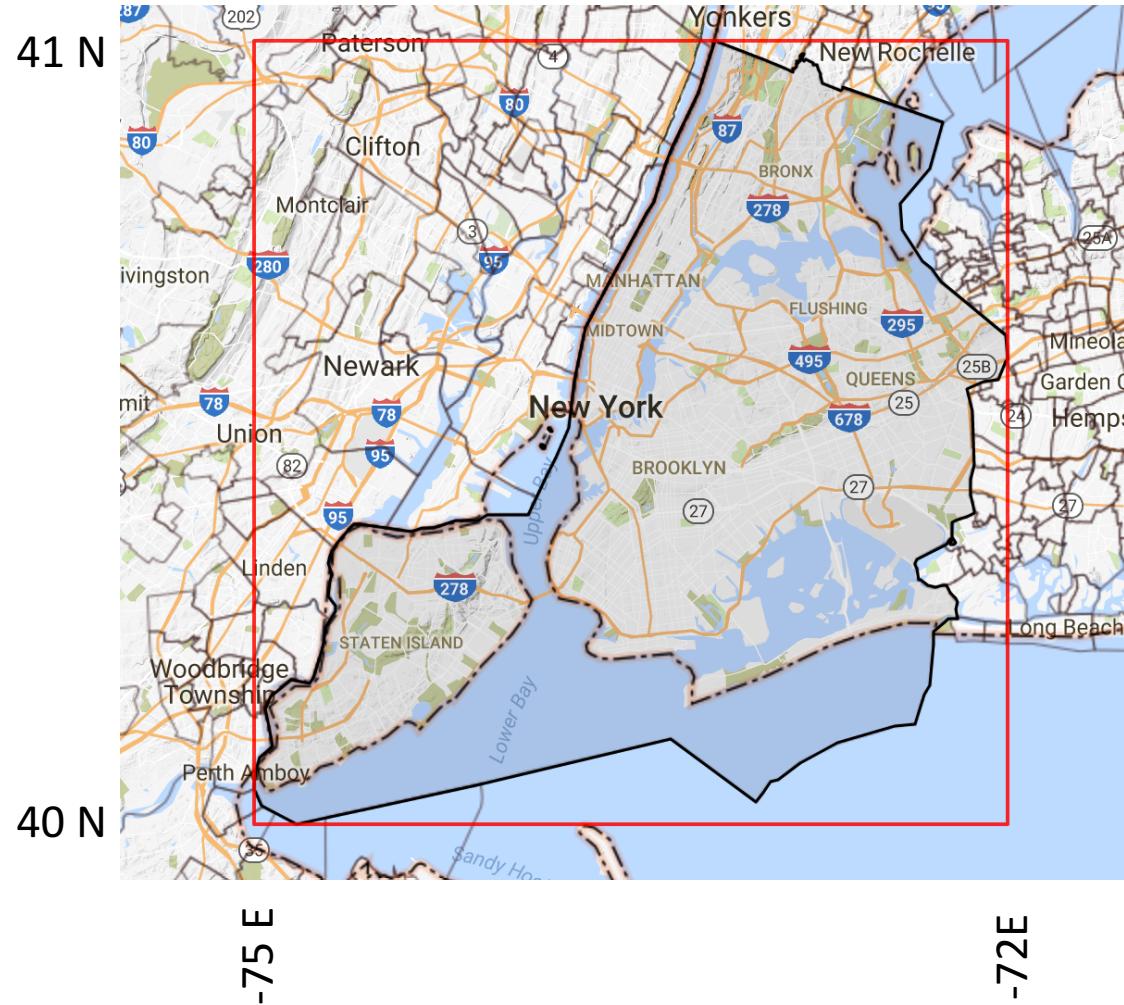
Select rows based on multiple conditions using std logic

```
install.packages("dplyr")
library(dplyr)

df <- filter(sales,
             total_price >= 100.00 ||
             store_name = "Grand Rapids")
```

dplyr::filter()

Let's take a look at a lat/long values





dplyr::filter()

Let's take a look at a lat/long values

```
summary(nyc_taxi[ , grep('long|lat', names(nyc_taxi), value = TRUE)])
```

pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude
Min. :-121.93	Min. : 0.00	Min. :-121.93	Min. : 0.00
1st Qu.: -73.99	1st Qu.:40.74	1st Qu.: -73.99	1st Qu.:40.73
Median : -73.98	Median :40.75	Median : -73.98	Median :40.75
Mean : -72.93	Mean :40.18	Mean : -73.00	Mean :40.21
3rd Qu.: -73.97	3rd Qu.:40.77	3rd Qu.: -73.96	3rd Qu.:40.77
Max. : 0.00	Max. :48.51	Max. : 0.00	Max. :44.62



Your turn – get rid of bad rows with filter()

1. Ensure the dplyr packages in installed and loaded
2. Using dplyr, filter the nyc_taxi data.frame to only include rows that fall within our geofence boundaries of (40N, -75E) and (41N, -72E)

*Remember that our data includes pickup and dropoff locations



Your turn – uh-oh we've found more bad rows

1. Good job filtering out bad locations. But we've found some bad values too. `total_amount` should be a positive number
2. Modify your filter to ensure that only rows with positive `total_amount` are included



dplyr::*_join()

Joins are used to merge two datasets together and combine their columns. Join will match on common variable names

```
install.packages("dplyr")
library("dplyr")

df1 <- left_join(df1, df2)
```



dplyr::*_join()

Control which variables are used for matching

```
install.packages("dplyr")
library("dplyr")

df1 <- left_join(df1, df2, by = c("a", "b"))
```



dplyr::*_join()

Specify a non-matching variable name

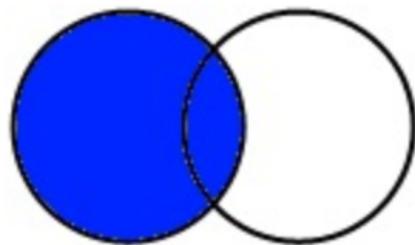
```
install.packages("dplyr")
library("dplyr")

df1 <- left_join(df1, df2, by = c("a" = "b"))
```

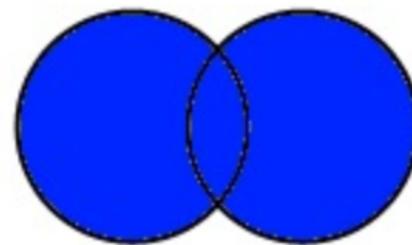
dplyr::*_join()

dplyr supports the following join types

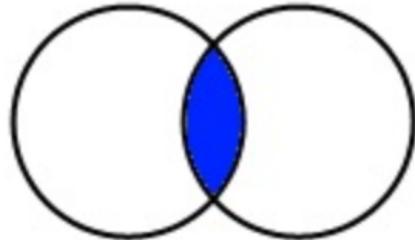
LEFT JOIN



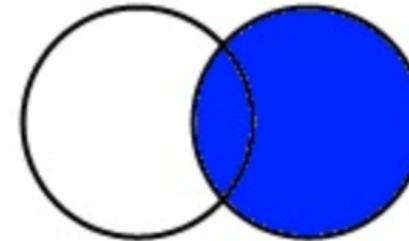
FULL OUTER JOIN



INNER JOIN



RIGHT JOIN





dplyr::*_join()

dplyr supports the following join types

`semi_join`: return all rows from `tbl1` where matched in `tbl2`. Only return columns from `tbl1`

`anti_join`: return all rows from `tbl1` where NOT matched in `tbl2`. Only return columns from `tbl1`



dplyr::mutate()

Mutate adds a new column to a data.frame using an expression

```
install.packages("dplyr")
library("dplyr")

sales <- mutate(sales,
                20percdisc = sale_amt * .8)
```



dplyr::mutate()

You can also use logic to create a new value

```
install.packages("dplyr")
library(dplyr)

sales <- mutate(sales,
                freq_shopper =
                  if_else(numVisits > 10, TRUE, FALSE)
              )
```



*dplyr::mutate() and dplyr::*_join()*

Often a new key needs to be created for a join

```
install.packages("dplyr")
library(dplyr)

sales <- mutate(sales,
                 datekey = year(saleDate))
)
sales <- join (sales, storeHours, by=c("datekey" = "date"))
```



Your turn – join nyc_taxi to holidays

1. Use mutate to create a integer based date based on pickup_time (hint load the lubridate package first).

```
year() * 10000 + month() * 100 + day()
```

2. left_join() to the holidays data.frame using the new column matched with the date column of holidays



Your turn – join nyc_taxi to weather

1. Now join nyc_taxi to the weather table using the pickup_time column.
2. Do you need to mutate again, or can you do it by building on your previous work?
3. Check to see if there are any columns that you can get rid of.



Engineering features with dplyr

Two functions for engineering features
mutate when you want to add a new column

```
install.packages("dplyr")
library("dplyr")

sales <- mutate(sales,
                datekey = year(saleDate),
                monthKey = datekey / 100)
            )
```



Engineering features with dplyr

Two functions for engineering features
transmute when you want to replace all columns

```
install.packages("dplyr")
library("dplyr")

sales <- transmute(sales,
                   discPerc = salePrice / listPrice)
                  )
```



Your turn – engineer some features

1. Use your dplyr skills to engineer the following new features.

Feature Name	Rule
Pickup/dropoff hour	The hour of pickup and dropoff. Hint: use lubridate.
Pickup/dropoff day	The day of pickup and dropoff. Hint: use lubridate.
isWetDay	Precipitation was more than .05"
isHoliday	The day was a holiday
tripLength – use integer value	Trips less than .5 mile are short (1), up to 1.5 miles are medium (2), and over 1.5 miles are long (3)
custTipped	Indicates if the customer tipped or not
tipPercent	The tip_amount divided by the fare_amount
isBigTip	The tipPercent is larger than 20%



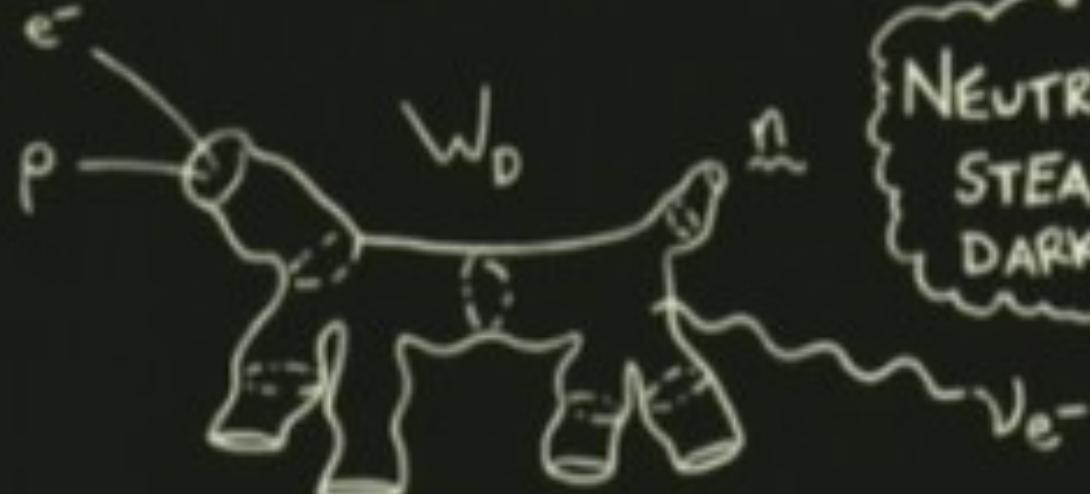
Final piece: adding geospatial features

Just follow along with this section and run the code

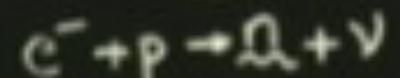
```
install.packages("dplyr")
library("dplyr")

sales <- transmute(sales,
                   discPerc = salePrice / listPrice)
                  )
```

TODAY'S LESSON : W_D OR "WITTEN'S DOG"



NEUTRON ENCRUSTED
STEAMING HOT
DARK MATTER



$$\Omega_{\nu} = \sum_{n=1}^{\infty} \left(\frac{m_n}{93 \text{ eV}} \right)^2 < \Omega_W W_D >$$

"SUPERDUPER SYMMETRIC
STRING THEORY"

Analytics and Modeling



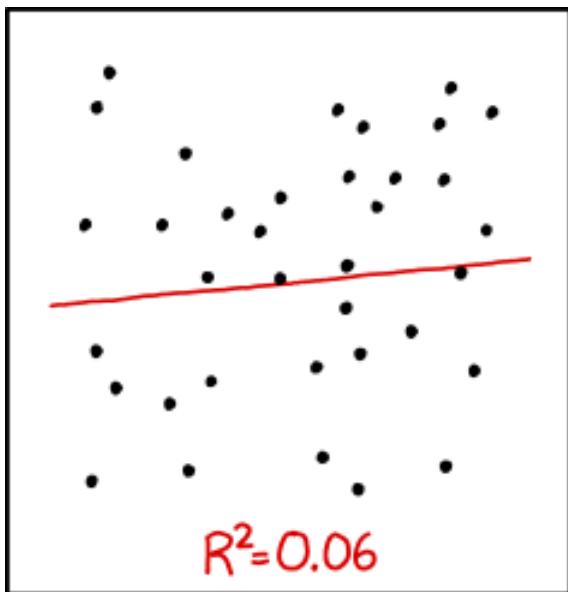
Analytic models

Analytic models are mathematical functions that are used to:

- Predict values
- Classify variables
- Determine probabilities

Prediction

Regression analysis is a common method of predicting an outcome

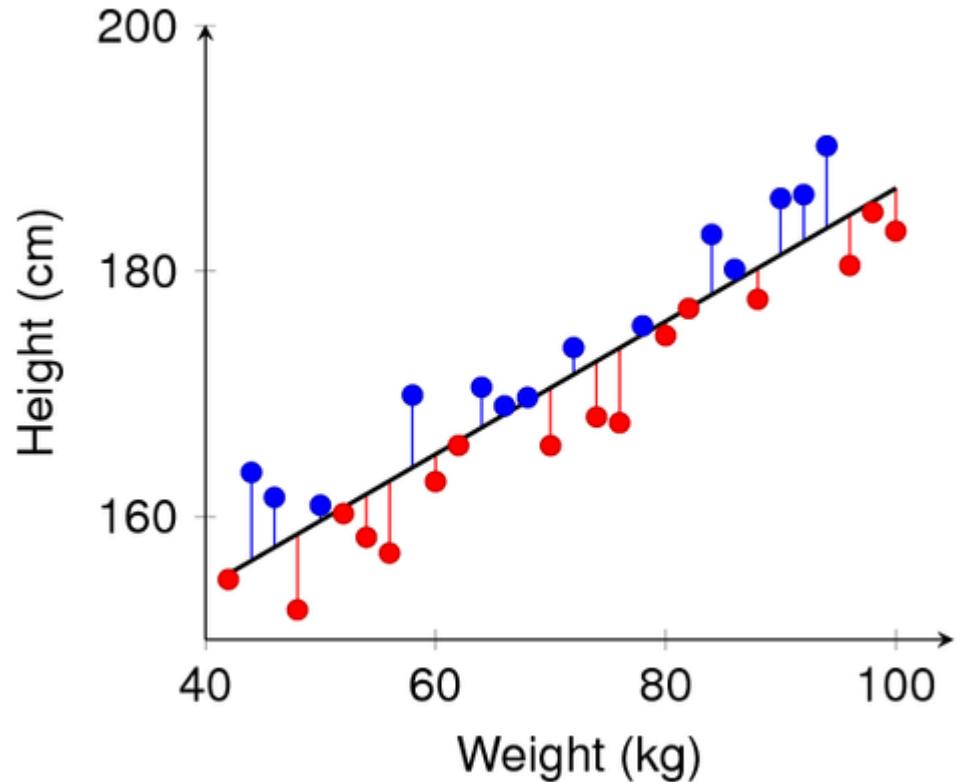


I DON'T TRUST LINEAR REGRESSIONS WHEN IT'S HARDER
TO GUESS THE DIRECTION OF THE CORRELATION FROM THE
SCATTER PLOT THAN TO FIND NEW CONSTELLATIONS ON IT.

Linear regression is good for predicting a continuous variable. Like an amount, or amount of something consumed.

Prediction

Linear regression: slope, intercept, and residuals.

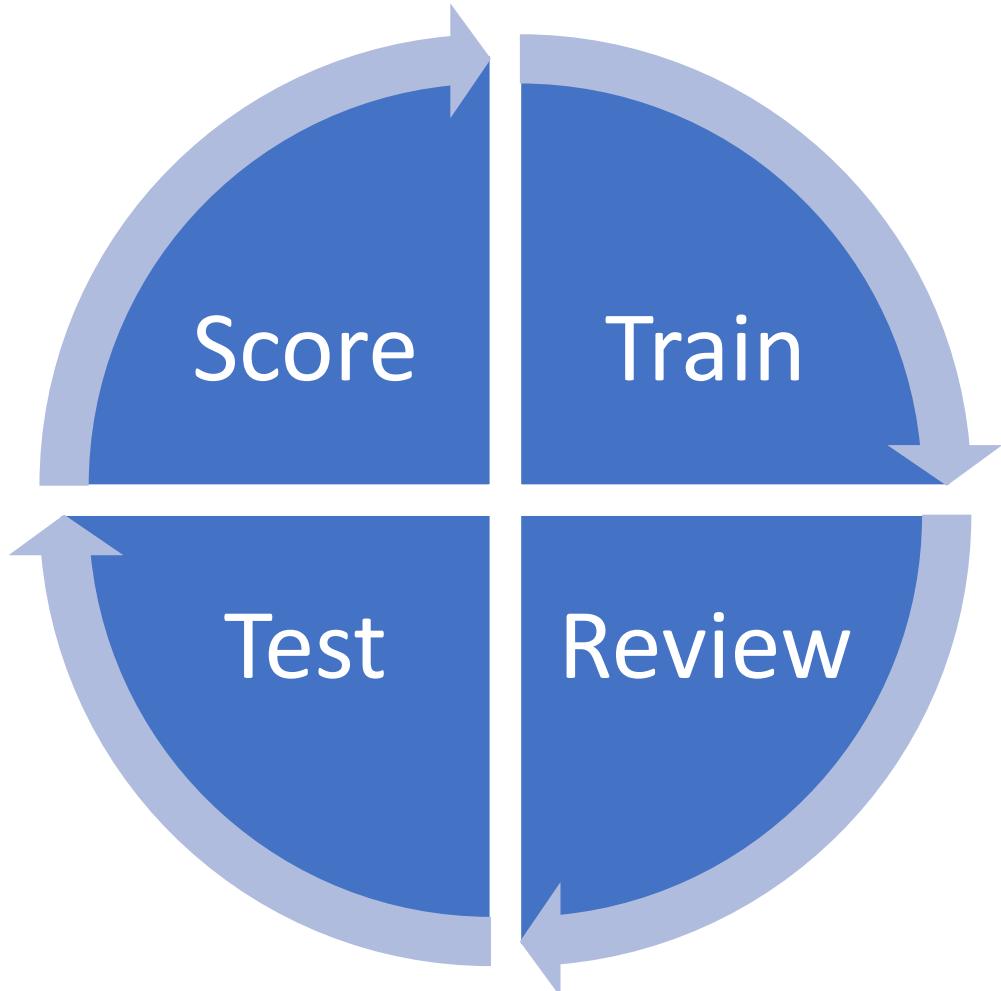


A line is fitted to the data points to attempt to correlate the dependent variable to the independent variable(s).

The difference between an observed value and the predicted value is called a residual.

Prediction

Supervised linear regression: The process.



1. **Train** the model using a sample of the dataset
2. **Review** the trained model's coefficients and values
3. **Test** the model against known observations
4. **Score** new data with the model

Linear Regression with R

Start by splitting nyc_taxi into training and testing datasets
dplyr makes this really easy with the sample_frac() function

```
train <- sample_frac(df, 0.8)  
  
rowids <- as.numeric(rownames(train))  
test <- df[-rowids,]
```

Linear Regression with R

The `lm()` function calculates a linear regression model

```
model <- lm(indep ~ dep1 + dep2 + dep3:dep4, data = df)
```

Linear Regression with R

Once the model is trained, you can review the diagnostics

```
print(model) #shows the model coefficients  
summary(model) #returns summary statistics  
str(model) #lists all info associated with the model
```

Linear Regression with R

Pay special attention to the model summary

```
Call:  
lm(formula = mpg ~ disp + hp, data = mtcars)  
  
Residuals:  
    Min      1Q  Median      3Q     Max  
-4.7945 -2.3036 -0.8246  1.8582  6.9363  
  
Coefficients:  
              Estimate Std. Error t value Pr(>|t|)  
(Intercept) 30.735904   1.331566  23.083 < 2e-16 ***  
disp        -0.030346   0.007405  -4.098 0.000306 ***  
hp         -0.024840   0.013385  -1.856 0.073679 .  
---  
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Residual standard error: 3.127 on 29 degrees of freedom
Multiple R-squared: 0.7482, Adjusted R-squared: 0.7309
F-statistic: 43.09 on 2 and 29 DF, p-value: 2.062e-09

P-value < .05

Your turn – predict fare_amount

1. Write a linear regression function to predict fare_amount.
2. Use many of our independent variables in your formula.
Remember that dropoff_nhood and pickup_nhood interact with each other. NOTE – using factors or character based variables will greatly increase the amount of time it takes to train your model.
3. Which variables appear to be significant? Retrain your model with only the significant variables.

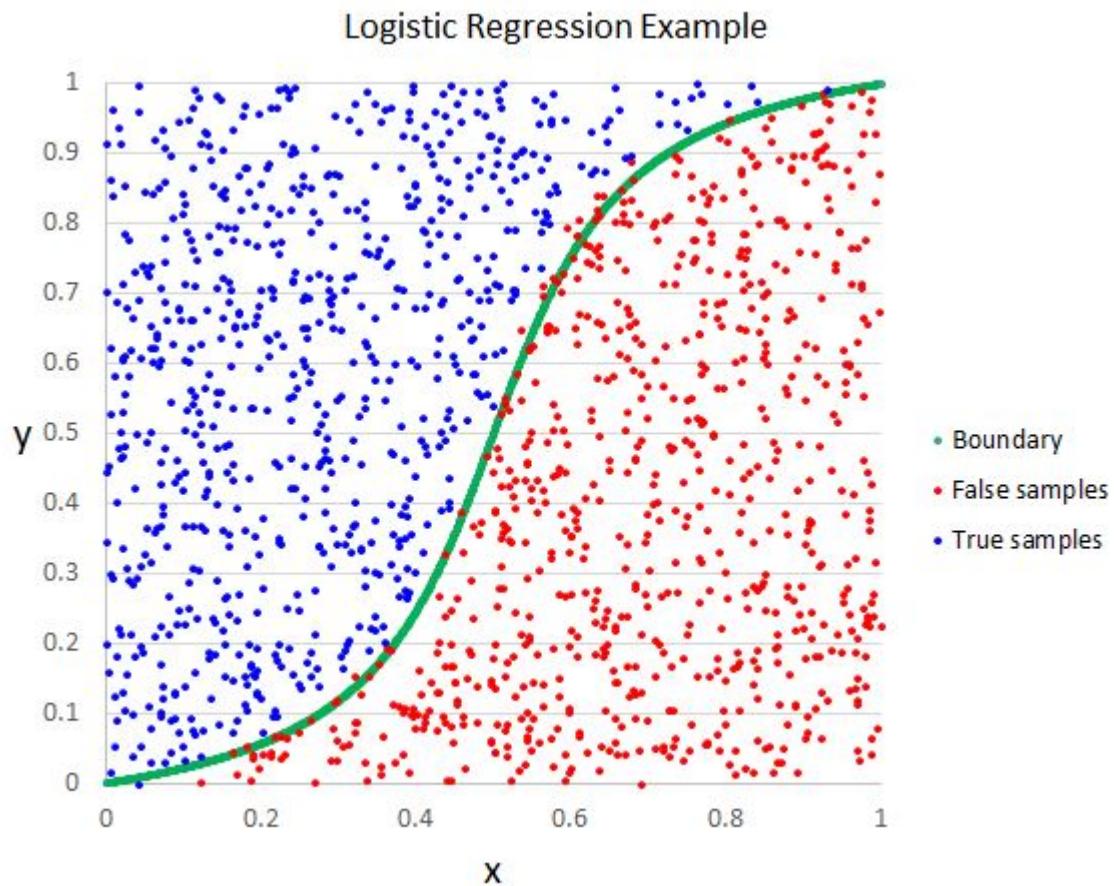
Linear Regression with R

After reviewing, it's a good idea to test your model

```
modelPred <- predict(model, test)
model <- cbind(test, modelPred)
```

Prediction

Logistic regression.



A *curve* is fit to the data to predict an outcome of a categorical variable.

Useful in determine if something happened or not.

Linear Regression with R

The `glm()` function calculates a linear regression model

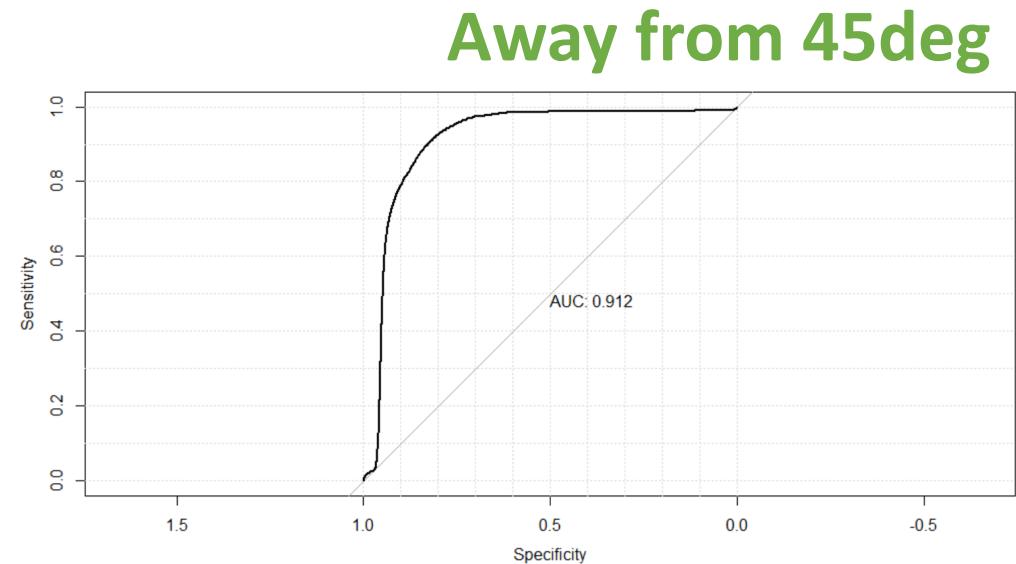
```
model <- glm(indep ~ dep1 + dep2 + dep3:dep4, data = df)
summary(model)
```

Linear Regression with R

In addition to p-values, generating a ROC curve is a good indicator of variable significance to a model

```
library(pROC)
```

```
roc(indep ~ dep,  
    data = df,  
    plot = TRUE)
```



Your turn – predict custTipped

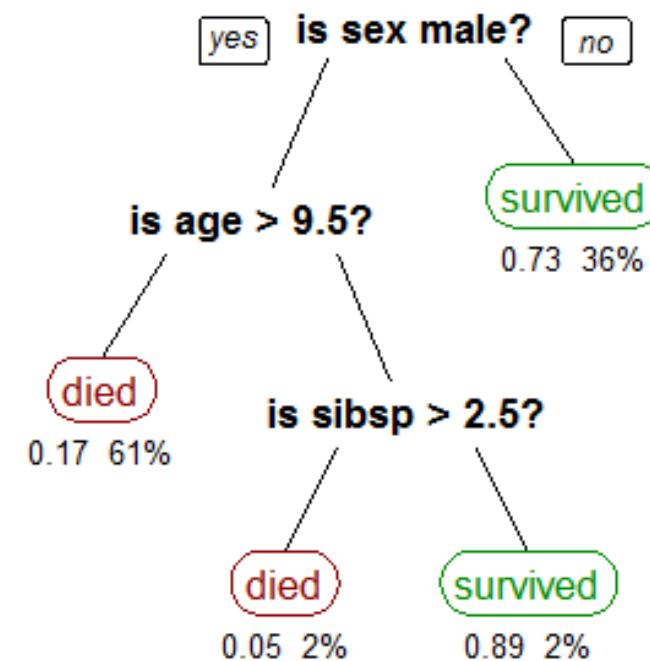
1. Write a logistic regression function to predict if a customer will tip.
2. Use many of our independent variables in your formula. Remember that `dropoff_nhood` and `pickup_nhood` interact with each other. NOTE: using factor or character based variables will greatly increase the amount of time it takes to train your model.
3. Which variables appear to be significant? Retrain your model with only the significant variables.
4. Try to plot a ROC curve to see how significant your variables are.

Prediction

Decision Tree

Decision Trees are a type of model that is used to show decision steps that are made to reach a binary outcome.

It displays the probabilities and weights of each decision point and is a great way to visualize a complex model.



Decision Trees with R

The rpart package is one way to create decision trees

```
install.packages("rpart")
library("rpart")
model <- rpart(indep ~ dep1 + dep2 + dep3:dep4,
               data = df)
summary(model)
```

Decision Trees with R

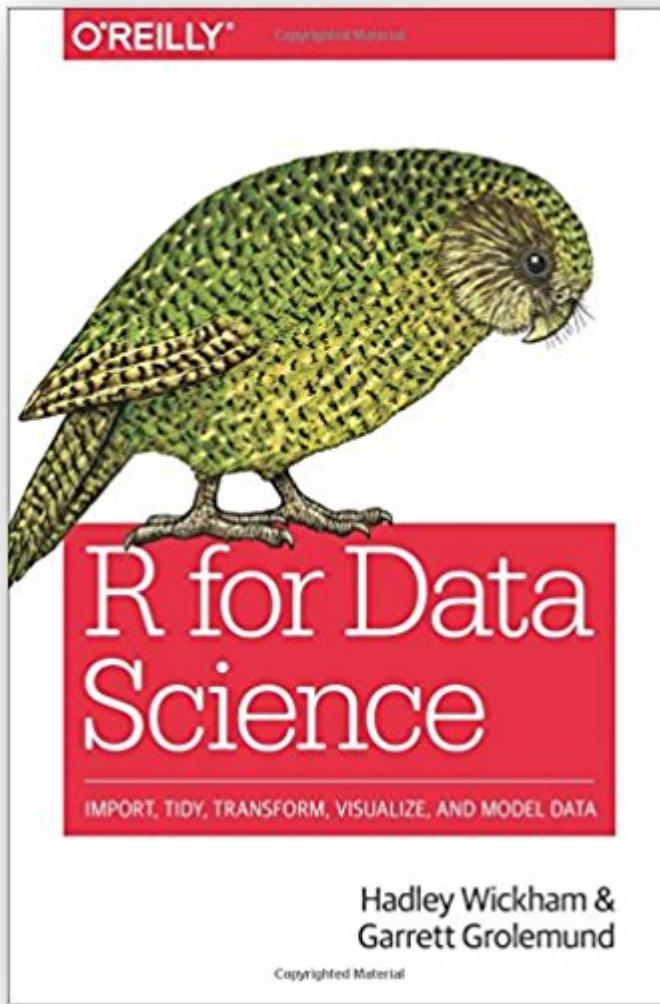
To plot an rpart tree, use the rpart.plot package

```
install.packages("rpart.plot")
library("rpart.plot")

rpart.plot(model)
```

Your turn – predict tip_amount

1. Build a decision tree model to predict how much a customer will tip.
2. Use many of our independent variables in your formula. Remember that `dropoff_nhood` and `pickup_nhood` interact with each other. Decisions trees work great with factor or character based variables. Often a better choice when you have many variables of these formats.
3. Which variables appear to be significant? Retrain your model with only the significant variables.
4. Plot your tree using `rpart.plot()`



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