

Working Title: the data science canon

Databrew

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Chapter 1

Welcome

Welcome to *Working Title*, the data science canon by *DataBrew*
Here is some teacher content.

Part I

Core theory

Chapter 2

Principles of data science

- 2.1 What is data science?
- 2.2 What is the data life cycle?
- 2.3 What is a pipeline?
- 2.4 Data science ‘in the wild’
- 2.5 The reproducibility crisis

Chapter 3

Visualizing data

3.1 Bad examples

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3.3 Edward Tufte

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3.5 Design principles

3.6 Plots & power

The politics of graphics

Chapter 4

Writing about data

Chapter 5

Data ethics

Part II

Getting started

Chapter 6

Setting up RStudio

Chapter 7

Running R code

Learning goals

- Understand the difference between R and RStudio.
- Learn how to run code in R
- Learn how to use R as a calculator
- Learn how to use mathematical and logical operators in R

Tutorial video

R and RStudio: what's the difference?

These two things are similar, but it is important to understand how they are different.

In short, R is a open-source (i.e., free) coding language: a powerful programming engine that can be used to do really cool things with data.

R Studio, in contrast, is a free *user interface* that helps you interact with **R**. If you think of **R** as an engine, then it helps to think of **RStudio** as the car that contains it. Like a car, **RStudio** makes it easier and more comfortable to use the engine to get where you want to go.

R Studio needs **R** in order to function, but **R** can technically be used on its own outside of **RStudio** if you want. However, just as a good car mechanic can get an engine to run without being installed within a car, using **R** on its own takes some expertise. For beginners (and everyone else, really), **R** is just so much more pleasant to use when you are operating it from within **RStudio**.

That is why this book *always* uses **RStudio** when working with **R**.

RStudio's *Console*

When you open RStudio, you see several different panes within the program's window. You will get a tour of RStudio in the next module. For now, look at the left half of the screen. You should see a large pane entitled the *Console*.

NOTE: Insert screenshot here

RStudio's *Console* is your window into R, the engine under the hood. The *Console* is where you type commands for R to run, and where R prints back the results of what you have told it to do.

Running code in the *Console*

Type your first command into the *Console*, then press **Enter**:

```
[1] 2
```

When you press **Enter**, R processes the command you fed it, then returns its result (2) just below your command.

Note that spaces don't matter. Both of the following two commands are legible to R and return the same thing:

```
[1] 8
```

```
[1] 8
```

However, it is better to make your code as easy to read as possible, which usually means using spaces.

Exercise 1

Type a command in the *Console* to determine the sum of 596 and 198.

Re-running code in the *Console*

If you want to re-run the code you just ran, or if you want to recall the code so that you can adjust it slightly, click anywhere in the *Console* then press your keyboard's **Up** arrow.

If you keep pressing your **Up** arrow, R will present you with sequentially older commands.

If you accidentally recalled an old command without meaning to, you can reset the *Console*'s command line by pressing **Escape**.

Exercise 2

- A. Re-run the sum of 596 and 198 without re-typing it.
- B. Recall the command again, but this time adjust the code to find the sum of 596 and 298.
- C. Practice escaping an accidentally called command: recall your most recent command, then clear the *Console*'s command line.

Incomplete commands in R

R gets confused when you enter an incomplete command, and will wait for you to write the remainder of your command on the next line in the *Console* before doing anything.

For example, try running this code in your *Console*:

You will find that R gives you a little + sign on the line under your command, which means it is waiting for you to complete your command.

If you want to complete your command, add a number (e.g., 3) and hit **Enter**. You should now be given an answer (e.g., 48).

If instead you want R to stop waiting and stop running, hit the **Escape** key.

Getting errors in R

R only understands your commands if they follow the rules of the R language (often referred to as its *syntax*). If R does not understand your code, it will throw an error and give up on trying to execute that line of code.

For example, try running this code in your *Console*:

```
4 + 6p
```

You probably received a message in red font stating **Error: unexpected symbol in "4 + 6p"**. That is because R did not know how to interpret the symbol `p` in this case.

Get used to errors! They happen all the time, even (especially?) to professionals, and it is essential that you get used to reading your own code to find and fix its errors.

Exercise 3

Type a command in R that throws an error, then recall the command and revise so that R can understand it.

Use R like a calculator

As you can tell from those commands you just ran, R is, at heart, a fancy calculator.

Some calculations are straightforward, like addition and subtraction:

```
[1] 1490
```

```
[1] -510
```

Division is pretty straightforward too:

```
[1] 12
```

For multiplication, use an asterisk (*):

```
[1] 48
```

R is usually great about following classic rules for Order of Operations, and you can use parentheses to exert control over that order. For example, these two commands produce different results:

```
[1] 9
```

```
[1] 2
```

You denote exponents like this:

```
[1] 4
```

```
[1] 8
```

```
[1] 16
```

Finally, note that R is fine with negative numbers:

```
[1] -91
```

Exercise 4

- A. Find the sum of the ages of everyone in your immediate family.
- B. Now recall that command and adjust it to determine the *average* age of the members of your family.

7.1 Using operators in R

You can get R to evaluate logical tests using *operators*.

For example, you can ask whether two values are equal to each other.

```
[1] FALSE
```

```
[1] TRUE
```

R is telling you that the first statement is **FALSE** (96 is not, in fact, equal to 95) and that the second statement is **TRUE** (95 + 2 is, in fact, equal to itself).

Note the use of *double* equal signs here. You must use two of them in order for R to understand that you are asking for this logical test.

You can also ask if two values are *NOT* equal to each other:

```
[1] TRUE
```

```
[1] FALSE
```

This test is a bit more difficult to understand: In the first statement, R is telling you that it is **TRUE** that 96 is different from 95. In the second statement, R is saying that it is **FALSE** that 95 + 2 is not the same as itself.

Note that R lets you write these tests another, even more confusing way:

```
[1] TRUE
```

```
[1] FALSE
```

The first line of code is asking R whether it is not true that 96 and 95 are equal to each other, which is **TRUE**. The second line of code is asking R whether it is not true that 95 + 2 is the same as itself, which is of course **FALSE**.

Other commonly used operators in R include greater than / less than (> and <), and greater/less than or equal to (>= and <=).

```
[1] FALSE
```

```
[1] TRUE
```

Exercise 5

A. Write and run a line of code that asks whether these two calculations return the same result:

```
2*7 - 2*5 / 2
(2*7 - 2*5) / 2
```

B. Now write and run a line of code that asks whether the first calculation is larger than the second:

7.2 Use built-in functions within R

R has some built-in functions for common calculations, such as finding square roots and logarithms.

```
[1] 4
```

```
[1] 1.386294
```

Note that the function `log()` is the *natural log* function (i.e., the value that e must be raised to in order to equal 4). To calculate a base-10 logarithm, use `log10()`.

```
[1] 2.302585
```

```
[1] 1
```

Another handy function is `round()`, for rounding numbers to a specific number of decimal places.

```
[1] 33.33333
```

```
[1] 33
```

```
[1] 33.3
```

```
[1] 33.33
```

```
[1] 33.333
```

Finally, R also comes with some built-in values, such as *pi*:

```
[1] 3.141593
```


Exercise 6

Find the square root of πi and round the answer to the 2 decimal places.

Review assignment:

NOTE: Under construction!

7.3 Other Resources

Hobbes Primer, Table 1 (Math Operators, pg. 18) and Table 2 (Logical operators, pg. 22)

Chapter 8

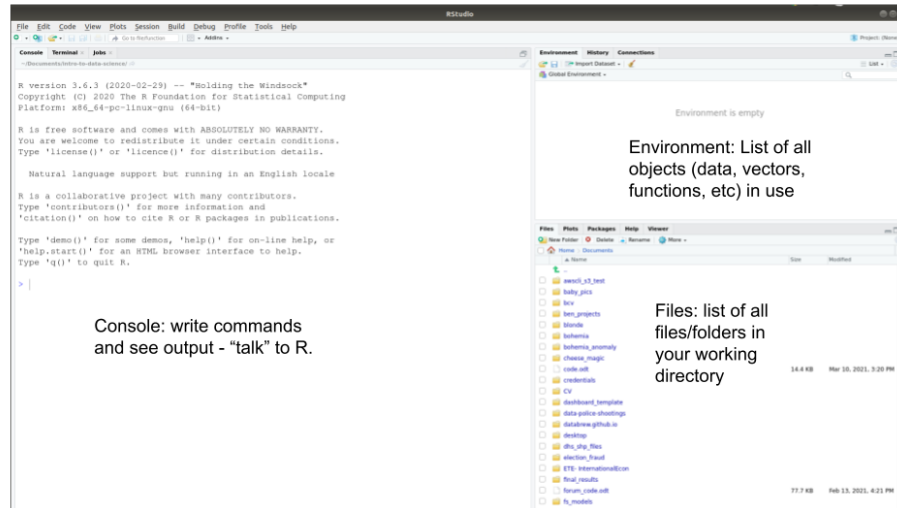
Introduction to Rstudio

Learning goals

- Understand the Rstudio working environment and window panes
- Creating and saving scripts
- Customizing your rstudio

Tutorial video

8.1 Tour of RStudio



8.2 Other tabs

8.3 Scripts

8.4 Typical workflows

8.5 Other Resources

Chapter 9

Variables in R

Learning goals

- How to define variables and work with them in R
- Learn the various possible classes of data in R

Tutorial video

Variables in R

So far we have strictly been using R as a calculator, with commands such as:

```
[1] 8
```

Of course, R can do much, much more than these basic computations. Your first step in uncovering the potential of R is learning how to use **variables**.

In R, a variable is a convenient way of referring to an underlying value. That value can be as simple as a single number (e.g., 6), or as complex as a spreadsheet that is many Gigabytes in size. It may be useful to think of a variable as a cup; just as cups make it easy to hold your coffee and carry it from the kitchen to the couch, variables make it easy to contain and work with data.

Declaring variables

To assign numbers or other types of data to a variable, you use the `<` and `-` characters to make the arrow symbol `<-`.

As the direction of the `<-` arrow suggests, this command stores the result of `3 + 5` into the variable `x`.

Unlike before, you did not see `8` printed to the *Console*. That is because the result was stored into `x`.

Calling variables

If you wanted R to tell you what “`x`” is, just type the variable name into the *Console* and run that command:

```
[1] 8
```

Want to create a variable but also see its value at the same time? Here’s a handy trick:

```
[1] 36
```

The semicolon simulates hitting **Enter**. It says: first run `x <- 3*12`, then run `x`.

You can also update variables.

```
[1] 108
```

```
[1] 324
```

You can also add variables together.

```
[1] 12.5
```

9.0.1 Naming variables

Variables are case-sensitive! If you misspell a variable name, you will confuse R and get an error.

For example, ask R to tell you the value of capital `X`. The error message will be **Error: object 'X' not found**, which means R looked in its memory for an object (i.e., a variable) named `X` and could not find one.

You can make variable names as complicated or simple as you want.

```
[1] 5
```

Note that periods and underscores can be used in variable names:

However, hyphens cannot be used since that symbol is used for subtraction.

Naming variables is a bit of an art. The trick is using names that are clear but are not so complicated that typing them is tedious or prone to errors.

Some names need to be avoided, since **R** uses them for special purposes. For example, **data** should be avoided, as should **mean**, since both are functions built-in to **R** and **R** is liable to interpret them as such instead of as a variable containing your data.

Note that **R** uses a feature called ‘Tab complete’ to help you type variable names. Begin typing a variable name, such as **supercalifragilistic.expialidocious** from the example above, but after the first few letters press the **Tab** key. **R** will then give you options for auto-completing your word. Press **Tab** again, or **Enter**, to accept the auto-complete. This is a handy way to avoid typos.

Exercise 1

- A. Estimate how many bananas you’ve eaten in your lifetime and store that value in a variable (choose whatever name you wish).
- B. Now estimate how many ice cream sandwiches you’ve eaten in your lifetime and store that in a different variable.
- C. Now use these variables to calculate your Banana-to-ICS ratio. Store your result in a third variable, then call that variable in the Console to see your ratio.
- D. Who in the class has the highest ratio? Who has the lowest?

Types of data in R

So far we have been working exclusively with numeric data. But there are many different data types in **R**. We call these “types” of data **classes**:

- Decimal values like 4.5 are called **numeric** data.
- Natural numbers like 4 are called **integers**. Integers are also numerics.
- Boolean values (TRUE or FALSE) are called **logical** data.
- Text (or string) values are called **character** data.

In order to be combined, data have to be the same class.

R is able to compute the following commands ...

[1] 10

... but not these:

That's because the quotation marks used in naming `y` causes R to interpret `y` as a **character** class.

To see how R is interpreting variables, you can use the `class()` function:

```
[1] "numeric"
```

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

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

Another data type to be aware of is **factors**, but we will deal with them later.

Exercise 3

NOTE: UNDER CONSTRUCTION!

Review assignment

NOTE: UNDER CONSTRUCTION!

Other Resources

Chapter 10

Structures for data in R

Learning goals

- Learn the various structures of data in R
- How to work with vectors in R.

Tutorial video

Types of data structures in R

Data belong to different *classes*, as explained above, and they can be arranged into various *structures*.

So far we have been dealing only with variables that contain a single value, but the real value of R comes from assigning *entire sets* of data to a variable.

Vectors

The simplest data structure in R is a **vector**. A vector is simply a set of values. A vector can contain only a single value, as we have been working with thus far, or it can contain many millions of values.

Declaring and using vectors

To build up a vector in R, use the function `c()`, which is short for “concatenate”.

```
[1] 5 6 7 8
```

You can use the `c()` function to concatenate two vectors together:

```
[1] 5 6 7 8 9 10 11 12
```

You can also use `c()` to add values to a vector:

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

When two vectors are of the same length, you can do arithmetic with them:

```
[1] 14 16 18 20
```

```
[1] -4 -4 -4 -4
```

```
[1] 45 60 77 96
```

```
[1] 0.5555556 0.6000000 0.6363636 0.6666667
```

You can also put vectors through logical tests:

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

This command is asking R to tell you whether each element in `x` is equal to 4.

You can create vectors of any data class:

```
[1] "Ben" "Joe" "Eric"
```

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

Note that all values within a vector *must* be of the same class (i.e., data type). You can't combine numerics and characters into the same vector. If you did, R would try to convert the numbers to characters. For example:

```
[1] "4" "6"
```

10.0.1 Useful functions for handling vectors

length() tells you the number of elements in a vector:

```
[1] 2
```

```
[1] 4
```

The **colon symbol** `:` creates a vector with every integer occurring between a min and max:

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

seq() allows you to build a vector using evenly spaced *sequence* of values between a min and max:

```
[1] 0 10 20 30 40 50 60 70 80 90 100
```

In this command, you are telling **R** to give you a sequence of values from 0 to 100, and you want the length of that vector to be 11. **R** then figures out the spacing required between each value in order to make that happen.

Alternatively, you can prescribe the interval between values instead of the length:

```
[1] 0 7 14 21 28 35 42 49 56 63 70 77 84 91 98
```

head() and **tail()** can be used to retrieve the first 6 or last 6 elements in a vector, respectively.

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

```
[1] 995 996 997 998 999 1000
```

You can also adjust how many elements to return:

```
[1] 1 2
```

```
[1] 991 992 993 994 995 996 997 998 999 1000
```

which() allows you to ask, “For which elements of a vector is the following statement true?”

```
[1] 4
```

If no values within the vector meet the condition, a vector of length zero will be returned:

```
integer(0)
```

%in% is a handy operator that allows you to ask whether a value occurs *within* a vector:

```
[1] TRUE
```

```
[1] FALSE
```

Exercise 2

NOTE: UNDER CONSTRUCTION!

Subsetting vectors

Since you will eventually be working with vectors that contain thousands of data points, it will be useful to have some tools for *subsetting* them – that is, looking at only a few select elements at a time.

You can subset a vector using square brackets `[]`.

```
[1] 59
```

This command is asking R to return the 10th element in the vector `x`.

```
[1] 59 60 61 62 63 64 65 66 67 68 69
```

This command is asking R to return elements `10:20` in the vector `x`.

Exercise 3

A. Figure out how to replicate the `head` function using your new vector subsetting skills.

B. Now replicate the `tail()` function, using those same skills as well as the `length()` function you just learned.

10.0.2 Dataframes & other data structures

A **vector** is the most basic data structure in R, and the other structures are built out of vectors.

As a data scientist, the most common data structure you will be working with is a **dataframe**, which is essentially a spreadsheet: a dataset with rows and columns, in which each column represents is a vector of the same class of data.

We will explore dataframes in detail later, but here is a sneak peak at what they look like:

```

      x    y
1  300 600
2  301 601
3  302 602
4  303 603
5  304 604
6  305 605
7  306 606
8  307 607
9  308 608
10 309 609
11 310 610

```

In this command, we used the `data.frame()` function to combine two vectors into a dataframe with two columns named `x` and `y`. R then saved this result in a new variable named `df`. When we call `df`, R shows us the dataframe.

The great thing about dataframes is that they allow you to relate different data types to each other.

```

      name height.inches
1   Ben           75
2   Joe           73
3  Eric           80

```

This dataframe has one column of class **character** and another of class **numeric**.

The two other most common data structures are **matrices** and **lists**, but we will wait on learning about those. For now, focus on becoming comfortable using vectors and dataframes.

Exercise 3

NOTE: UNDER CONSTRUCTION!

Review assignment

NOTE: UNDER CONSTRUCTION!

Other Resources

Chapter 11

Calling functions

Chapter 12

Base plots

Chapter 13

Packages

Chapter 14

Basics of ggplot

Part III

Working with data in R

Chapter 15

Importing data

15.1 Working directories

15.2 Reading in data

Chapter 16

Dataframes

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16.2 Summarization

Chapter 17

Data wrangling

17.1 Data transformation

17.1.1 Filtering

17.1.2 Grouping

17.1.3 Joining

17.2 The tidyverse and tibbles

17.3 Transformation with dplyr

17.3.1 Filtering

17.3.2 Grouping

17.3.3 Mutating

Part IV

Exploring & analyzing data

Chapter 18

Exploratory Data Analysis

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18.3 Descriptive statistics

Chapter 19

Significance statistics

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19.2 Comparison tests

19.3 Correlation tests

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Displaying data

20.1 Tables

20.2 Base plots

Advanced techniques

20.3 ggplot

Advanced techniques

Part V

Creating your own dataset

Chapter 21

Managing project files

Chapter 22

Formatting your own data

Chapter 23

Reading Excel files

Chapter 24

Reading GoogleSheets

Chapter 25

Reading online data

Part VI

Your R tool bag

Chapter 26

Joining datasets

Chapter 27

for loops

Learning goals

- What `for` loops are, and how to use them yourself
- How to use `for` loops for multi-pane plotting
- How to use `for` loops to achieve complex plots
- How to use `for` loops to summarize data efficiently

Coming soon

- Instructor notes and answer keys (hidden from students)

Tutorial video

(coming soon!)

Basics

A `for` loop is a super powerful coding tool. In a `for` loop, `R` loops through a chunk of code for a set number of repetitions.

A super basic example:

```
x <- 1:5
for(i in x){
  print(i)
}
```

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

Here's an example of a pretty useless for loop:

```
for(i in 1:5){
  print("I'm just repeating myself.")
}
```

```
[1] "I'm just repeating myself."
[1] "I'm just repeating myself."
[1] "I'm just repeating myself."
[1] "I'm just repeating myself."
[1] "I'm just repeating myself."
```

This code is saying:

- For each iteration of this loop, step to the next value in `x` (first example) or `1:5` (second example).
- Store that value in an object `i`,
- and run the code inside the curly brackets. - Repeat until the end of `x`.

Look at the basic structure:

- In the `for()` parenthetical, you tell R what values to step through (`x`), and how to refer to the value in each iteration (`i`).
- Within the curly brackets, you place the chunk of code you want to repeat.

Another basic example, demonstrating that you can update a variable repeatedly in a loop.

```
x <- 2
for(i in 1:5){
  x <- x*x
  print(x)
}
```

```
[1] 4
```



```
[1] 16
[1] 256
[1] 65536
[1] 4294967296
```

Another silly example:

```
professors <- c("Keri","Deb","Ken")
for(x in professors){
  print(paste0(x," is pretty cool!"))
}
```

```
[1] "Keri is pretty cool!"
[1] "Deb is pretty cool!"
[1] "Ken is pretty cool!"
```

Exercise 1

Use this space to practice the basics of `for` loop formatting.

First, create a vector of names (add at least 3)

```
# Add your names to this vector
famous.names <- c("Lady Gaga","David Haskell","Tom Cruise")
```

Using the examples above as a guide, create a `for` loop that prints the same silly statement about each of these names.

```
# Do your coding here
for(i in famous.names){
  print(paste0(i," has cooties!"))
}
```

```
[1] "Lady Gaga has cooties!"
[1] "David Haskell has cooties!"
[1] "Tom Cruise has cooties!"
```

Using `for` loops with data

These silly examples above do a poor job of demonstrating how powerful a `for` loop can be.

Multi-panel plots

For example, a `for` loop can be a very efficient way of making multi-panel plots.

Let's use a `for` loop to get a quick overview of the variables included in the `airquality` dataset built into R.

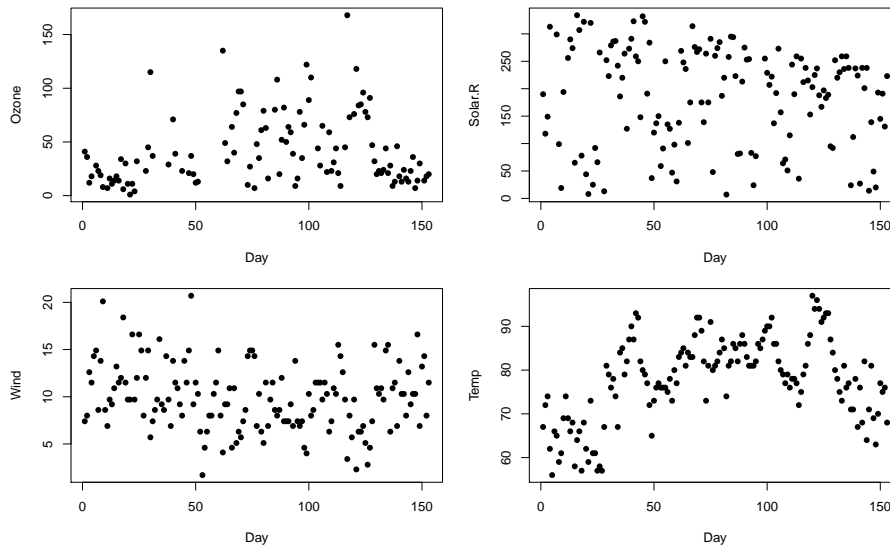
```
data(airquality)
head(airquality)
```

	Ozone	Solar.R	Wind	Temp	Month	Day
1	41	190	7.4	67	5	1
2	36	118	8.0	72	5	2
3	12	149	12.6	74	5	3
4	18	313	11.5	62	5	4
5	NA	NA	14.3	56	5	5
6	28	NA	14.9	66	5	6

Looks like the first four columns would be interesting to plot.

```
par(mfrow=c(2,2)) # Setup a multi-panel plot # format = c(number of rows, number of co
par(mar=c(4.5,4.5,1,1)) # Set plot margins

for(i in 1:4){
  y <- airquality[,i]
  var.name <- names(airquality)[i]
  plot(y,xlab="Day",ylab=var.name,pch=16)
}
```



```
par(mfrow=c(1,1)) # restore the default single-panel plot
```

Tricky plot solutions

for loops are also useful for plotting data in tricky ways. Let's use a different built-in dataset, that shows the performance of various car make/models.

```
data(mtcars)
head(mtcars)
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258	110	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	18.7	8	360	175	3.15	3.440	17.02	0	0	3	2
Valiant	18.1	6	225	105	2.76	3.460	20.22	1	0	3	1

Let's say we want to see how gas mileage is affected by the number of cylinders a car has. It would be nice to create a plot that shows the raw data as well as the mean mileage for each cylinder number.

```
# Let's see how many different cylinder types there are in the data
ucyl <- unique(mtcars$cyl) ; ucyl
```

```
[1] 6 4 8
```

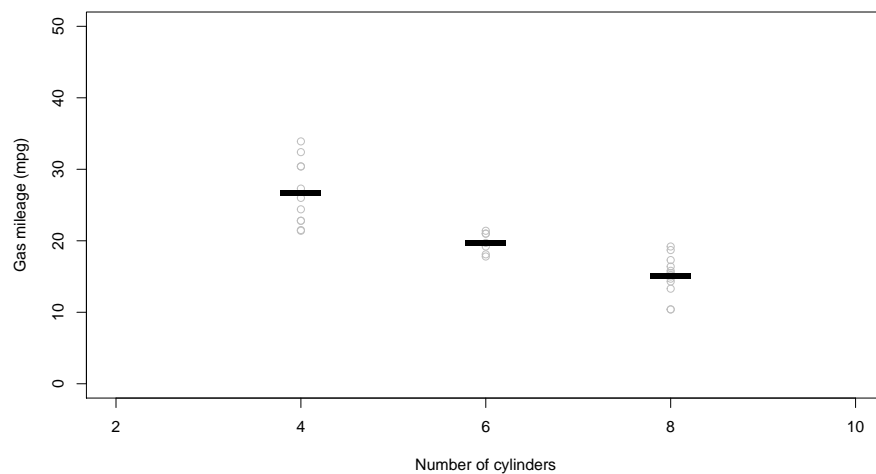
```
# Let's make an empty plot
plot(1,type="n", # tell R not to draw anything
     xlim=c(2,10),ylim=c(0,50),
     xlab="Number of cylinders",
     ylab="Gas mileage (mpg)")

# Write your for loop here to add the actual data
i=ucyl[1] # It's always good to use a known value of i as you build up your for loop
for(i in ucyl){

  # Subset the dataframe according to number of cylinders
  cari <- mtcars[mtcars$cyl==i,]

  # Plot the raw data
  points(x=cari$cyl,y=cari$mpg,col="grey")

  # Superimpose the mean on top
  points(x=i,y=mean(cari$mpg),col="black",pch="-",cex=5,)
}
```



Exercise 2

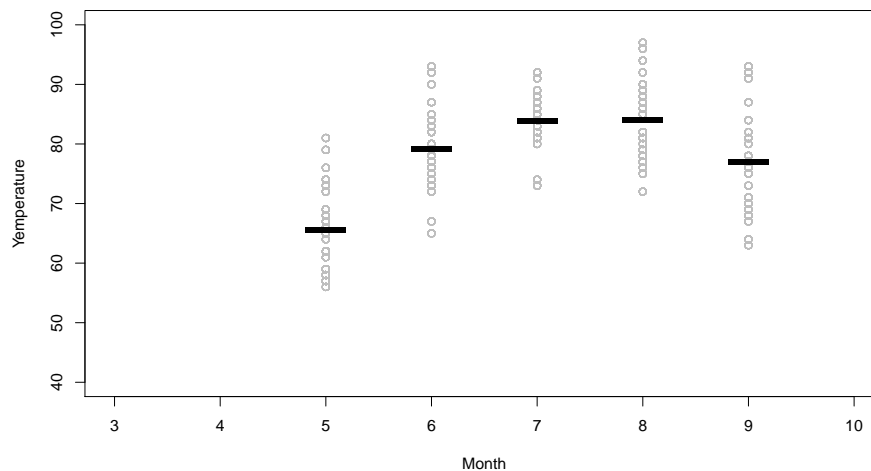
Now try to do something similar on your own with the `airquality` dataset. Use `for` loops to create a plot with Month on the x axis and Temperature on

the y axis. On this plot, depict all the temperatures recorded in each month in the color grey, then superimpose the mean temperature for each month.

We will provide the empty plot, you provide the `for` loop:

```
plot(1,type="n",
     xlim=c(3,10),ylim=c(40,100),
     xlab="Month",
     ylab="Yemperature")

# Write your for loop here to add the actual data
for(i in airquality$Month){
  airi <- airquality[airquality$Month==i,]
  points(x=airi$Month,y=airi$Temp,pch=1,col="grey")
  points(x=i,y=mean(airi$Temp),pch="-",cex=5,col="black")
}
```



Using a `for` loop with more complex data

Here's another good example of the power of a good `for` loop.

First, read in some cool data.

```
kc <- read.csv("../data/keeling-curve.csv") ; head(kc)
```

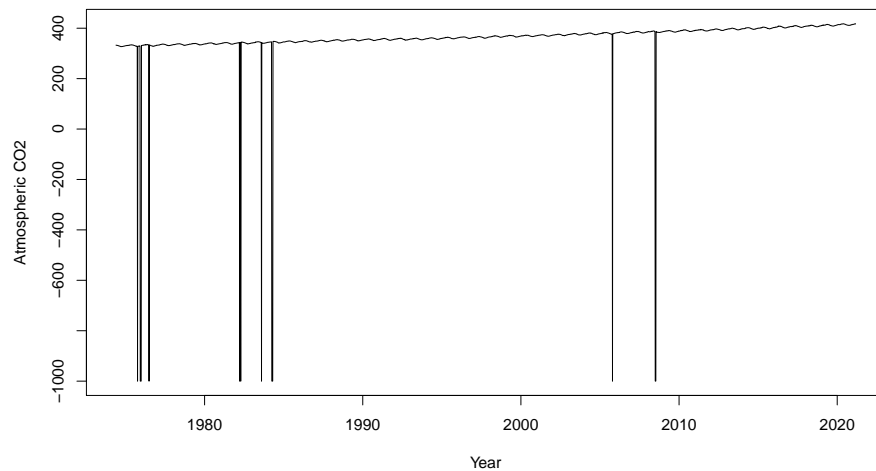
```
year month day_of_month day_of_year year_dec frac_of_year    CO2
```

1	1974	5	26	145.4890	1974.399	0.3986	332.95
2	1974	6	2	152.4970	1974.418	0.4178	332.35
3	1974	6	9	159.5050	1974.437	0.4370	332.20
4	1974	6	16	166.5130	1974.456	0.4562	332.37
5	1974	6	23	173.4845	1974.475	0.4753	331.73
6	1974	6	30	180.4925	1974.495	0.4945	331.68

This is the famous Keeling Curve dataset: long-term monitoring of atmospheric CO₂ measured at a volcanic observatory in Hawaii.

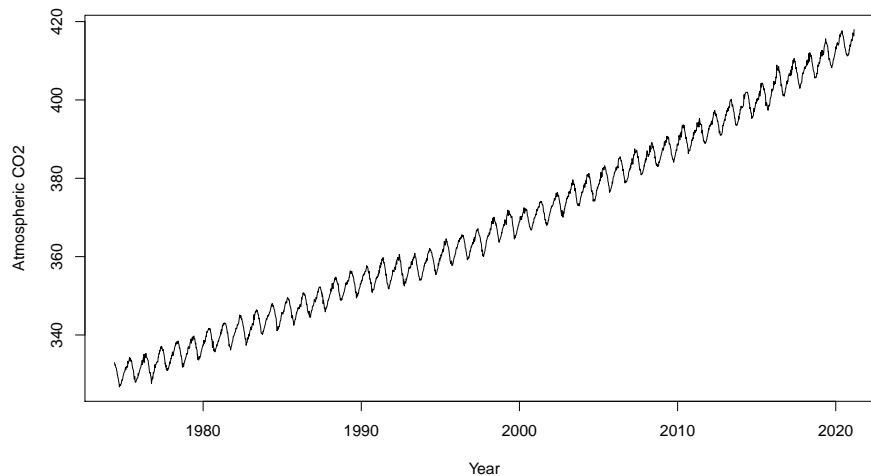
Try plotting the Keeling Curve:

```
plot(kc$C02 ~ kc$year_dec,type="l",xlab="Year",ylab="Atmospheric C02")
```



There are some erroneous data points! We clearly can't have negative CO₂ values. Let's remove those and try again:

```
kc <- kc[kc$C02 > 0,]
plot(kc$C02 ~ kc$year_dec,type="l",xlab="Year",ylab="Atmospheric C02")
```



What's the deal with those squiggles? Let's investigate!

Let's look at the data a different way: *by focusing in on a single year.*

```
# Stage an empty plot for what you are trying to represent
plot(1, # plot a single point
     type="n",
     xlim=c(0,365),xlab="Day of year",
     ylim=c(-5,5),ylab="CO2 anomaly")
abline(h=0,col="grey") # add nifty horizontal line

# Reduce the dataset to a single year (any year)
kcy <- kc[kc$year=="1990",] ; head(kcy)
```

	year	month	day_of_month	day_of_year	year_dec	frac_of_year	CO2
816	1990	1	7	6.4970	1990.018	0.0178	353.58
817	1990	1	14	13.5050	1990.037	0.0370	353.99
818	1990	1	21	20.5130	1990.056	0.0562	353.92
819	1990	1	28	27.4845	1990.075	0.0753	354.39
820	1990	2	4	34.4925	1990.094	0.0945	355.04
821	1990	2	11	41.5005	1990.114	0.1137	355.09

```
# Let's convert each CO2 reading to an 'anomaly' compared to the year's average.
CO2.mean <- mean(kcy$CO2,na.rm=TRUE) ; CO2.mean # Take note of how useful that 'na.rm=TRUE' inpu
```

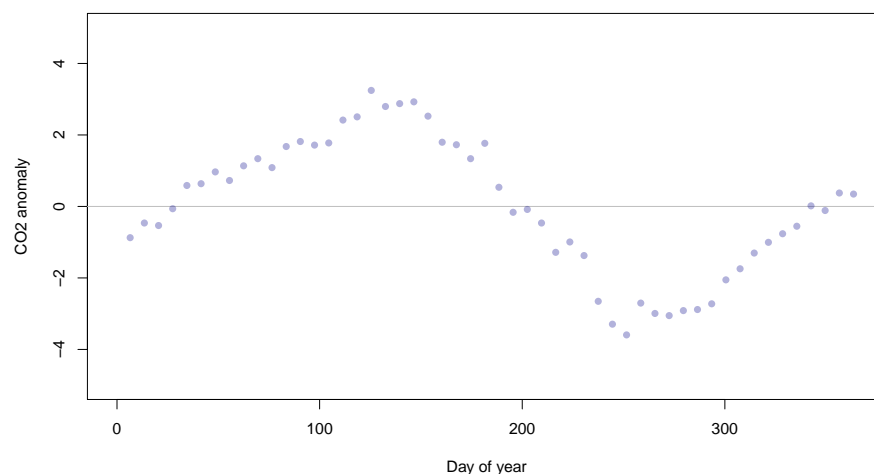
```
[1] 354.4538
```

```
y <- kcy$CO2 - CO2.mean ; y # Translate each data point to an anomaly
```

```
[1] -0.87384615 -0.46384615 -0.53384615 -0.06384615  0.58615385  0.63615385
[7]  0.96615385  0.72615385  1.13615385  1.33615385  1.08615385  1.67615385
[13]  1.81615385  1.71615385  1.77615385  2.41615385  2.50615385  3.24615385
[19]  2.79615385  2.87615385  2.92615385  2.52615385  1.79615385  1.72615385
[25]  1.33615385  1.76615385  0.53615385 -0.16384615 -0.08384615 -0.46384615
[31] -1.28384615 -0.99384615 -1.37384615 -2.65384615 -3.29384615 -3.59384615
[37] -2.70384615 -2.99384615 -3.05384615 -2.91384615 -2.88384615 -2.72384615
[43] -2.05384615 -1.74384615 -1.30384615 -1.00384615 -0.76384615 -0.55384615
[49]  0.01615385 -0.11384615  0.37615385  0.34615385          NA
```

```
# Add points to your plot
```

```
points(y~kcy$day_of_year,pch=16,col=adjustcolor("darkblue",alpha.f=.3))
```



But this only shows one year of data! How can we include the seasonal squiggle from other years?

Let's use a `for` loop!

OK – let's redo that graph and add a `for` loop into the mix:

```
# First, stage your empty plot:
plot(1,type="n",
     xlim=c(0,365),xlab="Day of year",
     ylim=c(-5,5),ylab="CO2 anomaly")
```

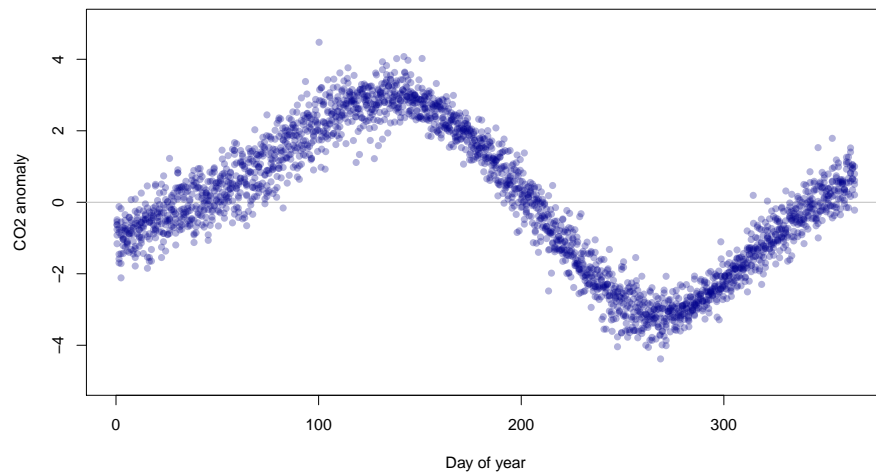


```
abline(h=0,col="grey")
```

```
# Now we will loop through each year of data. First, get a vector of the years included in the d  
years <- unique(kc$year) ; years
```

```
[1] "1974" "1975" "1976" "1977" "1978" "1979" "1980" "1981" "1982" "1983"  
[11] "1984" "1985" "1986" "1987" "1988" "1989" "1990" "1991" "1992" "1993"  
[21] "1994" "1995" "1996" "1997" "1998" "1999" "2000" "2001" "2002" "2003"  
[31] "2004" "2005" "2006" "2007" "2008" "2009" "2010" "2011" "2012" "2013"  
[41] "2014" "2015" "2016" "2017" "2018" "2019" "2020" "2021" NA
```

```
# Now build your for loop.  
# Notice that the contents of the `for loop` are exactly the same  
# as the single plot above -- with one exception.  
# Notice the use of the symbol i  
  
for(i in years){  
  
  # Reduce the dataset to a single year  
  kcy <- kc[kc$year==i,] ; head(kcy)  
  
  # Let's convert each CO2 reading to an 'anomaly' compared to the year's average.  
  CO2.mean <- mean(kcy$CO2,na.rm=TRUE) ; CO2.mean # Get average CO2 for year  
  
  y <- kcy$CO2 - CO2.mean ; y # Translate each data point to an anomaly  
  
  # Add points to your plot  
  points(y~kcy$day_of_year,pch=16,col=adjustcolor("darkblue",alpha.f=.3))  
}
```



Beautiful! So how do you interpret this graph? Why does the squiggle happen every year?

Review assignment

First, read in and format some other cool data. The code for doing so is provided for you here:

```
df <- read.csv("../data/renewable-energy.csv")
```

This dataset, freely available from World Bank, shows the renewable electricity output for various countries, presented as a percentage of the nation's total electricity output. They provide this data as a time series.

27.0.1 Summarize columns with a for loop

Task 1: Use a `for` loop to find the change in renewable energy output for each nation in the dataset between 1990 and 2015. Print the difference for each nation in the console.

```
# Write your code here
names(df)
```

```
[1] "year"          "World"         "Australia"     "Canada"
```

```
[5] "China"          "Denmark"          "India"            "Japan"
[9] "New_Zealand"    "Sweden"           "Switzerland"     "United_Kingdom"
[13] "United_States"
```

```
i=2
for(i in 2:ncol(df)){
  dfi <- df[,i] ; dfi
  diffi <- dfi[length(dfi)] - dfi[1] ; diffi
  print(paste0(names(df)[i], " : ",round(diffi,"% change."))
}
```

```
[1] "World : 3% change."
[1] "Australia : 4% change."
[1] "Canada : 1% change."
[1] "China : 4% change."
[1] "Denmark : 62% change."
[1] "India : -9% change."
[1] "Japan : 5% change."
[1] "New_Zealand : 0% change."
[1] "Sweden : 12% change."
[1] "Switzerland : 7% change."
[1] "United_Kingdom : 23% change."
[1] "United_States : 2% change."
```

Task 2: Re-do this loop, but instead of printing the differences to the console, save them in a vector.

```
# Write your code here
diffs <- c()
i=2
for(i in 2:ncol(df)){
  dfi <- df[,i] ; dfi
  diffi <- dfi[length(dfi)] - dfi[1] ; diffi
  print(paste0(names(df)[i], " : ",round(diffi,"% change."))
  diffs <- c(diffs,diffi)
}
```

```
[1] "World : 3% change."
[1] "Australia : 4% change."
[1] "Canada : 1% change."
[1] "China : 4% change."
[1] "Denmark : 62% change."
[1] "India : -9% change."
[1] "Japan : 5% change."
```

```
[1] "New_Zealand : 0% change."
[1] "Sweden : 12% change."
[1] "Switzerland : 7% change."
[1] "United_Kingdom : 23% change."
[1] "United_States : 2% change."
```

```
diffs
```

```
[1] 3.49241703 3.98181045 0.63273122 3.51887728 62.33064943 -9.14624362
[7] 4.73004321 0.07524008 12.26263811 7.21543884 23.01128298 1.69994636
```

Multi-pane plots with for loops

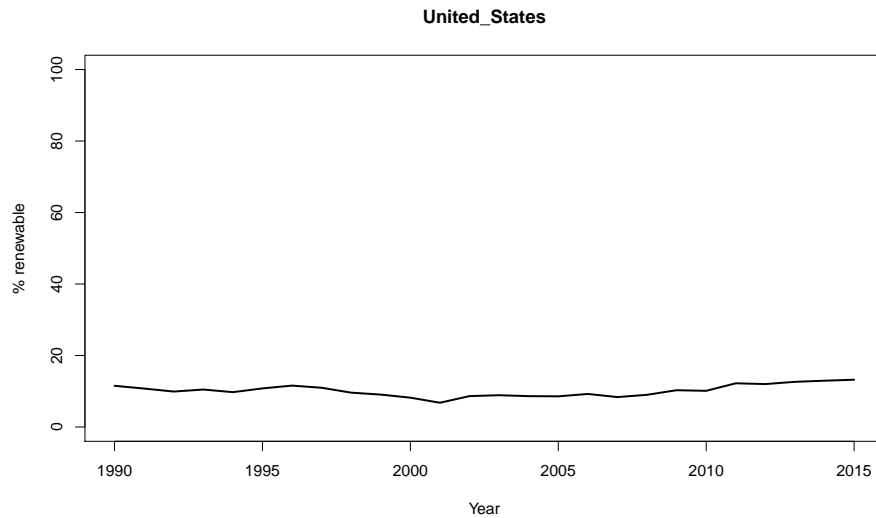
Practice with a single plot

Task 3: First, get your bearings by figuring out how to use the `df` dataset to plot the time series for the United States, for the years 1990 - 2015. Label the x axis “Year” and the y axis “% Renewable”. Include the full name of the county as the main title for the plot.

```
# Write code here
head(df)
```

	year	World	Australia	Canada	China	Denmark	India	Japan
1	1990	19.36204	9.656031	62.37872	20.40794	3.175275	24.48929	11.254738
2	1991	19.23357	10.598201	61.41041	18.47113	2.892325	22.80740	11.856735
3	1992	19.15840	10.066865	61.67921	17.58468	4.398464	20.75265	10.162888
4	1993	19.78795	10.549144	61.72233	18.12526	4.730088	19.55881	11.454528
5	1994	19.53812	10.194474	60.40045	18.08844	4.295431	21.21910	7.993026
6	1995	19.83536	9.624143	61.00410	19.21414	5.035639	17.26054	9.416323
		New_Zealand	Sweden	Switzerland	United_Kingdom	United_States		
1		80.00620	51.00011	54.98254	1.828767	11.528647		
2		77.18945	44.30088	57.16370	1.656439	10.757414		
3		72.58771	52.33321	56.90938	2.005662	9.916110		
4		77.02407	52.92433	59.57279	1.777626	10.484326		
5		82.05216	43.02873	60.57322	2.139842	9.747236		
6		83.85281	47.57878	57.42996	2.066535	10.801085		

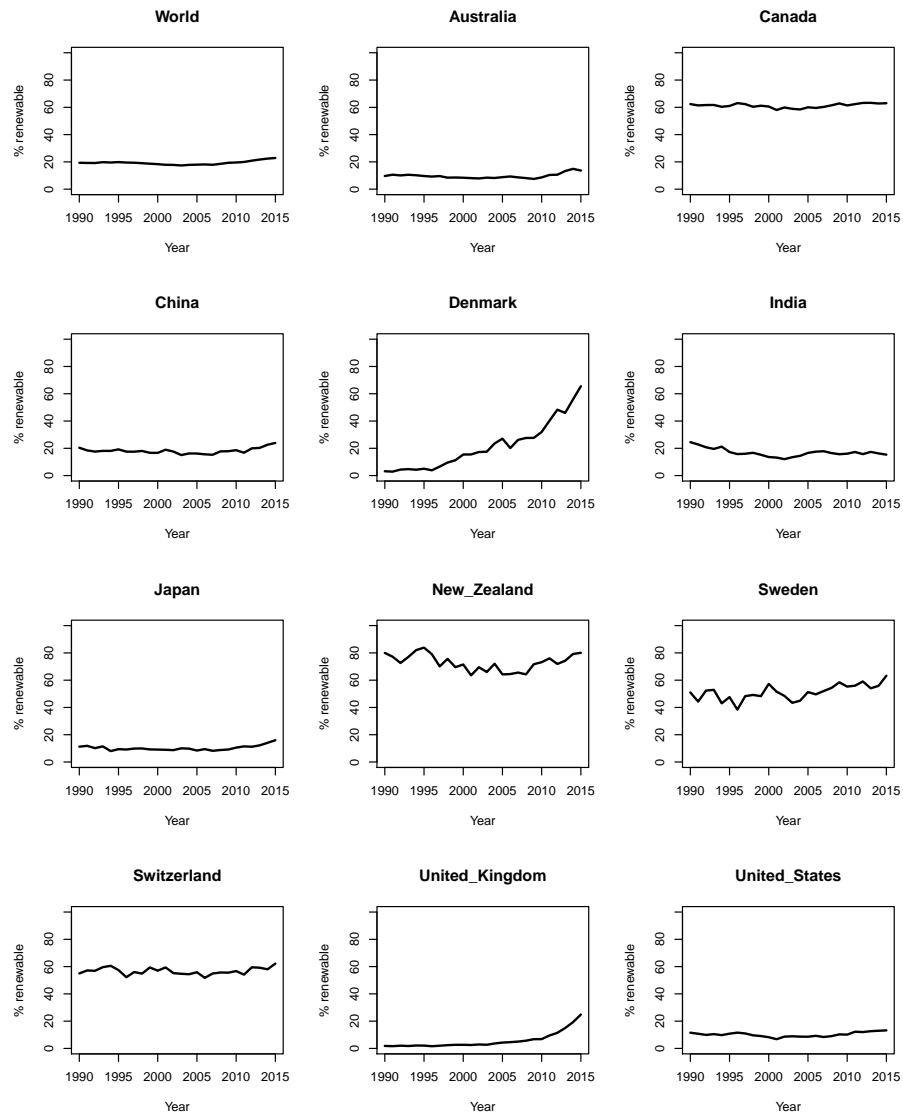
```
dfi <- df[,c(1,13)]
plot(x=dfi[,1],
     y=dfi[,2],
     type="l",lwd=2,
     xlim=c(1990,2015),ylim=c(0,100),
     xlab="Year",ylab="% renewable",
     main=names(dfi)[2])
```



Now loop it!

Task 4: Use that code as the foundation for building up a `for` loop that displays the same time series for every country in the dataset on a multi-pane graph that with 4 rows and 3 columns.

```
par(mfrow=c(4,3))
i=3
for(i in 2:ncol(df)){
  dfi <- df[,c(1,i)] ; dfi
  plot(x=dfi[,1],
       y=dfi[,2],
       type="l",lwd=2,
       xlim=c(1990,2015),ylim=c(0,100),
       xlab="Year",ylab="% renewable",
       main=names(dfi)[2])
}
```



Now loop it differently!

Task 5: Now try a different presentation. Instead of producing 12 different plots, superimpose the time series for each country on the *same single plot*.

To add some flare, highlight the USA curve by coloring it red and making it thicker.

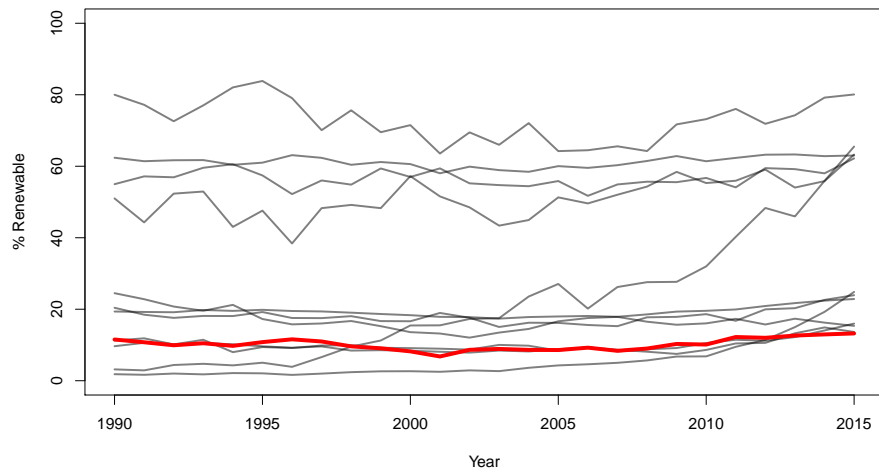
```

par(mfrow=c(1,1))
plot(1,type="n",lwd=2,
      xlim=c(1990,2015),ylim=c(0,100),
      xlab="Year",ylab="% Renewable")

for(i in 2:ncol(df)){
  dfi <- df[,c(1,i)] ; dfi
  lines(dfi[,2]~dfi[,1],lwd=2,col=adjustcolor("black",alpha.f=.5))
}

lines(df$United_States~df$year,lwd=4,col="red")

```



Chapter 28

Writing functions

Chapter 29

Working with text

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Working with factors

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Matrices & lists

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Learning goals

- Item 1
- Item 2
- Item 3

Tutorial video

Bangarang - Crew Briefing from Luke Padgett on Vimeo.

Basics

Exercise 1

Review assignment

Introduce data

Introduce task(s)

63.1 Other Resources

<https://desiree.rbind.io/post/2020/learnr-iframe/>

<https://rstudio.github.io/learnr/>