

Working Title: the data science canon

Databrew

2021-04-08

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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

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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

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Advanced techniques

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Joining datasets

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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.

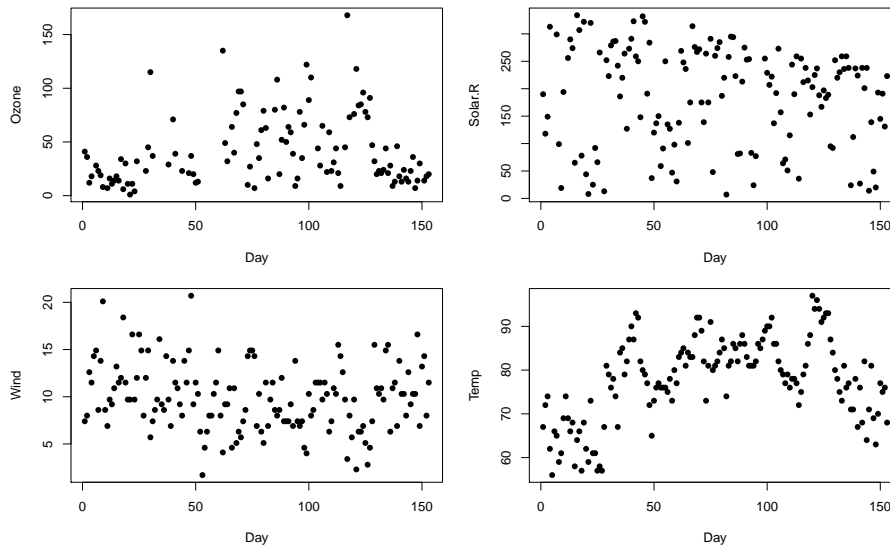
```
data(airquality)
head(airquality)
```

	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
```

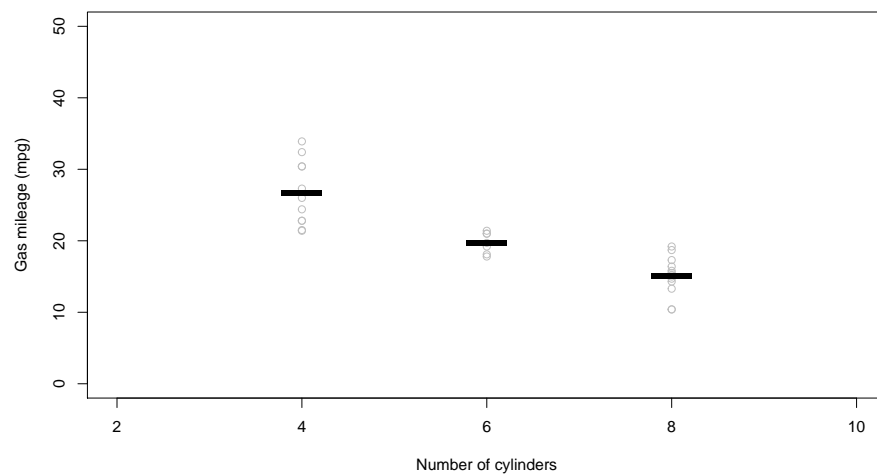
```
# Let's make an empty plot
plot(1,type="n", # tell R not to draw anything
     xlim=c(2,10),ylim=c(0,50),
     xlab="Number of cylinders",
     ylab="Gas mileage (mpg)")

# 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

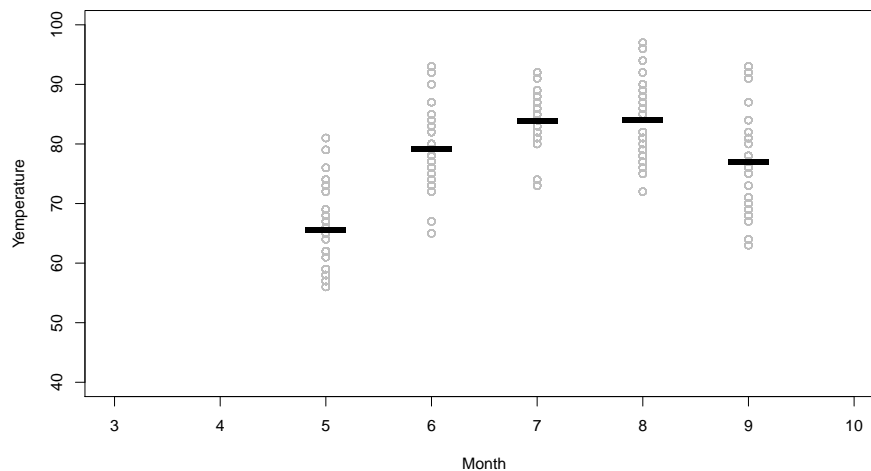
Now try to do something similar on your own with the `airquality` dataset. Use `for` loops to create a plot with Month on the x axis and Temperature on

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)
```

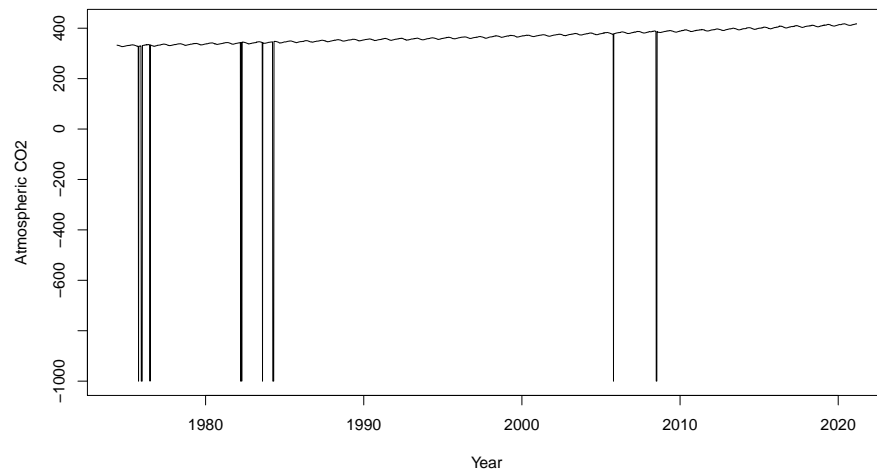
```
year month day_of_month day_of_year year_dec frac_of_year    CO2
```

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.

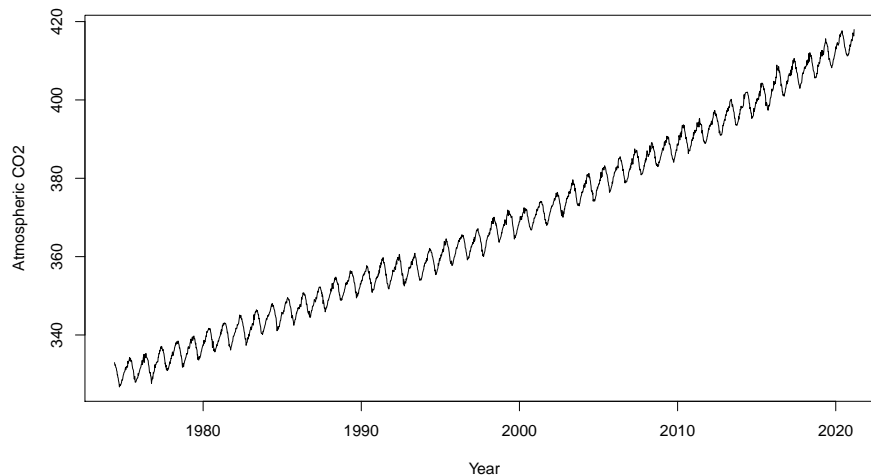
Try plotting the Keeling Curve:

```
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
```

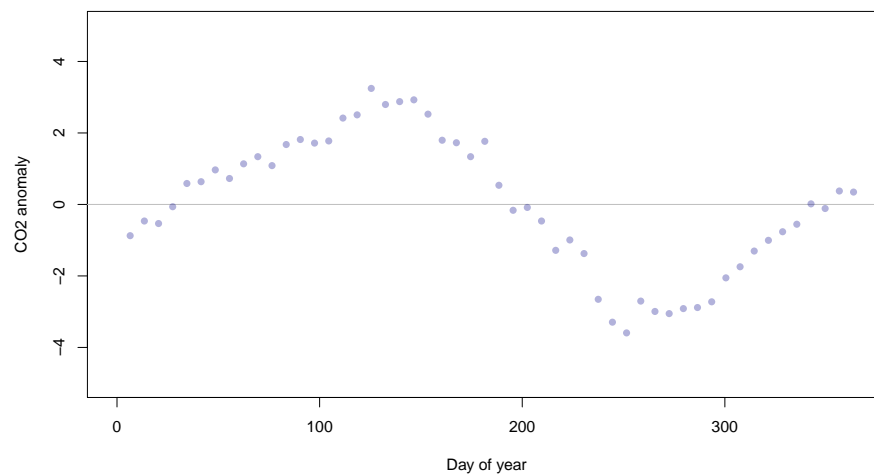
```
[1] 354.4538
```

```
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:

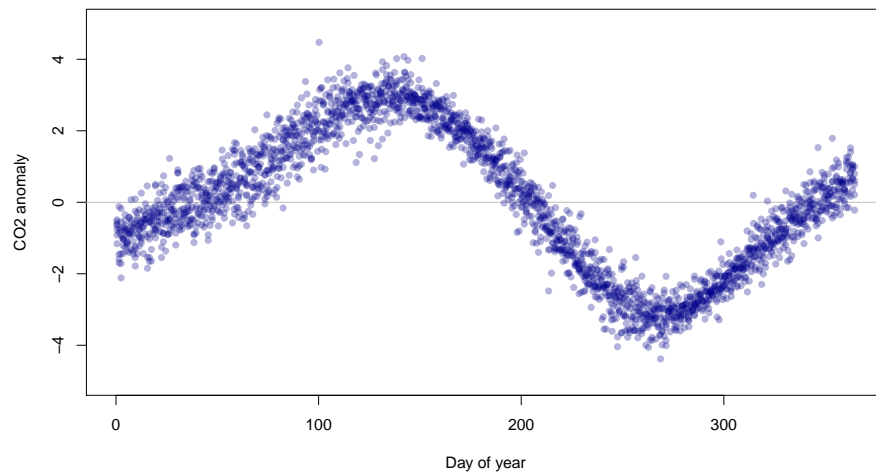
```
# First, stage your empty plot:
plot(1,type="n",
     xlim=c(0,365),xlab="Day of year",
     ylim=c(-5,5),ylab="CO2 anomaly")
```

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

```
# Now we will loop through each year of data. First, get a vector of the years included in the data  
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.

26.0.1 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

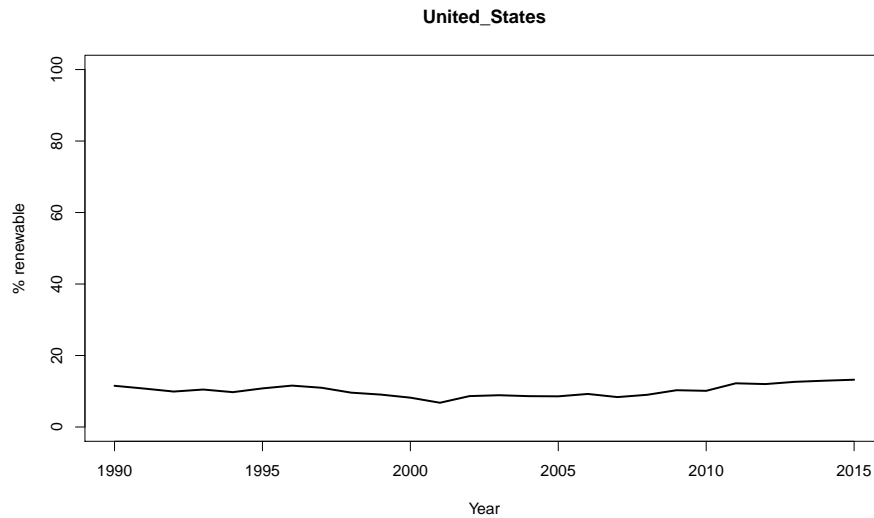
Practice with a single plot

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		

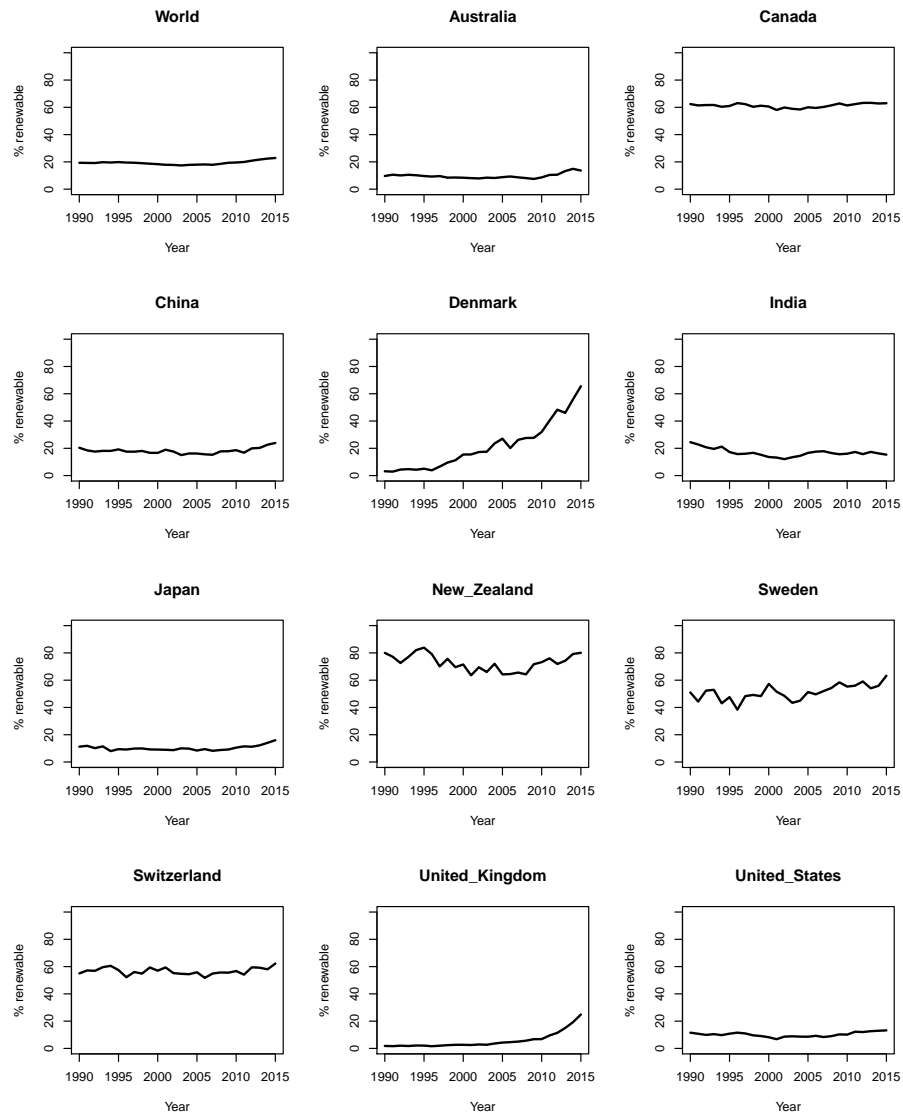
```
dfi <- df[,c(1,13)]
plot(x=dfi[,1],
     y=dfi[,2],
     type="l",lwd=2,
     xlim=c(1990,2015),ylim=c(0,100),
     xlab="Year",ylab="% renewable",
     main=names(dfi)[2])
```



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.

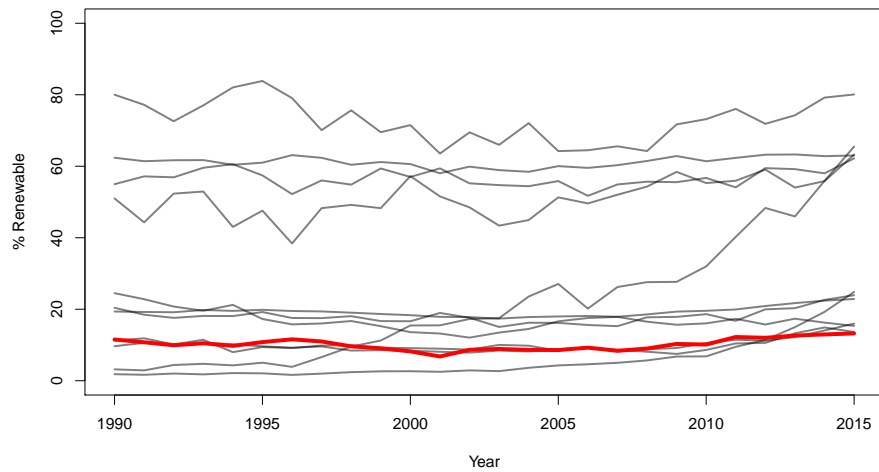

```

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")

```



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Working with factors

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Learning goals

- Item 1
- Item 2
- Item 3

Here is some teacher content.

Tutorial video

Bangarang - Crew Briefing from Luke Padgett on Vimeo.

Basics

Exercise 1

Review assignment

Introduce data

Introduce task(s)

62.1 Other Resources

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

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