

# Introduction to R

“How do you turn this thing on?”

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Sep. 4 2023

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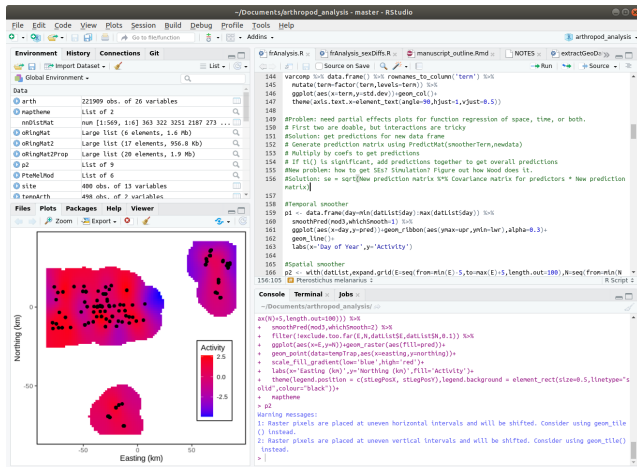
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  - ▶ No point-and-click interface; simple things can take more time
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- ▶ This is not a course in R programming (see [here](#), [here](#), [here](#) , but you do need some basic techniques

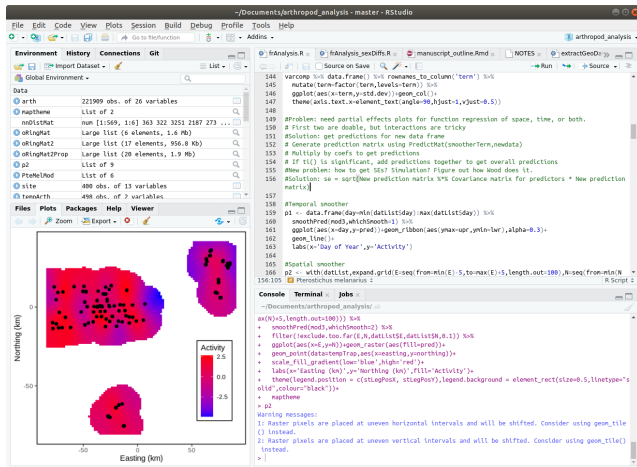
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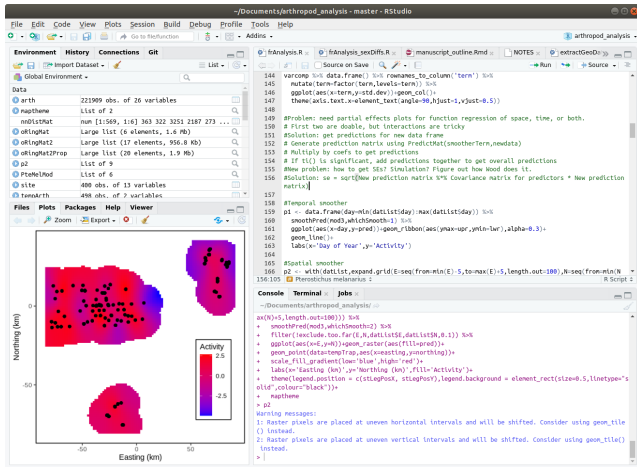
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- ▶ **Scripts** are lists of commands that get passed into the console
- ▶ If you're using RStudio, 2 of the 4 panes will be dedicated to the console and scripts



# Objects and Functions

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  - ▶ Control flow - *if* and *for*

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# Objects

- ▶ Let's make some objects. These are all single objects:

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myLogical <- TRUE          #A logical object
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- ▶ These are objects joined into a *vector*, joined by the function `c` (concatenate):

```
myCharVec <- c("I like pie", "I like cake", "I like anything you bake")  
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- ▶ How long are each of these vectors?

```
howLong <- c(length(myCharVec), length(myNumVec), length(myLogVec))
howLong  #This executes the `print` command on `howLong`
```

```
## [1] 3 5 6
```

## Vectors - “getting”

```
myCharVec  #Here's what's inside the whole thing
```

```
## [1] "I like pie"           "I like cake"
```

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- ▶ Results:

```
myCharVec  #Here's what's inside the whole thing
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```
## [1] "Parakeets" "Cats"      "Dogs"
```

## Class conversions

Vectors (or other data) can be converted between **classes**, usually using *as.something* statements:

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- ▶ Characters to **factors**: these represent *categories* or experimental levels

```
as.factor(myCharVec) #Default order is alphabetical
```

```
## [1] Parakeets Cats      Dogs
```

```
## Levels: Cats Dogs Parakeets
```



# Dataframes

- Dataframes look similar to matrices, but can hold different data types in each column:

```
myDF <- data.frame(stringCol = myCharVec,  
  numCol = myNumVec[c(1:3)],  
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myDF
```

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## 2      Cats     2   TRUE  
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```

- ▶ `summary(myDF)` *#This function summarizes each column*

```
##   stringCol           numCol       logCol  
## Length:3           Min.      :1.0     Mode :logical  
## Class :character    1st Qu.:1.5     FALSE:1  
## Mode  :character    Median  :2.0     TRUE  :2  
##                               Mean    :2.0  
##                               3rd Qu.:2.5  
##                               Max.    :3.0
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▶ `myDF[1, "numCol"]`

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

▶ `myDF$numCol[1]`

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

# Manipulating dataframe

Like other objects, you can alter dataframes

- ▶ You can add columns

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- ▶ We'll learn easier ways of doing this next week using the tidyverse

## Reading csv files

- One common practice is to read in your own dataframe from a csv file <sup>2</sup>

```
testDat <- read.csv("test_results.csv") #Path to csv file  
head(testDat) #head shows only the first 6 rows of dataframe
```

##	Concentration	Treatment	Lab.Member	Time.of.Day
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## 2	3.2	Control	Will	Morning
## 3	3.6	Control	Will	Morning
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- ▶ Make sure that the csv file is in your *working directory*

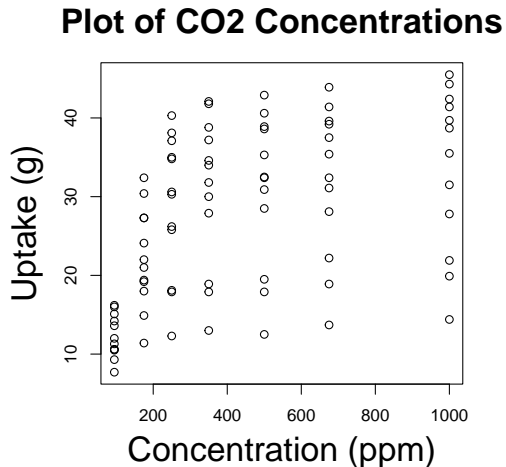
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## Plotting

- The *plot* command is useful for quickly looking at sets of data. The following CO2 dataset is built-in to R.<sup>3</sup>

```
#Makes a plot of the uptake (y) and  
# concentration (x) columns of CO2  
# dataframe, and customizes axis labels  
plot(x = CO2$conc, y = CO2$uptake,  
      xlab = 'Concentration (ppm)',  
      ylab = 'Uptake (g)',  
      main = 'Plot of CO2 Concentrations',  
      cex.lab = 2, cex.main=2)
```

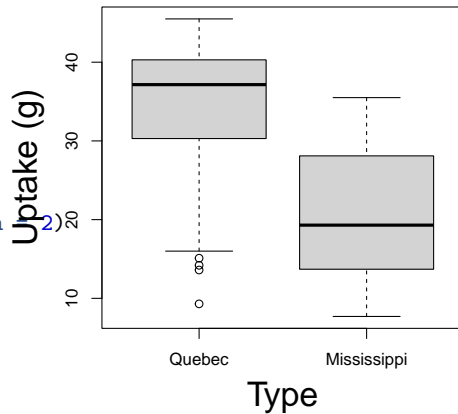


<sup>3</sup>To see others, type `data()` in the console

## More Plotting

- The boxplot command can summarize *continuous* and *categorical* data

```
# Boxplot uses a formula rather than  
# x,y vectors  
  
# Formula: uptake depends on (~) Type  
boxplot(CO2$uptake ~ CO2$Type, xlab = "Type",  
        ylab = "Uptake (g)", cex.lab = 2, cex.main = 2)
```





## First challenge

Your supervisor has just given you a dataset (*test\_results.csv*) recorded by two undergrads. However, these undergrads were in a hurry and have made some mistakes:

- ▶ Make a **script** in R, and use this to record what you do
- ▶ Read the *csv* file and fix any mistakes. Bonus if you do this without using Excel!
- ▶ Plot the concentration data by treatment group, then plot it for each undergrad. Does there look like much of a difference?
- ▶ Some useful commands: **read.csv**, **boxplot**, **is.na**, **as.factor**, **summary**

# Functions

- Functions take objects as **arguments** (input) and return other **objects** (output)

```
myNumVec <- c(1, 2, 3, 4, 5)
meanVec <- mean(myNumVec)  #Arithmetic mean (average)
sdVec <- sd(myNumVec)      #Standard deviation (sqrt(variance))
meanSdVec <- c(meanVec, sdVec)  #Joins mean and SD into a vector
meanSdVec
```

```
## [1] 3.000000 1.581139
```

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- ▶ If you can't remember how a command works, use ? in the console to access the help files (e.g. ?median)

# Homemade Functions

- You can make your own functions! This is useful if you have to do the same thing to many different input objects.

```
myFun <- function(input) {  
  # Takes a vector of numbers  
  A <- mean(input) #Take the mean of INPUT  
  B <- sd(input)   #Take the SD of INPUT  
  C <- c(A, B)     #Join A and B into a vector C  
  return(C)       #Return (output) C, then end the function  
}  
myFun(myNumVec)   #Same as previous slide  
  
## [1] 3.000000 1.581139
```

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  # Takes a vector of numbers  
  A <- mean(input) #Take the mean of INPUT  
  B <- sd(input)   #Take the SD of INPUT  
  C <- c(A, B)     #Join A and B into a vector C  
  return(C)       #Return (output) C, then end the function  
}  
myFun(myNumVec)   #Same as previous slide
```

```
## [1] 3.000000 1.581139
```

- ▶ The objects inside of functions (A, B, C in the one above) disappear after the function runs. However, *functions can see objects in the outer environment*, so beware of the Steve Problem\*

## Summary statistics

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- Using the CO2 plant example, how does *uptake* differ between *Type*?

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# Split up uptake by Type and Treatment, then take the mean  
tapply(CO2$uptake, list(CO2$Type, CO2$Treatment), mean)
```

```
##              nonchilled  chilled  
## Quebec             35.33333 31.75238  
## Mississippi        25.95238 15.81429
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## Mississippi          25.95238 15.81429
```

- ▶ Typing “CO2” over and over again is annoying. You can use *with* to avoid repeating the name of the dataframe (avoid using *attach*)

```
# Runs command inside the name space of the CO2 object
with(CO2, tapply(uptake, list(Type, Treatment), sd))
```



## if statements

- R can be told to do things only *if* certain conditions apply. This is useful inside of functions for error handling:

```
myFun2 <- function(x) {  
  xClass <- class(x) #What class is x? (Numeric, character, boolean)  
  
  if (xClass == "character") {  
    # == means 'are these things equal'?  
    return("This is a string") #If x is a character, returns a message  
  } else {  
    return(mean(x)) #If x isn't a character, returns the mean of x  
  }  
}
```

myFun2(myCharVec)

```
## [1] "This is a string"
```

```
myFun2(myNumVec)
```

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

## for loops

- R can be told to do things repeatedly, using an *index* inside a loop:

```
classVec <- rep(0, 10) #Storage vector of zeros, 10 long
classVec[c(1, 2)] <- 1 #Set first two slots to 1

# Each time the loop repeats, i will take on values 3 to 10
for (i in 3:length(classVec)) {
  # ith slot of classVec becomes the sum of the previous two slots
  classVec[i] <- classVec[i - 1] + classVec[i - 2]
}
```

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}
```

- ```
classVec
```

*#First 10 numbers in the Fibonacci sequence*

```
## [1] 1 1 2 3 5 8 13 21 34 55
```

## Second challenge

Population growth models are common in ecology, and usually often take the form  $n_t = n_{t-1} + rn_{t-1}$ , where  $n$  is the number of critters at some time point  $t$ , and  $r$  is the change in  $n$  from one point to the next ( $r = 0$ : no change).

- ▶ Write a `function` (with a `for` loop inside) that performs a simple population simulation using the following models:

Hint: functions need input variables that tell them what to do. The input variables here could be things like *starting population* ( $n_0$ ), *growth rate* ( $r$ ), and *number of time steps* ( $T$ ) to simulate

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  - ▶ Logistic growth:  $n_t = n_{t-1}(1 + r(1 - \frac{n_{t-1}}{k}))$

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- ▶ Make a simple plot of your results

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# Lists

- ▶ Lists look similar to vectors, but can hold anything in each slot, including other lists.
- ▶ LOTS of things in R (e.g. model output) are specially-structured lists at their core

```
myList <- list(charSlot = myCharVec,  
              numSlot = myNumVec, logSlot = myLogVec,  
              dfSlot = myDF)
```

```
## $charSlot  
## [1] "Parakeets" "Cats"      "Dogs"  
##  
## $numSlot  
## [1] 1 2 3 4 5  
##  
## $logSlot  
## [1] TRUE TRUE FALSE TRUE FALSE FALSE  
##  
## $dfSlot  
##   stringCol numCol logCol  
## 1 Parakeets      1  TRUE  
## 2      Cats      2  TRUE  
## 3      Dogs      3 FALSE
```



## Accessing Lists

Lists can be accessed numerically or logically, or by their name slots:

```
myList[[2]] #Needs 2 square brackets to isolate object
```

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

```
myList[["numSlot"]]
```

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

```
myList$numSlot
```

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

```
myList[[4]][, 3] #Same as myList$dfSlot$logCol
```

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

## *lapply* and *sapply*

Loops can be slow: using a **functional** is generally better (if each step doesn't depend on the previous one)

## *lapply and sapply*

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```
input <- c(1, 2, 3)  #Input vector
pFun <- function(N, type = "normal") {
  if (type == "poisson")
    rpois(N, 3) else rnorm(N, 3)
}
lapply(input, pFun, type = "poisson") #Generates a list of N Poisson random numbers
```

```
## [[1]]
## [1] 3
##
## [[2]]
## [1] 4 2
##
## [[3]]
## [1] 2 0 4
```

## *lapply* and *sapply*

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##
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```

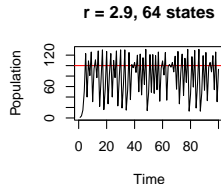
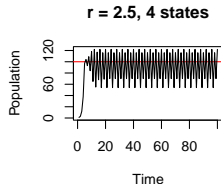
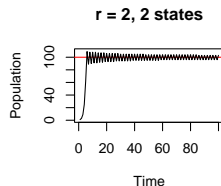
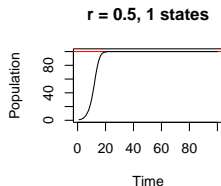
Different output formats: *lapply* uses a list, *sapply* uses a vector (or matrix)

## Third challenge

The discrete logistic growth equation has some interesting mathematical properties (see here). At certain values of  $r$  the population converges to the carrying capacity  $K$ , while at other values it cycles between multiple values.

Using *lapply*, *sapply* and the logistic function you wrote for the second challenge:

- ▶ Write a script that iterates across a range of  $r$  values:  $1 \leq r \leq 3$
- ▶ At each  $r$  value, how many unique values exist?
- ▶ Keep  $K$  at 100 and  $n_0$  at 1 for now. Use a simulation time of  $t = 1000$ , but discard the first 100 points



## To do this week:

Get a dataset to work with! This can be:

1. Your own dataset that you want to analyze

Try loading this data into R and play around with it: make some simple plots, or get some summary statistics. Bring it next week and we'll continue using it.

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  - ▶ Take a look at a data repository like Dryad

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