Programing fundamentals

- A program is a set of instructions for a computer to follow
- Programs are often used to manipulate data (in all type and formats you discussed last week)
- Simple to complex
  - scripts that you save in R-Markdown
  - instructions to analyze relationships in census data and visualize them
  - a model of global climate

Programing fundamentals

- Programs can be written in many different languages (all have their strengths and weakness)
- Languages expect instructions in a particular form (syntax) and then translate them to be readable by the computer
- Languages have evolved to make it help users write programs that are easy to understand, re-use, extend, test, run quickly, use lots of data…

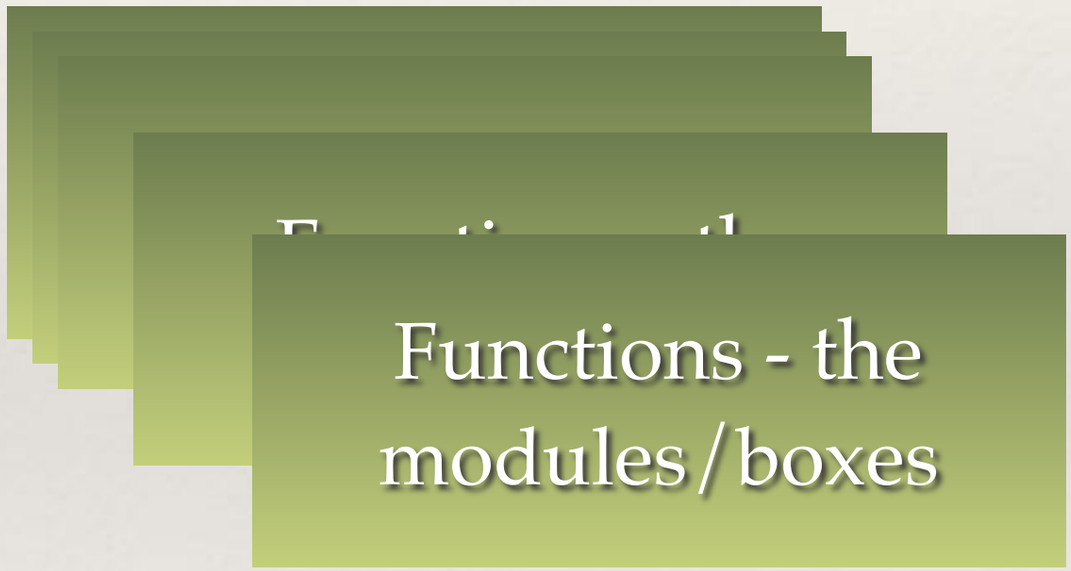
Programing fundamentals

- Operations (=,+,-,…concatenate, copy)
- Data structures (simple variables, arrays, lists…)
- Control structures (if then, loops)
- Modules…Functions

Concepts common to all languages through the syntax may be different

Modularity

Main controls the overall flow of program- calls to the functions/ modules/building blocks



- A program is often multiple pieces put together
- These pieces or modules can be used multiple times

Programing fundamentals

- Modularity
  - breaking your instructions down into individual pieces
  - identifying instructions that can be reused
    - an ecosystem model might re-use instructions for calculating how a species grows
    - an accounting program might re-use instructions for computing net present value from interest rates
- modules often become ‘black boxes’ which hides detail that might make understanding the program overly complex
- most languages have lots of black boxes already written and most allow you to write your own

Best practices for software development

- Read: Wilson G, Aruliah DA, Brown CT, Chue Hong NP, Davis M, et al. (2014) Best Practices for Scientific Computing. PLoS Biol 12(1): e1001745. doi:10.1371/journal.pbio.1001745
- Blanton, B and Lenhardt, C 2014. A Scientist's Perspective on Sustainable Scientific Software. Journal of Open Research Software 2(1):e17, DOI: http://dx.doi.org/10.5334/jors.ba
- but also
- http://simpleprogrammer.com/2013/02/17/principles-are-timeless-best-practices-are-fads/

Programing fundamentals

Box 1. Summary of Best Practices

1. Write programs for people, not computers.

(a) A program should not require its readers to hold more than a handful of facts in memory at once.
(b) Make names consistent, distinctive, and meaningful.
(c) Make code style and formatting consistent.

2. Let the computer do the work.

(a) Make the computer repeat tasks.
(b) Save recent commands in a file for re-use.
(c) Use a build tool to automate workflows.

3. Make incremental changes.

(a) Work in small steps with frequent feedback and course correction.
(b) Use a version control system.
(c) Put everything that has been created manually in version control.

4. Don't repeat yourself (or others).

(a) Every piece of data must have a single authoritative representation in the system.
(b) Modularize code rather than copying and pasting.
(c) Re-use code instead of rewriting it.

5. Plan for mistakes.

(a) Add assertions to programs to check their operation
(b) Use an off-the-shelf unit testing library.
(c) Turn bugs into test cases.
(d) Use a symbolic debugger.

6. Optimize software only after it works correctly.

(a) Use a profiler to identify bottlenecks.
(b) Write code in the highest-level language possible.

7. Document design and purpose, not mechanics.

(a) Document interfaces and reasons, not implementati
(b) Refactor code in preference to explaining how it wo
(c) Embed the documentation for a piece of software i software.

8. Collaborate.

(a) Use pre-merge code reviews.
(b) Use pair programming when bringing someone new speed and when tackling particularly tricky problem
(c) Use an issue tracking tool.

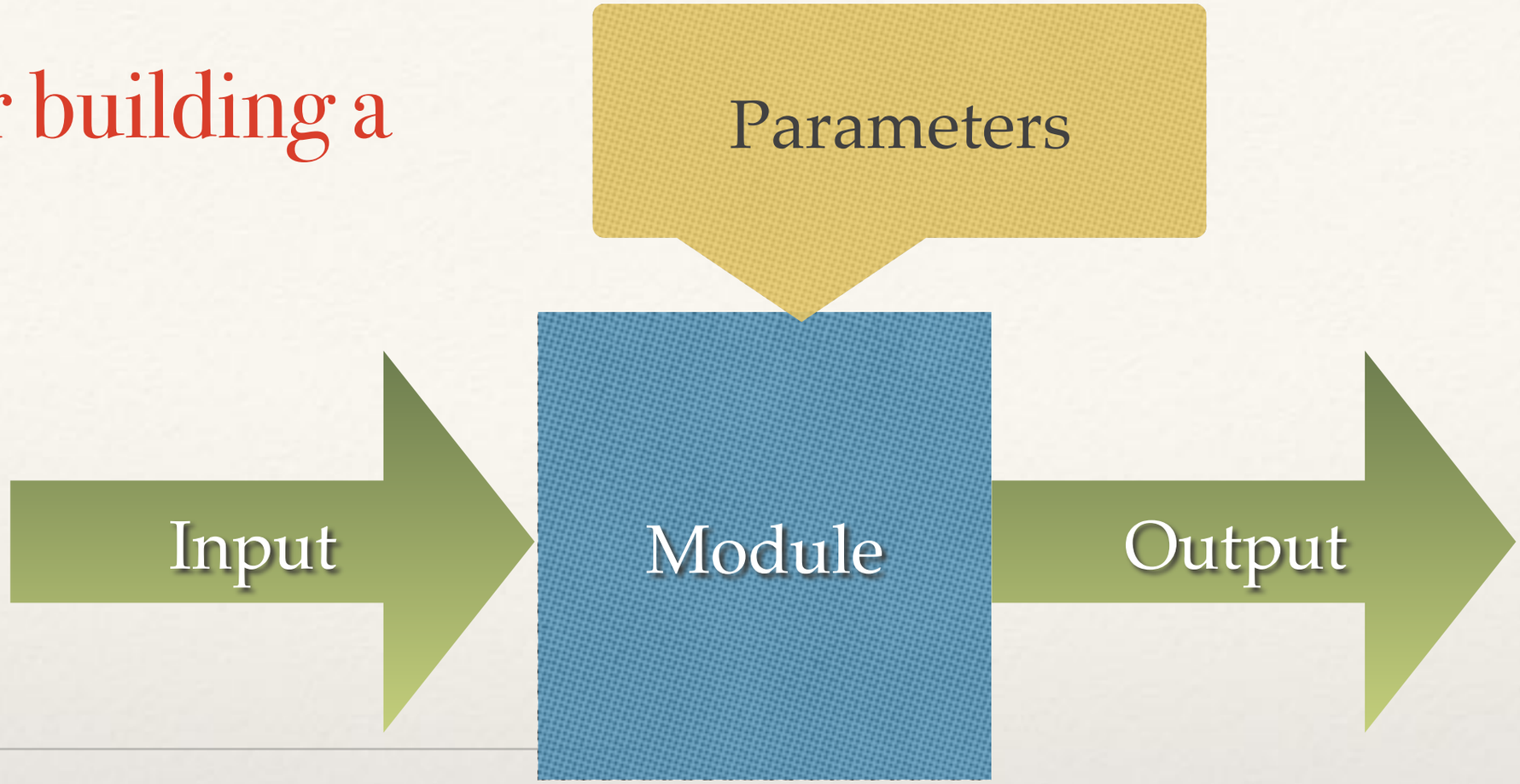
Best practices for model (software) development

- Common problems
  - Unreadable code (hard to understand, easy to forget how it works, hard to find errors, hard to expand)
  - Overly complex, disorganized code (hard to find errors; hard to modify-expand)
  - Insufficient testing (both during development and after)
  - Not tracking code changes (multiple versions, which is correct?)

STEPS: Program Design

1. **Clearly define your goal as precisely as possible, what do you want your program to do**
    1. **inputs/parameters**
    2. **outputs**
2. Implement and document
3. Test
4. Refine

Steps for building a module



1. Design the program “conceptually” - “on paper” in words or figures
2. Translate into a step by step representation
3. Choose programming language
4. Define inputs (data type, units)
5. Define output (data type, units)
6. Define structure
7. Write program
8. Document the program
9. Test the program
10. Refine…

Best practices for software development

- Automated tools (useful for more complex code development
- (note that GP's often create programs > 100 lines of code)
- Automated documentation
  - http://www.stack.nl/~dimitri/doxygen/
  - http://roxygen.org/roxygen2-manual.pdf
- Automated test case development
  - http://r-pkgs.had.co.nz/tests.html
- Automated code evolution tracking (Version Control)
  - https://github.com/

Designing Programs

- Inputs - sometimes separated into input data and parameters
    - input data = the “what” that is manipulated
    - parameters determine “how” the manipulation is done
    - “result = sort(BOD[,"demand"], decreasing=TRUE, method="quick")”
        - sort is the program - set of instructions - its a black box
        - input is BOD[,”demand”]
        - parameters are *decreasing* and *method*
        - output is a sorted version of saved to “*result*”
- my iphone app for calculating car mileage
    - inputs are gallons and odometer readings at each fill up
    - graph of is miles/gallon over time
    - parameters control units (could be km/liter, output couple be presented as a graph or an average value)

Designing Programs

- What's in the box (the program itself) that gives you a relationship between outputs and inputs
  - the link between inputs and output
  - breaks this down into bite-sized steps or calls to other boxes)
  - think of programs as made up building blocks
  - the design of this set of sets should be easy to follow
-

Building Blocks

- Instructions inside the building blocks/box
  - Numeric data operators
    - +,-,/,*, %*%
  - Strings
    - substr, paste..
  - Math
    - sin, cos, exp, min, max…
    - these are themselves programs - boxes
- R-reference card is useful!

Best practices for software development

- Structured practices that ensures
  - clear, readable code
  - modularity (organized “independent” building blocks)
  - testing as you go and after
  - code evolution is documented

Building Blocks

- Functions (or objects or subroutines)!
- The basic building blocks
- Functions can be written in all languages; in many languages (object-oriented) like C++, Python, functions are also objects
- Functions are the “box” of the model - the transfer function that takes inputs and returns outputs
- More complex models - made up of multiple functions; and nested functions (functions that call/user other functions)

Functions

- Write down what the function will do - given different inputs and parameters
- simple
  - input (temperature); output (growth rate)
- more complex
  - inputs (temperature, organism type)
  - output (if animal, respiration; if plant, growth)

- Write a contract for a function to compute net present value
- Write a contract for a function to estimate the impact of pollution concentration on microbial biomass

Functions in R

- Format for a basic function in R

#' documentation that describes inputs, outputs and what the function does

FUNCTION NAME = function(inputs, parameters) {

body of the function (manipulation of inputs)

return(values to return)

}

In R, inputs and parameters are treated the same; but it is useful to think about them separately in designing the model - collectively they are sometimes referred to as arguments

ALWAYS USE Meaningful names for your function, its parameters and variables calculated within the function

A simple program: Example

- Input: Reservoir height and flow rate
- Output: Instantaneous power generation (W/s)
- Parameters: $K_{Efficiency}$, ϱ (density of water), g (acceleration due to gravity)

$P = \varrho * h * r * g * K_{Efficiency};$

P is Power in watts, ϱ is the density of water (~1000 kg/m3), h is height in meters, r is flow rate in cubic meters per second, g is acceleration due to gravity of 9.8 m/s2, $K_{Efficiency}$ is a coefficient of efficiency ranging from 0 to 1.

Building Models

- Example (power_gen.R)

```
power_gen = function(height, flow, rho=1000, g=9.8, Keff=0.8) {
result = rho * height * flow * g * Keff
return(result)
}
```

Building Models

- Inputs/parameters are height, flow, rho, g, and K
- For some (particularly parameters) we provide default values by assigning them a value (e.g Keff = 0.8), but we can overwrite these
- Body is the equations between { and }
- *return* tells R what the output is

```
power_gen = function(height, flow, rho=1000, g=9.8, Keff=0.8) {

result = rho * height * flow * g * Keff
return(result)
}
```

Building Models: Using the model

```
> power_gen(20,1)
[1] 156800
> power_gen(height=20,flow=1)
[1] 156800
> power.guess = power_gen(height=20,flow=1)
> power.guess
[1] 156800
> power.guess = power_gen(flow=1, height=20)
> power.guess
[1] 156800
```

Arguments to the function follow the order they are listed in your definition
Or you can specify which argument you are referring to when you call the program

```
power_gen = function(height, flow, rho=1000, g=9.8, K=0.8) {

# calculate power
result = rho * height * flow * g * K
return(result)
}
```

Building Models

- Always write your function in a text editor and then copy into R
- By convention we name files with functions in them by the name of the function.R
  - so power_gen.R
- you can also have R read a text file by *source("power_gen.R")* - make sure you are in the right working directory
- Eventually we will want our function to be part of a package (a library of many functions) - to create a package you must use this convention (name.R)

Building Models: Using the model

```
> power_gen(height=20, flow=1)
[1] 156800
> power_gen(height=20, flow=1, Keff=0.8)
[1] 156800
> power_gen(height=20, flow=1, Keff=0.5)
[1] 98000
> power_gen(height=10, flow=1, Keff=0.5)
[1] 49000
```

Defaults take the value they were assigned in the definition,
but can be overwritten

```
power_gen = function(height, flow, rho=1000, g=9.8, Keff=0.8) {

# calculate power
result = rho * height * flow * g * Keff
return(result)
}
```

Scoping

The scope of a variable in a program defines where it can be “seen”

Variables defined inside a function cannot be “seen” outside of that function

There are advantages to this - the interior of the building block does not ‘interfere’ with other parts of the program

```
> power_gen
function(height, flow, rho=1000, g=9.8, Keff=0.8) {

    # calculate power
    result = rho * height * flow * g * K
    return(result)
}
> result
Error: object 'result' not found
> K
Error: object 'K' not found
>
```

Functions: Error

- what will your function do if user gives you garbage data
- Two options
  - error-checking
    - if temperature < -100 or > 100, or NA, output warning
  - assume user reads the contract :)
    - return unrealistic values
    - so if input -999.0, will still try to output growth rate
- Error-checking is helpful if you are going to build a model made up of many functions- why?

Building Models

- Add error checking

```
power_gen = function(height, flow, rho=1000, g=9.8, Keff=0.8) {

  # make sure inputs are positive
    if (height < 0) return(NA)
    if (flow < 0) return(NA)
    if (rho < 0) return(NA)


  # calculate power
    result = rho * height * flow * g * Keff


  return(result)
}
```

Functions - R style

- Documentation style that allows automatic generation of help pages (we will get there)

- Save the function as a SEPARATE file - named by the name of the function.R (autopower.R)

- Don’t include steps to run the function in that document (put these in another R script file or R markdown)

Building Models

- Add error checking

```
power_gen = function(height, flow, rho=1000, g=9.8, Keff=0.8) {

  # make sure inputs are positive
    check = ifelse(height < 0, NA, 0)
    check = ifelse(flow < 0, NA, 0)

    check = ifelse(rho < 0, NA, 0)

  # calculate power
     if (!is.na(check))
      result = rho * height * flow * g * Keff
     else
      result = NA


  return(result)
}
```

One of the equations used to compute automobile fuel efficiency is as follows this is the power required to keep a car moving at a given speed

$$Pb = c_{rolling} * m * g * V + 1/2\ A * p_{air} * c_{drag} * V^3$$

where $c_{rolling}$ and c_{drag} are rolling and aerodynamic resistive coefficients, typical values are 0.015 and 0.3, respectively.
V: is vehicle speed (assuming no headwind) in m/s (or mps)
m: is vehicle mass in kg
A is surface area of car (m2)
g: is acceleration due to gravity (9.8 m/s2)
p_{air} = density of air (1.2kg/m3)
Pb is power in Watts

Write a function to compute power, given a truck of m=31752 kg (parameters for a heavy truck) for a range of different highway speeds
plot power as a function of speed
how does the curve change for a lighter vehicle

Note that 1mph=0.477m/s

Simple Functions

```
#' Power Required by Speed
#'
#' This function determines the power required to keep a vehicle moving
at
#' a given speed
#' @param cdrag coefficient due to drag default=0.3
#' @param crolling coefficient due to rolling/friction default=0.015
#' @param v vehicle speed (m/2)
#' @param m vehicle mass (kg)
#' @param A area of front of vehicle (m2)
#' @param g acceleration due to gravity (m/s) default=9.8
#' @param pair (kg/m3) default =1.2
#' @return power (W)

autopower = function(cdrag=0.3, crolling=0.015,pair=1.2,g=9.8,V,m,A) {
P = crolling*m*g*V + 1/2*A*pair*cdrag*V**3
return(P)
}
```

Simple Functions

Now we can use the function - on console or in an Rmarkdown to keep track of steps

Note that we can use vectors (list of numbers) in addition to single numbers as inputs - see use of “v”

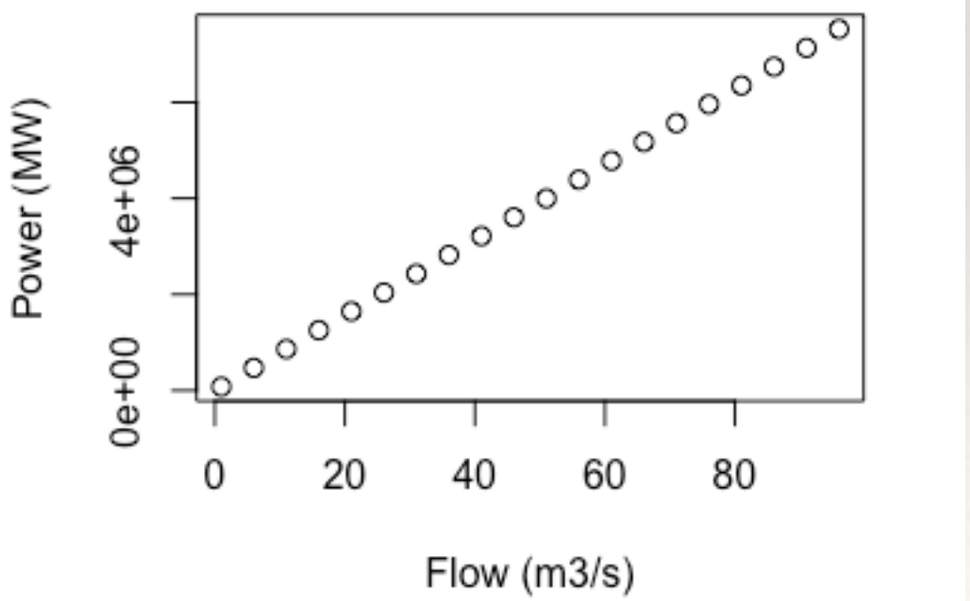
```
source(“autopower.R”)

v=seq(from=0, to=100, by=10)
plot(v, autopower(V=0.447*v, m=31752, A=25))
lines(v, autopower(V=0.447*v, m=61752, A=25))
```

Generating data for your function

- Generating data to test and use your function

```
# sequence
flow.ex = seq(from=1, to=100, by=5)
height.ex = 10

plot(flow.ex, power_gen(flow.ex, height=height
```

Why?: What is the power generated by a range of flow rates



Generating data for your function

- Random numbers from a uniform distribution

```
#random numbers
# uniform distribution
Keff.sen = runif(min=0.5, max=1, n=10)

flow.ex = seq(from=1, to=10)
height.ex = 10
# run model over uniform distribution

res = matrix(ncol=length(Keff.sen), nrow=length(flow.ex))
for (i in 1:length(Keff.sen))
  res[,i]=power_gen(flow.ex, height=height.ex, Keff.sen[i])
```

Why?: What is the power generated by a range of flow rates, how sensitivity are these to uncertainty in reservoir efficiency (we know its somewhere between 0.5-1 but all are equally likely

Plot. Power as a function of flow rate? How?

Generating data for your function

- Random numbers from a uniform distribution

```
# for plotting we need to WRANGLE

res = as.data.frame(res)
res$flow = flow.ex
res=gather(res, key=Keff, value=power, -flow)

head(res)

ggplot(res, aes(as.factor(flow), power))+geom_boxplot(col="red")
+labs(x="Flow Rate", y="Power")
```

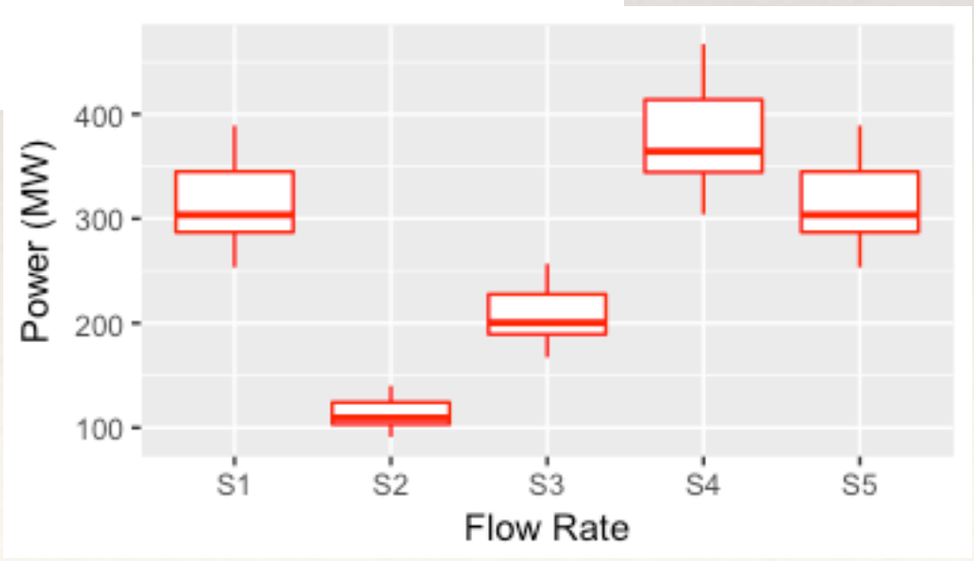
Generating data for your function

```
# random number generation - normal

Keff.sen = rnorm(mean=0.8, sd=0.1, n=20)

# provide a series of flow rates and heights - for different observation days
flow.ex = c(5,2,3,5,10)
height.ex = c(10,9,11,12,5)
res = apply(as.matrix(Keff.sen),1, power_gen, flow=flow.ex, height=height.ex)
```

Why?: We know heights and flow rates for 5 days - what is the power on those days? (reservoir efficiency is around 0.8 but some error in that estimate)

Generating data for your function

```
# random number generation - normal
# for plotting we need to WRANGLE


res = as.data.frame(res)
# name each day
res$day = sprintf("S%d", seq(from=1, to=length(flow.ex)))
res=gather(res, key=Keff, value=power, -day)


head(res)

ggplot(res, aes(day, power))+geom_boxplot(col="red") +
+ labs(x="Days", y="Power (MW)")
```

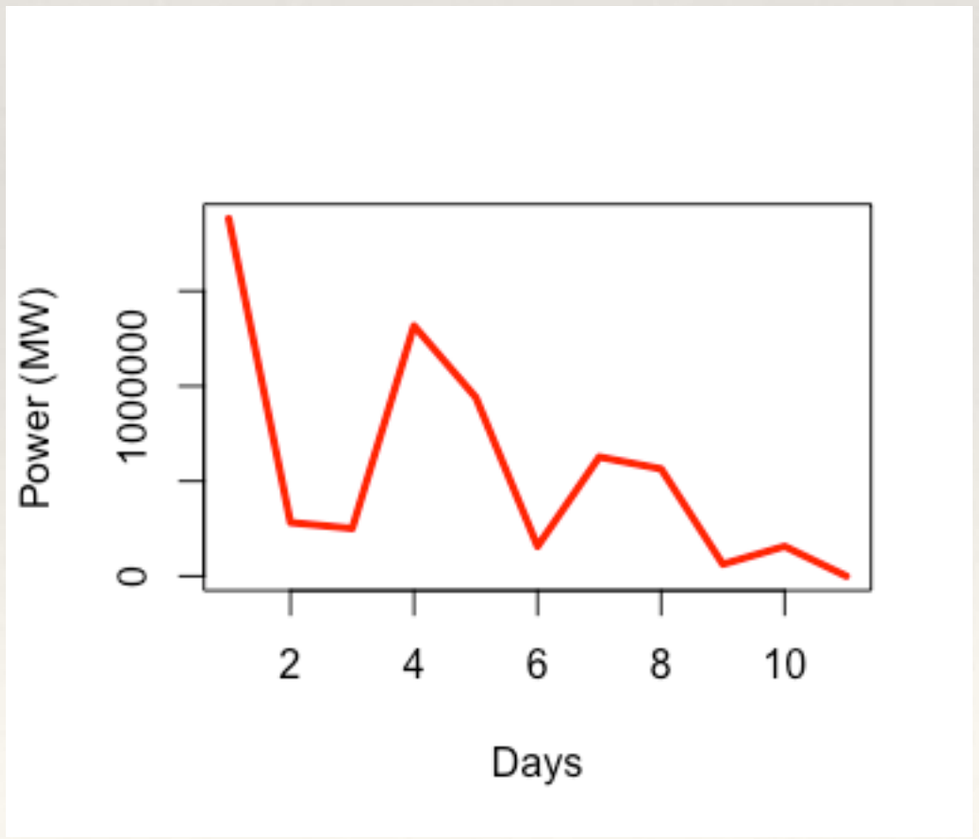


Generating data for your function

- Sampling from a set

```
height.ex = seq(from=20,to=0, by=-2)
possible.flow.rates = c(2,10,12)
flow.ex = sample(possible.flow.rates, replace=T, size=length(height.ex))
res = power_gen(flow=flow.ex, height=height.ex)
```

Why?: Reservoir height is slowly decreasing (in flows to reservoir are declining); managers use one of 3 possible release (flow) rates, what is a possible power trajectory over that period of decrease

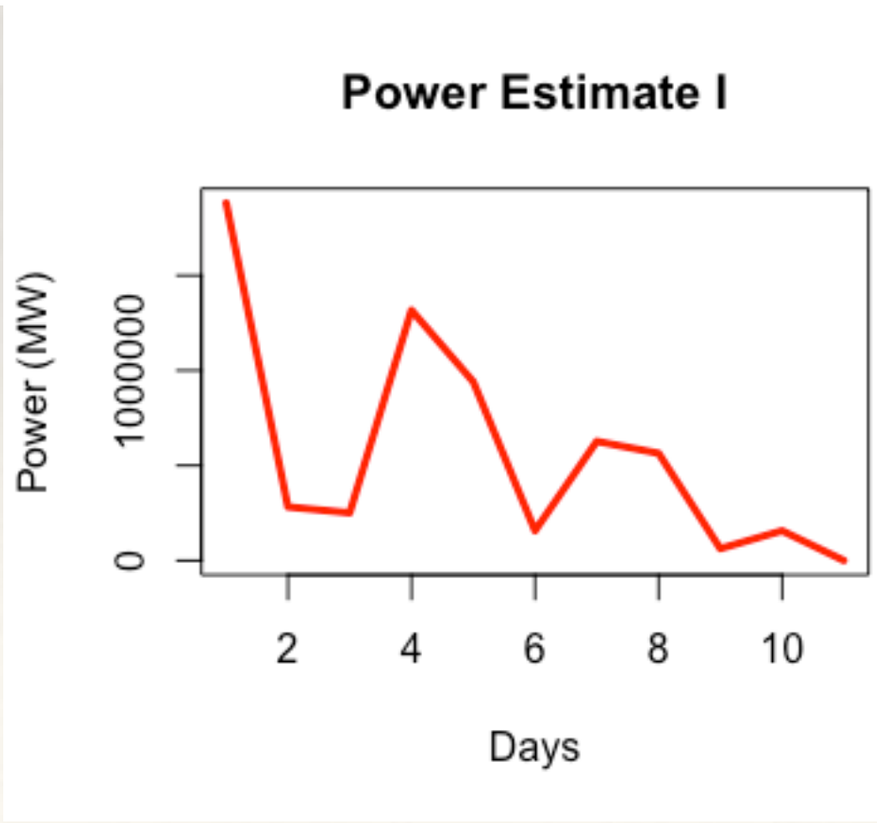


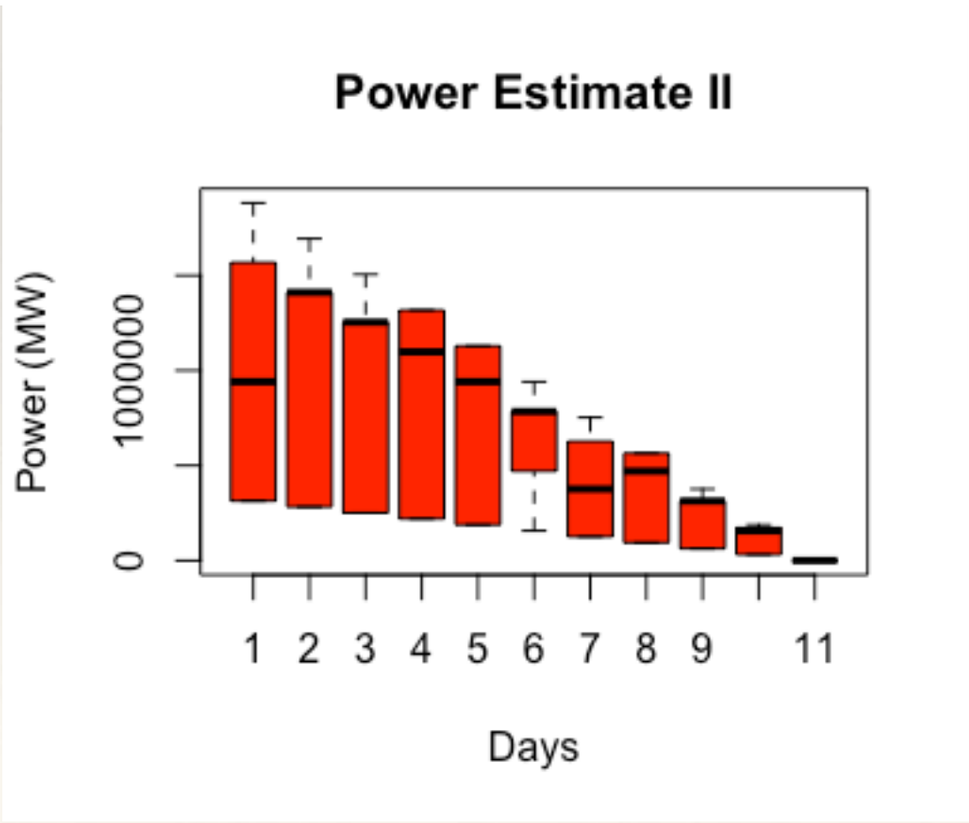
Generating data for your function

- Sampling from a set

Why?: Reservoir height is slowly decreasing (in flows to reservoir are declining); managers use one of 3 possible release (flow) rates, what is power trajectory over that period of decrease (accounting for uncertainty)

```
height.ex = seq(from=20,to=0, by=-2)
possible.flow.rates = c(2,10,12)
flow.ex = matrix(ncol=20, nrow=length(height.ex))
for(i in 1:20)
flow.ex[,i] = sample(possible.flow.rates, replace=T, size=length(height.ex))
res = apply(flow.ex,2, power_gen, height=height.ex)
boxplot(t(res), ylab="Power (MW)", xlab="Days", main= "Power Estimate II", col="red")
```

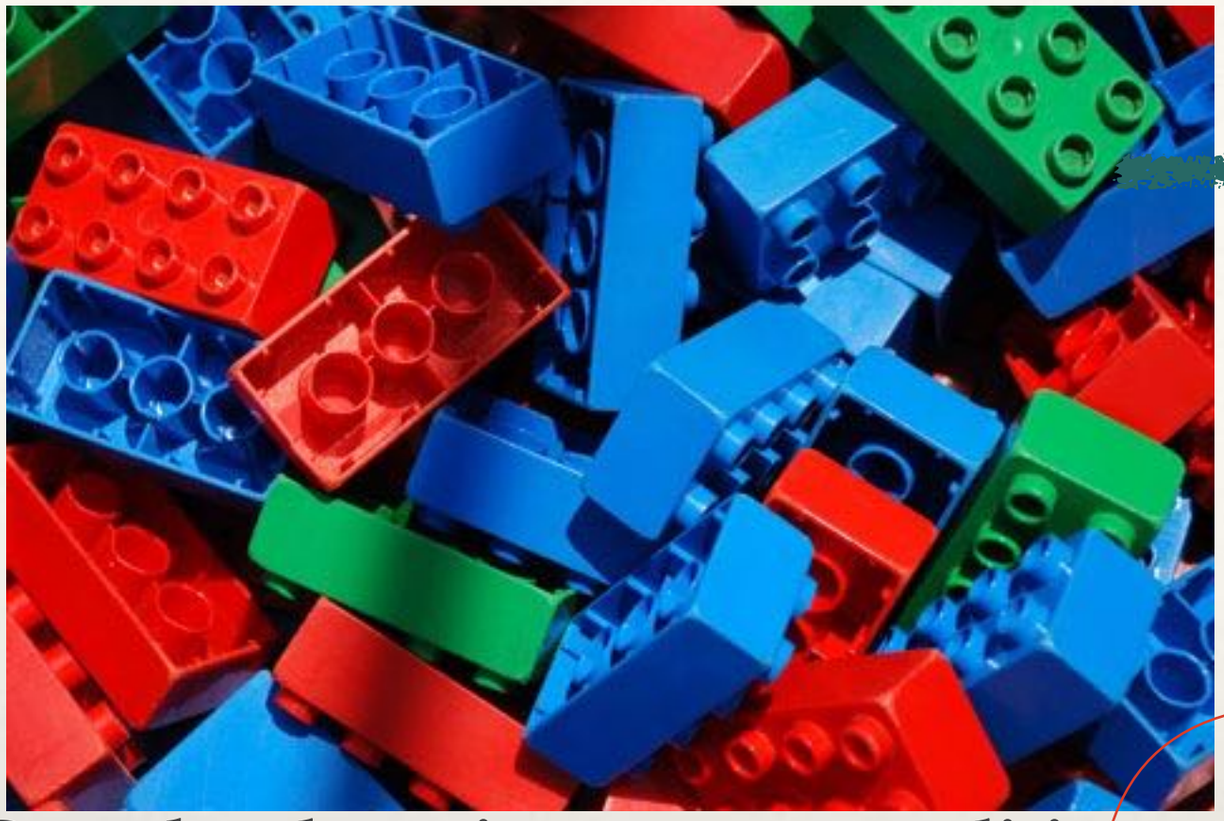




Generating data for your function

- Sampling can also come from categorical data

```
> # sampling categorical data
> flowers = c("iris","daisy","poppy","rose","dandelion","weed","violet")
> garden = sample(flowers, size=2, replace=T)
> garden
[1] "weed"  "daisy"
>
> ngardens=10
> nflowers=3
> gardens = matrix(nrow=nflowers, ncol=ngardens)
> for (i in 1:ngardens)
+     gardens[,i]=sample(flowers,size=nflowers, replace=T)
>
> gardens
     [,1]        [,2]    [,3]        [,4]    [,5]    [,6]    [,7]        [,8]    [,9]    [,10]
[1,] "weed"      "daisy" "poppy"     "poppy" "iris"  "daisy" "violet"    "poppy" "rose"  "weed"
[2,] "daisy"     "iris"  "dandelion" "poppy" "poppy" "iris"  "dandelion" "iris"  "daisy" "dandelion"
[3,] "dandelion" "poppy" "violet"    "daisy" "iris"  "daisy" "violet"    "weed"  "poppy" "dandelion"
>
```



MODEL

Complex data: time, space, conditions and their interactions

Building Programs

A core issue in modeling (both designing and using) are the **data structures**/formats used to hold data that is input and output from programs: In good programs, data structures support organization and program flow and readability

Key Programming concepts: Review of data types

- Understanding data types is important for designing your model I/O; specifying what the model will do
- Data types and data structures are necessary for creating more complex inputs and outputs

- All programming languages have sets of data types
  - single values: character, integer, real, logical/boolean (Y/N)
  - data structures: arrays, vectors, matrices,
    - in R core types; dataframes, lists, factors
    - in R defined types: spatial, date…

Key Programming concepts: Data types and structures

- Good data structures are:
  - as simple as possible
  - easy understand (readable names, and sub-names)
  - easy to manipulate (matrix operations, applying operations by category)
  - easy to visualize (graphs and other display)

Key Programming concepts: Review of data types

- Vectors - a 1-dimensional set of numbers
- a = c(1,5,8, 4, 22,33)
- Matrix - a 2-dimensional set of numbers (organized in rows and columns)
- b = matrix(a, nrow=2, ncol=3)

```
> a = c(1,5,8, 4, 22,33)
>
> b = matrix(a, nrow=2, ncol=3)
> a
[1]  1  5  8  4 22 33
> b
     [,1] [,2] [,3]
[1,]    1    8   22
[2,]    5    4   33
```

Key Programming concepts: Review of data types

- You can also define an "empty" matrix to fill values in later
- think of creating a data structure to store energy production in winter and summer for 6 different power plants)
- res = matrix(nrow=2, ncol=6)

```
> res = matrix(nrow=2, ncol=6)
> res
     [,1] [,2] [,3] [,4] [,5] [,6]
[1,]   NA   NA   NA   NA   NA   NA
[2,]   NA   NA   NA   NA   NA   NA
>
```

Key Programming concepts: Review of data types

- You can combine vectors into a matrix using
  - *cbind* by columns
  - *rbind* by rows

Key Programming concepts: Review of data types

- A really useful data structure in R is a data frame
- Dataframe's are like matrices = they have rows and columns but they don't have to be numeric (although they can be)
- Useful if you have data that is of mixed type

Key Programming concepts: Review of data types

- Why does this work?
- Because height, flow columns are both from reservoir.operation (a data frame) so they are vectors of the SAME length
- So when you multiply height* flow, you multiply
  - height[1]*flow[1],,, and then height[2]*flow[2] etc

```
>
>
> power_gen(height=reservoir.operation$height, flow=reservoir.operation$flow)
 [1] 511779.6 458449.1 408040.5 382352.4 285215.0 284782.4 227858.9 325553.4
 [9] 325453.5 416544.0 465744.0 457307.7
> power_gen
function (height, flow, rho = 1000, g = 9.8, Keff = 0.8)
{
    result = rho * height * flow * g * Keff
    return(result)
}
```

Try ..

- run your “autopower” function for a range of speed and vehicle weights - use different data generation approaches (use an Rmarkdown file to record this)
- save results in a data frame and graph with ggplot

Data Structures

- **vectors (c)**
- **matrices, arrays**
- **data frames**
- lists
- factors

2518

Key Programming concepts: Review of data types

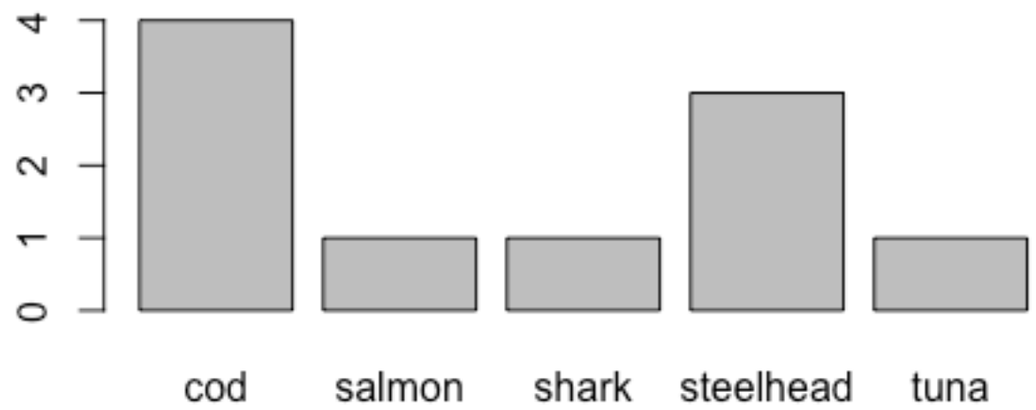
- Factors (a bit tricky, basically a vector of "things" that has different levels (classes); not really numeric - so you can't average them!)
- But can be useful for doing "calculations" with categories

```
>
> a = c(1,5,2.5,9,5,2.5)
> a
[1] 1.0 5.0 2.5 9.0 5.0 2.5
> mean(a)
[1] 4.166667
> a = as.factor(c(1,5,2.5,9,5,2.5))
> mean(a)
[1] NA
Warning message:
In mean.default(a) : argument is not numeric or logical: returning NA
> a
[1] 1   5   2.5 9   5   2.5
Levels: 1 2.5 5 9
> summary(a)
  1 2.5   5   9
  1   2   2   1
```

Key Programming concepts: Review of data types

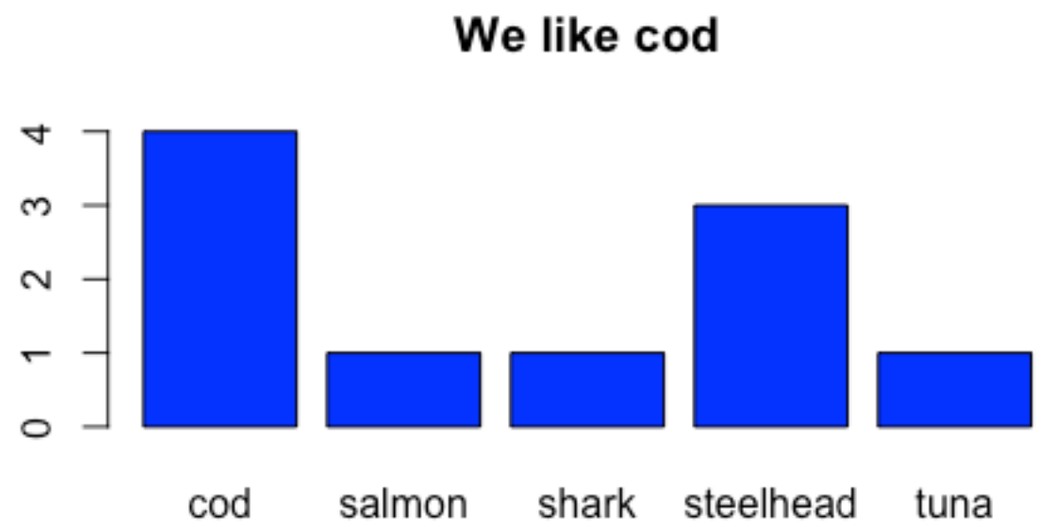
- ***summary*** can be used with factors to get frequencies in each category (or "level")

```
> catch1 = sample(possible.fish, size=10, replace=T)
> catch1
 [1] "cod"       "shark"     "tuna"      "cod"       "shark"
 [6] "steelhead" "cod"       "shark"     "tuna"      "shark"
> possible.fish = as.factor(c("salmon","steelhead","shark","tuna","cod"))
> # simulate a random recording of catch by fisherman
>
> catch1 = sample(possible.fish, size=10, replace=T)
> catch1
 [1] cod       steelhead cod       steelhead cod       salmon
 [7] tuna      shark     cod       steelhead
Levels: cod salmon shark steelhead tuna
> summary(catch1)
      cod    salmon     shark steelhead      tuna
        4         1         1         3         1
> plot(catch1)
```



You can “do things” (apply functions) to the summary (frequency of each “factor” level

```
> # use summary to explore and return information
> mean(summary(catch1))
[1] 2
> max(summary(catch1))
[1] 4
>
> tmp = which.max(summary(catch1))
> tmp
cod
  1
> names(tmp)
[1] "cod"
>
> plottitle=sprintf("We like %s", names(which.max(summary(catch1))))
> plot(catch1, col="blue", main=plottitle)
>
>
> plottitle=sprintf("We like %s", names(tmp))
> plot(catch1, col="blue", main=plottitle)
>
# see what happens if we do this
> plottitle  = sprintf("We like %s", names(summary(catch1)))
> plot(catch1, col="blue", main=plottitle)
>
```



Key Programming concepts: Review of data types

- Functions can be used to return information about factors

$$D = \sum (n / N)^2$$

where n is the number of individuals in each species, and N is total number

Key Programming concepts: Review of data types

```
#' Simpson's Species Diversity Index
#'
#' Compute a species diversity index
#' @param species list of species (names, or code)
#' @return value of Species Diversity Index
#' @examples
#' compute_simpson_index(c(“butterfly","butterfly","mosquito","butterfly",
#’ ”ladybug","ladybug")))
#' @references
#' http://www.tiem.utk.edu/~gross/bioed/bealsmodules/simpsonDI.html

compute_simpson_index = function(species) {

species = as.factor(species)
tmp = (summary(species)/sum(summary(species))) ** 2
diversity = sum(tmp)
return(diversity)
}
```

```
> catch1 = sample(possible.fish, size=10, replace=T)
> catch2 = as.factor(c(rep("salmon", times=6),
rep("cod",times=4)))
>
> compute_simpson_index(catch1)
[1] 0.26
> compute_simpson_index(catch2)
[1] 0.52
```

Data Structures

- a bit more on factors; a list of numbers can also be a factor but then they are not treated as actual numbers - you could think of them as "codes" or addresses or..
- use *as.numeric* or *as.character* to go back to a regular vector from a factor

```
>
>
> items = c(1,5,1,5,6,3)
> mean(items)
[1] 3.5
> items = as.factor(c(1,5,1,5,6,3))
> mean(items)
[1] NA
Warning message:
In mean.default(items) : argument is not numeric or logical: returning
NA
> summary(items)
1 3 5 6
2 1 2 1
> tmp = as.numeric(items)
> tmp
[1] 1 3 1 3 4 2
> mean(tmp)
[1] 2.333333
>
```

Data Structures

- **vector, (c)**
- **matrices, arrays**
- **data frames**
- lists
- **factors**

Key Programming concepts: Review of data types

- Lists are the most "informal" data structures in R
- List are really useful for keeping track of and organizing groups of things that are not all the same
- A list could be a table where number of rows is different for each column
- A list can have numeric, character, factors all mixed together
- List are often used for returning more complex information from function (e.g. lm)

Key Programming concepts: Review of data types

- A simple list: using names to identify elements

```
> sale = list(number=2, quality="high", what="apple", cost=4)
> sale
$number
[1] 2

$quality
[1] "high"

$what
[1] "apple"

$cost
[1] 4
```

```
>
> costs = c(20,40,22, 32, 5)
> quality = c("G","G","F","G","B")
> purchased = c(33,5,22,6,7)
>
> sales = data.frame(costs=costs, quality=quality, purchased=purchased)
>
>
> sales
  costs quality purchased
1    20       G        33
2    40       G         5
3    22       F        22
4    32       G         6
5     5       B         7
>
```

```
>costs = c(73,44)
>quality = c("G","G")
>purchased = c(100,22)

>sales2 = data.frame(costs=costs, quality=quality
purchased=purchased)
```

With lists we can combine sales data frames from two different places into a single data structure

Lists

```
>
> markets = list(site1=sales, site2=sales2)
> markets
$site1
  costs quality purchased
1    20       G        33
2    40       G         5
3    22       F        22
4    32       G         6
5     5       B         7

$site2
  costs quality purchased
1    73       G       100
2    44       G        22

> markets[[1]]$costs
[1] 20 40 22 32  5
>
> markets$site1$costs
[1] 20 40 22 32  5
>
```

Lists

```
>
>
> markets[[1]]
  costs quality purchased
1    20       G        33
2    40       G         5
3    22       F        22
4    32       G         6
5     5       B         7
>
> markets[[2]]
  costs quality purchased
1    73       G       100
2    44       G        22
>
> > markets[[1]][1,3]
[1] 33
>
```

***[[]]* is used to get elements from the list**

- one of the most useful things to do with list is to use them to return multiple ‘items’ from a function

```
#' Describe diversity based on a list of species
#'
#' Compute a species diversity index
#' @param species list of species (names, or code)
#' @return list with the following items
#' \describe{
#' \item{num}{ Number of distinct species}
#' \item{simpson}{Value of simpson diversity index}
#' \item{dominant}{Name of the most frequently occuring species}
#' }
#' @examples
#'
computediversity(c("butterfly","butterfly","mosquito","butterfly","ladybug","
ladybug")))
#' @references
#' http://www.tiem.utk.edu/~gross/bioed/bealsmodules/simpsonDI.html

computediversity = function(species) {

species = as.factor(species)
tmp = (summary(species)/sum(summary(species))) ** 2
diversity = sum(tmp)
nspecies = length(summary(species))
tmp = which.max(summary(species))
dominant = names(summary(species)[tmp])
return(list(num=nspecies, simpson=diversity, dominant=dominant))
}
```

Key Programming concepts: Review of data types

- example: returning lists from a function

-

```
>
> > computediversity(catch1)
$num
[1] 5

$simpson
[1] 0.26

$dominant
[1] "steelhead"

> computediversity(catch2)
$num
[1] 2

$simpson
[1] 0.52

$dominant
[1] "salmon"
```

Key Programming concepts: Review of data types

- Many functions that you use in R, return lists
- *names* (to see what is in a list)
- *attributes* (to see what is in a list)

```
> names(forest.res)
[1] "avg" "min" "max"
> attributes(forest.res)
$names
[1] "avg" "min" "max"
```

Key Programming concepts: Review of data types

- *lm* is an example of a function that returns a list

```
>
> res = lm(obs$prices~obs$forestC)
> names(res)
 [1] "coefficients"  "residuals"     "effects"
 [4] "rank"          "fitted.values" "assign"
 [7] "qr"            "df.residual"   "xlevels"
[10] "call"          "terms"         "model"
> res$coefficients
(Intercept) obs$forestC
 14.9789368   0.1865644
> res$model
  obs$prices obs$forestC
1         23          59
2         44          88
3         60         100
4          4          10
5          2           8
6         33          79
7         59         300
>
```

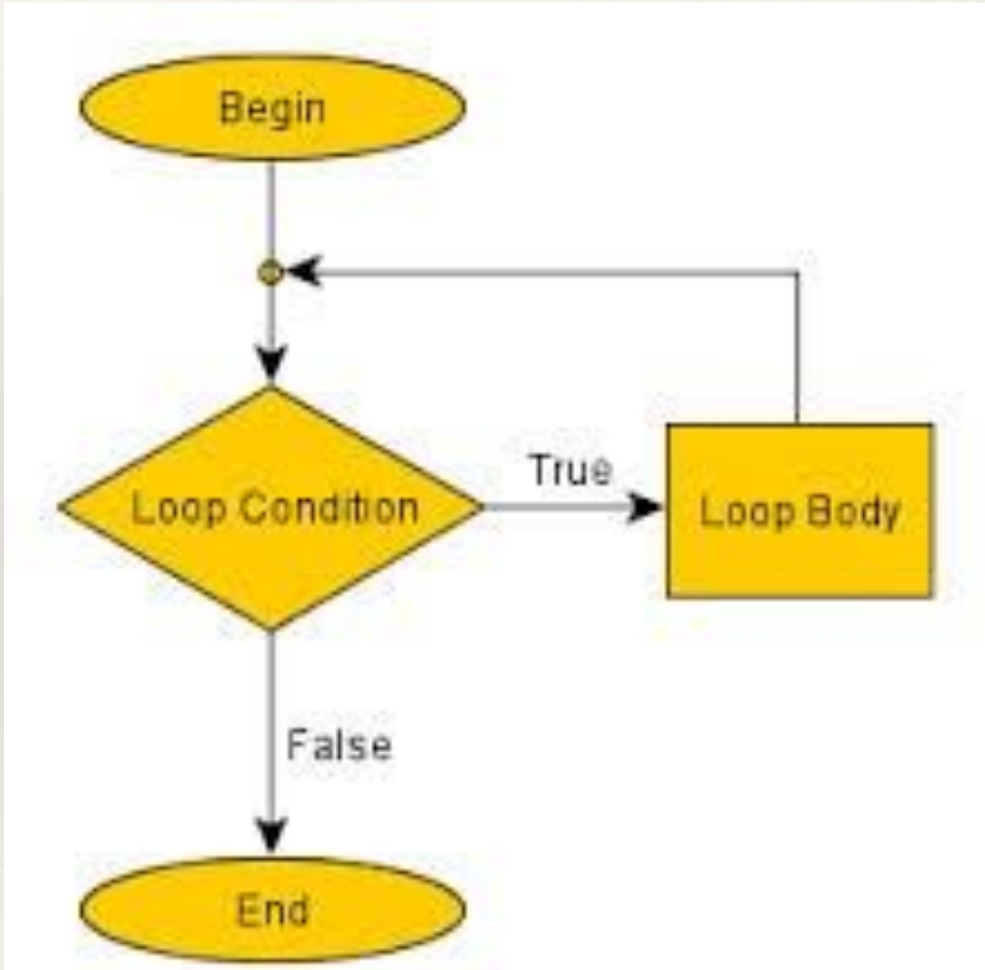
Key Programming concepts: Review of data types

- add some additional output for your auto power function - consider a range of speeds, return min, max and average power

```
> autopower
function(cdrag=0.3, crolling=0.015,pair=1.2,g=9.8,V,m,A) {

    P = crolling*m*g*V + 1/2*A*pair*cdrag*V**3


    maxP = max(P)
    minP = min(P)
    meanP = mean(P)



    return(list(P=P, maxP=maxP, minP=minP, meanP=meanP))
}
> > autopower(V=seq(from=0,to=100), m=12000, A=400)$maxP
[1] 72176400
```

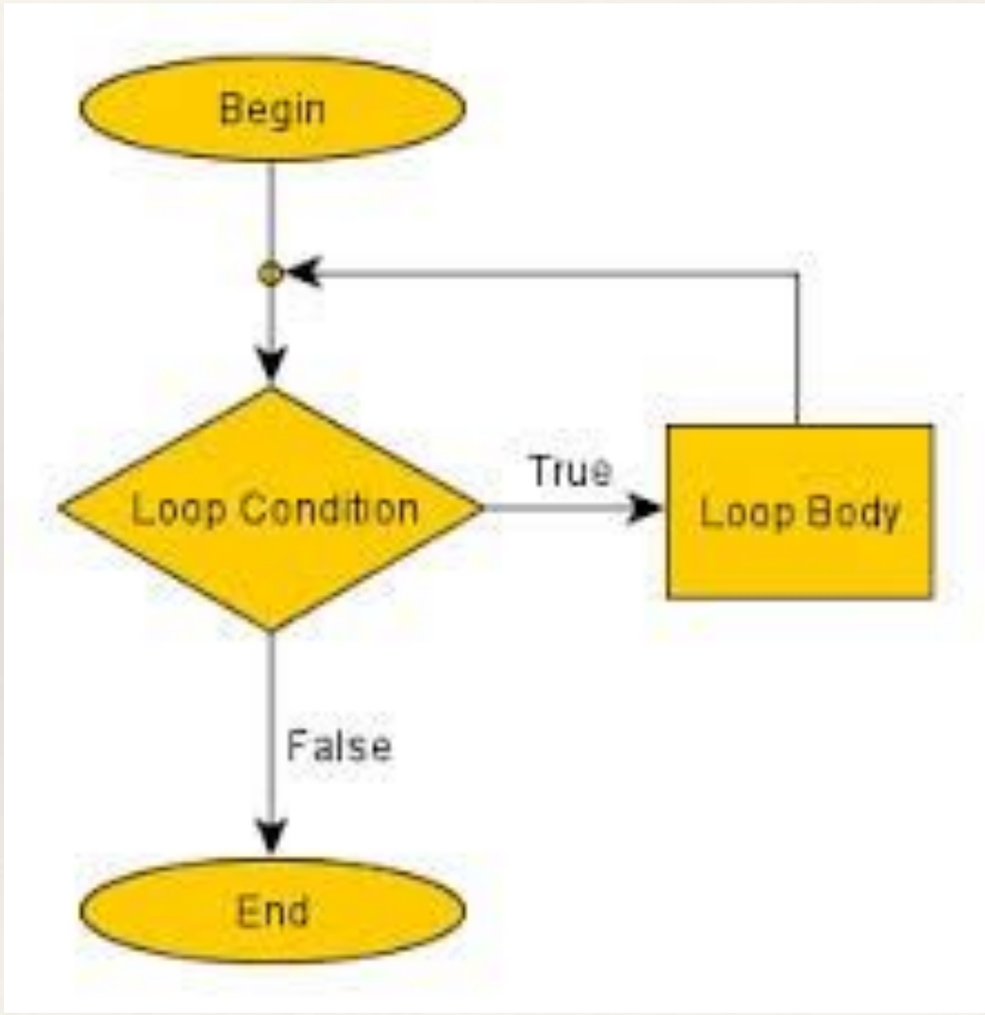
Key Programming concepts: Looping

- Loops are fundamental in all programming languages: and are frequently used in models



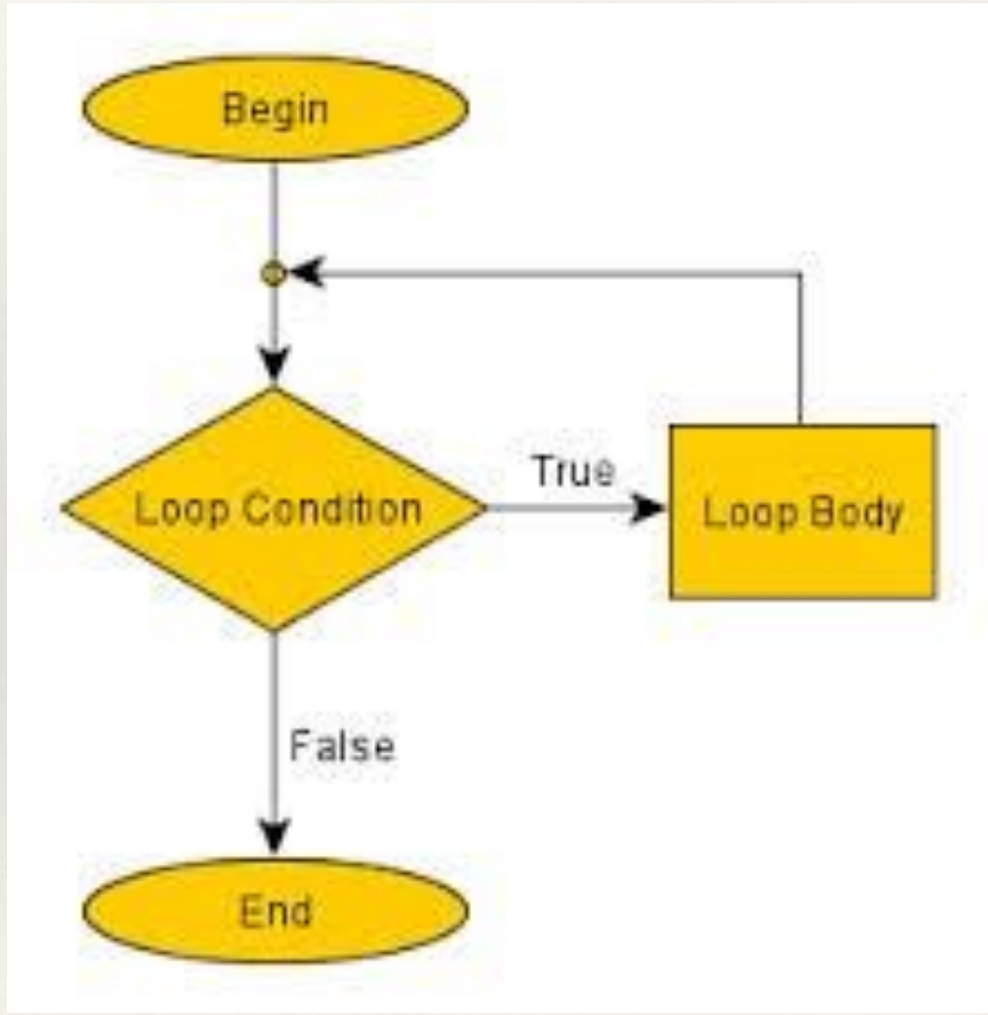
Key Programming concepts: Looping

- Two distinctive reasons for looping
- Apply the same equations (e.g for power generation) over a range of parameter values
- Evolve a variable through time (or space), when the variable's value at the next time step depends on the previous one (e.g growing a population)



Key Programming concepts: Looping

- All loops have this basic structure - repeat statements (loop body) until a condition is true



Key Programming concepts: Looping

- In R, the most commonly used loop is the ***For*** loop
- ***for (i in 1:n){ statements}***
- In "for" loops the i (or whatever variable you want to use as the counter, is automatically incremented each time the loop is gone through; and the looping ends when i (the counter) reaches n
- What is x? alpha? after this loop is run

```
>x=0
> for (alpha in 1:4) { x = x+alpha}
```

```
>
>
> x=0
> for (alpha in 1:4) { x = x+alpha}
>
>
> alpha
[1] 4
> x
[1] 10
```

Key Programming concepts: Looping

- Loops can be “nested” - one loop inside the other
- For example, if we want to calculate NPV for a range of different interest rates and a range of damages that may be incurred 10 years in the future
  - using a function called compute_npv
- Steps
  - define inputs (interest rates, damages)
  - define a data structure to store results
  - define function/model (already available)
  - use looping to run model for all inputs and store in data structure

```
#' compute_NPV
#'
#' compute net present value
#' @param value/cost ($)
#' @param time in the future that cost/value occurs (years)
#' @param discount rate
#' @return value in $


compute_NPV = function(value, time, discount) {
    result = value / (1 + discount)**time
    result
}
```

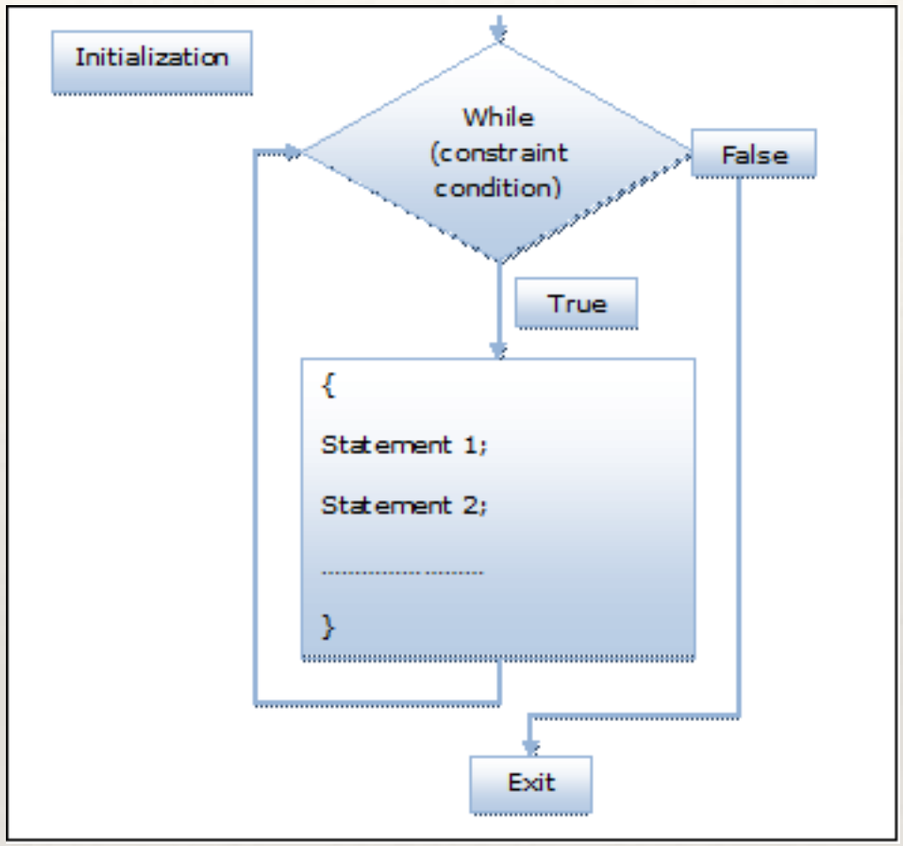
```
>
>
> damages = c(25,33,91,24)
> discount.rates = seq(from=0.01, to=0.04, by=0.005)
> yr=10
> npvs = as.data.frame(matrix(nrow=length(damages), ncol=length(discount.rates)))
> for (i in 1:length(damages)) {
+       for (j in 1:length(discount.rates)) {
+       npvs[i,j]= compute_npv(net=damages[i], dis=discount.rates[j],yr )
+       }
+ }
> npvs
       V1       V2       V3       V4       V5       V6       V7
1 22.63217 21.54168 20.50871 19.52996 18.60235 17.72297 16.88910
2 29.87447 28.43502 27.07149 25.77955 24.55510 23.39432 22.29362
3 82.38111 78.41172 74.65170 71.08905 67.71255 64.51161 61.47634
4 21.72689 20.68001 19.68836 18.74876 17.85825 17.01405 16.21354
> colnames(npvs)=discount.rates
> rownames(npvs)=damages
> npvs
      0.01    0.015     0.02    0.025     0.03    0.035     0.04
25 22.63217 21.54168 20.50871 19.52996 18.60235 17.72297 16.88910
33 29.87447 28.43502 27.07149 25.77955 24.55510 23.39432 22.29362
91 82.38111 78.41172 74.65170 71.08905 67.71255 64.51161 61.47634
24 21.72689 20.68001 19.68836 18.74876 17.85825 17.01405 16.21354
>
```

Reviewing some stuff from previous classes

```
library(tidyr)
npvs = gather(npvs, 1:7, key=dis, value=npv)
head(npvs)
 ggplot(npvs, aes(x=npv, col=as.factor(dis)))
+geom_density(size=2)+scale_color_brewer(type="seq",
name="Discount")
```

Key Programming concepts: Looping

- Another useful looping construct is the *While* loop
- keep looping until a condition is met
- Useful when you don't know what "n" in the for 1 in to "n" is
- often used in models where you are evolving
  - accumulate something until a threshold is reached (population, energy, biomass?



Key Programming concepts: Looping

- A simple *while* loop example

```
>
>
> alpha = 0
> x = 0
> while (alpha < 100) { alpha = alpha + x; x = x+1}
> x
[1] 15
> alpha
[1] 105
>
```

- alpha = (1+2+3+4+5+6+7+8+9+10+11+12+13+14) = 105

Key Programming concepts: Looping

- A more useful *while* loop example
- A question: if a metal toxin in a lake increases by 1% per year, how many years will it take for the metal level to be greater than 30 units, if toxin is current at 5 units
- there are other ways to do this, but a while loop would do it

why won't this work?

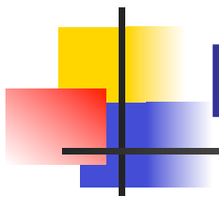
```
> >
> pollutant.level = 5
> while (pollutant.level < 30 ) {
+ pollutant.level = pollutant.level + 0.01* pollutant.level
+ yr = yr + 1
+ }
>
```

Key Programming concepts: Looping

```
> yr=1
> pollutant.level = 5
> while (pollutant.level < 30 ) {
+ pollutant.level = pollutant.level + 0.01* pollutant.level
+ yr = yr + 1
+ }
> > yr
[1] 182
> pollutant.level
[1] 30.2788
```

Key Programming concepts: Looping

- Most programming languages have For and while loops



File Loops

```
# average5.py
#     Computes the average of numbers listed in a file.

def main():
    fileName = raw_input("What file are the numbers in? ")
    infile = open(fileName,'r')
    sum = 0.0
    count = 0
    for line in infile.readlines():
        sum = sum + eval(line)
        count = count + 1
    print "\nThe average of the numbers is", sum / count
```

mcsp.wartburg.edu/zelle/python/ppics1/.../Chapter08.p

Key Programming concepts: Control Structures

- *if*(cond) expression

```
>
> a=4
> b=10
> if(a > b) win = "a"
> if(b > a) win = "b"
> win
[1] "b"
>
```

Conditions:
== equal
> greater than
>= greater than or equal to
< less than
<= less than or equal to
%in% is in a list of something

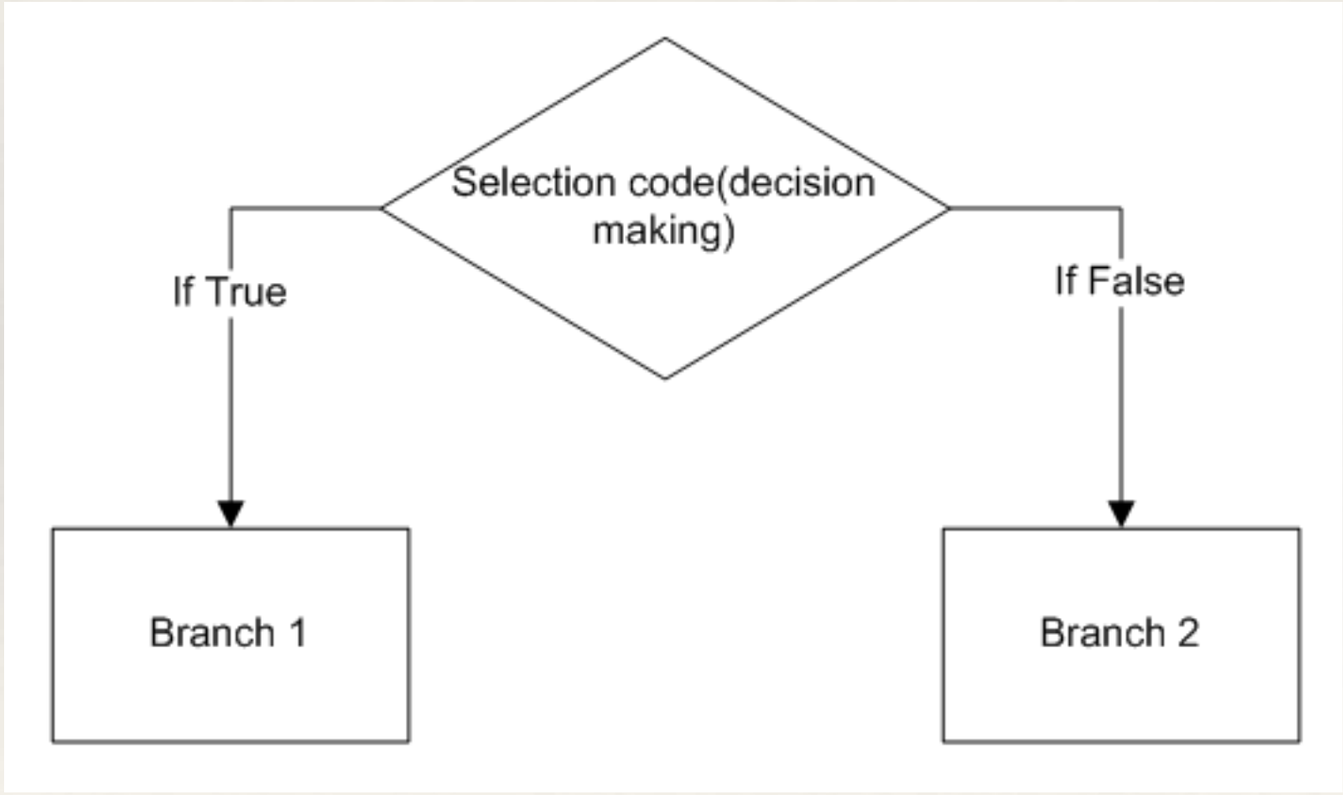
- *ifelse*(cond, true, false)

```
>
> win = ifelse(a > b, "a","b")
> win
[1] "b"
>
>
```

&& AND
|| OR
is.null()

Key Programming concepts: Looping

- Inside functions *if*(cond) {expression} *else* {expression}
- the expression can always have multiple statements using {}
- *If* can be useful for branching in your model



Key Programming concepts: Control Structures

```
#' compute annual yield
#'
#' Function to compute yeild of different fruits as a function of annual temperature and precipitation
#' @param T annual temperature (C)
#' @param P annual precipitation (mm)
#' @param ts slope on temperature
#' @param tp slope on precipitation
#' @param intercept  (kg)
#' @param irr  Y or  N (default N)
#' @return yield in kg

compute_yield = function(T, P, ts, tp, intercept, irr="N") {

if (irr=="N"){
yield = tp*P + ts*T + intercept
}
else {
yield = ts*T + intercept
}

return(yield)
}
```

```
>
> compute_yield(32,200, 0.2, 0.4, 500)
[1] 586.4
> compute_yield(32,200, 0.2, 0.4, 500, "N")
[1] 586.4
> compute_yield(32,200, 0.2, 0.4, 500, "Y")
[1] 506.4
```

```
#' compute annual yield NPV
#'
#' Function to compute yeild of different fruits as a function of annual temperature and precipitation
#' @param T annual temperature (C)
#' @param P annual precipitation (mm)
#' @param ts slope on temperature
#' @param tp slope on precipitation
#' @param intercept  (kg)
#' @param irr  Y or  N (default N)
#’ @param discount (default=0.02)
#’ @price price $ (default=2)
#' @return total yield in kg and NPV of yield


compute_yield_NPV = function(T, P, ts, tp, intercept, irr="N", discount=0.02, price=2) {

if ((length(T) != length(P)) & (irr=="N") ) {
  return("annual precip and annual T are not the same length")
}
yield = rep(0, times=length(T))

for ( in 1:length(T)) {
if (irr=="N"){
yield[i] = tp*P[i] + ts*T[i] + intercept
yieldnpv[i] = compute_NPV(yield[i]*price, discount, i)

}
else {
yield[i] = ts*T[i] + intercept
yieldnpv[i] = compute_NPV(yield[i]*price, discount, i)
}


return(list(totalyield=sum(yield), profit=sum(yieldnpv)))
}
```

```
>
> compute_yield(32,200, 0.2, 0.4, 500)
[1] 586.4
> compute_yield(32,200, 0.2, 0.4, 500, "N")
[1] 586.4
> compute_yield(32,200, 0.2, 0.4, 500, "Y")
[1] 506.4
```

```
> T = c(15,18,20,25,26)
> P = c(200,200,200,200,200)
> compute_yield_NPV(T, P, ts=0.5, tp=0.5, intercept=200,
irr="N", discount=0.02, price=2)
$totalyield
[1] 1552

$profit
[1] 3023.315
```

If can also be useful for creating classes of variables

Lets say we want to build a function that will compute mean spring, winter, summer, streamflow - from a dataset that looks something like this

```
> summary(str)
      year          month             day              mm
 Min.   :1953   Min.   : 1.000   Min.   : 1.00   Min.   : 0.08996
 1st Qu.:1967   1st Qu.: 4.000   1st Qu.: 8.00   1st Qu.: 0.24290
 Median :1981   Median : 7.000   Median :16.00   Median : 0.38685
 Mean   :1981   Mean   : 6.542   Mean   :15.73   Mean   : 1.07800
 3rd Qu.:1995   3rd Qu.:10.000   3rd Qu.:23.00   3rd Qu.: 0.98961
 Max.   :2010   Max.   :12.000   Max.   :31.00   Max.   :71.97168
>
> head(str)
  year month day        streamflow
1 1953    10   1 0.2608973
2 1953    10   2 0.2608973
```

```
#' Compute seasonal mean flows
#'
#' This function computes winter and summer flows from a record
#’ @param str data frame with columns month and streamflow
compute_seasonal_meanflow = function(str) {

  str$season = ifelse( str$month %in%
c(1,2,3,10,11,12),"winter","summer")

  tmp = subset(str, str$season=="winter")
  mean.winter = mean(tmp$streamflow)

  tmp = subset(str, str$season=="summer")
  mean.summer = mean(tmp$streamflow)
  return(list(summer=mean.summer, winter=mean.winter))
}
```

```
> compute_seasonal_meanflow(str)
$summer
[1] 1.538304

$winter
[1] 0.6200728

>
```

Key Programming concepts: Control Structures

```
#' Compute seasonal mean flows
#'
#' This function computes winter and summer flows from a record
#’ @param str data frame with columns month and streamflow
compute_seasonal_flow = function(str, kind="mean") {

  str$season = ifelse( str$month %in%
c(1,2,3,10,11,12),"winter","summer")


  tmp = subset(str, str$season=="winter")
  if(kind=="mean") winter= mean(tmp$streamflow)
  if(kind=="max") winter= max(tmp$streamflow)
  if(kind=="min") winter=min(tmp$streamflow)

  tmp = subset(str, str$season=="summer")
  if(kind=="mean") summer= mean(tmp$streamflow)
  if(kind=="max") summer= max(tmp$streamflow)
  if(kind=="min") summer=min(tmp$streamflow)

  return(list(summer=summer, winter=winter))
}
```

```
> compute_seasonal_meanflow(str)
$summer
[1] 0.02982467

$winter
[1] 0.06705754

> compute_seasonal_flow(str)
$summer
[1] 0.02982467

$winter
[1] 0.06705754

> compute_seasonal_flow(str, kind="max")
$summer
[1] 0.642605

$winter
[1] 0.657214
```

Assignment

Work in pairs

Write a function that takes as input

- a table that has prices for different fish
- a table that has the number caught for each fish species for each location
  - each location is in a different column
  - each fish is in a different row

Function output will be

- most frequently caught fish in each location
- total revenue for each location
- total fisheries revenue sum
- if user requests it graph of revenue by location and total revenue (as text)

* Store your function in an *.R file
* Generate some example data for your function; and show how this is created and used in an R markdown document
* Submit as usual as a git link on gauchospace