Week 11 Optimization, Performance Enhancement, and Debugging

```
knitr::opts_knit$set(root.dir = "D:/Davenport/Introduction-to-R/Data")
library(validate)
```

```
## Warning: package 'validate' was built under R version 4.0.3
```

```
library(magrittr)
```

No course on programming would be complete without an in-depth discussion on optimization, performance enhancement, and debugging. R-studio has some excellent debugging tools available, such as setting breakpoints and resuming, that students should use when creating R programs. This week will focus primarily on quality of code, both from a troubleshooting standpoint as well as optimization.

Weekly Learning Objectives

Create an R script with the following components:

1. Evaluate the execution time of a function in order to optimize the code
2. Create a function with error handling
3. Create a function that uses the validate and magrittr package to validate data
4. Using a previous simulation built in class, perform an optimization on it

1. Evaluate the excution time of a function in order to optimize the code

One of the easiest ways to optimize code is to check for execution time. Using the system.time function, you can check for the amount of time it takes a block of code to execute.

Full Points Build a simple function that will check the execution time starting and ending.

```
simplyDoSomething <- function(){     # Example function to print out 100 times
  for(j in 1:50){
    print("Do Something Here")
  }
}

system.time(simplyDoSomething())     # Timer call
```

```
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```

```
##    user  system elapsed
##    0.02    0.00    0.02
```

2. Create a function with error handling

Error handing is an essential part of any production quality application. There are multiple ways that you can do error handling, including various library packages. Here is one discussion that addresses the for main components:

http://mazamascience.com/WorkingWithData/?p=912

1. warning() - Generates warnings
2. stop() - Generates errors
3. suppressWarnings(expr) - Evaluates the expression and ignores any warnings from it
4. tryCatch() - Evaluates code and assigns exceptions

Of these four, the most common in other languages is the tryCatch() function.

For this example, I'm going to use the more manual approach and build my own function error_test(). It

will report if there is an error in the form of having a vector that is below a certain threshold. For testing, I will use the rivers preloaded data set.

Full Points You can use either the packaged library method or write your own function. The final product has to use an error handling technique.

```
summary(rivers)      # Generate Summary of Rivers
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   135.0   310.0   425.0   591.2   680.0  3710.0
```

```
error_test <- function(vector, threshold) {
  if (min(vector) < threshold) {
    cat("Error: At least one number is below the established threshold")
  } else {
    cat("No Error")
  }
}

# I will use it to test if any of the major North American rivers are less than 100 miles.
error_test(rivers,100)
```

```
## No Error
```

```
# No Error

# Now I will test with 1,000 miles.
error_test(rivers,1000)
```

```
## Error: At least one number is below the established threshold
```

```
# Error: At least one number is below the established threshold
```

3. Validate and Magrittr package to validate data

These are two common libraries used for validating and manipulating data. We have already used packages built on magrittr in previous assignments, so the syntax should be relatively straightforward.

The validate package is extremely useful when validating data. A detailed discussion on the proper use of validate is found in the documentation:

https://cran.r-project.org/web/packages/validate/vignettes/introduction.html

Out of the available functions, the most useful are:

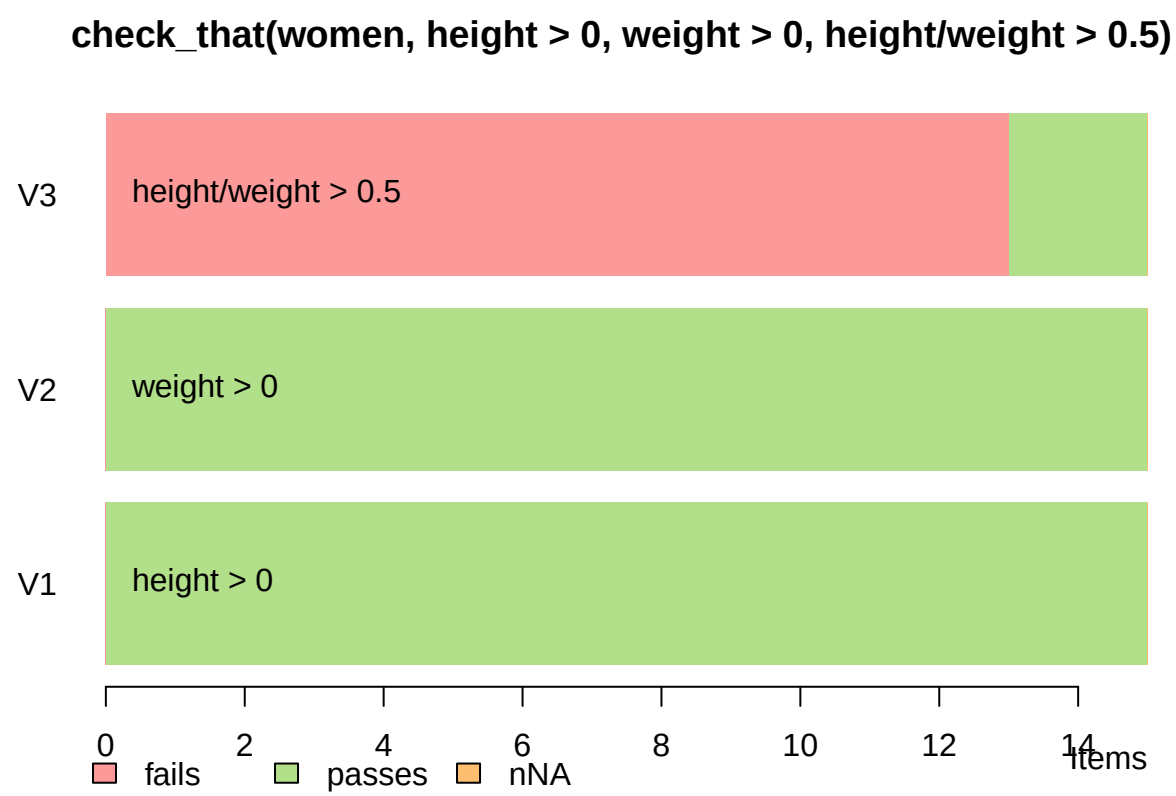
1. check_that() - Allows multiple parameters to be entered. It will run checks on each to see if the condition is met
2. validator() - Store a rule set to compare against

Full Points The result should be proper execution of functions in both validate and magrittr.

```
cf <- check_that(women, height > 0, weight > 0, height/weight > 0.5)
summary(cf)
```

```
##   name items passes fails nNA error warning          expression
## 1   V1    15     15     0   0 FALSE   FALSE          height > 0
## 2   V2    15     15     0   0 FALSE   FALSE          weight > 0
## 3   V3    15      2    13   0 FALSE   FALSE height/weight > 0.5
```

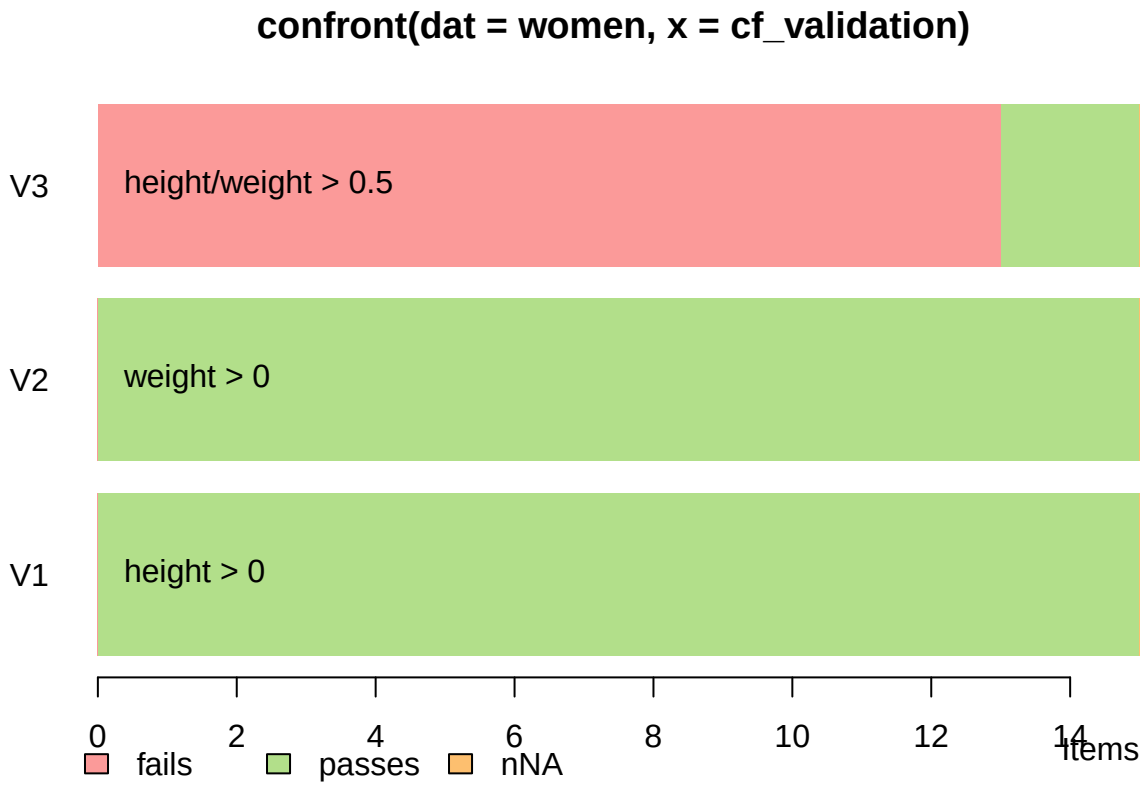
```r
barplot(cf)
```




```r
# Using the validate package to set rules.
cf_validation <- validator(height > 0, weight > 0, height/weight > 0.5)
cf_validation
```

```
## Object of class 'validator' with 3 elements:
##  V1: height > 0
##  V2: weight > 0
##  V3: height/weight > 0.5
```

```r
# Testing the rules.
confront_data <- confront(women, cf_validation)
barplot(confront_data)
```



4. Optimize a previous simulation

Using any variation of the techniques discussed, use one of your existing simulations and perform an optimization on it. The demonstrator will be a roulette simulation.

Full Points Comparing the before-and-after solutions, there should be optimization between the two.

```
Roulette<-c(0:36)
sample_size<-100
repeat_samples<-10000          # I increased the repeat samples from 1,000 to 10,000 to better display
                               # the time difference in the optimization.

# I have tweaked the for loop to generate one vector combining all of the simulations.
for(i in 1:repeat_samples){
  clt_y<-sample(Roulette,size=sample_size,replace=TRUE)
  if (exists("loop_wheel")==TRUE){
    clt_z <- c(clt_y)
    loop_wheel <- rbind(loop_wheel,clt_z)
    rm(clt_z)
  }else{
    loop_wheel <- c(clt_y)
  }
}
length(loop_wheel)             # Test to make sure length is 1,000,000
```

```
## [1] 1000000
```

```r
mean(loop_wheel)                # Mean should be close to 18
```

```
## [1] 17.99903
```

```r
# This simulation could be run as a vector:
vector_wheel <- c(sample(Roulette,size=sample_size*repeat_samples,replace=TRUE))
length(vector_wheel)            # Test to make sure length is 1,000,000
```

```
## [1] 1000000
```

```r
mean(vector_wheel)              # Mean should be close to 18
```

```
## [1] 17.99973
```

```r
# Now to show the time it takes to run each of those functions:

# First the untuned starting version:
system.time(for(j in 1:repeat_samples){
  clt_y<-sample(Roulette,size=sample_size,replace=TRUE)
  if (exists("sample_x")==TRUE){
    clt_z <- c(clt_y)
    sample_x <- rbind(sample_x,clt_z)
    rm(clt_z)
  }else{
    sample_x <- c(clt_y)
  }
})
```

```
##    user  system elapsed
##   33.72    1.77   35.50
```

```r
#    user  system elapsed
#   10.72    0.15   10.90

#  And the vector approach / tuned version
system.time(vector_wheel <- c(sample(Roulette,size=sample_size*repeat_samples,replace=TRUE)))
```

```
##    user  system elapsed
##    0.23    0.00    0.24
```

```r
#    user  system elapsed
#    0.01    0.00    0.02         <--- Much faster
```

Reviewed for 2020 - MSP