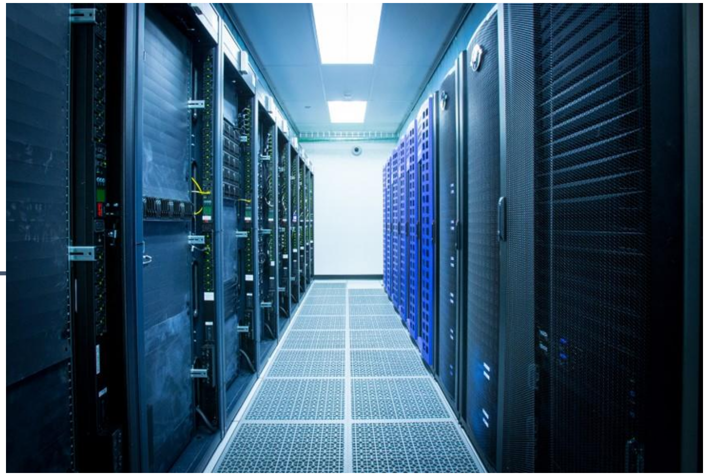
MAKING R RUN FASTER ON RIVANNA



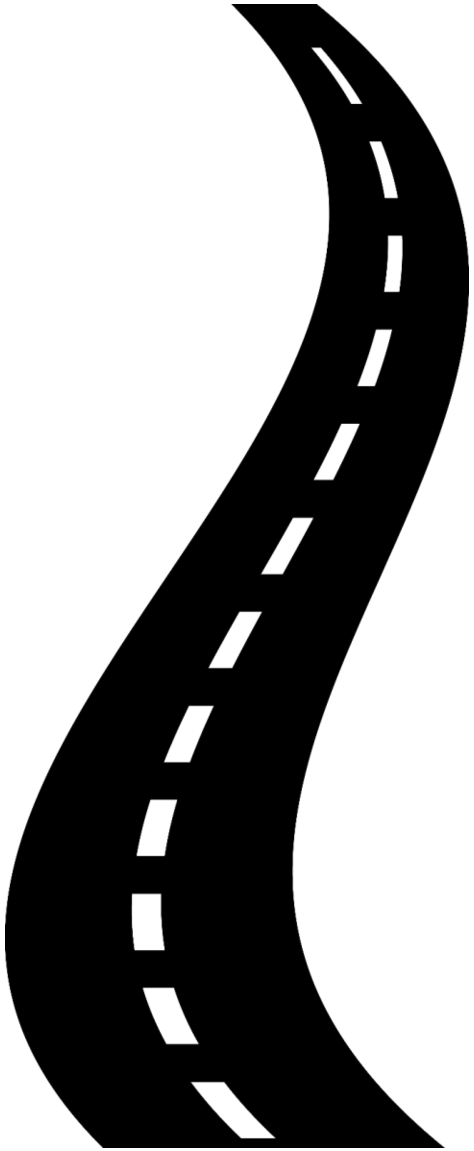
Jacalyn Huband

Senior Computational Scientist
UVA Research Computing

16 Mar. 2023 **https://github.com/jhuband/Making_R_Faster.git**

University of Virginia | Research Computing

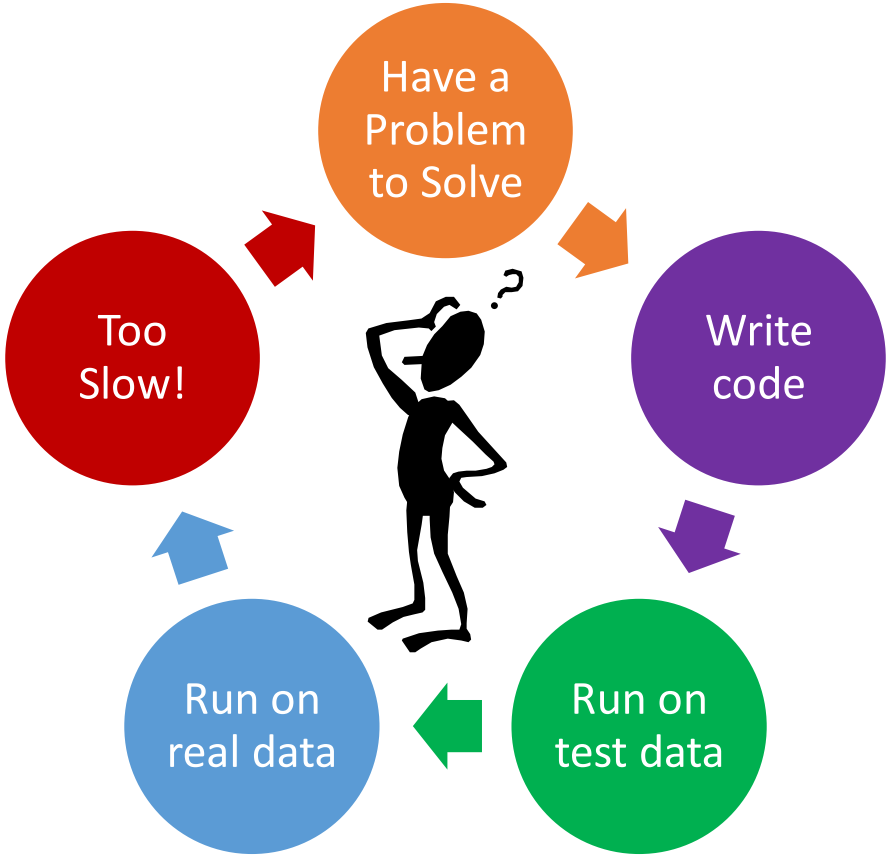
Roadmap for this Workshop



- Talk about optimization to speed up codes.
- Look at general techniques for speeding up R
- Walk through three case studies places where code can be slow

INTRODUCTION TO OPTIMIZING R

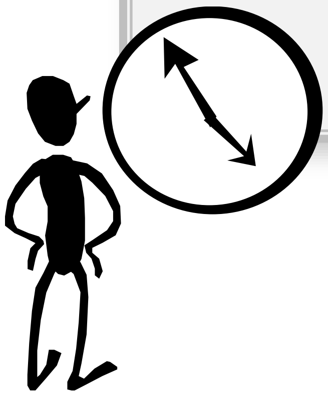
Your Software Project



It's About Time

- After getting your code to work, you may find that the code does not *scale* for larger data sets.

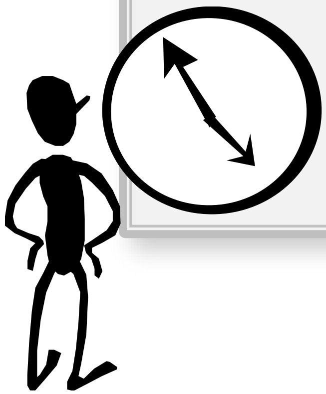
> - Suppose it takes only 40 sec for a simple data set.
> - But, when you run it on a data set that is twice the size of the first, the time takes 400 secs!
>
> $$400\ secs = \ 6.7\ mins$$



It’s About Time

- Or, you may find that repeating the algorithm multiple times takes too long.

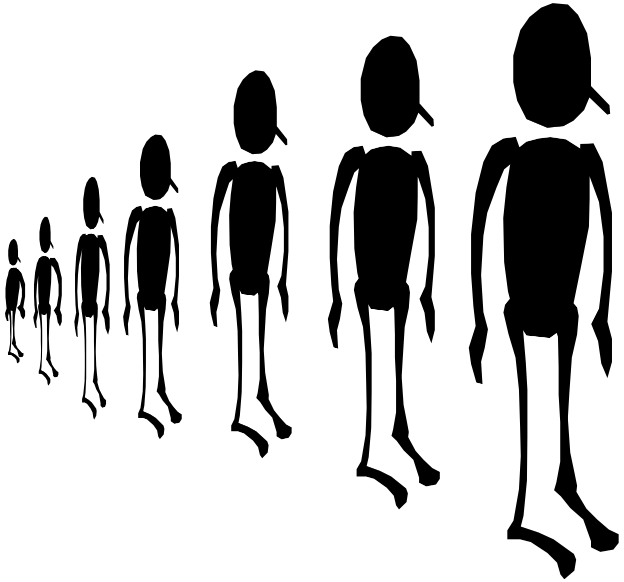
  - Suppose it takes only 40 sec for one iteration (or for one data set).
  - But, you need to run it for 5000 iterations (or on 5000 data sets).



$$40\frac{sec}{iteration} * 5000\, iter. = 200{,}000\, sec \quad \text{or} \quad 55.6\, hours$$

Should you parallelize it?

- Before requesting time on the cluster and parallelizing your code, you may want to **optimize** it.



What is Code Optimization?

- The process of making code more efficient (either with time or memory)

- Important caveats:

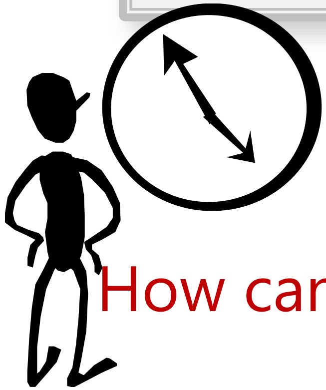
  - The correctness of the code must be preserved.
  - The code should run faster "on average".
  - There is a tradeoff between your efforts and the computer's efforts. (**Should you spend a week trying to make a program faster by 1 sec?**)

Going Back to Time

- Returning to our timing example with multiple iterations, suppose you were able to reduce the time of one iteration to 36 seconds.

$$36\frac{sec}{iteration} * 5000\ iter. = 180{,}000\ sec \text{ or } 50.0\ hours$$

- You just saved 5.6 hours!



- How can we reduce the time for R code to run?

General Advice

1. Do not re-compute values that are used frequently.
2. Avoid referencing a single value of an array (e.g., A[i] or M[i,j]) multiple times.
3. Consolidate or simplify mathematical functions.
4. Avoid using loops.
5. Pre-allocate memory whenever possible.
6. I/O is slow – try to consolidate it.
7. Avoid mathematical manipulations of entire dataframes.
8. Avoid overuse of parentheses.

Simple examples of these techniques are available in the Appendix of these slides.

R is different

- General advice that you hear with other language does not always work with R.

- We will look at 3 case studies
  1. Reading in a Large Data File
  2. Manipulating a column in a table
  3. Performing mathematical operations

- But first, to get these slides and the test cases with codes, you can use Open OnDemand.

USING OPEN ONDEMAND

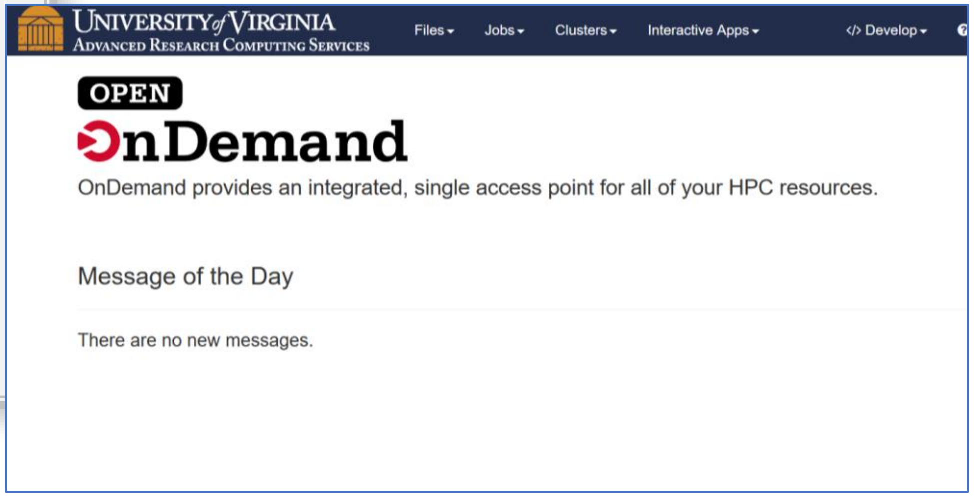
Open On-Demand

- For today's activities, we are going to use our web-based portal for Rivanna: Open OnDemand. To access it, follow the instructions below:

In your web browser go to
https://rivanna-portal.hpc.virginia.edu

You will need to "Netbadge" in

This will take you to a dashboard with some nice features.

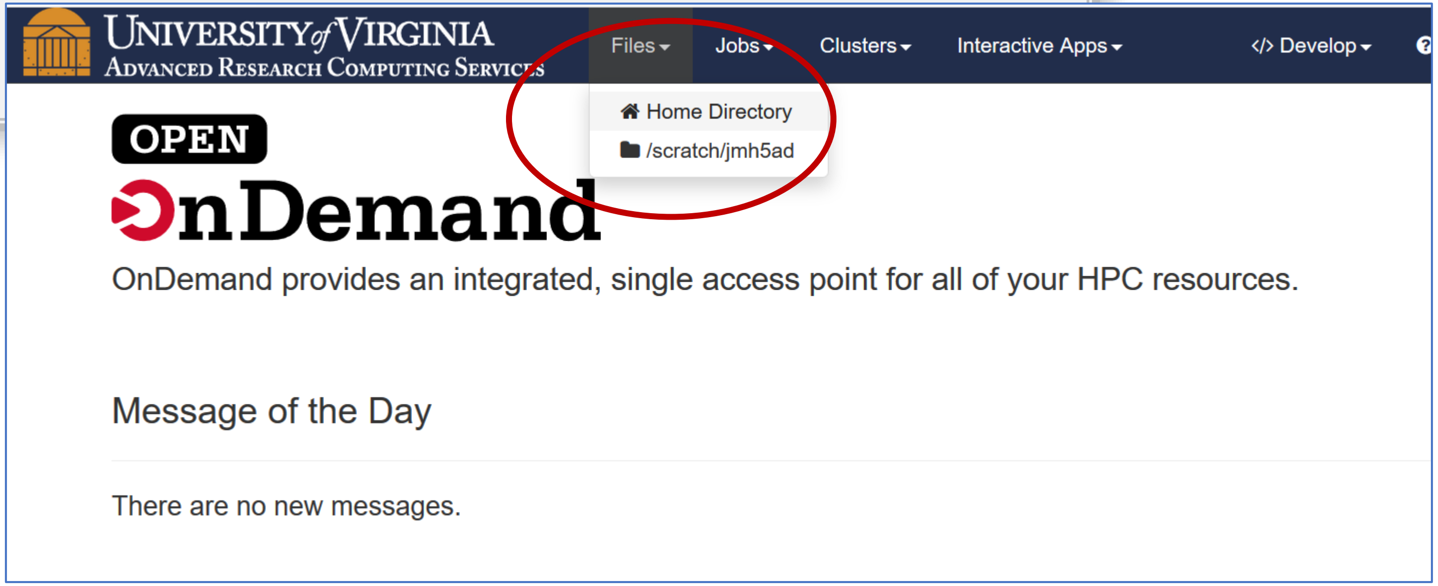


The Files Page

- First, you will use the Files tool to copy some files to your directory.

Click on Files > Home Directory

This will take you to a page where you can see the files in your home directory.

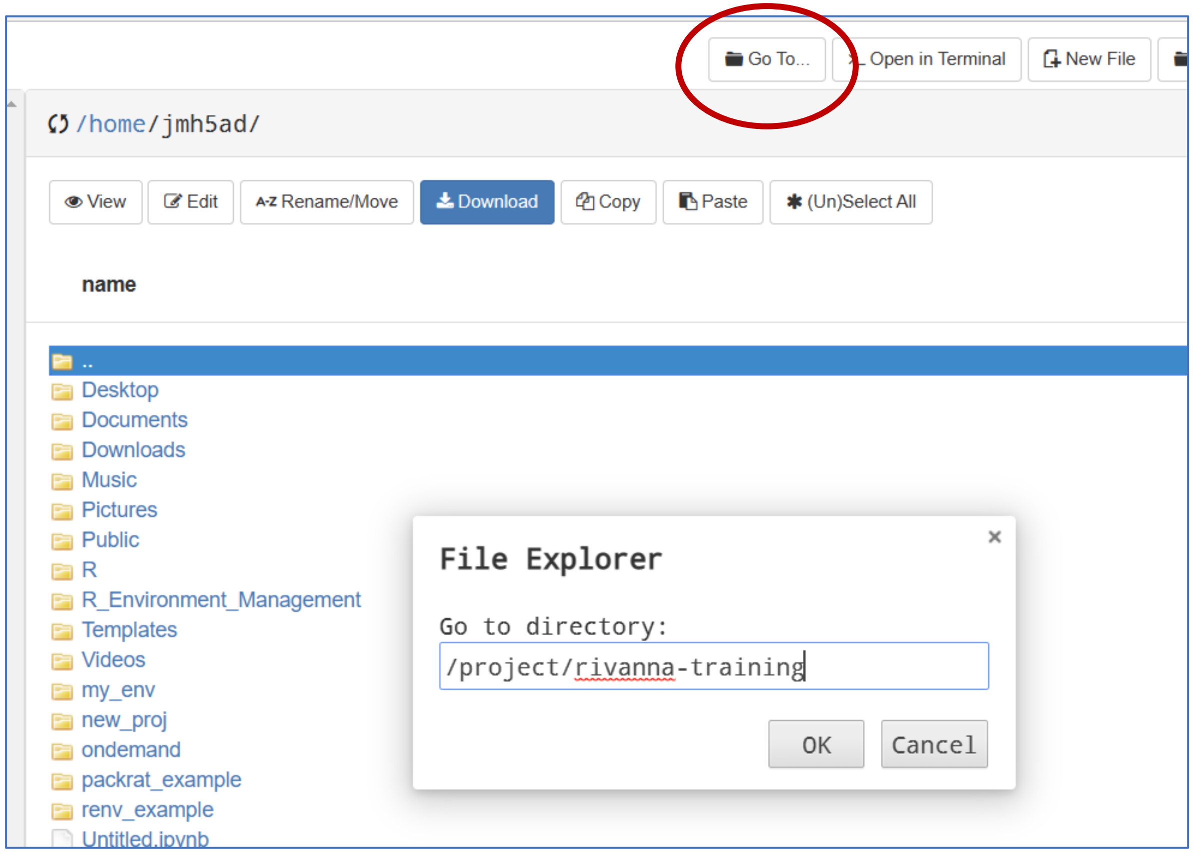


The Go To Feature

- Click on “Go To . . .” and enter

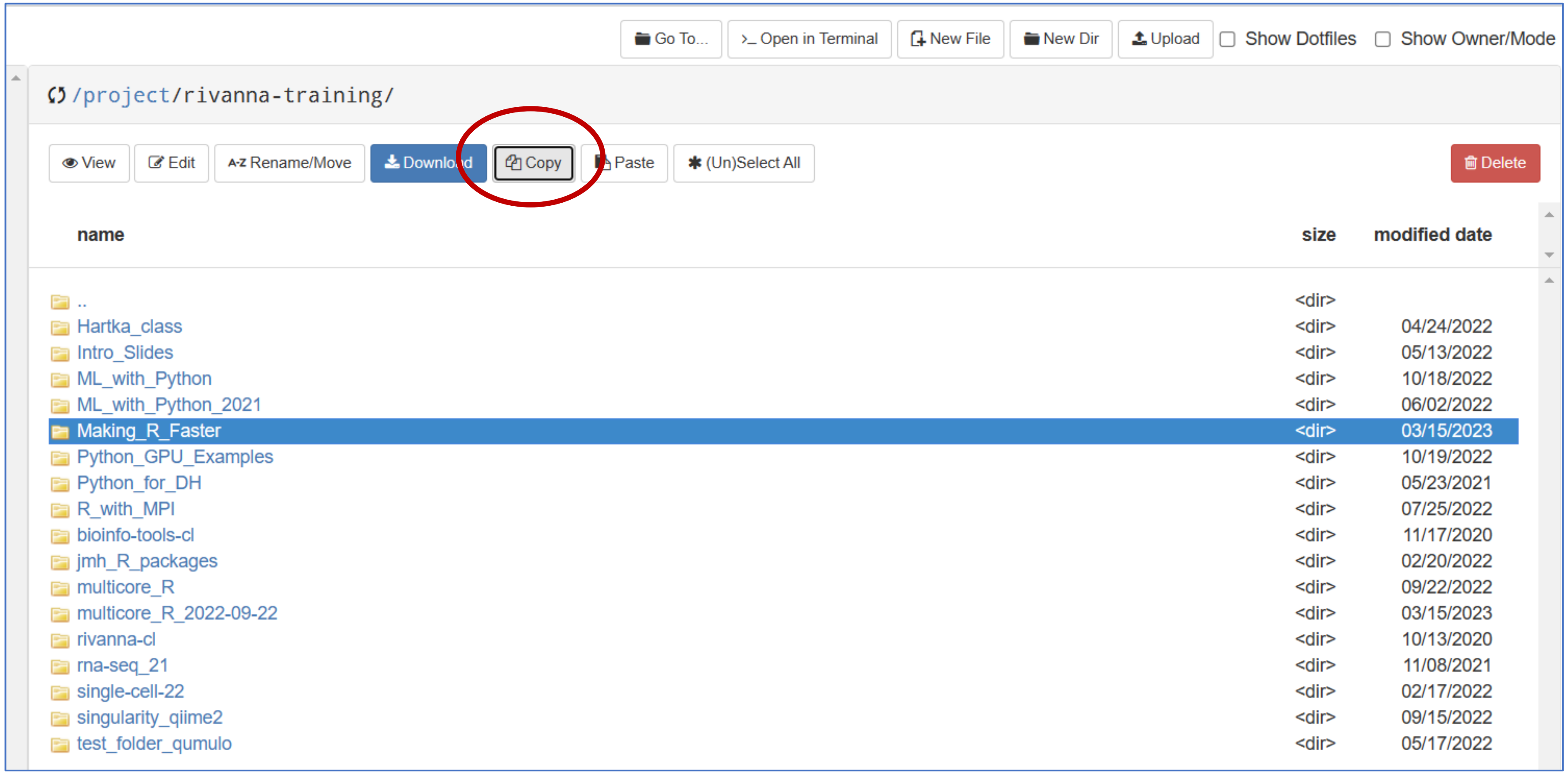
  /project/rivanna-training

  in the dialog box.



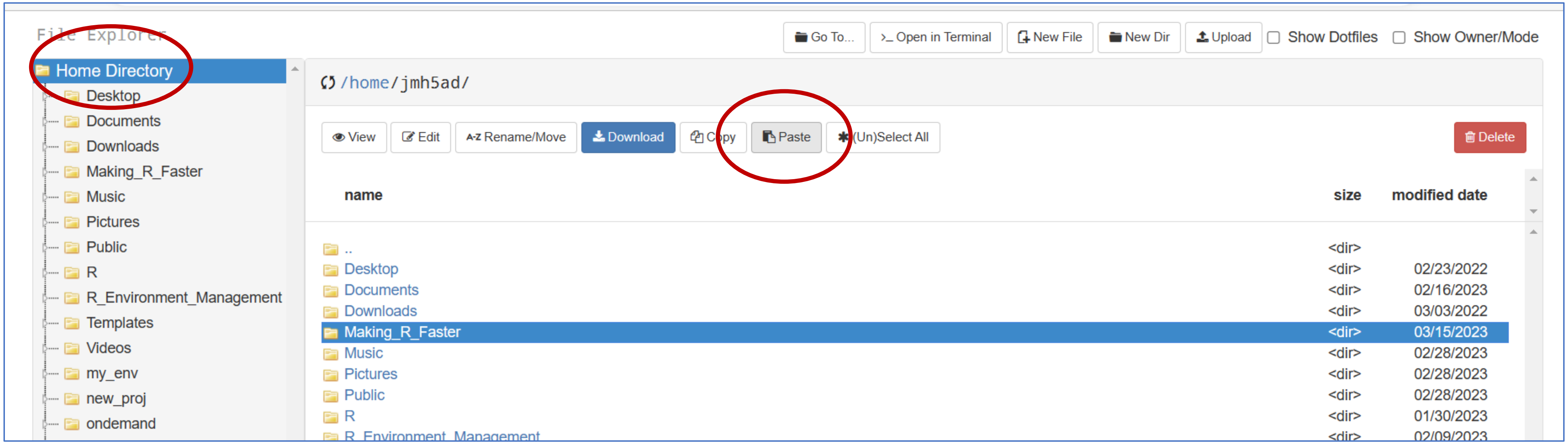
The Copy Feature

Highlight the folder called "Making_R_Faster" and click on "Copy".



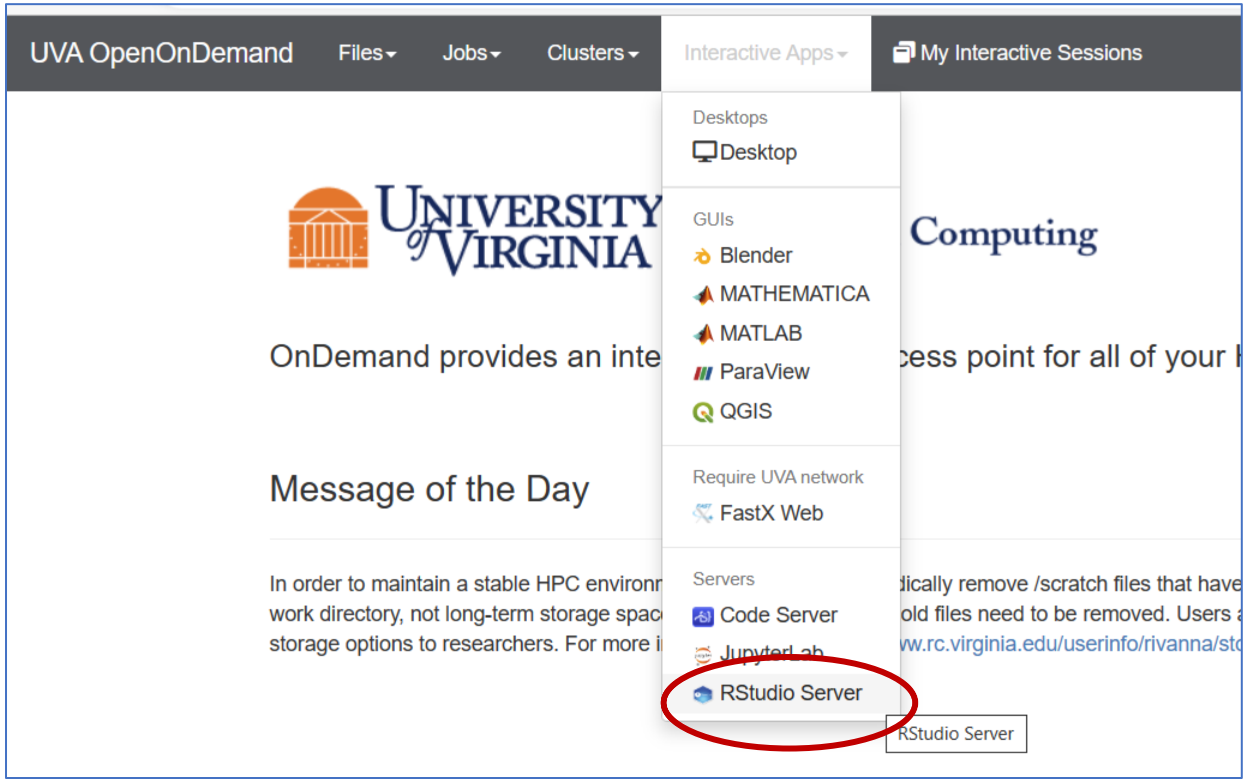
The Paste Feature

- Click on “Home Directory” in the left panel. Then click on “Paste”.

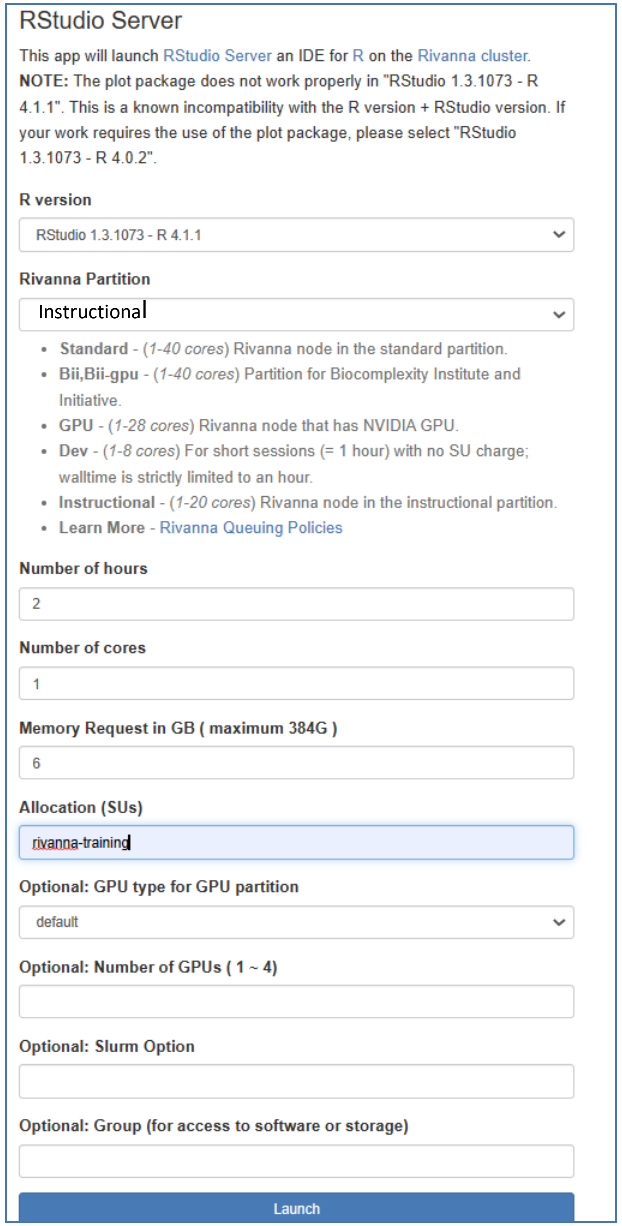


Return to the Dashboard

- Click the tab on your browser that is labeled “Dashboard”.
- Click on “Interactive Apps” and “RStudio Server”



RStudio Server


RStudio Server

This app will launch RStudio Server an IDE for R on the Rivanna cluster.
NOTE: The plot package does not work properly in "RStudio 1.3.1073 - R 4.1.1". This is a known incompatibility with the R version + RStudio version. If your work requires the use of the plot package, please select "RStudio 1.3.1073 - R 4.0.2".

R version

RStudio 1.3.1073 - R 4.1.1

Rivanna Partition

Instructional

- **Standard** - (*1-40 cores*) Rivanna node in the standard partition.
- **Bii,Bii-gpu** - (*1-40 cores*) Partition for Biocomplexity Institute and Initiative.
- **GPU** - (*1-28 cores*) Rivanna node that has NVIDIA GPU.
- **Dev** - (*1-8 cores*) For short sessions (= 1 hour) with no SU charge; walltime is strictly limited to an hour.
- **Instructional** - (*1-20 cores*) Rivanna node in the instructional partition.
- **Learn More** - Rivanna Queuing Policies

Number of hours

2

Number of cores

1

Memory Request in GB (maximum 384G)

6

Allocation (SUs)

rivanna-training

Optional: GPU type for GPU partition

default

Optional: Number of GPUs (1 ~ 4)

Optional: Slurm Option

Optional: Group (for access to software or storage)

Launch

- Fill out the requirements for running RStudio on Rivanna and click on Launch:

R version: Rstudio 1.3.1073-R 4.1.1
Rivanna Partition: Instructional

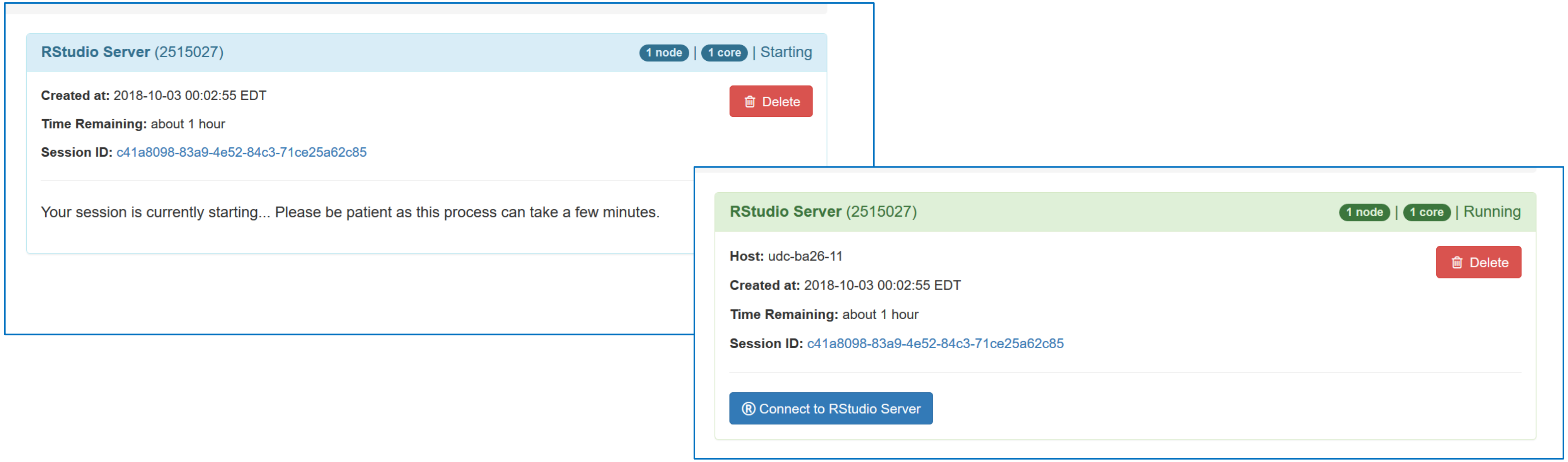
Number of Nodes: 1
Number of Hours: 2
Number of Cores: 1

Memory Request in GB: 6

Allocation: rivanna-testing

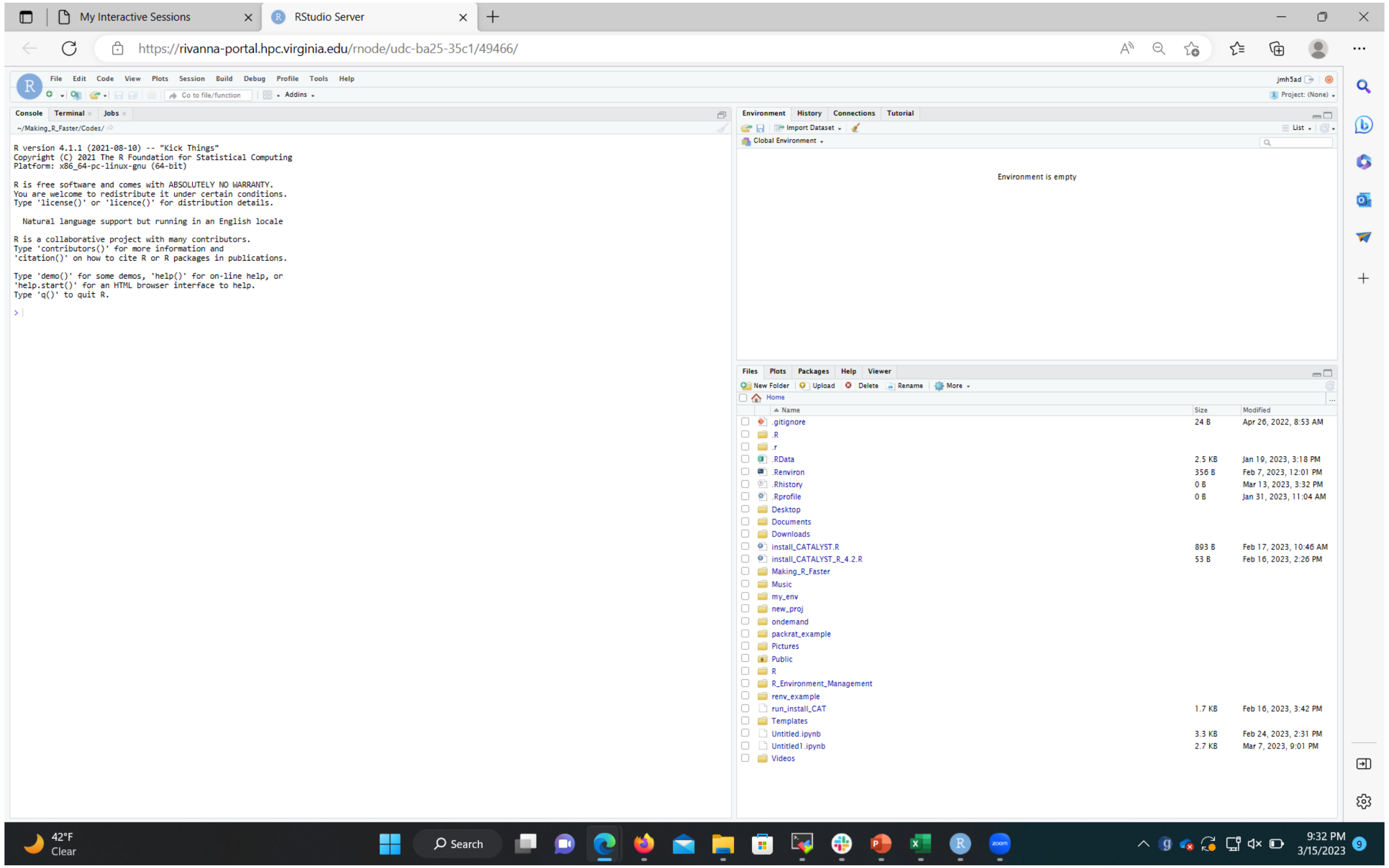
And, Wait

- RStudio Server runs on a compute node; so, we need to wait for the resources. A button labeled ‘Connect to RStudio Server” will pop up when it is ready. Click on the button.



RStudio

- RStudio will appear.
- Now we are ready to work on some code.



CASE STUDY #1

Reading a Large Data File

The Data

- The data are a collection of information about jobs running on Rivanna
  - The file is pipe-delimited
  - There are 514409 rows with 5 variables (features)

```
"NCPUS"|"CPUTime"|"Start"|"Elapsed"|"ReqTRES"
1|"00:00:00"|"2023-01-11T21:07:20"|"00:00:00"|"billing=1,cpu=1,gres/gpu=1,mem=30G,node=1"
6|"33-00:01:00"|"2022-12-26T16:25:46"|"5-12:00:10"|"billing=6,cpu=6,mem=100G,node=1"
4|"27-15:52:12"|"2022-12-26T16:39:47"|"6-21:58:03"|"billing=4,cpu=4,mem=36G,node=1"
80|"16-16:04:00"|"2022-12-31T19:36:12"|"05:00:03"|"billing=80,cpu=80,mem=720000M,node=2"
80|"12-22:13:20"|"2022-12-31T20:24:47"|"03:52:40"|"billing=80,cpu=80,mem=720000M,node=2"
80|"16-21:05:20"|"2022-12-31T20:47:16"|"05:03:49"|"billing=80,cpu=80,mem=720000M,node=2"
```

The Task

- Determine the "fastest" way to read in the data

```
"NCPUS"|"CPUTime"|"Start"|"Elapsed"|"ReqTRES"
1|"00:00:00"|"2023-01-11T21:07:20"|"00:00:00"|"billing=1,cpu=1,gres/gpu=1,mem=30G,node=1"
6|"33-00:01:00"|"2022-12-26T16:25:46"|"5-12:00:10"|"billing=6,cpu=6,mem=100G,node=1"
4|"27-15:52:12"|"2022-12-26T16:39:47"|"6-21:58:03"|"billing=4,cpu=4,mem=36G,node=1"
80|"16-16:04:00"|"2022-12-31T19:36:12"|"05:00:03"|"billing=80,cpu=80,mem=720000M,node=2"
80|"12-22:13:20"|"2022-12-31T20:24:47"|"03:52:40"|"billing=80,cpu=80,mem=720000M,node=2"
80|"16-21:05:20"|"2022-12-31T20:47:16"|"05:03:49"|"billing=80,cpu=80,mem=720000M,node=2"
```

Options for Reading the Data File

- *read.csv* from base packages
- *read_delim* from readr/tidyverse

Using read.csv for a pipe-delimited file

```
filename <- “../Data/collectedStats.csv"
start_time <- proc.time()

raw_data <- read.csv(filename, sep="|")

elapsedTime <- proc.time() - start_time

cat("\n*****************\n")
print(elapsedTime)
cat("\n*****************\n")
```

Codes/01_read_csv.R

Run #1:
0.899 sec

Using read_delim for a pipe-delimited file

```
library(readr)

filename <- “../Data/collectedStats.csv"
start_time <- proc.time()

raw_data <- read_delim(filename, delim="|", show_col_types=FALSE)

elapsedTime <- proc.time() - start_time

cat("\n*****************\n")
print(elapsedTime)
cat("\n*****************\n")
```

Codes/02_read_delim.R

Run #1:
0.607 sec

Times can vary

- How can we determine an overall best approach?

Run #1: 0.899 sec Run #2: 0.917 sec Run #3: 0.906 sec	Run #1: 0.607 sec Run #2: 0.569 sec Run #3: 0.565 sec

- Replicate the tests and take an average

REPEATING TIMING TEST

How to compare results

Times can vary

- How can we determine an overall best approach?

Codes/03_read_csv_repeated.R

Average Time across 10 runs:
0.8616 sec

Codes/04_read_delim_repeated.R

Average Time across 10 runs:
0.5400 sec

- Replicate the tests and take an average of the times.
- The more efficient process is the one that is the fastest on average.

CASE STUDY #2

Manipulating a Column in a Table

The Data

- We will use the same data as in the Case #1 study.
- Notice that the column CPUTime is in the format Days-HH:MM:SS

```
"NCPUS"|"CPUTime"|"Start"|"Elapsed"|"ReqTRES"
1|"00:00:00"|"2023-01-11T21:07:20"|"00:00:00"|"billing=1,cpu=1,gres/gpu=1,mem=30G,node=1"
6|"33-00:01:00"|"2022-12-26T16:25:46"|"5-12:00:10"|"billing=6,cpu=6,mem=100G,node=1"
4|"27-15:52:12"|"2022-12-26T16:39:47"|"6-21:58:03"|"billing=4,cpu=4,mem=36G,node=1"
80|"16-16:04:00"|"2022-12-31T19:36:12"|"05:00:03"|"billing=80,cpu=80,mem=720000M,node=2"
80|"12-22:13:20"|"2022-12-31T20:24:47"|"03:52:40"|"billing=80,cpu=80,mem=720000M,node=2"
80|"16-21:05:20"|"2022-12-31T20:47:16"|"05:03:49"|"billing=80,cpu=80,mem=720000M,node=2"
```

The Task

- We would like to convert it to convert the CPUTime to be the number of hours

```
"NCPUS"|"CPUTime"|"Start"|"Elapsed"|"ReqTRES"
1|"00:00:00"|"2023-01-11T21:07:20"|"00:00:00"|"billing=1,cpu=1,gres/gpu=1,mem=30G,node=1"
6|"33-00:01:00"|"2022-12-26T16:25:46"|"5-12:00:10"|"billing=6,cpu=6,mem=100G,node=1"
4|"27-15:52:12"|"2022-12-26T16:39:47"|"6-21:58:03"|"billing=4,cpu=4,mem=36G,node=1"
80|"16-16:04:00"|"2022-12-31T19:36:12"|"05:00:03"|"billing=80,cpu=80,mem=720000M,node=2"
80|"12-22:13:20"|"2022-12-31T20:24:47"|"03:52:40"|"billing=80,cpu=80,mem=720000M,node=2"
80|"16-21:05:20"|"2022-12-31T20:47:16"|"05:03:49"|"billing=80,cpu=80,mem=720000M,node=2"
```

Options for Converting the CPUTime to Hours

- Using a for loop
- Using tidyverse manipulations
- Using a multicore technique
  - mclappy
  - furrr

Basic Code for the Conversion

```
##---------- Compute CPU Hours----------------------##
## Given a single value, say 5-01:30:10 or 12:15:05
## Split the string into the numeric parts and convert each part to hours.
##
convert_time_to_hrs <- function(cputime){
  parts <- as.numeric(unlist(strsplit(cputime, "[[:punct:]]")))
  cpuhours <- 0
  if (length(parts)==4){
    cpuhours <- parts[1]*24
    parts <- parts[-1]
  }
  cpuhours <- cpuhours + parts[1] + parts[2]/60 + parts[3]/3600
  return(cpuhours)
}
```

To be consistent with all the approaches, I’m creating a function that will convert a single CPUTime to Hours.

Using a for loop

```
raw_data <- read_delim(filename, delim="|", show_col_types=FALSE)
N <- nrow(raw_data)
CPUHours <- rep(0.0, N)

 start_time <- proc.time()
 for (i in 1:N) {
    CPUHours[i] <- convert_time_to_hrs(raw_data$CPUTime[i])
 }

 raw_data$CPUours <- CPUHours
 elapsed_time <- proc.time() - start_time

 print(elapsed_time)
 print("******************")
 print(head(raw_data))
```

Codes/05_for_loop.R

Run #1:
  5.577 sec
Run #2:
  5.626 sec
Run #3:
  5.569 sec

Using tidyverse manipulations

```
raw_data <- read_delim(filename, delim="|", show_col_types=FALSE)
 N <- nrow(raw_data)

 start_time <- proc.time()
 raw_data <- raw_data %>%
         rowwise() %>%
         mutate(CPUHours=convert_time_to_hrs(CPUTime))
 elapsed_time <- proc.time() - start_time
 print(elapsed_time)
 print("*****************")
 print(head(raw_data))
```

Codes/06_tidyverse.R

Run #1:
  7.504 sec
Run #2:
  7.568 sec
Run #3:
  7.518 sec

Using multicore lapply

```
raw_data <- read_delim(filename, delim="|", show_col_types=FALSE)
 N <- nrow(raw_data)

 options(mc.cores=4)

 start_time <- proc.time()
 CPUHours <- unlist(mclapply(raw_data$CPUTime, convert_time_to_hrs))
 raw_data$CPUours <- CPUHours
 elapsed_time <- proc.time() - start_time
 print(elapsed_time)
 print("*****************")
 print(head(raw_data))
```

Codes/07_mclapply.R

Run #1:
  2.081 sec
Run #2:
  1.978 sec
Run #3:
  2.310 sec

Using furrr::map

```
 raw_data <- read_delim(filename, delim="|", show_col_types=FALSE)
  N <- nrow(raw_data)

plan("multisession", workers=4)

  start_time <- proc.time()
  raw_data$CPUHours <- unlist(future_map(raw_data$CPUTime, convert_time_to_hrs))
  elapsed_time <- proc.time() - start_time

  print(elapsed_time)
  print("*****************")
  print(head(raw_data))
```

Codes/08_furrr.R

Run #1:
  2.712 sec
Run #2:
  3.097 sec
Run #3:
  2.850 sec

Average Times for Converting the CPUTime to Hours

- Using a for loop

Average Time:
5.590

- Using tidyverse manipulations

Average Time:
7.530

- Using a multicore technique
  - mclappy

Average Time:
2.123

  - furrr

Average Time:
2.886

CASE STUDY #3

Performing Mathematical Operations

The Data

- For this case, we will use two sets of data: a table of x, y, coordinate values, and an array of electric charges for each location in the table
- The data are saved in .RData files and can be loaded with the load function.

```
head(coords)
    [,1]  [,2]  [,3]
[1,] 0.566 0.611 0.506
[2,] 0.817 0.183 0.585
[3,] 0.025 0.316 0.061
[4,] 0.977 0.978 0.874
[5,] 0.269 0.092 0.881
[6,] 0.664 0.981 0.962
```

```
head(q)
[1] 0.180 0.422 0.084 0.053 0.563 0.139
```

The Task

- Compute a value, E, defined as

$$E = \sum_{j<i} \frac{e^{r_{ij} * q_i} * e^{r_{ij} * q_j}}{r_{ij}} - \frac{1}{a} \quad \text{for } r_{ij} \leq cut$$

where r_{ij} is the distance between (x_i, y_i, z_i) and (x_j, y_j, z_j)

Inefficient Code for the Computations

```
total_e = 0.0
cut_count = 0

load("coords.RData")
load("q_values.RData")
natom <- 5000
cut <- 0.01
a <- 3.2

time1 <- proc.time()
```

```
for (i in 2:natom) {
  for (j in 2:natom) {

    if (j < i) {

      vec2 = (coords[i-1, 1]-coords[j-1, 1])^2.0 +
             (coords[i-1, 2]-coords[j-1, 2])^2.0 +
             (coords[i-1, 3]-coords[j-1,3])^2.0
      rij = sqrt(vec2);
      if ( rij <= cut ) {
        #   Increment the counter of pairs below cutoff
        cut_count = cut_count + 1;
        #   Compute the term to be added to E and add
        current_e = (exp(rij*q[i-1])*exp(rij*q[j-1]))/rij;
        total_e = total_e + current_e - 1.0/a;
      } # end rij <= cut
    } # end j < i
  } # end for j
} # end for i
```

Codes/09_slow_math_code.R

```
time2 = proc.time(); #time calculation
elapsedTime2 = time2 - time1
cat("Value of system clock after E calc = \n")
```

Techniques for Reducing the Mathematical Computations

- Do not recompute values that have already been computed, like `i-1`.
- Use vectorization whenever possible.
- Reduce the number of inner loops, if possible.
- Simplify the math whenever possible:

  x/2 + y/2 +z/2 = (x+y+z)/2

  exp(ax) * exp(ay) = exp(a*(x+y))
- Check that you have the right boundaries on your *for* loops – changing the boundaries could reduce the need for computing values like `i-1`

Before and After Changes

Codes/10_faster_math_code.R

```
for (i in 2:natom) {
  for (j in 2:natom) {

    if (j < i) {

      vec2 = (coords[i-1, 1]-coords[j-1, 1])^2.0 +
                  (coords[i-1, 2]-coords[j-1, 2])^2.0 +
                  (coords[i-1, 3]-coords[j-1,3])^2.0
      rij = sqrt(vec2);
      if ( rij <= cut ) {
        #   Increment the counter of pairs below cutoff
        cut_count = cut_count + 1;
        #   Compute the term to be added to E and add
        current_e = (exp(rij*q[i-1])*exp(rij*q[j-1]))/rij;
        total_e = total_e + current_e - 1.0/a;
      } # end rij <= cut
    } # end j < i
  } # end for j
} # end for i
```

```
N <- natom = 1
for (i in 2:N){
  j <- 1:(i-1)

  vec2 = (coords[i, 1]-coords[j, 1])^2.0 +
              (coords[i, 2]-coords[j, 2])^2.0 +
              (coords[i, 3]-coords[j,3])^2
  ri <-  sqrt(vec2)
  ndx <- which(ri <= cut)
  num_making_cut <- length(ndx)

  if (num_making_cut > 0){
   cut_count <- cut_count + 1
   jcut <- j[ndx]
   qj <- q[jcut] ;     rij <- ri[jcut]
   current_e = sum( exp( rij*(q[i]+qj) )  )/rij
   total_e <- total_e + current_e - a_inv
  }  # end if
}  #end for
```

LESSONS LEARNED

Observations from Working with Different Codes

- At times, tidyverse operations can be faster than than other techniques. This will often depend on the size of the dataframe/tibble.
- The best time to use parallelization is when there are independent tasks that take a significant amount of time to run.
  - There is a certain amount of overhead for splitting data for parallelism and combining results.
  - The time of the task itself needs to outweigh the time of splitting and combinint.
- R is constantly changing – what was efficient last year may be considered slow this year.

CONCLUSIONS

Optimization Strategy

- During optimization, your goal is to minimize the amount of work the computer is required to do. The strategy we recommend is a two-step approach:

1. Write code that is efficient from the start (e.g., use vectors instead of loops)

2. After your code is debugged and working, try more aggressive optimization techniques (e.g., manipulating the mathematical formulas to reduce calls to built-in math functions).

Wallclock Time is Important!

- The only metric that ultimately matters is the Wallclock time.
  - Wallclock is how long you have to wait for your program to run.
  - Wallclock is (sometimes) how much you get charged for.
  - Wallclock is how long your code is blocking other users from using the machine.

Disadvantages?

Optimizing code is time consuming

- Do not waste weeks optimizing code that will run once for 1 hour.

- Some optimizations can make the code harder to read and debug.
  - Which is more readable:

    y = a3*x^3 + a2* x^2 + a1*x + a0

    or

    y = a0 + x*(a1 + x*(a2 + x*a3))

- Be aware that different architectures can respond in different ways.
  - Just because code is optimized on your laptop does not necessarily mean that it is optimized on your colleague's computer.

- Some optimizations can adversely affect parallel scaling.

When to optimize?

- Code optimization is an iterative process requiring time, energy and thought. It is recommended for:
  - Codes that will be widely distributed and used often by the research community.
  - Projects that have time limitations, so that you can maximize the available time on the compute resources.

When optimization isn’t enough

- When you have done everything possible to optimize your code, and it still isn’t fast enough, you can
  - Find a better algorithm (if one exists).
  - Use parallelizing your code.

Need more help?

Office Hours	
Tuesdays:	3 pm - 5 pm
Thursdays:	10 am - noon

Zoom links for the office hours are available at https://www.rc.virginia.edu/support/#office-hours

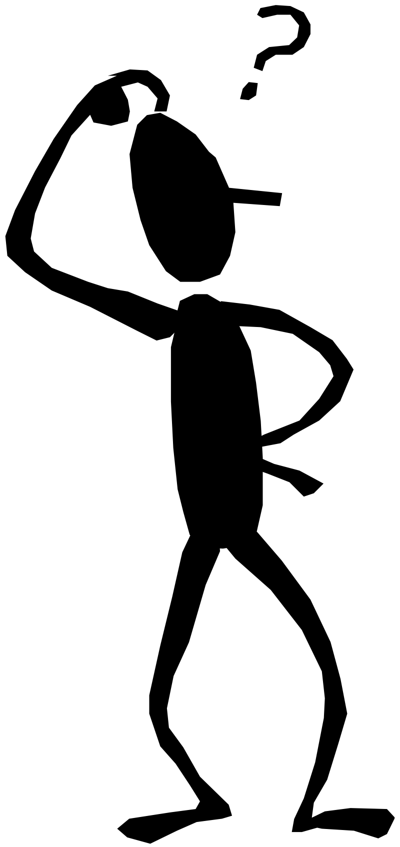
Lots of information is available on our website:

rc.Virginia.edu

Or, you submit a request for help through the web for at:

https://www.rc.virginia.edu/form/support-request/

Questions?



APPENDIX

Simple examples for optimizing R code

General Advice #1

- **Do not re-compute values that are used frequently.**

  Compute once and store in a variable. This is especially critical in loops. Re-computing a single value thousands or millions of times will increase the time it takes for your code to run.

- Before:

```
variance = 0


 for (x in values) {
    distToMean = x - mean(values)
    variance = variance +
           (distToMean^2)/length(values)
 }
```

After:

```
variance = 0
meanOfValues = mean(values)
N = length(values)

for (x in values){
   distToMean = x - meanOfValues
   variance = variance + (distToMean^2)/N
}
```

General Advice #2

- Avoid referencing a single value of an array (e.g., A[i] or M[i,j]) multiple times.

  If you know that you will be using the value frequently in a block of code, save it to a variable.

- Before:

```
y = 0


for (x in values) {
   y = y + ( sin(M[i, j] * x) * exp(M[i, j]) )/M[i, j]
}
```

After:

```
y = 0
mij = M[i, j]

for (x in values) {
   y = y + ( sin(mij * x) * exp(mij) )/mij
}
```

General Advice #3

- Consolidate/minimize mathematical functions.
  - This may require some analytical manipulations. Keep in mind that math intrinsics (e.g., trig functions, exponential/logarithmic function) tend to be slow.

$$\exp\left(\frac{a*x}{L}\right) * \exp\left(\frac{b*x}{2*L}\right) = \exp\left(\frac{(2*a+b)*x}{2*L}\right)$$

4 multiplications
2 divisions
2 exponentials

3 multiplications
1 divisions
1 addition
1 exponential

General Advice #4

- Avoid using loops.
  - Take advantage of vectorizations.

- Before:

```
variance = 0
meanOfValues = mean(values)
N = length(values)

for (x in values){
  diffMean = x - meanOfValues
  variance = variance + (diffMean^2)/N
}
```

After:

```
diffMean = values - mean(values)
variance = sum((diffMean)^2 /length(values))
```

General Advice #5

- Pre-allocate memory whenever possible.
  - If you know the size and type of the list or array, reserve memory for the entire list/array before doing calculations.
- Before:

```
theValues = c( )


for (xValue in seq(1, N)){
  theValues = c(theValues, sqrt(xValue))

}
```

After:

```
theValues = rep(0.0, N)
i = 1

for (xValue in seq(1, N)){
  theValues[i] = sqrt(xValue)
  i = i + 1
}
```

General Advice #6

- I/O is slow – try to consolidate it.
  - When processing data and writing results to a file, don't write each result separately. Save and write everything with one command.
- Before:

```
filename = "outputTest1.txt"
outFile = file(filename, "w")

for (xValue in x){
  line = paste("The square root of",
                    xValue, "is", sqrt(xValue))
  write(line, outFile)
}
close(outFile)
```

After:

```
lines = rep(" ", numValues)
for (xValue in x){
  lines[i] = paste("The square root of“,
                 xValue , "is", sqrt(xValue))
}

filename = "outputTest2.txt"
outFile = file(filename, "w")
write(lines, outFile)
close(outFile)
```

General Advice #7

- Avoid mathematical manipulations of entire dataframes.
  - If the data is all numeric, convert the dataframe to a matrix. Otherwise, pull out only the needed columns.

- Before:

```
ndx = which(theData$temps > 85.3)
 lastYear = max(theData$years)
 numHotDays =
        sum(theData$years[ndx]==lastYear)
```

After:

```
theData = as.matrix(theData)

ndx = which(theData[,"temps"] > 85.3)
lastYear = max(theData[ , "years"])
numHotDays =
        sum(theData[ndx ,"years"]==lastYear)
```

General Advice #8

- Avoid overuse of parentheses.
  - The contents inside parentheses are evaluated and stored in a special list structure. There is overhead for allocating the list, storing, and retrieving the results.

- Before:

```
y = ( 1 + (x) ) / ( (1) + (x)^2 )
```

After:

```
y = ( 1 + x ) / ( 1 + x^2 )
```

The End