# INTRODUCTION TO R AND RHADOOP

Janez Povh and Lucia Absalom Bautista
EuroHPC Competence Center Slovenia
October 19–20 2022

# Outline

- Schedule
- Introduction to R
- Advanced and Big data management with R
- Big data management with RHadoop
- Parallelization with Rmpi

# Timetable

| *March 4th* | |
|---|---|
| 13:00–13:15 | **Introduction to Day 2** |
| 13:15–14:00 | **Introduction to R** |
| 14:00–14:15 | *break* |
| 14:15–15:00 | **Advanced and Big data management with R** Dana manipulations with apply functions apply, lapply, sapply, vapply, tapply, and mapply. Big Data management with function for efficient parallel loops parLapply, parSapply, mcLapply and foreach-dopar. |
| 15:00–15:15 | *break* |
| 15:15–16:00 | **Big data management with RHadoop** Preparing and storing big data to HDFS using rhdfs library. Retriving from and managing big data in HDFS by plyrmr and rhdfs library. |
| 16:00–16:15 | *break* |
| 16:15–17:00 | **Big data analysis with RHadoop and Rmpi** Preparing map-reduce scripts to make basic data analysis tasks (extreme values, counts, mean values, dispersions) using rhdfs library. Creating jobs for parallel computations with Rmpi. |

# Outline/next

- Schedule
- Introduction to R
- Advanced and Big data management with R
- Big data management with RHadoop
- Parallelization with Rmpi

# Introduction to R

# What is R

- Software for Statistical Data Analysis
- Based on S
- Programming Environment
- Interpreted Language
- Data Storage, Analysis, Graphing
- Free and Open Source Software

# How to obtain R

- R current version 4.2.1 (released on 2022-06-23).
- http://cran.r-project.org
- Binary source codes
- Windows executables

# Pros and Cons

Pros:

- Free and Open Source
- Strong User Community
- Highly extensible, flexible
- Implementation of high-end statistical methods
- Flexible graphics and intelligent defaults

Cons

- Steep learning curve
- Slow for large datasets

# Data types

- R Supports virtually any type of data
- Numbers, characters, logicals (TRUE/ FALSE)
- Arrays of virtually unlimited sizes
- Simplest: Vectors and Matrices
- Lists: Can Contain mixed type variables
- Data Frame: Rectangular Data Set

# Data structures in R

Linear

- vectors (all same type)
- lists (mixed types)

Rectangular

- data frame
- matrix

# Running R

- I recommend RStudio, an IDE for R.
- It is available as RStudio Desktop and **RStudio Server**, which runs on a remote server and allows accessing RStudio using a web browser.

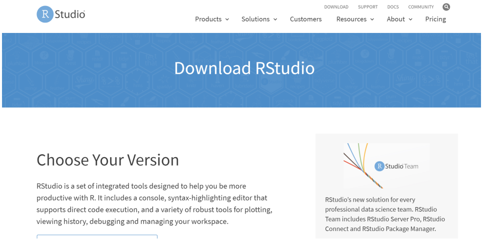



Figure 1: `https://rstudio.com/products/rstudio/download/`

# RStudio on HPCFS

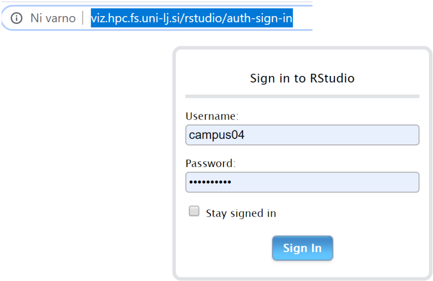
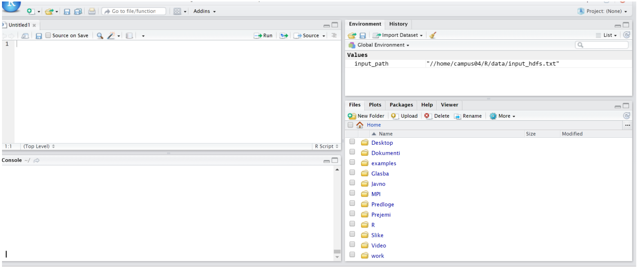



Figure 2: `http://viz.hpc.fs.uni-lj.si/rstudio/auth-sign-in`

# RStudio on HPCFS



# The first R script file

- Open new script file CTRL+SHIFT+N
- Save the script file.

## Create directory for R scripts

```
work_dir=paste("/home", Sys.getenv("USER"),"resources", sep="/")

if (file.exists(work_dir)){
  setwd(work_dir)
  system("git pull")
} else {
  dir.create(work_dir)
  setwd(work_dir)
  system("git clone git@bitbucket.org:bdtrain/resources.git")
}
dir()
dir("data/")
```

# Creating the first scrip file

## Create and save simple data file

```
N=1000;
set.seed(2021)
Data=data.frame(group=character(N),ints=numeric(N),reals=numeric(N))
Data$group=sample(c("a","b","c"), 1000, replace=TRUE);
Data$ints=rbinom(N,10,0.5);
Data$reals=rnorm(N);

head(Data)
Data

write.table(Data, file='Data/Data_Ex_1.txt', append = FALSE, dec = ".",col.names = TRUE)

ls()
rm(list = ls())
```

# Load and analyse the data

## Load data

```
Data_read<-read.table(file='data/Data_Ex_1.txt',header = TRUE)
# first few rows
head(Data_read)

#10 th row
Data_read[10,]
# column group
Data_read$group
Data_read[,1]
```

# Load and analyse the data

## Load data

```
  # compute means and counts by groups
  group count_ints mean_ints
a | 337 | 5.014837
b | 338 | 5.032544
c | 325 | 4.990769

# primitive solution
Group_lev=sort(unique(Data_read$group))

Tab_summary=data.frame(group=character(3),count_ints=integer(3),mean_ints=numeric(3))
Tab_summary$group<-Group_lev
for (i in c(1:3)){
  sub_data = subset(Data_read,group==Group_lev[i])
  Tab_summary$count_ints[i]<-nrow(sub_data)
  Tab_summary$mean_ints[i]<-mean(sub_data$ints)
}
```

# Analyse the data with dplyr, magrittr

- Library dplyr: ”select", "filter", "group_by","arrange", "mutate" and ”summarize".
- Library magrittr: "%>%"

## dplyr

```
library(dplyr)
library(magrittr)
Tab_summary1<-group_by(Data_read,group) %>% dplyr::summarise(count_ints=n(),mean_ints=
     mean(ints))

# other operations on rows and columns
Data_read_group_ints<-Data_read %>% select(group,ints)
# add new variable reals/ints
Data_read<-mutate(Data_read,ratio=reals/ints)
Data_read<-Data_read %>% mutate(ratio1=ints/reals)
#arrange
#sort accordind to increasing group
Data_read<-Data_read %>% arrange(desc(group))
Data_read<-Data_read %>% arrange(group)
```

# Analyze the data by split, aggregate, sapply

## split, aggregate, sapply

```
s <- split(Data_read, Data_read$group)
Tab_summary1<-t(sapply(s, function(x) return(c(mean(x$ints),length(x$group)) )))

Tab_summary2<-cbind(aggregate(ints~group,data = Data_read,FUN=length),aggregate(ints~
    group,data = Data_read,FUN=mean))
Tab_summary2<-Tab_summary2[,-3]
```

# Outline/next

- Schedule
- Introduction to R
- Advanced and Big data management with R
- Big data management with RHadoop
- Parallelization with Rmpi

# Advanced and Big data management with R

 Advanced and Big data management with R

# apply, lapply, sapply

## apply, lapply, sapply

```
apply(X, MARGIN, FUN)
Here:
-x: an array or matrix
-MARGIN=1: the manipulation is performed on rows
-MARGIN=2: the manipulation is performed on columns
-MARGIN=c(1,2): the manipulation is performed on rows and columns
-FUN: tells which function to apply. Built functions like mean, median, sum, min, max and
      even
user-defined functions can be applied
```

 Advanced and Big data management with R

# apply

For data constructed above (Data_read) compute row and columns means using apply

## apply

```
Data_read<-read.table(file='data/Data_Ex_1.txt',header = TRUE)

Data_col_means_1 <- colMeans(Data_read[,-1])
Data_col_means_2 <- apply(Data_read[,-1],2,FUN =mean)

Data_row_means_1 <- rowMeans(Data_read[,-1])
Data_row_means_2 <- apply(Data_read[,-1],1,FUN =mean)

Data_both_squares <- apply(Data_read[,-1],c(1,2),FUN = function(x) return(x^2))
```

# lapply

- lapply function takes list, vector or data frame as input and returns only list as output
- sapply function takes list, vector or data frame as input. It is similar to lapply function but returns only vector as output.

For data constructed above (Data_read) compute row and columns sums using lapply

## lapply

```
Data_col_sums_1 <- apply(Data_read[,-1],2,FUN =sum)
Data_col_sums_2 <- lapply(Data_read[,-1],FUN =sum)

typeof(Data_col_sums_1)
typeof(Data_col_sums_2)


Data_abs <- lapply(Data_read[,-1],FUN =abs)
Data_sq <- lapply(Data_read[,-1],FUN = function(x){x^2})

typeof(Data_abs)
length(Data_abs)
```

# sapply

For data constructed above (Data_read) compute row and columns sums using sapply

## sapply

```
Data_col_sums_1 <- apply(Data_read[,-1],2,FUN =sum)
Data_col_sums_2 <- lapply(Data_read[,-1],FUN =sum)
Data_col_sums_3 <- sapply(Data_read[,-1],FUN =sum)

typeof(Data_col_sums_1)
typeof(Data_col_sums_2)
typeof(Data_col_sums_3)


Data_col_sums_4 <- lapply(list(Data_read$ints,Data_read$reals),FUN =sum)
Data_col_sums_5 <- sapply(list(Data_read$ints,Data_read$reals),FUN =sum)
Data_col_len_1 <- lapply(list(Data_read$ints,Data_read$reals),FUN =length)
Data_col_len_2 <- sapply(list(Data_read$ints,Data_read$reals),FUN =length)
```

 Advanced and Big data management with R

# for loop

Let us compute sums of all elements of 12 random matrices of order $3000 \times 3000$

## for

```
N=3000
set.seed(2021)
sum_rand=rep(0,11);
tic()
for (i in c(1:12)){
  A=randn(N,N)
  sum_rand[i]=sum(A)
}
time_for=toc()
```

 Advanced and Big data management with R

# foreach do loop

Let us compute sums of all elements of 12 random matrices of order $3000 \times 3000$

## for

```
N=3000
set.seed(2021)
sum_rand=rep(0,11);
tic()
foreach (i = c(1:12)) %do% {
  A=randn(N,N)
  sum_rand[i]=sum(A)
}
time_foreach=toc()
```

 Advanced and Big data management with R

# Parallel foreach dopar loop

Let us compute sums of all elements of 12 random matrices of order $3000 \times 3000$ using `foreach ...dopar` from `foreach` and `doParallel`

## for

```
N=3000
set.seed(2021)
sum_rand=rep(0,11);
tic()
foreach (i = c(1:12)) %dopar% {
  A=randn(N,N)
  sum_rand[i]=sum(A)
}
time_foreach_dopar=toc()
```

Do you observe any difference?

 Advanced and Big data management with R

# Parallel foreach dopar loop

Let us compute sums of all elements of 12 random matrices of order $3000 \times 3000$ using `foreach ...dopar` from `foreach`, `doParallel`. Create cluster!

## for

```
N=3000
set.seed(2021)
registerDoParallel(12)  # use multicore, set to the number of our cores - needed for
     foerach dopar

sum_rand=rep(0,11);
tic()
foreach (i = c(1:12)) %dopar% {
   A=randn(N,N)
   sum_rand[i]=sum(A)
}
time_foreach_dopar_1=toc()
registerDoSEQ()
```

Do you observe any difference?

 Advanced and Big data management with R

# Library parallel

- encapsulates existing libraries `multicore, snow`
- two ways of parallelization:
  - The socket approach: launches a new version of R on each core via networking (e.g. the same as if you connected to a remote server), but the connection is happening all on your own computer.
    - pros: (i) Works on any system (including Windows); (ii) Each process on each node is unique so it can't cross-contaminate.
    - cons: (i) Each process is unique so it will be slower (ii) Things such as package loading need to be done in each process separately. Variables defined on your main version of R don't exist on each core unless explicitly placed there. (iii) More complicated to implement.
  - use `parLapply, parSapply`

# Library `parallel`

- The forking approach copies the entire current version of R and moves it to a new core.
  - (i) Faster than sockets. (ii) Because it copies the existing version of R, your entire workspace exists in each process. (iii) Easy to implement.
  - Cons (i) Only works on POSIX systems (Mac, Linux, Unix, BSD) and not Windows. (ii) it can cause issues specifically with random number generation or when running in a GUI (such as RStudio). This doesn't come up often.
- use `mclapply`

# Parallel versions of lapply

By using library parallel and parSapply, mclapply compute sums of all elements of 12 random matrices of order $3000 \times 3000$. Create cluster!

## parallel versions of apply

```
mat_sum<-function(x){
  A=rand(x)
  return(sum(A))
}
tic()
time_lapply<-system.time({
  set.seed(2021)
  sum_rand_lapply=lapply(rep(3000,12),FUN=mat_sum)
  time_lapply=toc()
})

time_sapply<-system.time({
  set.seed(2021)
  sum_rand_sapply=sapply(rep(3000,12),FUN=mat_sum)
})
```

# Parallel versions of lapply

## parallel versions of apply

```
time_mcLapply<-system.time({
  set.seed(2021)
  sum_rand_mcLapply=mclapply(X=rep(3000,12),FUN=mat_sum,mc.cores = 12)
})

time_parLapply<-system.time({
  clust <- makeCluster(12, type="PSOCK")
  set.seed(2021)
  sum_rand_parLapply=parLapply(cl,rep(3000,1000),fun=mat_sum)
  stopCluster(clust)
})

time_parSapply<-system.time({
  clust <- makeCluster(12, type="PSOCK")
  set.seed(2021)
  sum_rand_parSapply=parSapply(cl,rep(3000,20),FUN=mat_sum)
  stopCluster(clust)
})
```

 Advanced and Big data management with R

# Parallel versions of lapply

## parallel versions of apply

```
times_apply<-rbind(time_lapply,time_sapply,time_parLapply,time_parSapply,time_mcLapply)

> times_apply[,1:3]
               user.self sys.self elapsed
time_lapply        5.120    0.954   6.072
time_sapply        5.049    0.885   5.932
time_parLapply     0.076    0.209  47.999
time_parSapply     0.021    0.105   4.286
time_mcLapply      0.003    0.040   0.531
```

# Libraries for shared memory parallelization in R

- Parallel for-loop (`foreach...dopar`). Cluster created by `registerDoParallel(N)` and `registerDoSEQ()`. Library `foreach`, `doParalel` needed.
- Parallel `apply`: `parLapply`, `parSapply`, `mcLapply` need library parallel.

# Outline/next

- Schedule
- Introduction to R
- Advanced and Big data management with R
- Big data management with RHadoop
- Parallelization with Rmpi

# Big data management with RHadoop

# The goals of the second part

- Demonstrating basic data management operations with RHadoop;
- By few examples showing basic data analysis with RHadoop;

 Big data management with RHadoop

# Motivation

- Do data analysis (statistics), do not bother with low level settings
- Stay within `R` (and `RStudio`)

# Overall picture

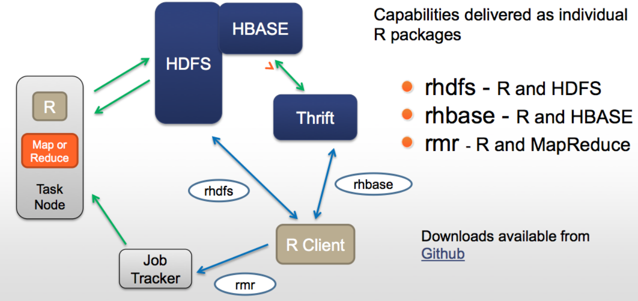
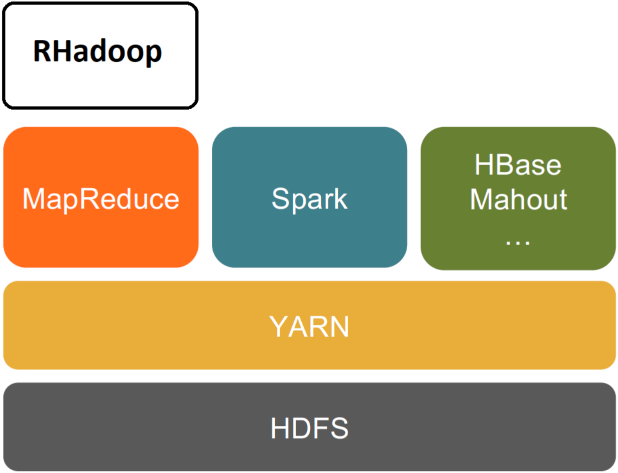



Figure 3:
https://www.r-bloggers.com/slides-and-replay-from-r-and-hadoop-webinar/

# Overall picture



# First little example

content...

# Setting up RHadoop using terminal window

```
export LD_LIBRARY_PATH=/opt/apps/software/Java/1.7.0_80/lib:${LD_LIBRARY_PATH}
export PATH=/opt/apps/software/Java/1.7.0_80:${PATH}
export JAVA_HOME=/opt/apps/software/Java/1.7.0_80
export PATH=/opt/apps/software/Hadoop/2.6.0-cdh5.8.0-native/bin:${PATH}
export PATH=/opt/apps/software/Hadoop/2.6.0-cdh5.8.0-native/sbin:${PATH}
export LD_LIBRARY_PATH=/opt/apps/software/Hadoop/2.6.0-cdh5.8.0-native/lib:${LD_LIBRARY_PATH}
export HADOOP_HOME=/opt/apps/software/Hadoop/2.6.0-cdh5.8.0-native/share/hadoop/mapreduce
```

# Rhadoop

5 R packages provided by RevolutionAnalytics[1,2]:

- `rhdfs` - basic connectivity to the Hadoop Distributed File System (browse, read, write, and modify files stored in HDFS)
- `rhbase` - basic connectivity to the HBASE distributed database, using the Thrift server.
- `plyrmr` - enables the R user to perform common data manipulation operations, as found in plyr and reshape2
- `rmr2` - allows R developer to perform statistical analysis in R via Hadoop MapReduce functionality on a Hadoop cluster.
- `ravro` - adds the ability to read, write and manipulate avro files from local and HDFS file system.

[1] https://github.com/RevolutionAnalytics

[2] https://github.com/RevolutionAnalytics/RHadoop/wiki/Downloads

 Big data management with RHadoop

# Setting up the Rhadoop - cnt.

- Establish the connectivity to the Hadoop Distributed File System by loading the library rhdfs. `library(rhdfs)`
- Load libraries to work with Hadoop MapReduce `library(rmr2)`
- Initialize HDSF `hdfs.init()`.
- All together:

```
library(rmr2)
library(rhdfs)
hdfs.init()
```

# Basic data operations with RHadoop.

List files in the root directory of DFS `hdfs.ls("/")`

```
> hdfs.ls("/")
permission  owner      group      size          modtime                  file
1 -rw-r--r-- hadoop supergroup 184814018 2021-09-25 22:16      /BigData_reg_class
2 -rw-r--r-- hadoop supergroup  33602002 2021-09-25 22:16             /CEnetBig
3 -rw-r--r-- hadoop supergroup 476054348 2021-09-25 22:16 /electricity-energy.txt
4 drwxrwxrwx hadoop supergroup         0 2021-09-28 02:14                  /tmp
5 drwxr-xr-x hadoop supergroup         0 2021-09-25 11:49                 /user
```

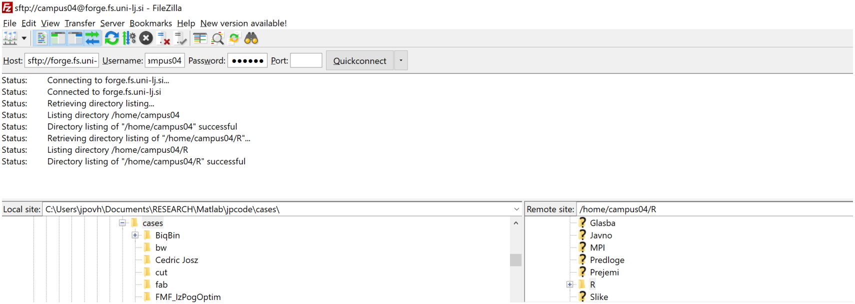
# Basic data operations with RHadoop.

List files in the home directory of each user
`hdfs.ls("/user/campus01")`

```
hdfs.ls("/user/campus01")
permission    owner   group        size          modtime
     file
1 -rw-r--r-- campus01 hadoop       12466 2020-09-16 06:47  /user/campus01/
     OurSmallData
2 -rw-r--r-- campus01 hadoop 18836041094 2020-09-11 09:16  /user/campus01/safecast.
     csv
3 -rw-r--r-- campus01 hadoop   336031560 2020-09-15 15:30     /user/campus01/
     wiki321MB
4 drwxr-xr-x campus01 hadoop           0 2020-09-15 15:30 /user/campus01/wordcount_
     out
```

 Big data management with RHadoop

# Moving data around - FileZilla



# Moving data around with Linux

## Copy from other account

```
cp /home/campus01/R/data/iris.csv /home/campusxx/R/data/iris.csv
```

## Copy from internet

```
curl -o  /home/campus01/R/data/iris.csv
 https://gist.githubusercontent.com/curran/a08a1080b88344b0c8a7/raw/
 639388c2cbc2120a14dcf466e85730eb8be498bb/iris.csv
```

# Moving data around with Linux or RHadoop

Copy from internet address or local folder to hdfs within RHadoop

```
curl https://gist.githubusercontent.com/curran/a08a1080b88344b0c8a7/raw/639388
     c2cbc2120a14dcf466e85730eb8be498bb/iris.csv |
hadoop fs -appendToFile - /user/campus01/iris.csv

system('curl https://gist.githubusercontent.com/curran/a08a1080b88344b0c8a7/raw/639388
     c2cbc2120a14dcf466e85730eb8be498bb/iris.csv |
hadoop fs -appendToFile - /user/campus01/iris.csv')

system('curl file:///home/campus01/R/data/iris.csv | hadoop fs -appendToFile - /user/
     campus01/iris.csv')

system('hadoop fs -appendToFile  /home/campus01/R/data/iris.csv /user/campus01/iris.csv')
```

# Create and store data in HDFS

Use small data created at the beginning and stored as

```
file_name = paste("/home", Sys.getenv("USER"),'myRscripts','Data_Ex_1.txt', sep="/")
Data_read<-read.table(file=file_name,header = TRUE)

myDFS_File=paste("/user", Sys.getenv("USER"), "OurSmallData", sep="/")
hdfs.rm(myDFS_File)
OurSmallData=to.dfs(Data_read, myDFS_File,format="native")
SmallData1_DFS=from.dfs(OurSmallData)
system("hdfs fsck /user/campus01/OurSmallData")
```

# CEnetBig

CEnetBig contains data about customers of company X: for each customer we have one row containing

- ID of the customer;
- the values of their bills for period January 2016-December 2016;
- type of product that they have;

```
> head(CEnetBig)
    id  2016_1  2016_2  2016_3  2016_4  2016_5  2016_6  2016_7  2016_8  2016_9  2016_10  2016_11
     2016_12 type
1 1001    2957    2624    2931    2342    1829    1982    2273    3142    2384     2369     2714
     2821    2
2 1002    2564    2710    2307    2632    2471    2330    2051    2785    2784     2696     2884
     2751    4
3 1003    2955    2618    2431    2217    2033    1823    2081    3264    2765     2687     2143
     3024    1
4 1004    2856    2849    2826    2818    2123    2094    2890    3040    2270     2794     2538
     2642    4
5 1005    2558    3086    2667    2457    2430    1752    2355    2959    2059     2388     2995
     2609    4
6 1006    3182    3248    2483    2315    1838    2391    2345    3253    2559     2017     2003
     2866    3
```

# HDFS statistics for CEnetBig

- From RStudio `system("hdfs fsck /tmp/CEnetBig")`
- From command line: `hadoop fsck /tmp/CEnetBig`

```
> system("hdfs fsck /tmp/CEnetBig")
Status: HEALTHY
 Number of data-nodes:  20
 Number of racks:    1
 Total dirs:      0
 Total symlinks:    0

Replicated Blocks:
 Total size:  28987096 B
 Total files: 1
 Total blocks (validated):  1 (avg. block size 28987096 B)
 Minimally replicated blocks: 1 (100.0 %)
 Over-replicated blocks:  0 (0.0 %)
 Under-replicated blocks: 0 (0.0 %)
 Mis-replicated blocks:   0 (0.0 %)
 Default replication factor:  3
 Average block replication: 3.0
 Missing blocks:    0
 Corrupt blocks:    0
 Missing replicas:    0 (0.0 %)
 Blocks queued for replication: 0
 FSCK ended at Thu Oct 20 09:45:12 CEST 2022 in 1 milliseconds
 The filesystem under path '/tmp/CEnetBig' is HEALTHY
```

# HDFS statistics for CEnetBig

- From RStudio `system("hdfs fsck /user/jpovh/safecast.csv")`

```
Connecting to namenode via http://viz.hpc:50070
FSCK started by campus01 (auth:SIMPLE) from /10.0.2.99 for path /user/campus01/
     safecast.csv at Wed Sep 16 07:39:21 CEST 2020
.Status: HEALTHY
Total size: 18836041094 B
Total dirs: 0
Total files:  1
Total symlinks:   0
Total blocks (validated): 141 (avg. block size 133588943 B)
Minimally replicated blocks:  141 (100.0 %)
Over-replicated blocks: 0 (0.0 %)
Under-replicated blocks:  0 (0.0 %)
Mis-replicated blocks:    0 (0.0 %)
Default replication factor: 3
Average block replication:  3.0
Corrupt blocks:   0
Missing replicas:   0 (0.0 %)
Number of data-nodes:   16
Number of racks:    8
FSCK ended at Wed Sep 16 07:39:21 CEST 2020 in 10 milliseconds

The filesystem under path '/user/campus01/safecast.csv' is HEALTHY
```

# CEnetBig

- Load data into active memory:

```
CEnetBig<-from.dfs("/tmp/CEnetBig")
```

- CEnetBig is a key-value pair with void key.

```
> CEnetBig$key
NULL
> CEnetBig$val[1:3,]
    id 2016_1 2016_2 2016_3 2016_4 2016_5 2016_6 2016_7 2016_8 2016_9 2016_10 2016_
     11 2016_12 type
1 1001    2957    2624    2931    2342    1829    1982    2273    3142    2384     2369
     2714     2821    2
2 1002    2564    2710    2307    2632    2471    2330    2051    2785    2784     2696
     2884     2751    4
3 1003    2955    2618    2431    2217    2033    1823    2081    3264    2765     2687
     2143     3024    1
```

 Big data management with RHadoop

# First Big Data challenge

EURO

**Goal:** In the column 2016_1 find the maximum value.

**Use:** $\max\{\cup_i A_i\} = \max_i\{\max A_i\}$.

$$\begin{aligned} 9 &= \max\{1,5,4,7,9,2,3,5\} \\ &= \underbrace{\max\{1,5,4,7\}, \max\{9,2,3,5\}}_{\max} \end{aligned}$$

Suppose $XX$ is submatrix of `CEnetBig` of 1st 100 rows. We find the maximum of column 2016_1 by

```
XX=CEnetBig$val[1:100,]
M=max(XX[,2])
```

# Finding maximum by Map-Reduce

- MAP:

```
mapper = function (., X) {
  M=max(X[,2]);
  keyval(1,M)
}
```

- REDUCE:

```
reducer = function(k, A) {
  keyval(k, list(Reduce("max", A))) # take maximum of maxima
}
```

# Finding maximum by Map-Reduce - cnt.

- MAP-REDUCE:

```
GlobalMaxMR = from.dfs(
  mapreduce(
  input = "/tmp/CEnetBig",
  map = mapper,
  reduce = reducer
  )
)
```

- Final code:

```
GlobMax =GlobalMaxMR$val
```

- Result

```
> GlobalMaxMR$val
[[1]]
[1] 3500
```

 Big data management with RHadoop

# Finding maximum, number of map calls and block sizes

```
mapper2 = function (., X) {
  M=max(X[,2]);
  keyval(1:3,list(1,M,dim(X)[1]))
}

reducer2 = function(k, A) {
  if(k==1){
    keyval(k, list(Reduce("+", A))) # take sum
  } else if (k==2) {
    keyval(k, list(Reduce("max", A))) # take maximum of maxima
  } else {
    keyval(k, A)
  }
}

GlobalMaxNumMR = from.dfs(
  mapreduce(
    input = "/tmp/CEnetBig",
    map = mapper2,
    reduce = reducer2
  )
)
```

 Big data management with RHadoop

# Finding maximum, number of map calls and block sizes - cnt.

```
> GlobalMaxMR
$key
[1] 1

$val
$val[[1]]
[1] 3500


> GlobalMaxMR$val
[[1]]
[1] 3500

> GlobalMaxNumMR
$key
 [1] 1 2 3 3 3 3 3 3 3 3

$val
$val[[1]]
[1] 8

$val[[2]]
[1] 3500

$val[[3]]
[1] 490752

$val[[4]]
[1] 83331
```

# Second Big Data challenge

**Goal:** Compute the mean value of the column 2016_1 ..

**Note:** $\bar{x} = \sum_i X_i / n$

Suppose $XX$ is submatrix of CEnetBig of 1st 100 rows. We find mean value of column 2016_1 by

```
XX=CEnetBig$val[1:100,]
m=mean(XX[,2])
```

- If $s_i$ and $n_i$ are sums and sizes of blocks of data, respectively, then the mean value of all data is

$$\bar{x} = \frac{\sum_i s_i}{\sum_i n_i}$$

 Big data management with RHadoop

# Finding mean value by Map-Reduce

EURO

- MAP:

```
mapper_mean = function (., X) {
  n=nrow(X);
  mi=sum(X[,2]);
  keyval(1:2,list(n,mi));
}
```

- REDUCE:

```
reducer_mean = function(k, A) {
  keyval(k,list(Reduce('+', A)))
}
```

# Finding mean value by Map-Reduce - cnt.

- MAP-REDUCE:

```
Block_means <-   from.dfs(
  mapreduce(
    input = "/tmp/CEnetBig",
    map = mapper_mean,
    reduce = reducer_mean
  )
)
```

- Final code:

```
GlobalMean=Block_means$val[[2]]/Block_means$val[[1]]
```

- Result

```
> GlobalMean
[1] 3000.127
```

# Third Big Data challenge

Goal: Compute the variance of $\sigma^2$ of the CEnetBig[,2] .

Note: $\sigma^2 = \frac{\sum_k (X_{k,2} - \bar{x}_2)^2}{n} = \frac{\sum_k X_{k,2}^2}{n} - \bar{x}_2^2$.

 Big data management with RHadoop

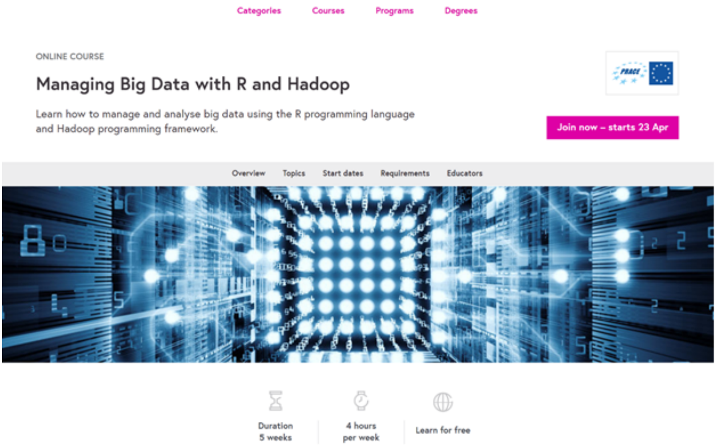
# Third Big Data challenge - cnt.

```
mapper_var = function (., X) {
  n=nrow(X);
  mi=sum(X[,2]);
  si=sum(X[,2]^2);
  keyval(1:3,list(n,mi,si));
}


reducer_var = function(k, A) {
  keyval(k,list(Reduce('+', A)))
}

Block_var <-   from.dfs(
  mapreduce(
    input = "/tmp/CEnetBig",
    map = mapper_var,
    reduce = reducer_var
  )
)

globalVar=Block_var$val[[3]]/Block_var$val[[1]]-(Block_var$val[[2]]/Block_var$val[[1]])^2
> globalVar
[1] 83361.3
```

 Big data management with RHadoop

# MOOC

Visit our MOOC:



# Challenge

Count the number of consumers with total consumption larger than 30000.

 Big data management with RHadoop

# Word count example

Count the words in text document by Map-Reduce

## Word count

```
library(readr)
library(rmr2)
library(rhdfs)
hdfs.init()
#rmr.options(backend = "local")
rmr.options(backend = "hadoop")
ebookLocation_hdfs <- "/public/ullyses.txt"
wikiLocation_hdfs <- "/public/wiki_1k_lines"
m <- mapreduce(input = ebookLocation_hdfs,
#                output = ebookLocation_hdfs,
               input.format  =  "text",
               map = function(k, v){
                 words <- unlist(strsplit(v, split = "[[:space:][:punct:]]"))
                 words <- tolower(words)
                 words <- gsub("[0-9]", "", words)
                 words <- words[words != ""]
                 wordcount <- table(words)
                 keyval(
                   key = names(wordcount),
                   val = as.numeric(wordcount)
                 )
               },
               reduce = function(k, counts){
                 keyval(key = k
```

 Big data management with RHadoop

# Word count example

Count the words in text document by Map-Reduce

## Word count

```
# Retrieve results and prepare to plot -------------------------------------
x <- from.dfs(m)
dat <- data.frame(
  word  = keys(x),
  count = values(x)
)
dat <- dat[order(dat$count, decreasing=TRUE), ]
> head(dat, 6)
    word count
825  the 15130
121   of  8260
201  and  7285
1      a  6581
152   to  5043
93    in  5004
```

# Fourth Big Data challenge

EURO

Goal: Compute the covariance matrix $\Sigma$ of the CEnetBig[,2:13] .

Note: $\Sigma_{ij} = \frac{\sum_k (X_{ik} - \bar{x}_i)(X_{jk} - \bar{x}_j)}{n} = \frac{1}{n}(\tilde{X}^T \tilde{X})_{ij}$.

Suppose $XX$ is submatrix of `CEnetBig` of 1st 100 rows and with columns `'2016_1',...,'2016_12'`. We find covariance matrix of XX

```
XX=CEnetBig$val[1:100,2:13]
Sigma=cov(XX)
```

Note: Naive approach will visit the data several times.

# Fourth Big Data challenge - cnt.

```
> Sigma
2016_1    2016_2    2016_3    2016_4    2016_5    2016_6    2016_7    2016_8    2016_9   2016_10
      2016_11  2016_12
2016_1  554.66627 197.7795 144.7789 131.1854 249.1535 124.1262 252.6528  53.31369
     199.2839 120.2593 257.9729 158.0299
2016_2  197.77949 687.8934 302.7297 307.0862 266.9029 261.8073 280.3199 252.36691
     274.6391 247.4709 310.5588 140.8925
2016_3  144.77895 302.7297 762.0102 284.1748 247.8277 175.4163 283.0150 217.00145
     321.8898 244.9201 413.3578 173.4369
2016_4  131.18542 307.0862 284.1748 605.7750 169.2399 253.4410 292.7296 209.68617
     283.8475 247.4226 422.2579 219.1580
2016_5  249.15355 266.9029 247.8277 169.2399 541.3642 171.9361 227.3288 194.71391
     293.5147 218.3279 253.6789 219.2686
2016_6  124.12617 261.8073 175.4163 253.4410 171.9361 567.5522 232.6065 183.04757
     219.4846 192.3792 272.8218 140.0295
2016_7  252.65276 280.3199 283.0150 292.7296 227.3288 232.6065 681.2422 261.19614
     293.7390 211.6760 450.0655 208.6689
2016_8   53.31369 252.3669 217.0015 209.6862 194.7139 183.0476 261.1961 639.62214
     260.6902 101.4208 189.6450 187.1990
2016_9  199.28392 274.6391 321.8898 283.8475 293.5147 219.4846 293.7390 260.69023
     635.4909 186.6704 370.9400 294.8569
2016_10 120.25931 247.4709 244.9201 247.4226 218.3279 192.3792 211.6760 101.42076
     186.6704 706.0847 296.6746 169.5678
2016_11 257.97290 310.5588 413.3578 422.2579 253.6789 272.8218 450.0655 189.64504
     370.9400 296.6746 877.7393 243.8821
2016_12 158.02993 140.8925 173.4369 219.1580 219.2686 140.0295 208.6689 187.19898
     294.8569 169.5678 243.8821 561.2406
```

 Big data management with RHadoop

## Covariance matrix - cnt.

- Some mathematics:

$$\begin{aligned}\Sigma_{ij} &= \frac{\sum_k (X_{ik}-\bar{x}_i)(X_{jk}-\bar{x}_j)}{n} = \frac{\sum_k X_{ik}X_{jk}}{n} - \bar{x}_i\bar{x}_j.\\ \Sigma &= \frac{1}{n}X^T X - \bar{x}\bar{x}^T\end{aligned}$$

- Block structure: Suppose we decompose

$$X = \begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^k \end{bmatrix}$$

where $X^i$ is a block of $X$ having $n_i$ rows.
- The "tough" product rewrites as

$$X^T X = \sum_{i=1}^{k} (X^i)^T X^i.$$

 Big data management with RHadoop

# Covariance matrix - cnt.

- Similarly: if $n_i, s_i$ are row-sizes and column sums of blocks $X^i$

$$\bar{x} = \frac{\sum_i s_i}{\sum_i n_i}. \tag{1}$$

```
mapperSS = function (., X) {
  ni=nrow(X);
  si=colSums(X[,2:13]);
  SSi=t(X[,2:13])%*%X[,2:13];
  keyval(1:3,list(ni,si,SSi));
}
```

- REDUCE:

```
reducerSS = function(k, A) {
  keyval(k,list(Reduce('+', A)))
}
```

# Covariance matrix - cnt.

- MAP-REDUCE:

```
CovMatrixRaw <-   from.dfs(
  mapreduce(
    input = "/tmp/CEnetBig",
    map = mapperSS,
    reduce = reducerSS
  )
)
```

- Final code

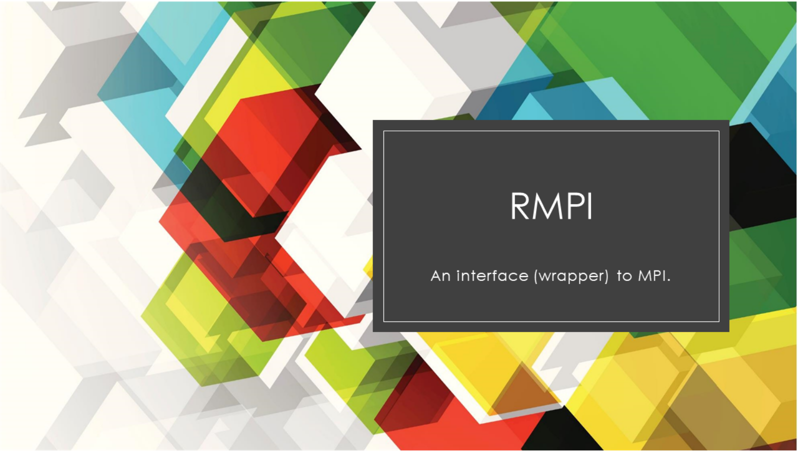
```
meanVec <- CovMatrixRaw$val[[2]]/CovMatrixRaw$val[[1]]
CovMat <- CovMatrixRaw$val[[3]]/CovMatrixRaw$val[[1]] -outer(meanVec,meanVec)
```

# Outline/next

- Schedule
- Introduction to R
- Advanced and Big data management with R
- Big data management with RHadoop
- Parallelization with Rmpi

# Parallelization with Rmpi

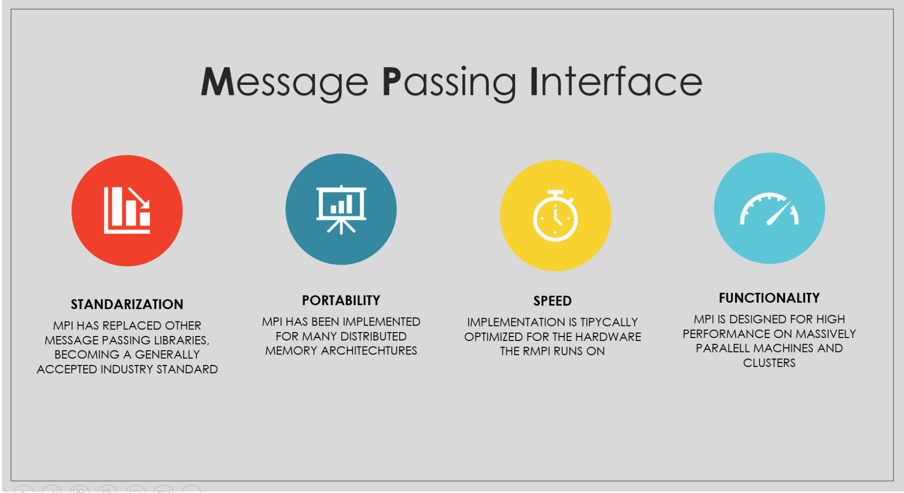
# Rmpi



# What's Rmpi?

- Rmpi is an interface to MPI;
- MPI is a standardized means of exchanging messages between multiple computers running a parallel program across distributed memory;
- MPI jobs consist of running copies of the same program in multiple processes.

# Benefits of the message passing interface



# Rmpi, the library

# Rmpi, the library

As any other library in R, we will first install the package running:

- **install.packages("Rmpi")**

An call out library by executing:

- **library(Rmpi)**

# Spawning Slave CPUs

- In MPI term, master is the main CPU that sends messages to dependent CPUs called slaves to complete some tasks. We use **mpi.spawn.Rslaves()**
- You can use nslave option to define the specific number of CPUs you want to use for MPI.
- You can use higher number than actual CPUs available in your system, but you will not get any benefit from doing it.

# Execute A Command Using Slaves

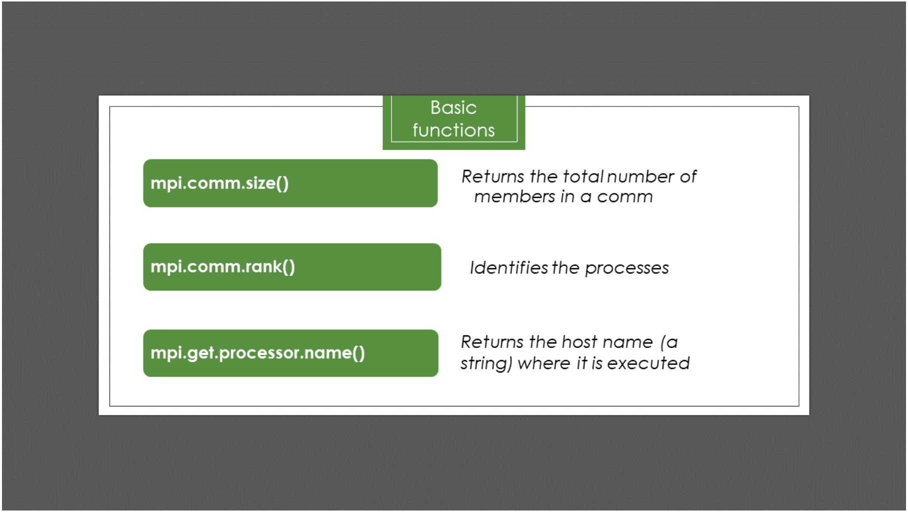
There are several commands to execute codes in slaves. **mpi.remote.exec()** and **mpi.bcast.cmd()** are examples.

- **mpi.remote.exec(cmd, . . . , simplify = TRUE, comm =1, ret =TRUE)**
- If you use **mpi.bcast.cmd()** command to execute the following code, the slaves will execute the command but there will be no return values from them.

# Rmpi basic functions

- Two important questions that arise in a parallel program are
  - How many processes are participating in this computation?
  - Which one am I?

# Rmpi basic functions



# Rmpi basic functions

Other interesting functions are...

- **mpi.universe.size**, returns the total number of CPUs available in a cluster.
- **mpi.gather**, gather each member's message to the member specified by the argument root. The root member receives the messages and stores them in rank order.
- For example the following line would give us for each node, his id, his size and the host where he is running on.

```
print(paste("I am", rank, "of", size, "running on", host,"with pwd =",where))
```

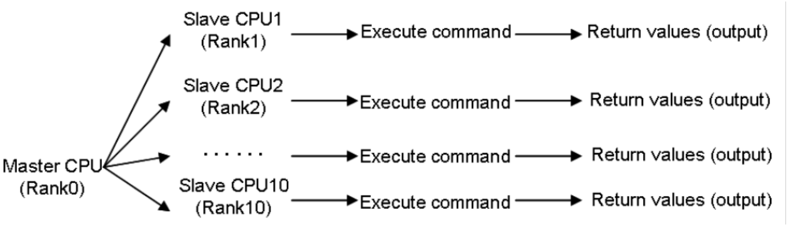
# Rmpi basic functions

If we run the code above state we would get the following output:

```
>mpi.remote.exec(paste("I am",mpi
.comm.rank(),"of",mpi.comm.size()))

$slave1
[1] "I am 1 of 11"

$slave2
[1] "I am 2 of 11"

........

$slave10
[1] "I am 10 of 11"
```

# Rmpi basic functions

As you can see **mpi.comm.rank()** and **mpi.comm.size()** give the slave CPU number and total size of spawned slaves. The diagram below shows how this command is executed.



# Rmpi basic example

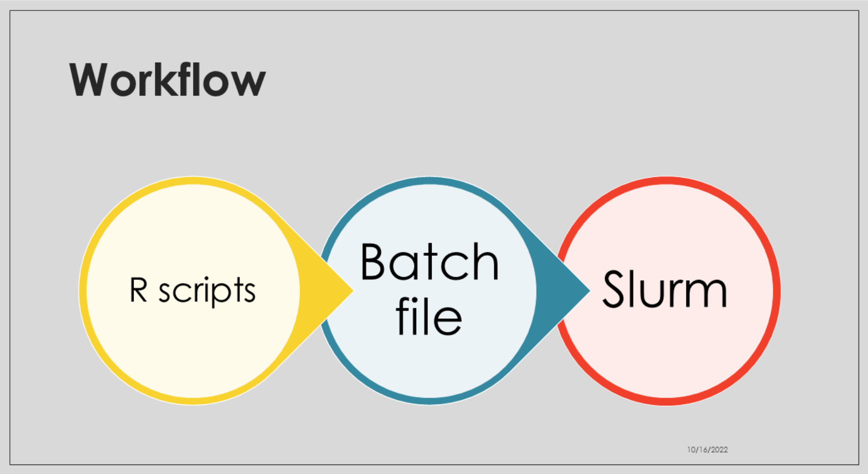
Following the philosophy of our previous example, we will now run a very basic example.

- We will use 8 nodes and spawn 24 processes per node.
- Each slave will generate a 6x6 random matrix and will compute its eigenvalues.

Our output will be similar to the one shown in the previous slide but as well as identifying themselves, each slave will give us its eigenvalues.

But this time we will do it in a different way:

# Running our code



# The R script:

Preview of the code:

```r
library(Rmpi)
size <- Rmpi::mpi.comm.size(0)
rank <- Rmpi::mpi.comm.rank(0)
host <- Rmpi::mpi.get.processor.name()
N=50
if (rank == 0){
  print('I am the master')
} else {
  #rm(list = ls())
  if (Sys.info()[["user"]]=="jpovh"){
    pwd <- "/home/jpovh/3TAV_electricity_project/Prace_Sohpc2021_Shape/"
  } else if (Sys.info()[["user"]]=="janez"){
    pwd <- "C:/Users/janez/Documents/RCNM/CRRI/Projekti/2019/3TAV-Eureka/Prace_Shape/Prace_Sohpc2021_Shape/"
  }
  if (Sys.info()[["user"]]=="lbautista"){
    pwd <- "~/Prace_Sohpc2021_Shape/"
  }
  setwd(pwd)
  #source('test_scripts/Test_script_parallel_Rmpi_slave_v0.R')
  where=getwd()
  a = eigen(matrix(rnorm(36),nrow=6))
  print(paste("I am", rank, "of", size, "running on", host,"and the eigenvalues of my matrix are",a,"with pwd =",where)
  #Test_script_parallel_Rmpi_slave_v0(N*rank,N*(rank+1)-1)
}
```

Figure 4: **Test_script_parallel_Rmpi_master.R**

# The Batch file

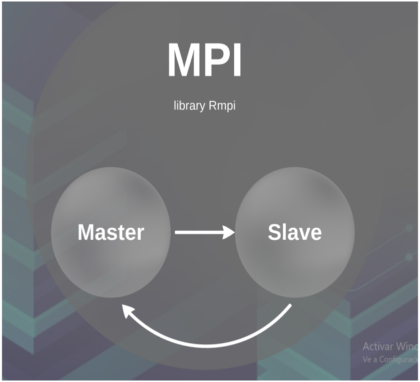
Batch files are often used to help load programs, run multiple processes at a time, and perform common or repetitive tasks.

```
#!/bin/bash
#SBATCH --export=ALL,LD_PRELOAD=
#SBATCH --job-name MyR
#SBATCH --partition=haswell --mem=24GB --time=02:00
#SBATCH --nodes=8
#SBATCH --ntasks-per-node=24 ## maximum is 24
#SBATCH --output=logs/%x_%j.out
module load OpenMPI/4.1.4-GCC-11.3.0
module load R/4.2.1-foss-2022a
srun  Rscript Test_script_parallel_Rmpi_master.R
sacct -S $(date -d '2 hour ago' +%D-%R)   --format=JobID,Elapsed,ExitCode,CPUTime,Start,End[lbautista@gpu02 R
```

Figure 5: **rmpi-test-master-slave.sbatch**

- 8 nodes
- 24 tasks per node

# Distribution of the processes




We will have two different scripts:

- **Master script:** distributes the workflow across the slaves.
- **Slave script:** runs actual code for the indexes given by the master.