

A photograph of the San Diego Supercomputer Center building at night. The building is a modern, multi-story structure with large glass windows and concrete pillars. The interior lights are on, and the building is illuminated by streetlights. The sky is a deep blue.

SDSC Summer Institute 2021

Scalable Machine Learning

Mai H. Nguyen & Paul Rodriguez

2021-August-04

Scalable Machine Learning Agenda

8:00 - 8:20 -- Machine Learning Overview

8:20 - 9:00 -- R on HPC

9:00 - 9:15 -- Break

9:15 - 10:15 -- Spark

10:15 - 10:45 -- Spark Hands-On

Scalable Machine Learning Agenda

8:00 - 8:20 -- Machine Learning Overview

8:20 - 9:00 -- R on HPC

9:00 - 9:15 -- Break

9:15 - 10:15 -- Spark

10:15 - 10:45 -- Spark Hands-On

R on HPC

Paul Rodriguez, Ph.D.

Table of Contents

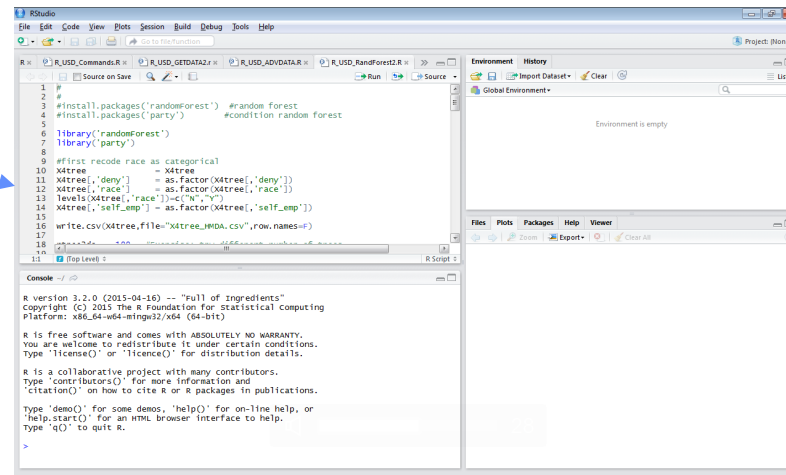
- A Glimpse of R
- R and Scaling
- Parallel options for R
- Other considerations
- doParallel demo on Expanse portal

A typical R development workflow

- R studio: An Integrated development environment for R

*Edit window to
Build scripts*

R console



*Environment
Information on
variables and
command history*

*Plots, help
docs, package
lists*

R commands in brief

- A typical R code workflow:

#READ DATA (housing mortgage cases)

```
X = read.csv('hmda_aer.csv', header=T, stringsAsFactors=T)
```

#SUBSET DATA

```
indices_2keep = which(X[, 's13'] %in% c(3,4,5))
```

```
X = X[unique(indices_2keep),]
```

#CREATE/TRANSFORM VARIABLES

```
pi_rat = as.numeric(X[, 's46']/100)
```

#debt2income ratio

```
race = as.numeric(X[, 's13'] %in% c(3,4))
```

#make race values 1-4 into values 0 or 1

```
deny = as.numeric(X[, 's7']==3)
```

#make deny values into 0 or 1,
1 only for deny='3'

#RUN MODEL and SHOW RESULTS

```
lm_result = lm(deny~race+pi_rat)
```

#lm is 'linearmodel'

```
summary(lm_result)
```

R strengths for HPC

- Data Wrangling

R strengths for HPC

- **Data Wrangling**
- **Sampling/bootstrap methods**

R strengths for HPC

- **Data Wrangling**
- **Sampling/bootstrap methods**
- **Particular Statistical procedures that you won't find implemented anywhere else, e.g.**
 - Multiple Imputation methods,
 - Instrument Variable (2 stage) Regression
 - Matching subjects for pairwise analysis
 - MCMC routines

Scaling, practically

- **Scaling (with or without more data):**
 - more complex analysis (ie optimizations)
 - more sampling (ie more trees in Random Forest)

Scaling, practically

- **Scaling (with or without more data):**
 - more complex analysis (ie optimizations)
 - more sampling (ie more trees in Random Forest)
- **Sometimes easy to parallelize (like with sampling)**

Scaling, practically

- **Scaling (with or without more data):**
 - more complex analysis (ie optimizations)
 - more sampling (ie more trees in Random Forest)
- **Sometimes easy to parallelize (like with sampling)**
- **Sometimes maybe too much communication between parts (like with matrix inversion)**

R Scaling In a nutshell

- R takes advantage of math libraries (like BLAS) for vector and linear algebra operations

```
> sessionInfo()
R version 4.0.2 (2020-06-22)
Platform: x86_64-pc-linux-gnu (64-bit)
Running under: CentOS Linux 8 (Core)

Matrix products: default
BLAS/LAPACK: /cm/shared/apps/spack/cpu/opt/spack/linux-centos8-zen2/gcc-9.2.0/openblas
grrcfayp3br6kmcnelbgrepqmadwv43e/lib/libopenblas_zenp-r0.3.10.so

locale:
 [1] LC_CTYPE=en_US.UTF-8      LC_NUMERIC=C
 [3] LC_TIME=en_US.UTF-8      LC_COLLATE=en_US.UTF-8
 [5] LC_MONETARY=en_US.UTF-8  LC_MESSAGES=en_US.UTF-8
```

R Scaling In a nutshell

- R takes advantage of math libraries (like BLAS) for vector and linear algebra operations
- R packages provide multicore, multinode, or distributed data (SparkR) options

R Scaling In a nutshell

- R takes advantage of math libraries (like BLAS) for vector and linear algebra operations
- R packages provide multicore, multinode, or distributed data (SparkR) options
- However, model implementations are not necessarily built to use parallel backends
 - Some models more amenable to parallel versions

Consider Regression Computations

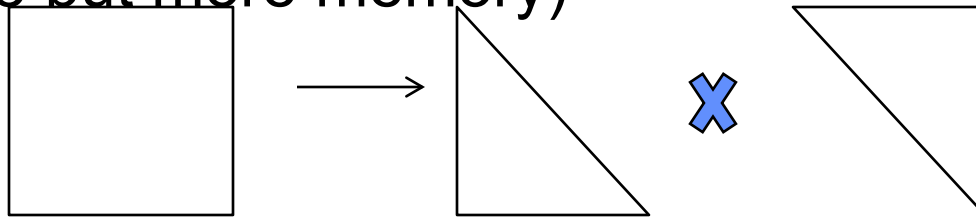
- **Linear Model:** $Y = X * B$
where Y =outcomes , X =data matrix

Consider Regression Computations

- **Linear Model:** $Y = X * B$
where Y =outcomes , X =data matrix
- **Algebraically, we could:**
 - take “inverse” of $X * Y = B$ (time consuming)
 - use derivatives to search for solutions (very general)

Consider Regression Computations

- **Linear Model:** $Y = X * B$
where Y =outcomes , X =data matrix
- **Algebraically, we could:**
 - take “inverse” of $X * Y = B$ (time consuming)
 - use derivatives to search for solutions (very general)
- **Or, better:**
 - QR decomposition of X into triangular matrices (easier to solve but more memory)



Consider Regression models in R

- **Related Models and Functions :**

lm() Linear Model

glm() Generalized Linear Model

(logistic regression,
LASSO version from Hastie et al.,etc)

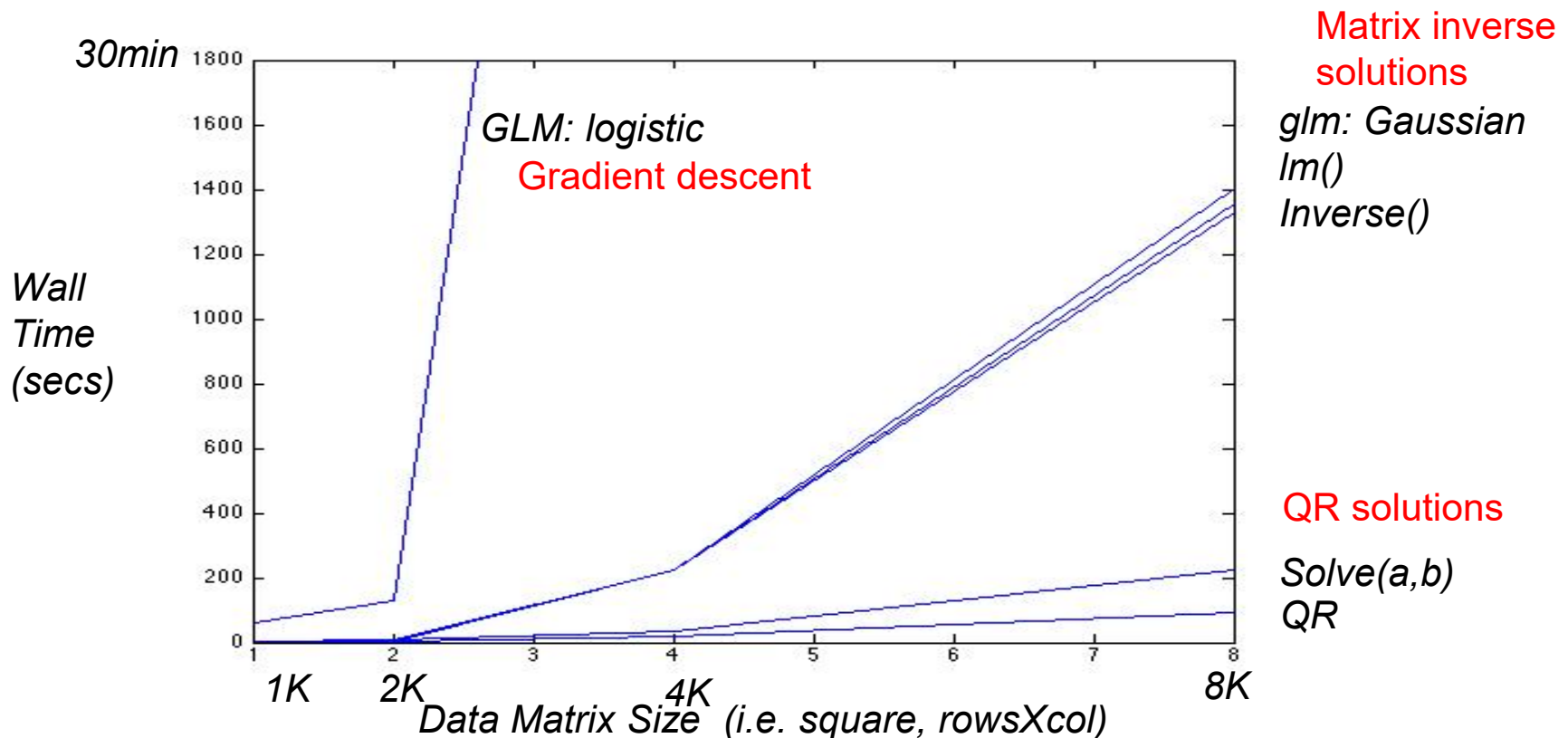
Solving Linear Systems

Performance with R, 1 compute node

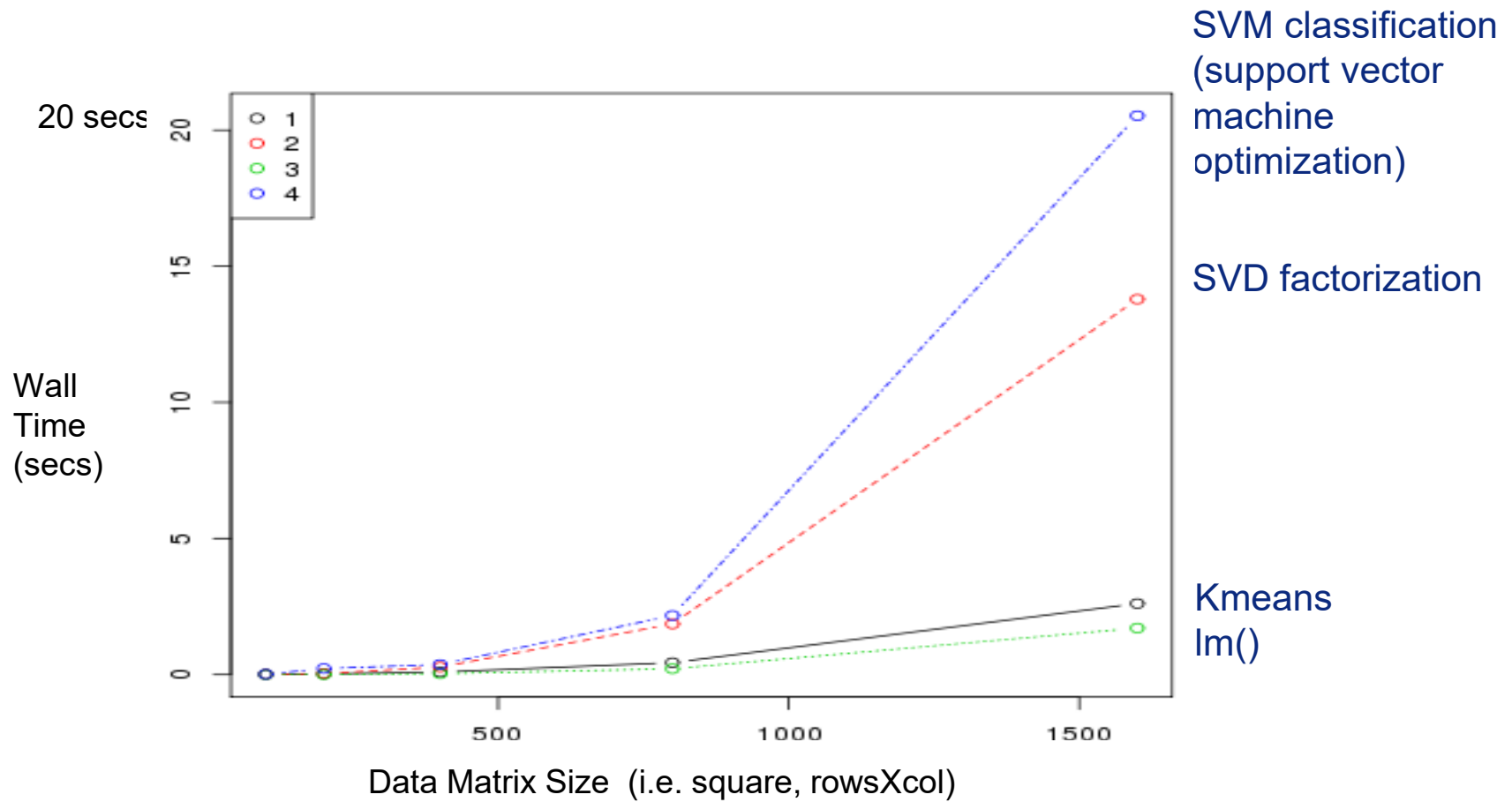
R:

`glm(Y~X,family=gaussian)` #gaussn regrssn (like `lm`)

`glm(Y~X,family=binomial)` # logistic regrssn ($Y=0$ or 1)



Machine learning models: Performance on 1 compute node



R multicore processing

- **‘doParallel’ package – provides the back end to the ‘for each’ parallel processing command**

R multicore processing

- **‘doParallel’ package – provides the back end to the ‘for each’ parallel processing command**
- **uses threads across cpu cores to pass data & commands**


R multicore processing

- ‘doParallel’ package – provides the back end to the ‘for each’ parallel processing command
- uses threads across cpu cores, or Rmpi across nodes, to pass data & commands
- Updates and combines older packages

See <https://cran.r-project.org/web/packages/doParallel/vignettes/gettingstartedParallel.pdf>

R multicore coding


```
install.packages(doParallel)  
library(doParallel)  
registerDoParallel(cores=24)
```

1. allocate workers 

R multicore coding

```
install.packages(doParallel)
library(doParallel)
registerDoParallel(cores=24)
```

1. allocate workers



```
my_data_frame = .....
```

2. Make 'foreach' loop

R multicore coding

```
install.packages(doParallel)  
library(doParallel)  
registerDoParallel(cores=24)
```

1. allocate workers



```
my_data_frame = ..... 2. Make 'foreach' loop
```

```
my_results = foreach(i=1:24,.combine=rbind)
```

**3. specify how to
combine results**



R multicore coding

```
install.packages(doParallel)  
library(doParallel)  
registerDoParallel(cores=24)
```


1. allocate workers




```
my_data_frame = ..... 2. Make 'foreach' loop
```

```
my_results = foreach(i=1:24,.combine=rbind) %dopar%  
{ ...
```

**4. %dopar%
runs it across
cores,
(%do% runs it
serially)**



**3. specify how to
combine results**



R multicore coding


```
install.packages(doParallel)  
library(doParallel)  
registerDoParallel(cores=24)
```

1. allocate workers




```
my_data_frame = ..... 2. Make 'foreach' loop
```

4. %dopar% runs it across cores, (%do% runs it serially)



```
my_results = foreach(i=1:24,.combine=rbind) %dopar%  
{ ...  
    your code here  
    return( a variable or object )  
})
```

3. specify how to combine results



R multicore coding

```
install.packages(doParallel)  
library(doParallel)  
registerDoParallel(cores=24)
```

1. allocate workers

```
my_data_frame = .....
```

2. Make 'foreach' loop

```
my_results = foreach(i=1:24,.combine=rbind) %dopar%
```

```
{ ...
```

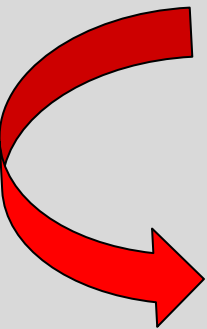
```
  your code here
```

```
  return( a variable or object )
```

```
})
```

4. %dopar% runs it across cores, (%do% runs it serially)

3. specify how to combine results



BEWARE: foreach will copy data it thinks is need to every core

R multinode: parallel backend

```
library(doParallel)
```

```
cl <- makeCluster(48)  
registerDoParallel(cl)
```

**1. allocate cluster as
parallel backend**



R multinode: parallel backend

```
library(doParallel)
```

```
cl <- makeCluster(48)  
registerDoParallel(cl)
```


**1. allocate cluster as
parallel backend**



```
my_data_frame = .....
```

```
results = foreach(i=1:48,.combine=rbind) %dopar%  
{ ... your code here
```

**2.
%dopar% puts
loops across
cores and
nodes**



```
    return( a variable or object )  
  })  
stopCluster(cl)
```

R multinode: parallel backend

```
library(doParallel)
```

```
cl <- makeCluster(48)  
registerDoParallel(cl)
```


**1. allocate cluster as
parallel backend**



```
my_data_frame = .....
```

```
results = foreach(i=1:48,.combine=rbind) %dopar%  
{ ... your code here
```

**2.
%dopar% puts
loops across
cores and
nodes**



```
return( a variable or object )
```

```
})  
stopCluster(cl)
```

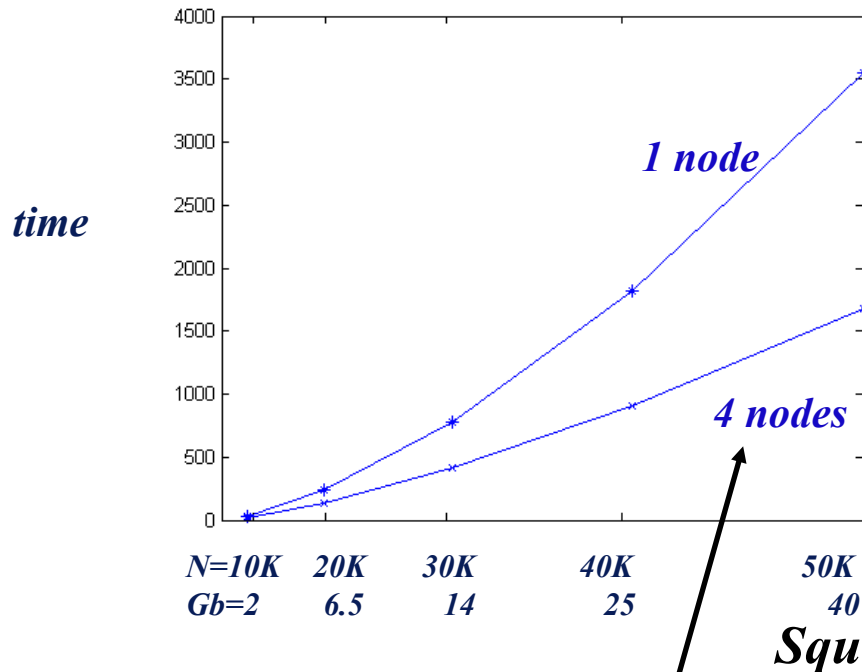


BEWARE: foreach will copy data it thinks is need to every core and node

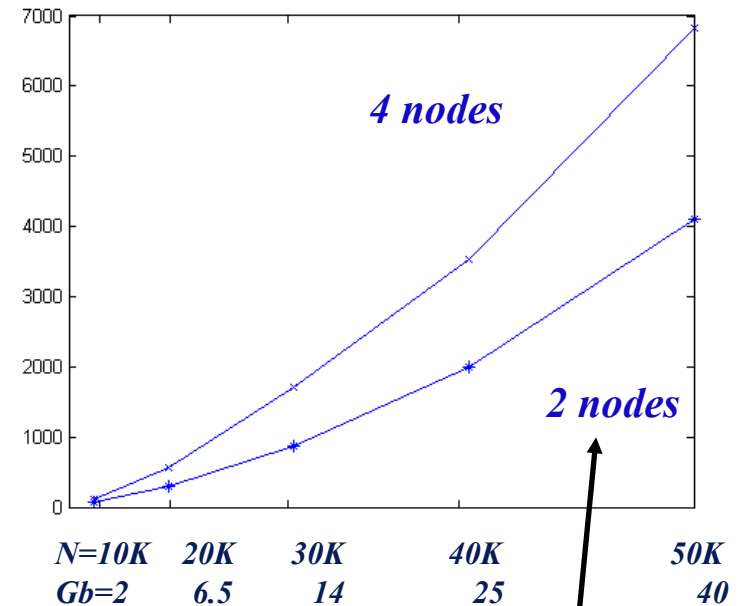
Multiple Compute Nodes not always help

(tested on Gordon)

Matrix Multiplication



Matrix Inversion

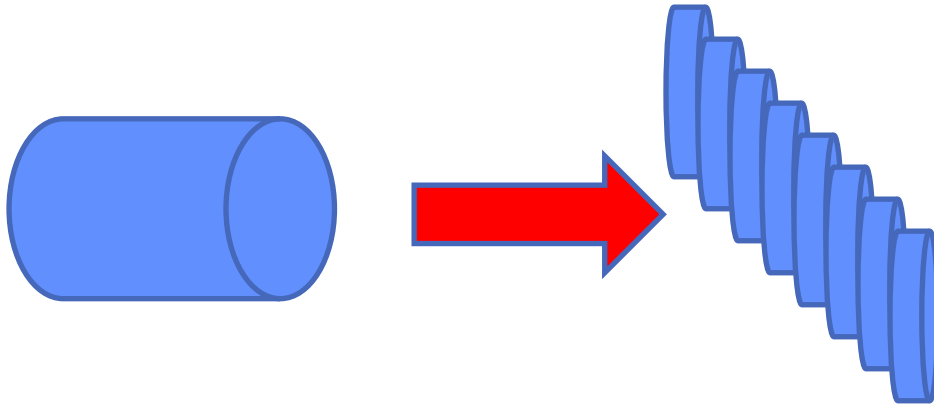


multinodes: more nodes is less time for multiplication,

less nodes is better for inversion

An option for (embarrassingly) Parallel R

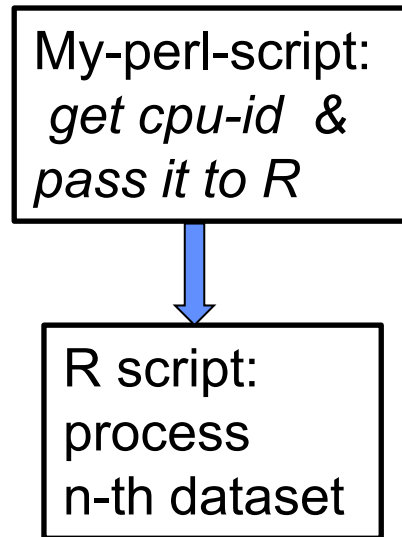
1. Split up
data into N
parts



An option for (embarrassingly) Parallel R

1. Split up
data into N
parts

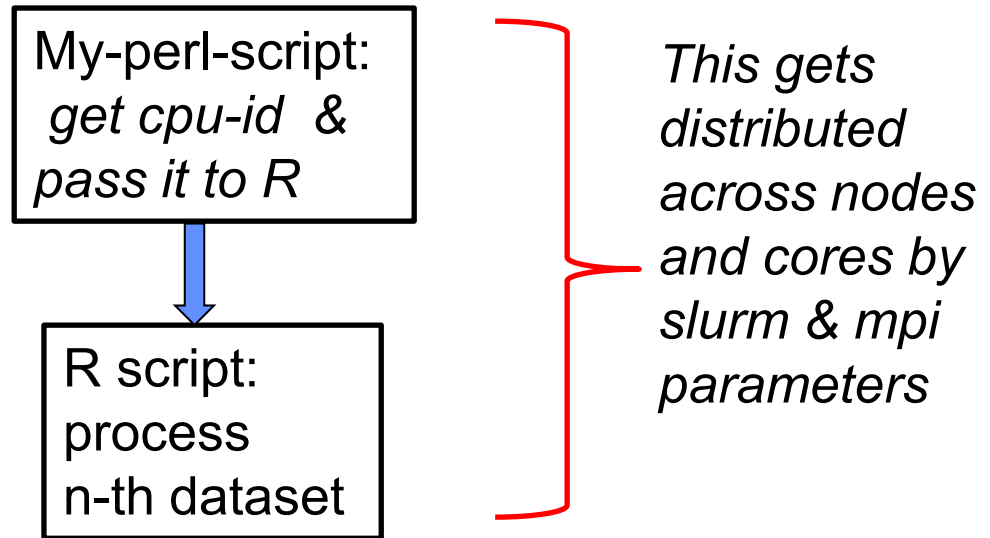
2. In slurm batch script:
`mpirun ... my-perl-script`



An option for (embarrassingly) Parallel R

1. Split up
data into N
parts

2. In slurm batch script:
`mpirun ... my-perl-script`



An option for (embarrassingly) Parallel R

1. Split up
data into N
parts

2. In slurm batch script:
`mpirun ... my-perl-script`

Two Ways to run:

*one R instance per
core across all nodes*

*one R instance per
node with 128 cores
per R instance*

My-perl-script:
*get cpu-id &
pass it to R*

R script:
process
n-th dataset

*This gets
distributed
across nodes
and cores by
slurm & mpi
parameters*

Slurm parameters: one R instance per core across all nodes

Normal
batch
job info

```
...  
#SBATCH --partition=compute  
#SBATCH --nodes=2  
#SBATCH --ntasks-per-node=128  
#SBATCH --cpus-per-task=1
```

2 x 128 = 256 mpi ranks

```
module load slurm  
module load cpu  
module load gcc  
module load intel-mpi
```

256 perl script/R instances
1 core each

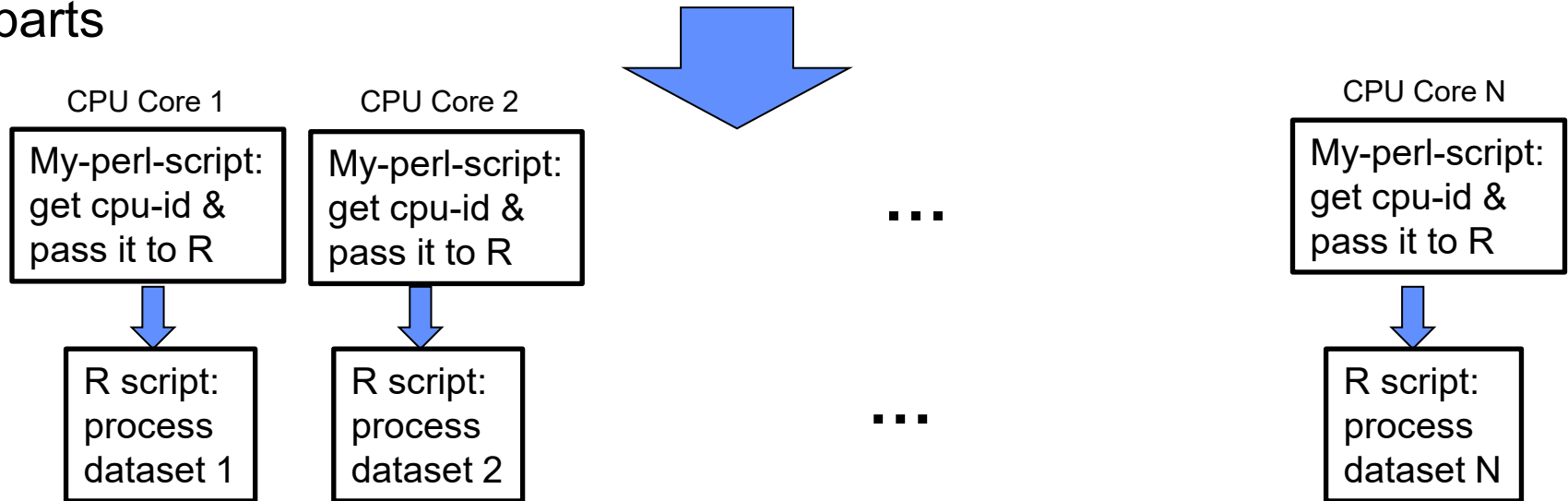
```
mpirun -genv I_MPI_PIN_DOMAIN=omp:compact ./get_mpirank_runcmd.pl
```

(based on /cm/shared/examples/sdsc/mpi-openmp-hybrid/hybrid-slurm.sb)

one R instance per core across all nodes

1. Split up
data into N
parts

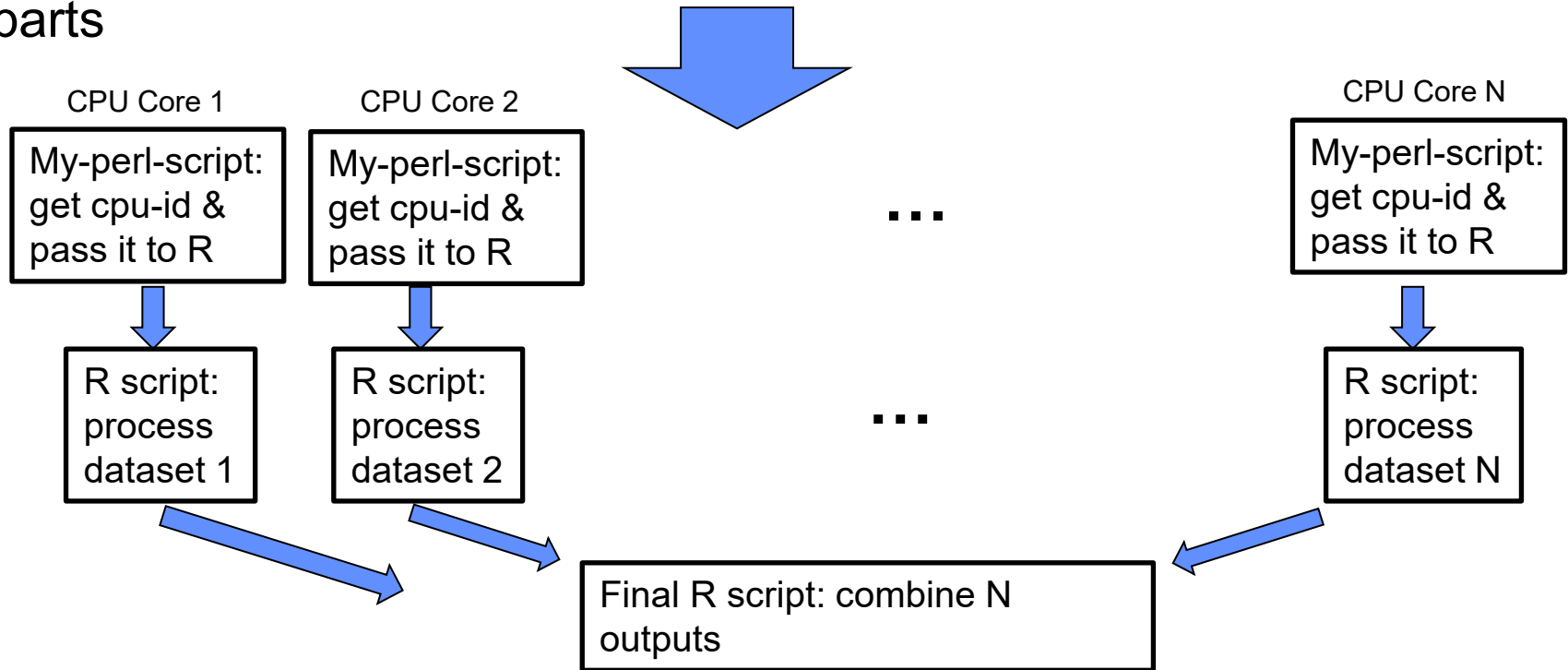
2. In slurm batch script:
mpirun ... my-perl-script



one R instance per core across all nodes

1. Split up data into N parts

2. In slurm batch script:
mpirun ... my-perl-script



More programming but perhaps more useful

Slurm parameters: one R instance per node with 128 cores per R instance

Normal
batch
job info

```
...  
#SBATCH --partition=compute  
#SBATCH --nodes=2  
#SBATCH --ntasks-per-node=1  
#SBATCH --cpus-per-task=128  
  
module load slurm  
module load cpu  
module load gcc  
module load intel-mpi  
  
module load r  
  
mpirun -genv I_MPI_PIN_DOMAIN=omp:compact ./get_mpirank_runcmd.pl
```

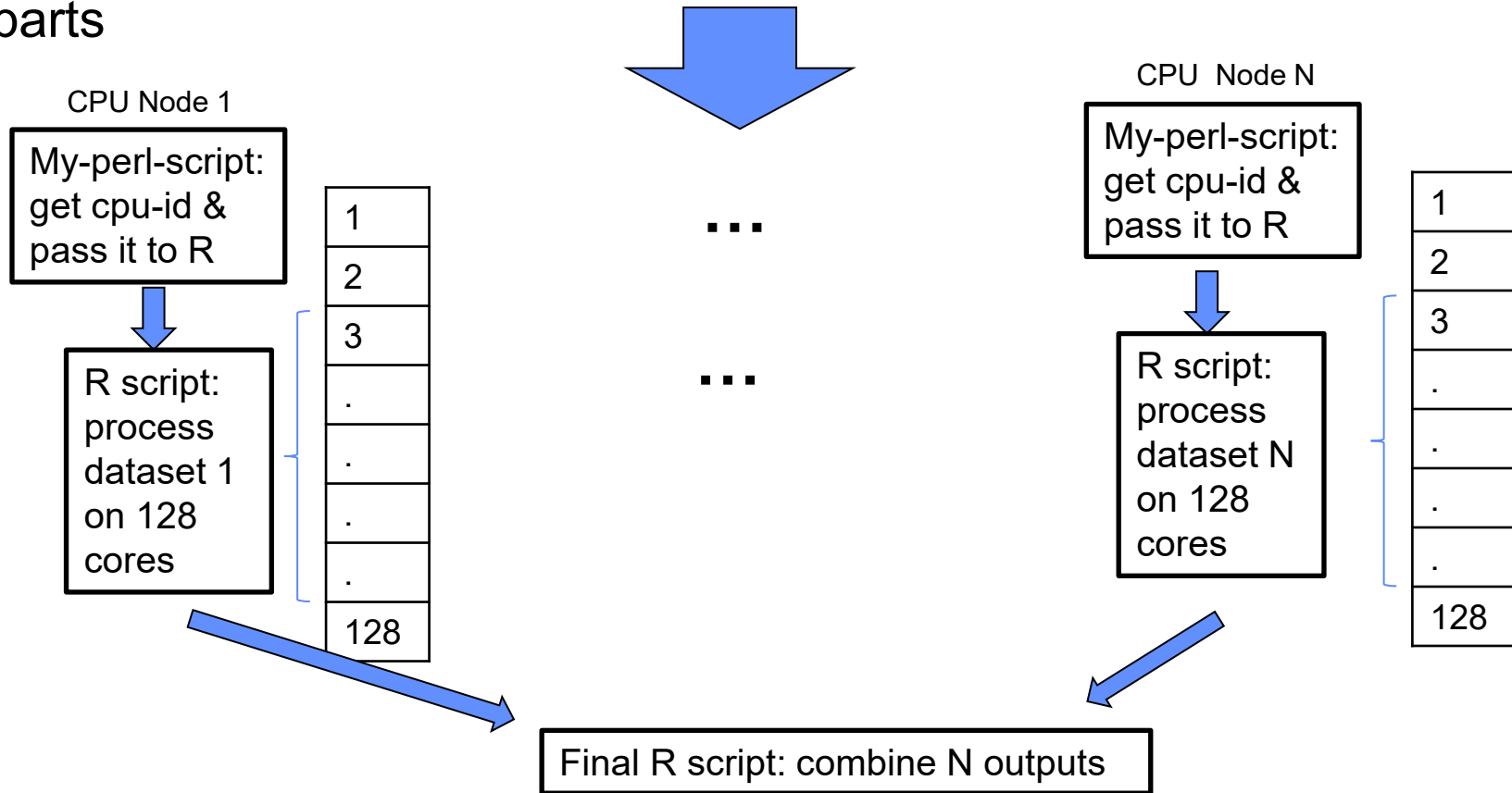
2 x1 = 2 mpi ranks

2 perl script/R instances
128 cores each
(doParallel can use them)

Example: One R instance per node, doParallel across all cores in each node

1. Split up data into N parts

2. In slurm batch script:
mpirun ... my-perl-script



Example: scaling MCMC

*Distributed Markov Chain Monte Carlo for Bayesian Hierarchical Models,
Frederico Bumbaca, UCIrvine,*

- *MCMC calculates the joint probability $P(\text{Data}, \text{Parameters})$
1000s of times in a sequence (must be serial)*
- *Sometimes parameters can be ‘partitioned’*
- *Using R package, “bayesm”, it was run on Comet with embarrassing parallelization*

# Individuals	Cores	Individ per Core	Total Minutes (I/O time)
100 million	1,7282 (max)	~ 58K	206 (38)

Another MCMC option: “Stan”

R or Python interface, with many options

you write a script → Stan translates into C++ code

script sets up probability:

$$P(data, parameters) = \prod P(data_i, parameters)$$

Another MCMC option: “Stan”

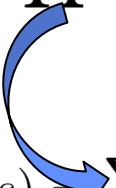
R or Python interface, with many options

you write a script → Stan translates into C++ code

script sets up probability:

$$P(\text{data}, \text{parameters}) = \prod P(\text{data}_i, \text{parameters})$$

If you set up log likelihood:

$$\log P(\text{data}, \text{parameters}) \Rightarrow \sum_i^N \log P(\text{data}_i, \text{parameters})$$


Another MCMC option: “Stan”

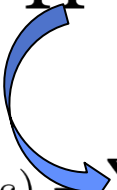
R or Python interface, with many options

you write a script → Stan translates into C++ code

script sets up probability:

$$P(\text{data}, \text{parameters}) = \prod P(\text{data}_i, \text{parameters})$$

If you set up log likelihood:

$$\log P(\text{data}, \text{parameters}) \Rightarrow \sum_i^N \log P(\text{data}_i, \text{parameters})$$


then Stan will partition the data across cores.

Other R packages:

Also, for big data or big matrix

- **Rspark - R interface to Spark (upcoming session)**
- **pdbR - distributed matrix support (better for dense matrices vs Spark)**

Also:

- **R openMP, Rmpi –**
- **Ff, bigmemory – map data to files**
- **Rgputools – GPU support**

A note on using R in terminal window

1. Get an interactive compute node:

2. Try

`$ module spider r` *(this tells you what modules you need)*

3. Enter

`$ module load cpu/0.15.4`

`$ module load gcc/9.2.0`

`$ module load r/4.0.2-openblas`

`$ R`

R version 4.0.2 (2020-06-22) -- "Taking Off Again"

Copyright (C) 2020 The R Foundation for Statistical Computing

Platform: x86_64-pc-linux-gnu (64-bit)

.....

Type 'q()' to quit R.

>

```
[p4rodrig@login02 ~]$ module spider r
-----
r: r/4.0.2-openblas
-----

Other possible modules matches:
  AMDuProf, amber, aria2, arm-forge, berkeley-db, bism

You will need to load all module(s) on any one of the li
"r/4.0.2-openblas" module is available to load.

  cpu/0.15.4  gcc/9.2.0

Help:
```

A note on installing R Packages (into your own directories)

- In R:

install.packages('package-name')

(see <https://cran.r-project.org/> for package lists and reviews)

- Sometimes on Comet, you have to be explicit:

*install.packages('ggmap',
repos='http://cran.us.r-project.org',dependencies=TRUE)*

- if compiling is required and you get an error, call support
- packages are put into your /home/user/R directory

- **pause**

TestdoParallel R script

1 start Rstudio from portal (use shared and say <48 cores)
and run script

(it repeatedly does a regression)

2 review execution using 'top' utility

3 vary the NxP matrix size or number of cores

Goal: look for tradeoffs in memory vs execution
e.g. If N gets too large then use less cores

portal.expense.sdsc.edu/pun/sys/dashboard

Expance Portal Files Jobs Clusters Interactive Apps

SDSC

The Expance portal provides an interface to use interface to access Expance HF

With the portal, researchers can manage files, edit, move, upload, and download, vi

use.sdsc.edu/pun/sys/dashboard/batch_connect/sys/rstudio/session_contexts/new

Interactive Apps

GUIs

MATLAB

RSTUDIO

RSTUDIO

This app will launch a **RSTUDIO** GUI on **Expance**. You will be able to interact with the **RSTUDIO** GUI through a VNC session.

Partition

compute

Number of hours

```
-----
Last login: Fri Jun 4 15:01:29 2021 from 71.128.8.73
[p4rodrig@login02 ~]$ queue -u p4rodrig
JOBID PARTITION NAME USER ST TIME NODES NODELIST(REASON)
3246260 compute Sys/dash p4rodrig R 0:27 1 exp-2-15
[p4rodrig@login02 ~]$ ssh exp-2-15
Last login: Sat Jun 5 13:09:04 2021
[p4rodrig@exp-2-15 ~]$ top -u $USER
```

Open portal ->
Interactive Apps ->
Rstudio

Enter
Node: "compute"
Cores: "64"
Memory: 124 Gb
(other fields defaults ok)

Also login:
login.expance

\$ queue -u \$USER
\$ ssh exp-##-##
\$ top -u \$USER

'H' will toggle threads

'f', highlight P, space, esc
will toggle last cpuid

Open the 'Test_doParallel' Rscript

Select 'source' to run the whole script

Apps Assess your Mental... Become Acquaint... Opinion | Quiz: Let... 2017 CCES Commo... tds An Overview of Res... » Reading list

RStudio

File Edit Code View Plots Session Build Debug Profile Tools Help

Go to file/function Addins Project: (None)

TestDoParallel_v1.R x

Source on Save Run Source

```
1 #Install package if needed into home directory
2 if(!require(doParallel)){
3   install.packages("doParallel", repos="http://cran.r-project.org")
4 }
5
6 library(doParallel)
```

7:28 (Top Level) R Script

Environment History Connections Tutori

R Global Environment

Data

B	num [1:200, 1] 5 1.03 0...
X	Large matrix (200000 el...

Files Plots Packages Help Viewer

New Folder Delete Rename More

Home

Name	Size
.r	
chap15_rnnv4.ipynb	136 KB
e494_Practical_NNet_exercise...	18.5 KB
environment_tests_v1	1.8 KB
getcpu_scratch.sh	274 B
getid.c	324 B

Console Terminal x Jobs x

~/

```
>
>
>
> source('~/.TestDoParallel_v1.R')
[1] "starting dopar test"
[1] "X size is: 1.5 Mb"
```

Review the top output

```
p4rodrig@exp-9-27:~  
top - 15:35:51 up 87 days, 21:07, 1 user, load average: 20.97, 5.74, 4.37  
Tasks: 1788 total, 41 running, 1747 sleeping, 0 stopped, 0 zombie  
%cpu(s): 32.6 us, 0.1 sy, 0.0 ni, 67.0 id, 0.0 wa, 0.2 hi, 0.1 si, 0.0 st  
MiB Mem : 257517.8 total, 210968.9 free, 42132.2 used, 4416.7 buff/cache  
MiB Swap: 0.0 total, 0.0 free, 0.0 used, 210846.5 avail Mem  
  
  PID USER      PR  NI  VIRT  RES  SHR  S  %CPU  %MEM    TIME+  COMMAND  
 54587 p4rodrig  20    0  17.5g 896016 4196 R 100.0  0.3  0:37.27 rsession  
 54562 p4rodrig  20    0  17.5g 896016 4196 R  99.7  0.3  0:37.48 rsession  
 54568 p4rodrig  20    0  17.5g 896016 4196 R  99.7  0.3  0:37.46 rsession  
 54571 p4rodrig  20    0  17.5g 896016 4196 R  99.7  0.3  0:37.35 rsession  
 54572 p4rodrig  20    0  17.5g 896016 4196 R  99.7  0.3  0:37.33 rsession  
 54574 p4rodrig  20    0  17.5g 896016 4196 R  99.7  0.3  0:37.38 rsession  
 54579 p4rodrig  20    0  17.5g 896016 4196 R  99.7  0.3  0:37.33 rsession  
 54591 p4rodrig  20    0  17.5g 896016 4196 R  99.7  0.3  0:37.24 rsession
```

Notice the elapsed time and memory size

Change the NxP matrix size and rerun

(start with N=10K, P=2K)

```
7:28 (Top Level)   
Console Terminal x Jobs x  
~/   
>   
> source('~/TestDoParallel_v1.R')  
[1] "starting dopar test"  
[1] "X size is: 1.5 Mb"  
      user system elapsed  
1.176  1.969  30.620  
> |
```

```
10 # Make up some random data and lis  
11 N=100000;      #N rows start with  
12 P=2000;        #P columns 200 for  
13  
14 #make random data with 1 column ar  
15 X =matrix(rnorm(N*P),N,P)  
16 X[,1] =X[,1]+1  
17  
16:28 (Top Level)   
Console Terminal x Jobs x
```

```
~/   
Loading required package: foreach  
Loading required package: iterators  
Loading required package: parallel  
[1] "starting dopar test"  
[1] "X size is: 1.5 Gb"
```


Try this at home:

Let $N=100K$, $P=2000$

Notice the memory used is close to 124Gb we asked for

p4rodrig@exp-9-27:~

```
top - 15:38:40 up 87 days, 21:10, 1 user, load average: 10.77, 6.29, 4.76
Tasks: 1749 total, 19 running, 1730 sleeping, 0 stopped, 0 zombie
%Cpu(s): 14.0 us, 0.0 sy, 0.0 ni, 85.8 id, 0.0 wa, 0.0 hi, 0.0 si, 0.0 st
MiB Mem : 257517.8 total, 130239.0 free, 123199.7 used, 4079.0 buff/cache
MiB Swap: 0.0 total, 0.0 free, 0.0 used, 129947.3 avail Mem
```

PID	USER	PR	NI	VIRT	RES	SHR	S	%CPU	%MEM	TIME+	COMMAND	P
55219	p4rodrig	20	0	24.2g	7.6g	2696	R	100.0	3.0	0:24.52	rsession	68
55227	p4rodrig	20	0	24.2g	7.6g	3064	R	100.0	3.0	0:24.55	rsession	88
55235	p4rodrig	20	0	24.2g	7.6g	2696	R	100.0	3.0	0:24.56	rsession	80
55236	p4rodrig	20	0	24.2g	7.6g	2696	R	100.0	3.0	0:24.70	rsession	100
55237	p4rodrig	20	0	24.2g	7.6g	2696	R	100.0	3.0	0:24.50	rsession	47
55242	p4rodrig	20	0	24.2g	7.6g	2696	R	100.0	3.0	0:24.36	rsession	32
55253	p4rodrig	20	0	24.2g	7.6g	2696	R	100.0	3.0	0:24.69	rsession	126
55259	p4rodrig	20	0	24.2g	7.6g	2696	R	100.0	3.0	0:24.00	rsession	16
55261	p4rodrig	20	0	24.2g	7.6g	2696	R	100.0	3.0	0:24.25	rsession	24
55265	p4rodrig	20	0	24.2g	7.6g	2696	R	100.0	3.0	0:23.96	rsession	6
55239	p4rodrig	20	0	24.2g	7.6g	2696	R	99.7	3.0	0:24.61	rsession	20
55241	p4rodrig	20	0	24.2g	7.6g	2696	R	99.7	3.0	0:24.43	rsession	8
55243	p4rodrig	20	0	24.2g	7.6g	2836	R	99.7	3.0	0:24.53	rsession	104

If you ask for 248Gb will it run?

What if you use only 24 cores?

THE END