CIML



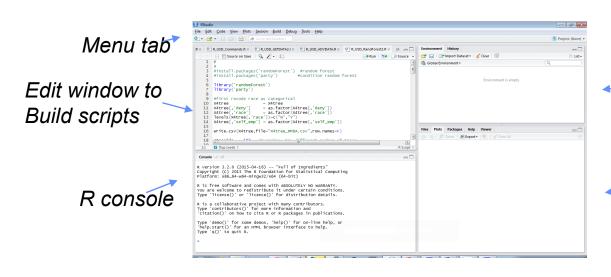


R, Scaling R, Parallel R

- A Glimpse of R (recap)
- R and Scaling
- Parallel options for R
- doParallel demo on Expanse portal

A typical R development workflow

R studio: An Integrated development environment for R



Environment
Information on
variables and
command history

Plots, help docs, package lists

R commands in brief

A typical R code workflow:

```
#READ DATA (housing mortage cases)
              =read.csv('hmda aer.csv',header=T,stringsAsFactors=T)
#SUBSET DATA
indices 2\text{keep} = \text{which}(X[,'s13'] \% \text{in}\% c(3,4,5)))
               =X[unique(indices_2keep),]
#CREATE/TRANSFORM VARIABLES
              = as.numeric(X[,'s46']/100)
                                               #debt2income ratio
pi rat
           = as.numeric(X[,'s13'] %in% c(3,4)) #make race values 1-4 into values 0 or 1
race
                                                #make deny values into 0 or 1,
              = as.numeric(X[,'s7']==3)
deny
                                                   1 only for deny='3'
#RUN MODEL and SHOW RESULTS
Im result
              =lm(deny~race+pi_rat)
                                            #lm is 'linearmodel'
summary(Im 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)



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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 too much communication between parts (matrix inversion)

R Scaling In a nutshell

R takes advantage of math libraries for vector operations



R Scaling In a nutshell

- R takes advantage of math libraries for vector operations
- R packages provide multicore, multimode, or distributed data (SparkR) options



R Scaling In a nutshell

- R takes advantage of math libraries for vector operations
- R packages provide multicore, multinode, or distributed data (SparkR) options
- However, model implementations 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

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- 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 * Bwhere 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

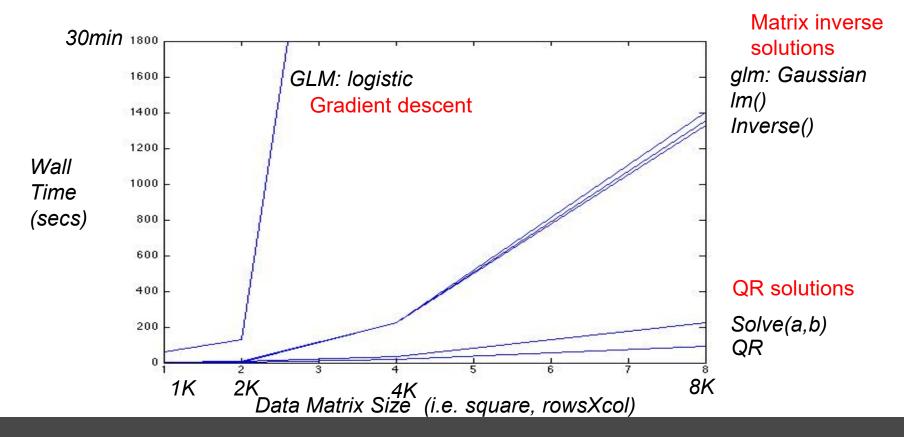
Related Models and Functions :

```
Im() Linear Model
glm() Generalized Linear Model
(logistic regression,
LASSO version from Hastie et al.,etc)
```



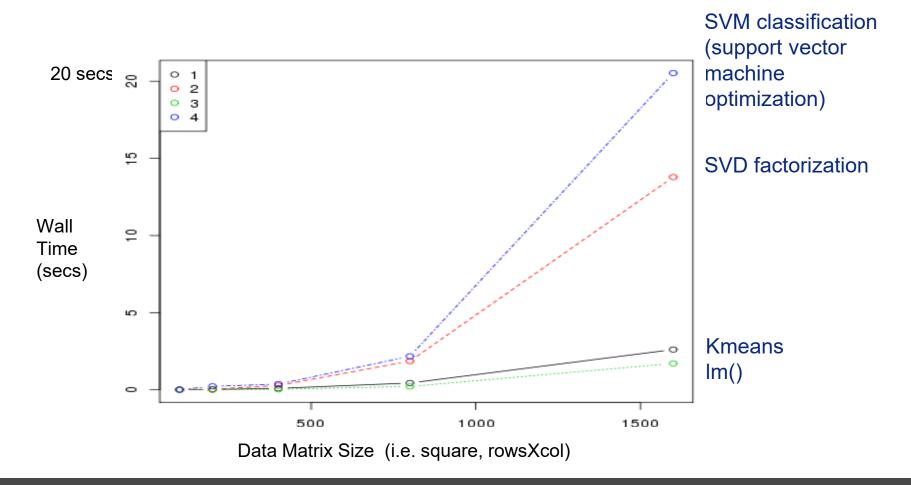
Solving Linear Systems Performance with R, 1 compute node

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 to pass data & commands
- Updates and combines the previous 'snow' and 'multicore' packages, so that is also works for multinode (and it's similar to doMPI, both run on top of RMPI).

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

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

1. allocate workers

```
install.packages(doParallel)
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my_data_frame = ..... 2. Make 'foreach' loop
my_results = foreach(
```

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3. specify how to combine results
```

```
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my_data_frame = .....
2. Make 'foreach' loop
my_results = foreach(i=1:24,.combine=rbind) %dopar%
{ ...
3. specify how to combine results
```

```
install.packages(doParallel)
                             1. allocate workers
                                                       4. %dopar%
library(doParallel)
                                                       runs it across
registerDoParallel(cores=24)
                                                       cores,
                                                       (%do% runs it
   my_data_frame = ..... 2. Make 'foreach' loop
   my results = foreach(i=1:24,.combine=rbind) %dopar%
           your code here
                                                    3. specify how to
                                                    combine results
        return( a variable or object)
   })
```

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           your code here
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                                                    combine results
        return( a variable or object)
```

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



R multinode: parallel backend

library(doParallel)

cl <- makeCluster(48)
registerDoParallel(cl)</pre>

1. allocate cluster as parallel backend



R multinode: parallel backend

```
library(doParallel)
                            1. allocate cluster as
                           parallel backend
cl <- makeCluster(48)
registerDoParallel(cl)
                                                    %dopar% puts
my_data_frame = .....
                                                loops across
                                                    cores and
results = foreach(i=1:48,.combine=rbind) %dopar%
                                                    nodes
 { ... your code here
    return( a variable or object)
})
stopCluster(cl)
```

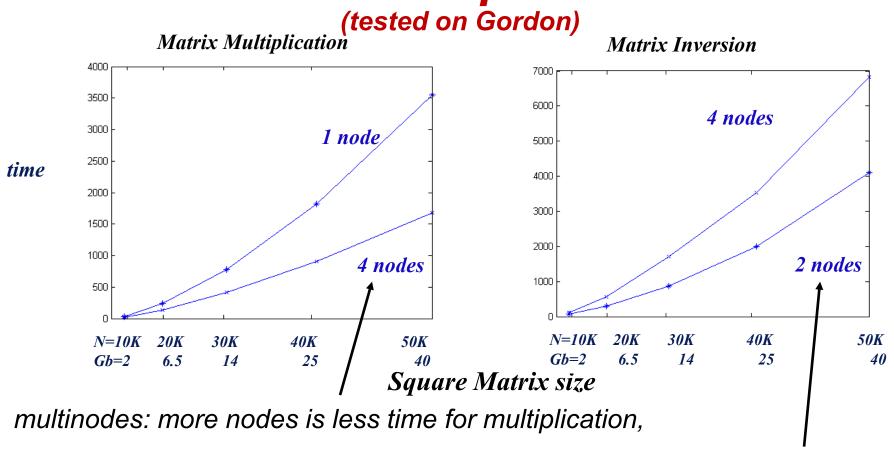
R multinode: parallel backend

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my_data_frame = .....
                                                     loops across
                                                     cores and
results = foreach(i=1:48,.combine=rbind) %dopar%
                                                     nodes
 { ... your code here
    return( a variable or object)
stopCluster(cl)
```

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



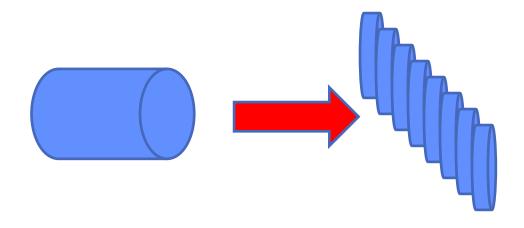
Multiple Compute Nodes not always help



less nodes is better for inversion

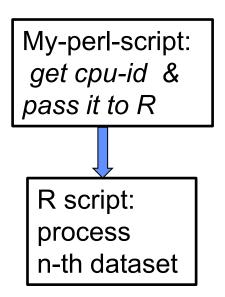
An option for (embarrassingly) Parallel R

Split up data into N parts



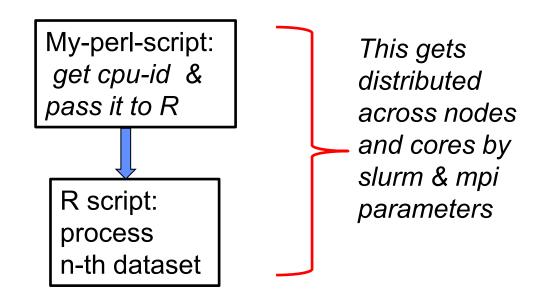
An option for (embarrassingly) Parallel R

- 1. Split up data into N parts
- 2. In slurm batch script: mpirun ... my-perl-script



An option for (embarrassingly) Parallel R

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



Slurm parameters: one R instance per core across all nodes

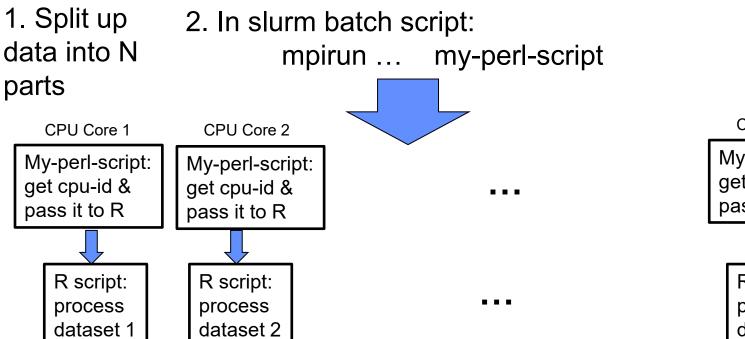
Normal batch job info

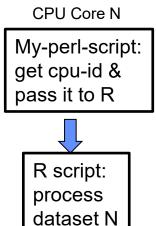
```
#SBATCH --partition=compute
                                       2 \times 128 = 256 \text{ mpi ranks}
#SBATCH --nodes=2
#SBATCH --ntasks-per-node=128
#SBATCH --cpus-per-task=1
module load slurm
module load cpu
module load gcc
module load intel-mpi
                                       256 perl 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)

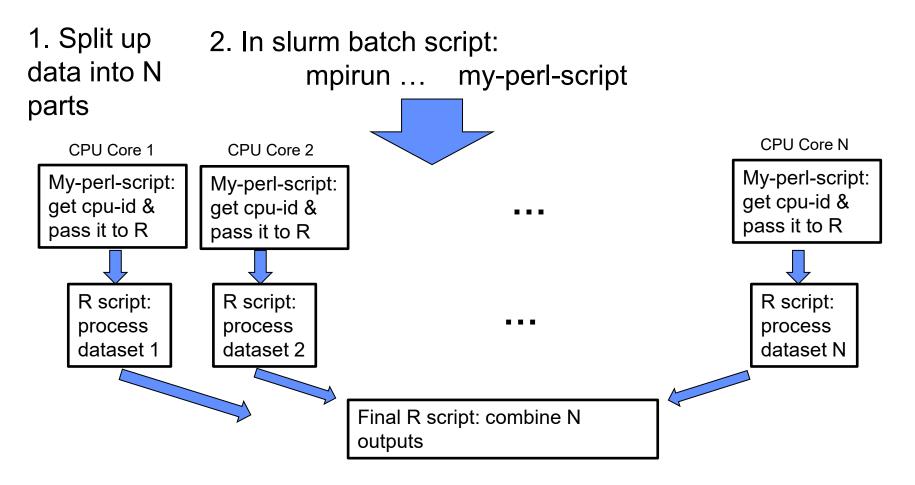


one R instance per core across all nodes





one R instance per core across all nodes



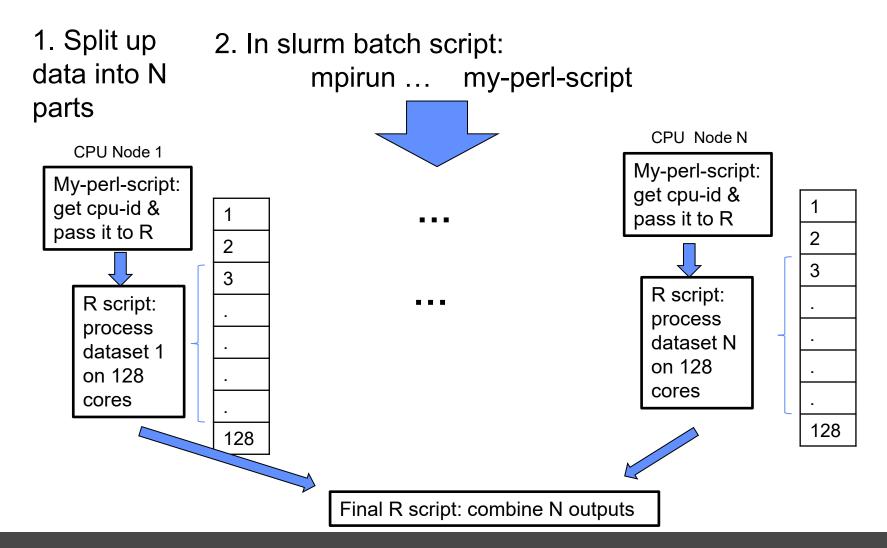
More programming but perhaps more useful



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

```
Normal
batch
          #SBATCH --partition=compute
job info
                                                2 x1 = 2 mpi ranks
          #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
                                                2 perl script/R instances
                                                 128 cores each
                                                (doParallel can use them)
          module load r
          mpirun -genv I_MPI_PIN_DOMAIN=omp:compact ./get_mpirank_runcmd.pl
```

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



Example: scaling MCMC

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

- MCMC searches parameter space through long sequences of updates to get complete probability distribution
- Individual sequences are not parallelizable, but sometimes parameters can be 'partitioned'
- Used the R package, "bayesm"
- Ran on SDSC Comet with embarrasing parallelization

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

Another MCMC option: Stan program

R or Python interface, with many options

Stan script → translated into C++ code and compiled

If you take log likelihood:

$$P(data, parameters) = \prod_{i} P(data_i, parameters)$$

$$\log P(data, parameters) = \sum_{i}^{N} \log P(data_i, parameters)$$

then Stan will partition the data across cores. (P() is calculated 1000's of times in a sequential chain)



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

How to use R directly on Expanse

- 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
```

```
[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:
```

```
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.
```

\$R

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 had 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

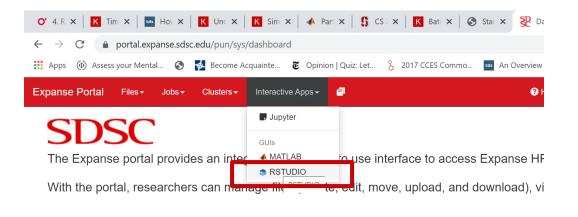
1 start Rstudio from portal (use shared and say <48 cores) and run script (it repeatedly does a regression)

2 review execution using 'top' utility

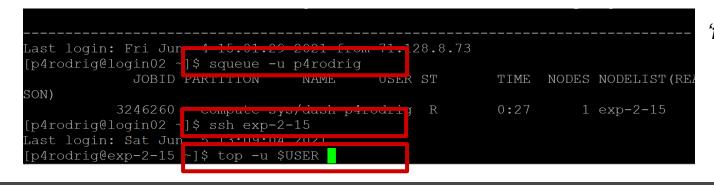
3 vary the NxP matrix size or number of cores

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









Open portal ->
Interactive Apps ->
Rstudio

Enter

Node: "compute"

Cores: "64"

(other fields defaults ok)

Also login: login.expanse

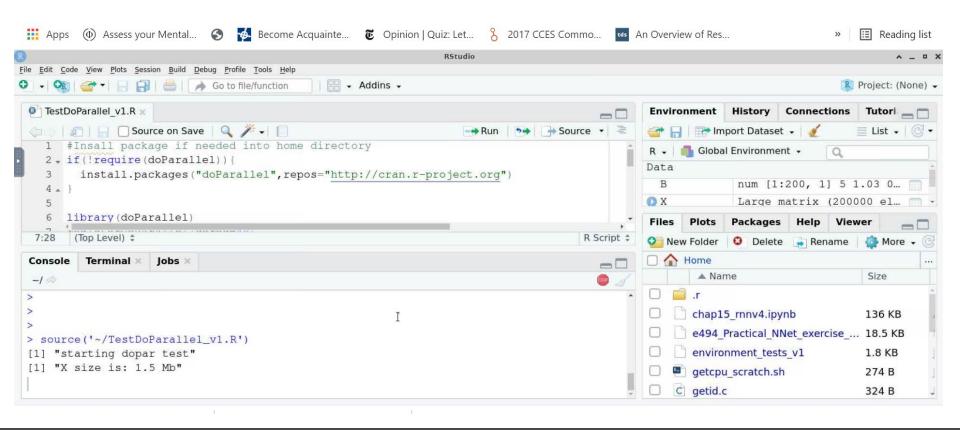
\$ squeue -u \$USER \$ ssh exp-##-## \$ top -u \$USER

'H' will toggle threads

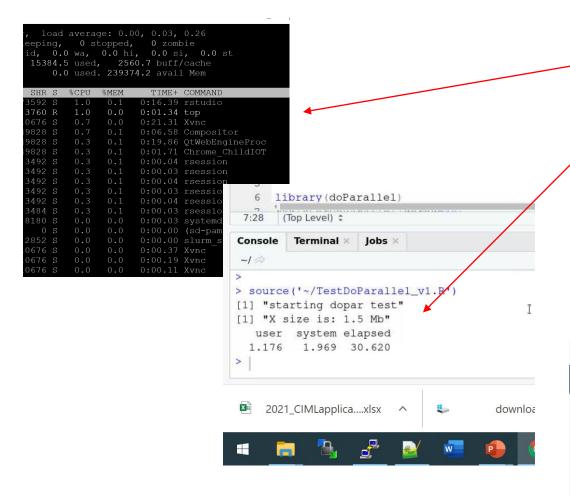
fP' will toggle last cpuid

Open the 'Test_doParallel ' Rscript

Select 'source' to run the whole script



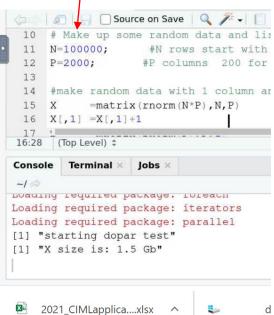




Review the top output

Notice the elapsed time and memory size

Change the NxP matrix size and rerun







THE END

