Lecture 9: Cluster computing

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BIOST 561: Computational Skills For Biostatistics I

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In Lecture 8, you learned how to compute without R.

Today, you'll learn how to transfer those skills to computing on a cluster.

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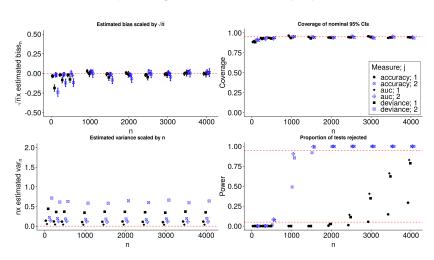
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- showcase operating characteristics of proposed method

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Data analysis:

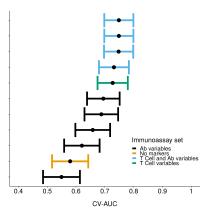
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Assay combination IgG + IgA + IgG3 + T Cells	CV-AUC [95% CI] 0.749 [0.698, 0.799]
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All markers	0.748 [0.697, 0.799]
T Cells + Fx Ab	0.732 [0.680, 0.784]
T Cells	0.727 [0.675, 0.780]
lgG3	0.695 [0.638, 0.751]
IgG + IgA + IgG3	0.688 [0.629, 0.746]
IgG + IgA + IgG3 + Fx Ab	0.658 [0.598, 0.718]
IgG + IgA	0.620 [0.559, 0.682]
No markers	0.580 [0.517, 0.643]
Fx Ab	0.550 [0.485, 0.614]



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analyses without keeping an R session open (for the duration!) on my personal machine?

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*: we will discuss this further!

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 $u \sim \mathcal{N}(0,1),$ independent of X ; $Y \mid X, u = \beta_0 + \beta_1 X + \epsilon,$ where $\epsilon = |X|u.$

Questions: can we use

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Running example: robust SEs

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We will use the cluster to do this!

Part I: coding for the cluster

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Today, I'll provide an alternative method (this should not always replace the simulator!).

Coding for the cluster: modular code

Modular code: each file has a single task

Coding for the cluster: modular code

Modular code: each file has a single task

Your turn!

Go to the code subdirectory. Then answer these questions with a partner:

- 1. what does do_one do? What are its arguments?
- 2. what does generate_data do? What are its arguments?
- 3. Write effective comments in each file so that **future you** understands each!

Coding for the cluster: modular code

Answers and Brian's comments (to be posted after class)

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Executables (e.g., /bin/sh):

- actually run your code
- other examples: /bin/bash, /usr/local/bin/Rscript, /usr/local/bin/python3

Coding for the cluster: saving output

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This is important regardless of whether or not you use the simulator!

Handy functions for saving output: saveRDS.

Coding for the cluster: saving output

Your turn!

In the robust SEs example, our goal is to compare model-based to robust SEs. **With a partner**, answer the following questions:

- 1. What output should we save?
- 2. How should we evaluate performance of the SEs?

Coding for the cluster: robust SEs

Check out run_sim_robust_se.R in the code directory!

Debugging is hard without a GUI.

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Best practices (in my opinion):

• debug everything on your machine first

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Debugging is hard without a GUI.

- debug everything on your machine first
- modular code (isolate bugs)
- run one job for subset of parameters prior to cluster

Coding for the cluster: compiling output

Check out load_sim_robust_se.R in the code directory!

Part II: using the cluster

Department resources for HPC*:

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A cluster consists of:

• a head node (where you are)

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- a head node (where you are)
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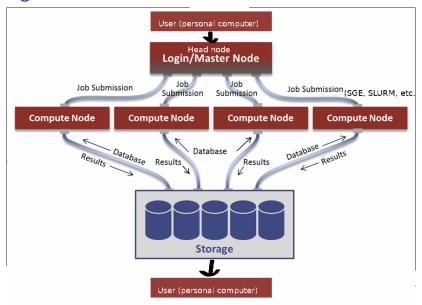
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- a head node (where you are)
- compute nodes (where your code gets run)
- submission system (how your code gets run)
- *other groups have similar resources, e.g.,
 - hyak (managed by UW-IT)
 - pearson (statistical genetics group only)
 - gizmo (Fred Hutchinson Cancer Research Center only)
 - Microsoft Azure, Amazon Web Services (AWS)



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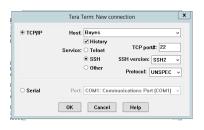
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We'll practice good habits for being nice as we go along.

Using the cluster: logging in (Windows, incl. box)

- 1. Open TeraTerm [or your favorite secure shell (SSH) client]
- 2. Enter the address of your favorite cluster, e.g., bayes.biostat.washington.edu
- 3. Make sure that the "New connection" window is filled out as in the figure, except for "Host" (screenshot from box)
- 4. Click OK, enter your UW BIOST username and password when prompted (user and pass you use for box)



Using the cluster: logging in

First step: make sure you are through the department firewall.

How: OpenSesame (on biost intranet)

- 1. Navigate to OpenSesame website
- 2. Select host (e.g., Bayes)
- 3. Click OpenSesame

Using the cluster: logging in (Mac/Linux)

- 1. Open a Terminal window
- 2. Type ssh mynetid@cluster.washington.edu
 - replace mynetid with Your UW NetID, and
 - replace cluster with Your cluster, e.g., bayes
- Enter password (same password as box) when prompted (the field will remain blank but your password will be received)

Using the cluster: logging in

Your turn! Take 2 minutes to complete this activity **by yourself** (if you don't have a computer, write down how you would do this).

- 1. Log into bayes
- 2. What is the name of the directory that you are when you log in?
- Create a directory called robust_ses in your home directory
- Create a directory called robust_ses on your computer, under biost561/lecture9

Using the cluster: moving around

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- navigation,
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- commands, and
- shell scripts

are all used in exactly the same way!

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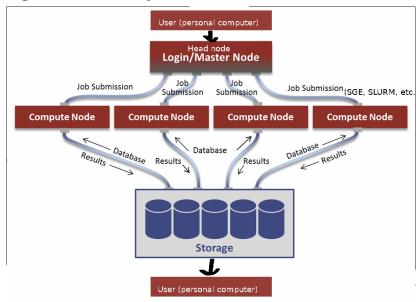
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Jobs:

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Example job: run run_sim_robust_se.R with 50 replicates



Using the cluster: calling your R script

Your turn!

Check out the file call_sim_robust_se.sh. With a partner, answer the following questions:

- 1. What does the \$ mean?
- 2. How many command-line arguments does run_sim_robust_se.R take?
- 3. What do the command-line arguments do?

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- t <task1-taskn> submits a job array with taskn-task1 tasks (more to come on this)

Options are specified with a single -, as you saw in Lecture 8.

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- displays nicely on cluster (part of not flooding)

Using the cluster: batch submission scripts

Your turn!

Check out the file submit_sim_robust_se.sh. With a partner, answer the following questions:

- 1. What do lines 3 and 4 do?
- 2. How many jobs are in my array if I want 5000 total jobs and 50 replicates per job?

Using the cluster: batch submission

Your turn!

Run the executable file submit_sim_robust_se.sh, with command line arguments

- "robust_se"
- 5000
- 50

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```
list_of_names <- <get correct names>
simulate_from_model(nsim = 1000,
          index = 1:3,
          parallel = list(socket_names = list_of_names))
```

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- qrls <job_id> removes a hold on a job
- qdel <job_id> deletes a job
- qalter <job_id> alters a job

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Ways to help share the cluster:

- Submit batch jobs in job arrays
- Use holds on jobs, using tc argument in qsub
- Estimate timing of smallest job, consider this when creating and submitting job arrays

Your turn!

- 1. Check the status of **your** job array (replace my netid with yours): qstat -f -u brianw26
- 2. Allow only 20 jobs to run at a time (replace <job_id> with your job id): qalter <job_id> -tc 20

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Then run your downstream code to compile results!

After all jobs are finished, pull results back to your machine.

Then run your downstream code to compile results!

Your turn!

- 1. Pull results files back to your computer
- 2. Run load_sim_robust_se.R
- 3. What can you conclude based on these results?

Today, you practiced how to

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Remember to be nice: the cluster is a shared resource!

Appendix: other useful cluster things

Useful things: Windows file compatability

Editing files in Windows carries risks.

One such risk is adding *control characters* that cannot be processed on Unix systems (e.g., Linux on department cluster).

A helpful tool to remove this characters is dos2unix: to remove control characters from myfile.sh, run dos2unix myfile.sh.

Useful things: emails and other defaults

You can set default behavior (on bayes, but similar for other systems) by creating a file called .sge_request.

Mine reads

- -ј у
- -cwd
- -S /bin/bash
- -q normal.q
- -M brianw26@uw.edu
- -m e

Which means:

- submit either binary or script file
- run using bash
- email me
- email me at end of job

Useful things: aliases and functions (Mac/Linux)

You will probably end up logging into the cluster or sending files back and forth quite often.

Having aliases and bash functions set up makes this easier.

Creating aliases:

- go to your .ssh folder (in your home directory on your computer)
- 2. create a file called config (using, e.g., vim)
- 3. edit it using the template below

```
Host <replace with, e.g., bayes>
   HostName <replace with, e.g., bayes.biostat.washington.edu>
   User <replace with, e.g., brianw26>
```

Useful things: Useful things: aliases and functions (Mac/Linux)

Creating functions:

- 1. go to your home directory
- 2. create a file called, e.g., .bash_funcs
- 3. edit it using the template below
- 4. edit your .bashrc file to include the lines if [-f ~/.bash_funcs]; then . ~/.bash_funcs fi
 fi
 (moleco cure that he sh funcs is sourced)

(makes sure that .bash_funcs is sourced when you open a new Terminal window)

```
function_name () {
    commands
}
```

E.g.: send R files from cwd to specified directory on bayes:

```
send_r_bayes () {
    scp *.R brianw26@bayes.biostat.washington.edu:~/$1
}
```

Useful things: FileZilla (all, but esp. Windows)

FileZilla is a nice program for pulling results back to your computer (via scp).

It can be used on all types of computers, but is especially helpful for Windows (since command prompt is strange!).