An Example Workflow Featuring a Regression Simulation

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1 Introduction

This example illustrates a workflow for a simple simulation. Consider a linear regression model with

$$y_i = \boldsymbol{x}_i^{\top} \boldsymbol{\beta} + \epsilon_i, \quad \epsilon_i \stackrel{\text{iid}}{\sim} N(0, \sigma^2), \quad i = 1, \dots, n,$$
 (1)

where $x_i \in \mathbb{R}^d$ is a given covariate which is considered to be fixed. Let $\boldsymbol{\theta} = (\boldsymbol{\beta}, \sigma^2)$ represent the unknown parameters and let $\hat{\boldsymbol{\theta}} = (\hat{\boldsymbol{\beta}}, \hat{\sigma}^2)$ be the maximum likelihood estimator (MLE). Here the MLE has well-known closed form expressions

$$\hat{oldsymbol{eta}} = (oldsymbol{X}^ op oldsymbol{X})^{-1} oldsymbol{X}^ op oldsymbol{y}, \quad \hat{\sigma}^2 = rac{1}{n} oldsymbol{y}^ op (oldsymbol{I} - oldsymbol{H}) oldsymbol{y},$$

where \boldsymbol{X} is the $n \times d$ matrix with rows \boldsymbol{x}_i^{\top} and $\boldsymbol{H} = \boldsymbol{X} (\boldsymbol{X}^{\top} \boldsymbol{X})^{-1} \boldsymbol{X}^{\top}$. A property of interest for the MLE is its mean-squared error

$$MSE(\hat{\boldsymbol{\theta}}, \boldsymbol{\theta}) = E\left[\|\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}\|^2\right]$$

with respect to the true data generating parameter $\boldsymbol{\theta}$. We will prepare a small simulation to evaluate the MSE for $\beta=(-1,1), \sigma\in\{1,2,3\}$, and $n\in\{50,100,200\}$. For each combination of (σ,n) ("level" of the simulation), we will repeat the following for $r=1,\ldots,R=200$: first generate observations $\boldsymbol{y}^{(r)}=(y_1^{(r)},\ldots,y_n^{(r)})$ from model (1) using the current level of $\boldsymbol{\theta}$ and n, then obtain the MLE $\hat{\boldsymbol{\theta}}^{(r)}$. Using the empirical sampling distribution of $\hat{\boldsymbol{\theta}}^{(1)},\ldots,\hat{\boldsymbol{\theta}}^{(R)}$, we may then approximate

$$\text{MSE}(\hat{\boldsymbol{\theta}}, \boldsymbol{\theta}) \approx \frac{1}{R} \sum_{r=1}^{R} ||\hat{\boldsymbol{\theta}}^{(r)} - \boldsymbol{\theta}||^2$$

This simple simulation can be run within an R script in a matter of seconds or minutes. We can create nested loops to iterate through the crossed levels of σ and n, and then the R repetitions. Now imagine a more involved study where computing each estimate takes a matter of minutes or hours. Also, instead of having only 9 levels of the simulation, perhaps we have hundreds. Rather than saving just the MLE repetitions, we may also want to save the generated data $y^{(r)}$, and diagnostics from each fit. This motivates the following workflow:

- Each level of the simulation will be placed into its own dedicated folder with a launcher script. Any log files and output from the level will be saved here as well.
- The folders and launcher scripts will be generated by a script that we write.
- We will utilize one or more "workers", whose job is to search the folders for available work. A folder is reserved and has its launcher executed by at most one worker.
- If a level fails, or if we wish to investigate its result, we can manually enter the folder and run the launcher or load the results.
- We will write a script to extract results from the folders and produce the desired results.

This kind of "embarrassingly parallel" computing is typical in many statistical projects: no communication is needed across levels during the simulation. Coordination is only needed to initially generated the workload and in post-processing. We may therefore wish to take advantage of multiple CPUs to process our workload faster, without the extra sophistication of frameworks such as MPI or the parallel package.

2 Workflow Implementation

The following scripts are used to implement our workflow for the regression simulation:

- 'gen.R' generates the folder structure and creates a 'launch.R' script in each folder.
- 'util.R' contains several utility functions used by other scripts.
- 'sim.R' contains the main logic to run each level of the simulation. The program sleeps for a few moments after each repetition to give the feeling of a more computationally demanding simulation.
- 'launch.R' is responsible for setting variables specific to the simulation level and running 'sim.R'.
- 'worker.py' is a Python script that seeks simulation levels which have yet been run and attempts to run them
- 'analyze.R' handles post-processing after the simulation is completed. A table of MSEs is presented as the final result.

All scripts mentioned above, except for worker.py, are specific to this simulation and must be rewritten or customized for other applications.

Let us run gen.R on the command line. The following displays will shown as a Linux prompt, but other environments should work similarly.

```
$ R CMD BATCH gen.R
```

The following folders and directories are produced.

```
sigma1_n1 sigma1_n3 sigma2_n2 sigma3_n1 sigma3_n3 xmat-n2.rds
sigma1_n2 sigma2_n1 sigma2_n3 sigma3_n2 xmat-n1.rds xmat-n3.rds
```

Folders of the form sigmaA_nB correspond to the simulation level for the Ath value of σ and the Bth value of n, for $A, B \in \{1, 2, 3\}$. Files of the form xmat-nB.rds represent the design matrix X to be used when n is taken to be the Bth level.

Let's inspect launch.R in the folder sigma1_n1.

```
set.seed(1234)

beta_true = c(-1,1)
sigma_true = 2.000000
xmat_file = "../xmat-n1.rds"
N_sim = 200

source("../sim.R")
save.image("results.Rdata")
```

We could run this manually to verify that our code generation script is correct and that all resources are in the appropriate place. Note that it assumes the sigma1_n1 folder is our current working directory. Furthermore, sim.R and xmat-n1.rds should be in the parent directory.

Once we are certain the code and folders are laid out correctly, we will want to use a worker(s) instead of running the study manually. Suppose

• The script 'worker.py' is located at '/path/to/worker.py'.

• The path to our generated simulation folders is located at '/path/to/study'.

The following command invokes one worker.

```
python3 /path/to/worker.py -b /path/to/study -p "sigma(.*)_n(.*)" -c 'R CMD BATCH launch.R'
```

Note that -b is used to specify one or more paths which contain work folders, -p is used to specify one or more patterns used to identify work folders (as opposed to other folders which we should ignore), and -c specifies a command to run if we find a work folder whose job has not yet been attempted. Use the -h flag to display a help message, including the command line format, for worker.py.

A worker logs its activity to stdout. This can be redirected to a file if desired.

Let us look in sigma2_n1, which was completed by the worker above.

```
$ ls sigma2_n1
launch.R launch.Rout results.Rdata worker.err worker.lock worker.out
```

The files worker.out and worker.err capture any output from stdout and stderr while running the job. The file worker.lock is placed as a marker to indicate that a job has been reserved by a worker; only one worker may create this file, and it can run the job only upon successful creation of the file. If a job fails and you would like a worker to consider it again, delete the corresponding worker.lock.

The file worker.lock contains the ID of the worker that reserved it. This can be linked back to the Worker ID reported in the log output, which may help if it is necessary to determine which worker ran a job.

```
$ cat sigma2_n1/worker.lock
Reserved by worker: 75e1421210cc92d62e5403313cab33f0
```

After the simulation is complete, we may run analyze.R to extract the estimates from each folder and build a table of MSEs.

As we may expect, the MSE increases as σ increases with n fixed, but decreases when n is increased and σ is fixed.