

Parallel programming in R

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Introduction

Simple example

Practical use

The end...

Background

- ▶ R is single-threaded
- ▶ There are several packages for parallel computation in R, some of which have existed a long time, e.g. `Rmpi`, `nws`, `snow`, `sprint`, `foreach`, `multicore`
- ▶ As of 2.14.0, R ships with a package `parallel`
- ▶ R can also be compiled against multi-threaded linear algebra libraries (BLAS, LAPACK) which can speed up calculations

Today's focus is the `parallel` package.

Overview of `parallel`

- ▶ Introduced in 2.14.0
- ▶ Based on packages `multicore` and `snow` (slightly modified)
- ▶ Includes a parallel random number generator (RNG); important for simulations
- ▶ Particularly suitable for 'single program, multiple data' (SPMD) problems
- ▶ Main interface is parallel versions of `lapply` and similar
- ▶ Can use the CPUs/cores on a single machine (`multicore`), or several machines, using MPI (`snow`)
- ▶ MPI support depends on the `Rmpi` package (installed on Abel)

Simple example: serial

- ▶ `parallel` provides substitutes for `lapply`, etc.
- ▶ 'Silly' example for illustration: calculate $(1:100)^2$

Serial version:

```
## The worker function to do the calculation:
```

```
workerFunc <- function(n) { return(n^2) }
```

```
## The values to apply the calculation to:
```

```
values <- 1:100
```

```
## Serial calculation:
```

```
res <- lapply(values, workerFunc)
```

```
print(unlist(res))
```

Simple example: `mclapply`

- ▶ Performs the calculations in parallel on the local machine
- ▶ (+) Very easy to use; no set-up
- ▶ (+) Low overhead
- ▶ (-) Can only use the cores of *one* machine
- ▶ (-) Uses fork, so it will not work on MS Windows

```
workerFunc <- function(n) { return(n^2) }  
values <- 1:100
```

```
library(parallel)
```

```
## Number of workers (R processes) to use:  
numWorkers <- 8
```

```
## Parallel calculation (mclapply):  
res <- mclapply(values, workerFunc, mc.cores = numWorkers)
```

```
print(unlist(res))
```

Simple example: `parLapply`

- ▶ Performs the calculations in parallel, possibly on several nodes
- ▶ Can use several types of communications, including `PSOCK` and `MPI`
- ▶ `PSOCK`:
 - ▶ (+) Can be used interactively
 - ▶ (-) Not good for running on several nodes
 - ▶ (+) Portable; works 'everywhere'
 - ▶ => Good for testing
- ▶ `MPI`:
 - ▶ (-) Needs the `Rmpi` package (installed on Abel)
 - ▶ (-) Cannot be used interactively
 - ▶ (+) Good for running on several nodes
 - ▶ (+) Works everywhere where `Rmpi` does
 - ▶ => Good for production

Simple example: `parLapply` (PSOCK)

```
workerFunc <- function(n) { return(n^2) }  
values <- 1:100  
  
library(parallel)  
  
## Number of workers (R processes) to use:  
numWorkers <- 8  
  
## Set up the 'cluster'  
cl <- makeCluster(numWorkers, type = "PSOCK")  
  
## Parallel calculation (parLapply):  
res <- parLapply(cl, values, workerFunc)  
  
## Shut down cluster  
stopCluster(cl)  
  
print(unlist(res))
```


Simple example: `parLapply` (MPI)

`simple_mpi.R`:

```
workerFunc <- function(n) { return(n^2) }  
values <- 1:100  
library(parallel)  
numWorkers <- 8  
cl <- makeCluster(numWorkers, type = "MPI")  
res <- parLapply(cl, values, workerFunc)  
stopCluster(cl)  
mpi.exit() # or mpi.quit(), which quits R as well  
print(unlist(res))
```

Running:

```
mpirun -n 1 R --slave -f simple_mpi.R
```

Note: Use R \geq 2.15.2 for [MPI](#), due to a bug in earlier versions of [parallel](#).

Preparation for calculations

- ▶ Write your calculations as a function that can be called with `lapply`
- ▶ Test interactively with `lapply` serially, and `mclapply` or `parLapply` (`PSOCK`) in parallel
- ▶ Deploy with `mclapply` on single node or `parLapply` (`MPI`) on one or more nodes
- ▶ For `parLapply`, the worker processes must be prepared with any loaded packages with `clusterEvalQ` or `clusterCall`.
- ▶ For `parLapply`, large data sets can be exported to workers with `clusterExport`.

Extended example

(Notes to self:)

- ▶ Submit jobs
- ▶ Go through scripts
- ▶ Look at results

Efficiency

- ▶ The time spent in each invocation of the worker function should not be too short
- ▶ If the time spent in each invocation of the worker function vary very much, try the load balancing versions of the functions
- ▶ Avoid copying large things back and forth:
 - ▶ Export large datasets up front with `clusterExport` (for `parLapply`)
 - ▶ Let the values to iterate over be indices or similar small things
 - ▶ Write the worker function to return as little as possible
- ▶ Reduce waiting time in queue by not asking for whole nodes; if possible, use `--ntask` instead of `--ntasks-per-node + --nodes`.

Other topics

There are several things we haven't touched in this lecture:

- ▶ Parallel random number generation
- ▶ Alternatives to `*apply` (e.g. `mcparrallel` + `mccollect`)
- ▶ Lower level functions
- ▶ Using multi-threaded libraries
- ▶ Other packages and techniques

Resources:

- ▶ The documentatin for `parallel`: `help(parallel)`
- ▶ The book *Parallel R*, McCallum & Weston, O'Reilly
- ▶ The HPC Task view on CRAN:
<http://cran.r-project.org/web/views/HighPerformanceComputing.html>