Parallel **R**

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Outline

Motivation

Why **R**? The **R** language has a lot of advantages:

- Open Source.
- Cross-Platform.
- Free.
- Many basic tools.
- **R** extensions.
- Arguable fast with **R**-way style and well-implemented **R** distribution.

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Solution: Parallel Execution. How exactly?

- Single-threaded: multiple CPU's (and cores).
- Memory-bound: spread data from one computer (master) to several computers (slaves).

Basic Terminology

The two types of parallelism:

- **Implicit** — the OS abstracts parallelism from the user.
- **Explicit** — user controls details of the process.

A **computer cluster** consists of a set of loosely or tightly connected computers that work together so that, in many respects, they can be viewed as a single system (Wiki).

Master/slave is a model of communication where one device or process has unidirectional control over one or more other devices (Wiki).

snow

Usage: Explicit parallelism by using clusters (works on Linux, Windows, Mac OS X).

Solves: Single-threaded, memory-bound.

multicore [deprecated]

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Overview

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Hadoop

R + `Hadoop, RHIPE, Segue`.

Epigraph

"... R was not built in anticipation of the Big Data revolution. R was born in 1995. Disk space was expensive, RAM even more so, and this thing called The Internet was just getting its legs. Notions of "large-scale data analysis" and "high-performance computing" were reasonably rare. Outside of Wall Street firms and university research labs, there just wasn't that much data to crunch."

— Q. Ethan McCallum and Stephen Weston "Parallel **R**"

Outline

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snow: quick look

General use case:	main word is cluster, provides explicit parallelism.
Examples:	Monte Carlo simulations, bootstrapping, cross validation, ensemble machine learning algorithms.
Solves:	Single-threaded, memory-bound.
Cool features:	• Different transport mechanisms between Master and Slaves: Sockets, MPI (`rmpi`), NWS (`nws`), PVM (`rpvm`). • Good support of RNG (`rsprng`, `rlecuyer`).
Problems:	No communication between the workers (slaves).

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Problems:	No communication between the workers (slaves).
Warning:	The input arguments **must fit** into memory when calling `snow` function. Its up to the user to arrange high-performance distributed file systems.

Structure of API

Start and stop clusters:	makeCluster, stopCluster.
Low-level (cluster-level) functions:	`cluster*` — `clusterApply`, `clusterApplyLB`, `clusterEvalQ`, `clusterCall`, `clusterSplit`, etc.
High-level functions:	`par[L,S,A,R,C]apply` — parallel versions of apply and related functions.
(Uniform) RNG:	L'Ecuyer (package: `rlecuyer`), SPRNG *[deprecated]* (package: `rsprng`).
Timing:	`snow.time(expr)` — very useful.

Start and stop clusters

Basic way:

```
cl <- makeCluster(8, type = "SOCK") # or you may use
                                    # makeSOCKcluster(),
                                    # makePVMcluster(), etc.
stopCluster(cl)
```

First parameter is `spec` — specification. It is `ssh`-configurable unless you type `"localhost"`:

```
cl <- makeCluster(c("localhost","localhost"), type = "SOCK")
stopCluster(cl)
```

Warning: Be aware of computational costs of cluster setup.

Low-level API

All of them are `cluster*` and designed for computing *on* a cluster. Most interesting are as follows.

`clusterApply(cl, x, fun, ...)`	Jjobs are being "recycled".
`clusterApplyLB(cl, x, fun, ...)`	Load Balancing version of clusterApply().
`clusterCall(cl, fun, ...)`	Calls a function fun with identical arguments ... on each node in the cluster cl and returns a list of the results.
`clusterEvalQ(cl, expr)`	Evaluates an expression expr on each node in the cluster cl; implemented using clusterCall().
`clusterMap(cl, fun, ..., MoreArgs = NULL, RECYCLE = TRUE)`	Similar to `mapply`.

Example, K-means

Basic one-core way:

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library(MASS)
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Before using `snow` it is easier to think `*apply`-way:

```
results <- lapply(rep(25, 4),
  function(nstart)
    kmeans(Boston, 4, nstart=nstart)
  )
i <- sapply(results,
  function(result)
    result$tot.withinss
  )
result <- results[[which.min(i)]]
```

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  )
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```

Finally snow version.

```
ignore <-
  clusterEvalQ(cl, {library(MASS); NULL})
results <-
  clusterApply(cl, rep(25, 4),
    function(nstart)
      kmeans(Boston, 4, nstart=nstart)
  )
i <- sapply(results,
  function(result)
    result$tot.withinss
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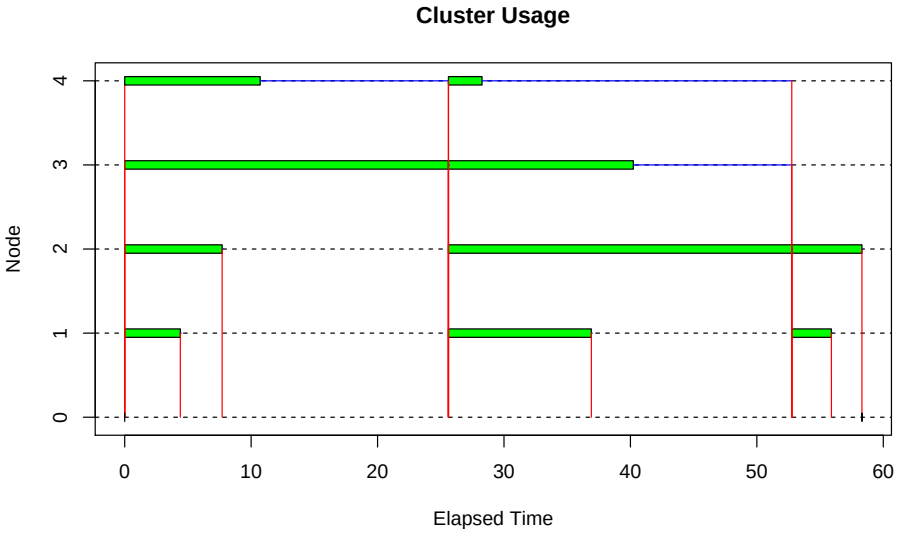
result <- results[[which.min(i)]]
```

Load Balancing

`clusterApply()` uses a *robin-round* fashion for scheduling tasks for clusters. It means one time for every cluster. It could be not very wise to do that.

```
set.seed(123)
sleeptime <- abs(rnorm(10, 10, 10))
tm <- snow.time(clusterApply(cl, sleeptime, Sys.sleep))
```

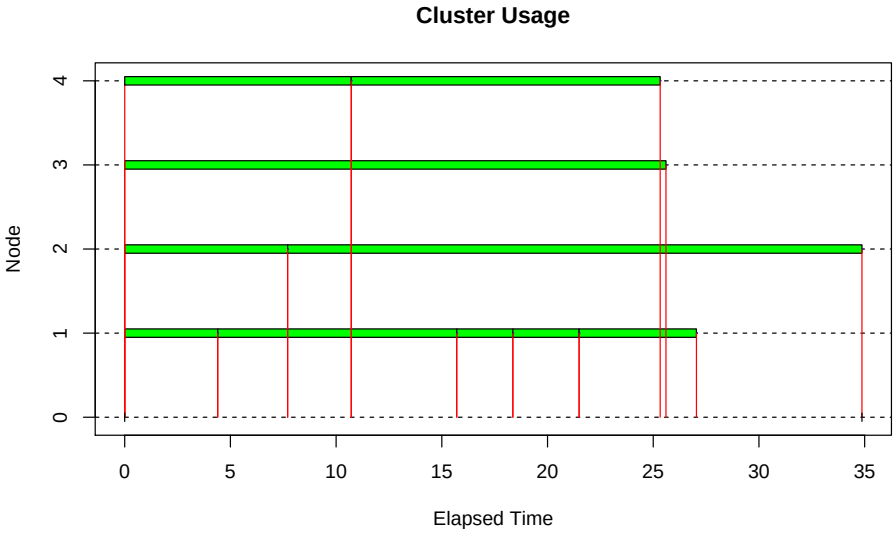
Load Balancing



Load Balancing

So we waited for more than 50 seconds. A more efficient way would be pull the tasks to clusters when they are needed. This technique is called "load balancing". Function `clusterApplyLB()` uses that technique.

```
set.seed(123)
sleeptime <- abs(rnorm(10, 10, 10))
tm <- snow.time(clusterApplyLB(cl, sleeptime, Sys.sleep))
```


Cluster Usage
Node
0
1
2
3
4
0
5
10
15
20
25
30
35
Elapsed Time

So, here we waited for about 30 seconds. This is an improvement. The only wasted time was at the end.

High-level API

`parLapply(cl, x, fun, ...)`	Parallel version of lapply().
`parSapply(cl, X, FUN, ..., simplify = TRUE, USE.NAMES = TRUE)`	Load Balancing version of clusterApply().
`parApply(cl, X, MARGIN, FUN, ...)`	Parallel version of apply().
`parRapply(cl, x, fun, ...)`	Row apply() for matrix.
`parCapply(cl, x, fun, ...)`	Column apply() for matrix.

The most useful is `parLapply()` function. It is different from `clusterApply()` because it splits the task into "equal" tasks.

```
parLapply
```

```
## function (cl, x, fun, ...)
## docall(c, clusterApply(cl, splitList(x, length(cl)), lapply,
##     fun, ...))
## <environment: namespace:snow>
```

where `splitList()` is an internal snow function.

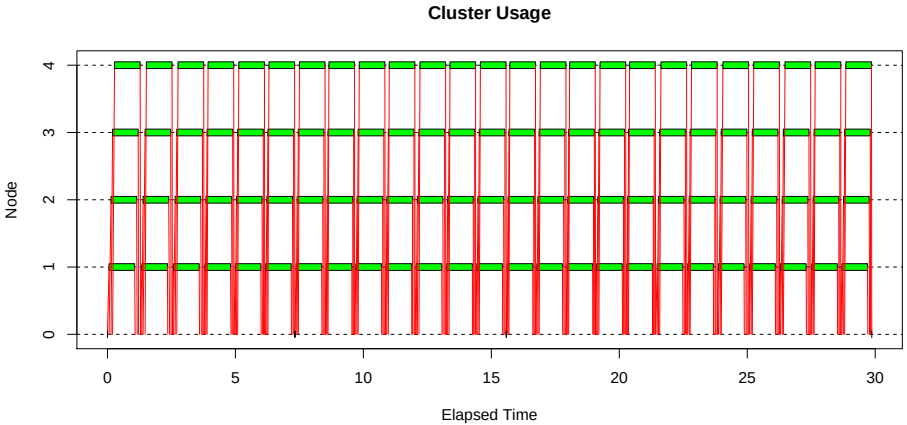
Example of comparison clusterApply() and parLapply()

`parLapply()` could be more efficient if you have more tasks than workers. Another situation — you send large arguments to `parLapply()`. Let's take a look at the example.

```
bigsleep <- function(sleeptime, mat) Sys.sleep(sleeptime)
bigmatrix <- matrix(0, 2000, 2000)
sleeptime <- rep(1, 100)
```

Firstly, let's try `clusterApply()`.

Example of comparison `clusterApply()` and `parLapply()`



Example of comparison `clusterApply()` and `parLapply()`

Definitely not highly efficient. Those gaps are due to I/O time. Ideally we should have 25 seconds... Let's give `parLapply()` a try.

Example of comparison `clusterApply()` and `parLapply()`

Load Balancing parLapply?

Load Balancing parLapply?

Short answer: no, there is no such a function in snow package.
Good news: it is possible to write your own.

Random Number Generation

There are 2 basic steps.

1. Configure your cluster workers to use a generator.

```
library(rlecuyer)
clusterSetupRNG(cl, type = 'RNGstream')
```

```
## [1] "RNGstream"
```

2. Be happy to generate your numbers.

```
unlist(clusterCall(cl, runif, 1))
```

```
## [1] 0.12701112 0.75958186 0.72850979 0.09570262
```

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`Multicore` *[deprecated]* : quick look

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General use case:	Main word is fork (thus no Windows support), provides implicit parallelism.
Examples:	`lapply()` runs for ages on your Intel Core i999.
Solves:	Single-threaded.
Problems:	• No Windows support. • No internal RNG support. • Runs only on one computer. • Cannot be used with **R** `GUI`. • No internal Load Balancing, however, it can be imitated.

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Problems:	• No Windows support. • No internal RNG support. • Runs only on one computer. • Cannot be used with **R** `GUI`. • No internal Load Balancing, however, it can be imitated.
Warning:	Jobs started by `multicore` share the same state (because of `fork`).

Multicore *[deprecated]* : quick look

We will only consider *high-level* API and let *low-level* to be out-of-scope.

`mclapply()`	parallel version of `lapply()`.
`mcmapply()`	parallel version of `mapply()`.
`pvec()`	Somewhat an high-level analog of low-level `clusterSplit()` function.
`parallel()` and `collect()`	`parallel()` creates a new process with `fork()`, evaluate expression in parallel and after that the result is retrieved by the `collect()`.

Multicore: mclapply

`mclapply()` is a parallel `lapply()`.

Syntax is as follows:

```
mclapply(X, FUN, ..., mc.preschedule = TRUE, mc.set.seed = TRUE,
  mc.silent = FALSE, mc.cores = getOption("mc.cores"))
```

where

1. `mc.preschedule = TRUE` — how jobs are created for `X`.
2. `mc.set.seed = TRUE` — do you need to randomly seed slaves, or fork it?
3. `mc.silent = FALSE` — hide info from 'stdout' for all parallel forked processes. 'stderr' is not affected.
4. `mc.cores == getOption("mc.cores")` — number of **workers** (not cores, actually) to start.

Meaning:

- TRUE: divide data in `mc.cores`-jobs beforehand and fork it to `mc.cores`-processes.
- FALSE: for each piece of data construct a new job (up to `mc.cores`).

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Rule of thumb: use

- TRUE: you don't need load balance (for instance, if there are lot's of values in the data).
- FALSE: the variance of job completion is very high (so, you need load balance).

Outline

parallel

General use case:	Main word is mainstream, almost a wrapper of `snow` and `multicore` packages.
Examples:	Anything above.
Solves:	Single-threaded and (partially) memory-bound.
Cool features:	• Preinstalled into **R** since 2.14.0. • Full RNG support with no dependency on `rlecuyer` package. • Almost nothing to learn (if you are still awake). • Can be easily used on any platform including Windows. • Highly compatible with `snow` and `multicore`.

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Warning:	On Windows you can't use more than one machine. It also can be difficult to configure multiple Linux machines.

How many cores?

```
library(parallel)
mc.cores <- detectCores()
mc.cores
```

```
## [1] 8
```

Warning: It is important to take into account that you maybe have hyper-threading.

Parallel RNG

Unlike `snow` package no additional packages (like `rlecuyer`) are needed.

Fork (no Windows) way:

```
RNGkind("L'Ecuyer-CMRG")
unlist(mclapply(rep(1,4), runif))

## [1] 0.3768615 0.3824588 0.3845725 0.9092709
```

Cluster way:

```
detach("package:snow", character.only=TRUE)
library(parallel)
RNGkind("L'Ecuyer-CMRG")
cl <- makeCluster(2, type="PSOCK")
unlist(clusterCall(cl, function(x) runif(2)))

## [1] 0.4434804 0.9242494 0.4784403 0.3226038

stopCluster(cl)
```

parallel RNG: reproducible results

Basic way to get reproducible results would be `mc.reset.stream()` — the parallel random number generator is reinitialized using the current seed on the master.

```
detach("package:snow", character.only=TRUE)
library(parallel)
RNGkind("L'Ecuyer-CMRG")
cl <- makeCluster(2, type="PSOCK")
clusterSetRNGStream(cl, 123)
unlist(clusterCall(cl, function(x) runif(2)))
```

```
## [1] 0.1663742 0.3898457 0.3411064 0.9712727
```

```
clusterSetRNGStream(cl, 123)
unlist(clusterCall(cl, function(x) runif(2)))
```

```
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```

```
stopCluster(cl)
```

Differences from `multicore` and `snow`

Let's sum up the differences between modern `parallel` package and his predecessors.

`parallel` > `multicore`

- Prefix `mc` in `mcfork()`, `mcexit()`, `mckill()`, `mcparallel()`, `mccollect()`, `mc.cores`.
- Different default value of `mc.cores` argument.
- New mc.reset.stream() function.

Also useful `detectCores()` is added.

`parallel` $\neq$ `snow`

- New function `clusterSetRNGStream()` initializes parallel RNG.
- `snow.time()` function not included.
- `makeCluster()` supports additional types FORK.

Outline

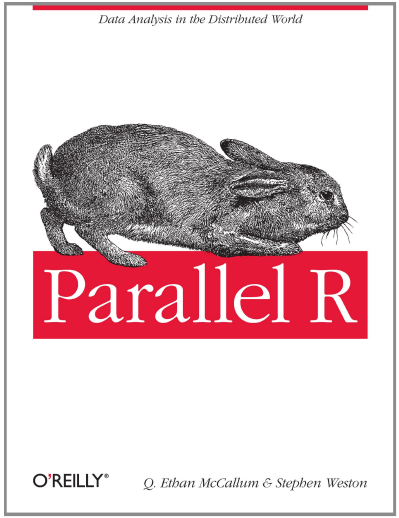
Out of scope

We covered 3 (2.5 really) packages: `snow`, `multicore`, `parallel`. What else?

- *Revolution Analytics* `foreach` package for iteration over a set of values.
- MapReduce via Java Hadoop: `RHIPE` (negotiator between you with your MapReduce functions and Hadoop).
- `Segue` for Amazon Elastic MapReduce lovers. Be aware of terminating clusters.
- `doRedis`.
- `http://cloudNumbers.com`
- **R** and GPUs: `gputools` etc.

Literature

Main reference:



Useful links:

- Advanced **R** by Hadley Wickham.
- The **R** Inferno by Patrick Burns.
- **R** Packages by Hadley Wickham.
- Writing **R** Extensions.
- Los Angeles **R** Users Group: Parallelization in **R**, Revisited by Ryan R. Rosario.
- Package parallel manual.