Tutorial on Parallel Programming in R

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Setup

Requirements:

- Hardware cluster
- PVM (MPI)
- RPVM (Rmpi)
- R packages for higher level parallel programming: snow + snowFT
- R packages for distr. random number generation: rlecuyer, rsprng

PVM Setup

Setting environment variables in your .cshrc (.bashrc,...) file:

```
setenv PVM_ROOT /usr/lib/pvm3
setenv PVM_ARCH LINUX
set path=( $path $PVM_ROOT/lib
           $PVM_ROOT/lib/$PVM_ARCH
           $PVM_ROOT/bin/$PVM_ARCH ) # in 1 line
setenv PVM_RSH /usr/bin/ssh
setenv PVM_EXPORT LD_LIBRARY_PATH:PATH
```

Check:

```
pvm
pvm> quit
```

RPVM Setup

startpvm.R

```
library(rpvm)
hostfile <- paste(Sys.getenv("HOME"),
                  "/.xpvm_hosts",sep="")
.PVM.start.pvmd(hostfile)
.PVM.config()
```

.xpvm_hosts (in $HOME directory)

```
* ep=/net/home/hana/lib/rpvm  # optional,
     # dir where slaveR.sh resides, if local
mos1.csde.washington.edu
mos2.csde.washington.edu
  :
```

RPVM Setup (cont.)

- Set the environment variable `R_LIB` to directory with your local packages. E.g. in `.cshrc`:
  `setenv R_LIBS /net/home/hana/lib/inst`
- Halt your PVM deamon (`pvm> halt`, or in XPVM).
- Run `startpvm.R`.
- Check result in XPVM.

SNOW: Simple Network of Workstations

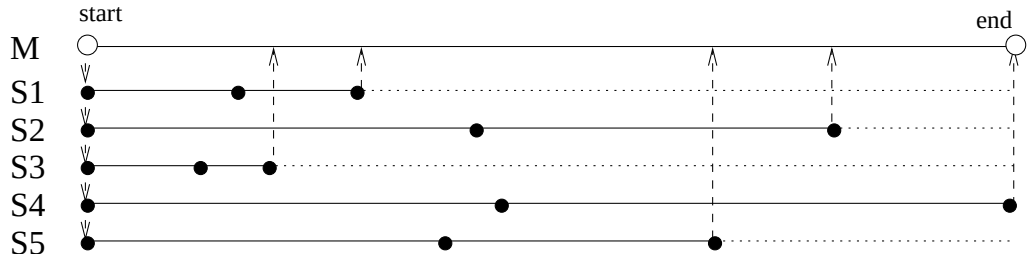
(L. Tierney, A. Rossini, M. Na Li, 2003)

- higher level framework for simple parallel jobs
- communication: via socket, rpvm or rmpi
- based on master-slave model
- one call creates the cluster (`makeCluster(size)`)
- automatic handling of parallel random number generator – rlecuyer, rsprng (`clusterSetupRNG(...)`)
- one call for repeated evaluation of an arbitrary function on the cluster

SNOW Example

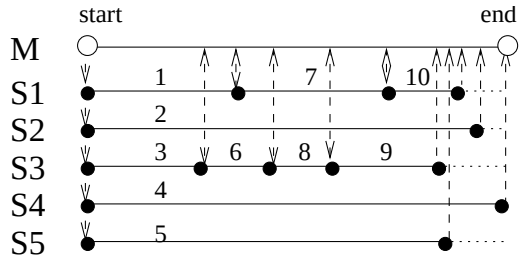
Execute function `fun` 10 times on 5 nodes

1. `clusterApply (cl, rep(2,5), fun)`



- runtime depends on the slowest node, results reproducible

2. `clusterApplyLB (cl, rep(1,10), fun)`



- faster but not reproducible

snowFT: Fault Tolerant SNOW

(H. Ševčíková, A. Rossini, 2004)

- Built on SNOW.
- Load balancing AND reproducibility:
  one RN stream associated with one replicate.
- Fault tolerance: failure detection and recovery in master's waiting time.
- Computation transparency (define a print function, file .proc, .proc_fail).
- Dynamic cluster resizing (file .clustersize).
- Easy to use.

snowFT: Usage

Only one function needed for all features.

```
performParallel(count, vector_of_length_n,
                fun, ...)
```

- creates a cluster of size `count`
- [initializes each node with a given function]
- [initializes RNG (rlecuyer or rsprng)]
- performs the actual computation on the cluster (n $\times$ `fun`)
- [performs aftermath operations on each node]
- stops the cluster and returns a list of results

Programming

- Implement the peace of code to be run in parallel as a separate function.
- Make sure that all user-defined functions that are called on slave nodes can be seen by slave.
  - ```
    initfct <- function(){
      source(file_with_local_functions.R)
    }
    performParallel(..., initfun=initfct, ...)
    ```
  - ```
    fun <- function(...) {
      localfun <- function(...) {...}
              :
      a <- localfun (...)
    }
    ```

Tips

- Integrate a sequential and a parallel version of your code in one program.

```
myprogram <- function(..., parallel=1,...) {
  if (parallel > 1) {
    require(snowFT)
    res <- performParallel(parallel, 1:n,
                           fun, myargs, ...)
  } else {
    res <- list()
    for (i in 1:n)
      res <- c(res, list(fun(i, myargs)))
  }
}
```

Tips (cont.)

- Always check the output of `performParallel`. It may contain error messages from slaves.
- Check the behavior of your program in XPVM.
- Be aware of the total load of the system!!! (`mosmon`)
  - There are other people using it.
  - No performance gain by adding slaves if no. of processes $>$ no. of processors.

Example 1

Estimation of fractal dimension (via variogram) of time series of size n repeated r times.

$n = 50000$, $r = 100$

Code at www.stat.washington.edu/hana/code/example1.R

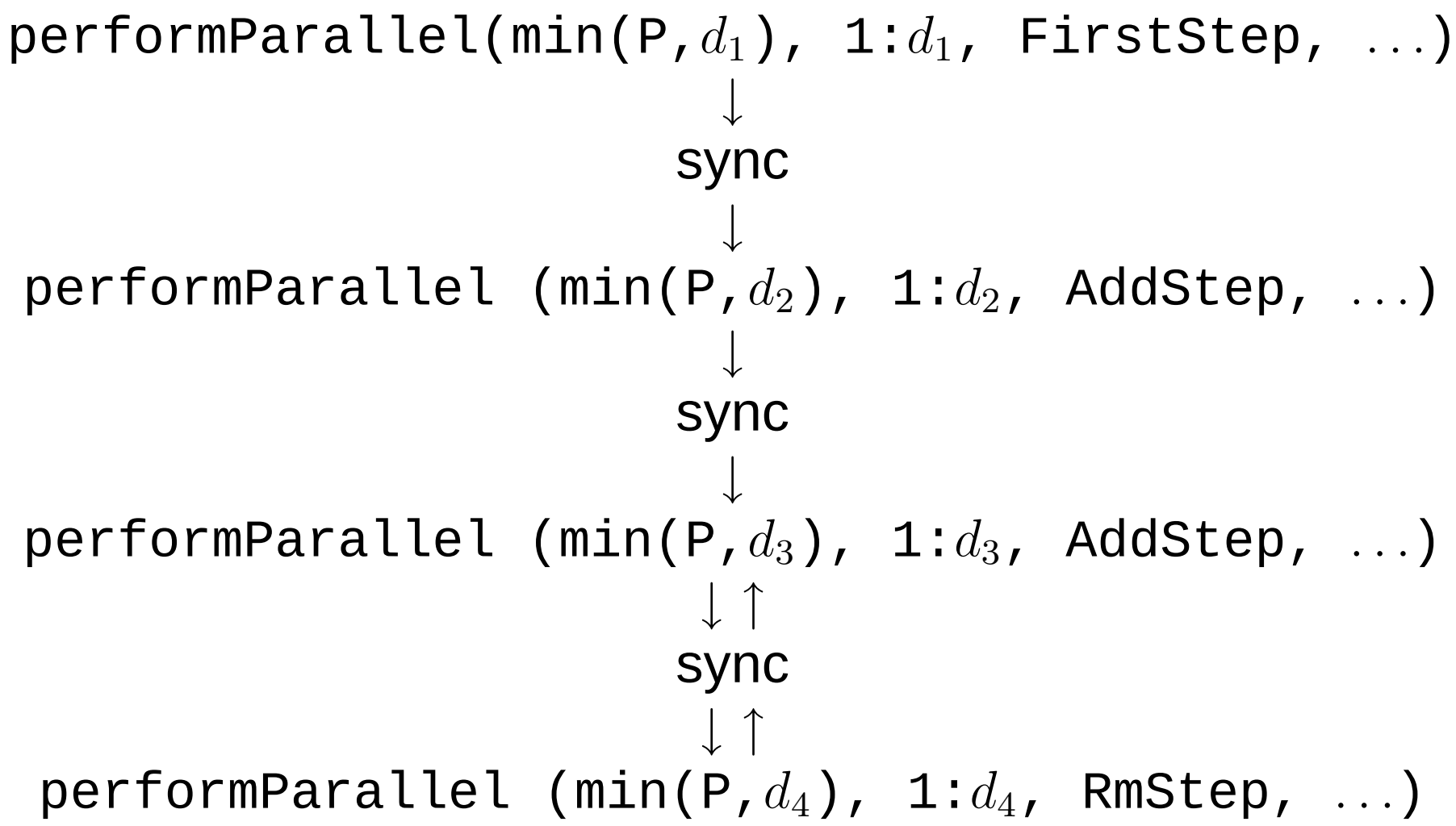
Sequential version:	$142.2s$
Parallel version (6 processors):	$29.0s$
Speedup:	4.9

Example 2

Variable selection for model-based clustering (Nema Dean).

1. First step: Select the best variable in terms of univariate clustering.
   $\Rightarrow$ Run `EMclust` for $i = 1, \ldots, d_1$.
2. Second step: Select the best variable in terms of bivariate clustering.
   $\Rightarrow$ Run `EMclust` for $i = 1, \ldots, d_2$.
3. Iterate:
   (a) Addition step: Propose a variable for adding.
   $\Rightarrow$ Run `EMclust` for $i = 1, \ldots, d_3$.
   (b) Removal step: Propose a variable for removal.
   $\Rightarrow$ Run `EMclust` for $i = 1, \ldots, d_4$.

Example 2 (cont.)



Example 2 (cont.)

Data with 15 variables:

$d_1 = 15 \rightarrow d_2 = 14 \rightarrow d_3 = 13 \rightarrow d_4 = 2 \rightarrow$ stop

Sequential version:	$418.8s$
Parallel version (6 processors):	$90.0s$
Speedup:	4.7

Code at www.stat.washington.edu/hana/code/example2.R

Conclusions

Parallel programming in R is VERY EASY !!!