

Efficient R Parallel Loops on Long-Latency Platforms

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Interface 2012
Rice University, May, 2012

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how to make this fast in R?

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Major point: time(task i) \searrow in i, thus issue of load balancing.

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- Discussion of a possible algorithmic shortcut.

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- However, most are for shared-memory machines, in which the overhead (task queue access latency) is low.
- Some work for the long-latency case, e.g. (Yang and Chang, 2011), but limited.

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Bottom line: R typically needs larger applications, compared to C, in order to yield a “win.”

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- above are options in the shared-memory system OpenMP

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 - **guided** option in OpenMP

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$$\frac{\sqrt{(1 - \frac{c}{ni})c\sigma^2}}{c\mu} \rightarrow 0 \text{ as } c \rightarrow \infty$$

- Etc.

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- So, total task time \approx constant across processes, i.e. have load balance.

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- both limited to a fixed chunk size of 1
- chunk size > 1 must be programmed with user's own code

Code for All Possible Regressions

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```
1 prsnow <- function(cls ,x,y,k,  
2   rnd=F,chunk=NULL,dyn=F) {  
3   p <- ncol(x); allc <<- genallcombs(p,k)  
4   if (rnd) allc <- randperm(allc)  
5   ni <<- nrow(allc); np <- length(cls))  
6   if (is.null(chunk)) chunk <- floor(ni/np))  
7   chunk <<- chunk  
8   clusterExport(cls ,c(" allc " ," ni " ," chunk " ," x"  
9   clusterExport(cls ," do1pset")  
10  is <- seq(1,ni,chunk)  
11  if (!dyn) { ar2s <<-  
12    clusterApply(cls ,is ,dochunk)  
13  } else { ar2s <<-  
14    clusterApplyLB(cls ,is ,dochunk)  
15  }  
16 }
```

Code, cont'd.

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```
1  dochunk <- function(psetchunk) {
2    lasttask <- min(psetchunk+chunk-1,nc)
3    out <- NULL
4    for (tasknum in psetchunk:lasttask) {
5      out <- c(out,do1pset(tasknum))
6    }
7    return(out)
8  }
9
10 do1pset <- function(pset) {
11   onerow <- allcombs[pset,]
12   nps <- onerow[1]
13   ps <- onerow[2:(1+nps)]
14   slm <- summary(lm(y ~ x[,ps]))
15   return(Reduce(paste,c(slm$adj.
16     r.squared,myinfo$id,onerow[-1])))
17 }
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- **rnd:** Use random scheduling. Default value is False.

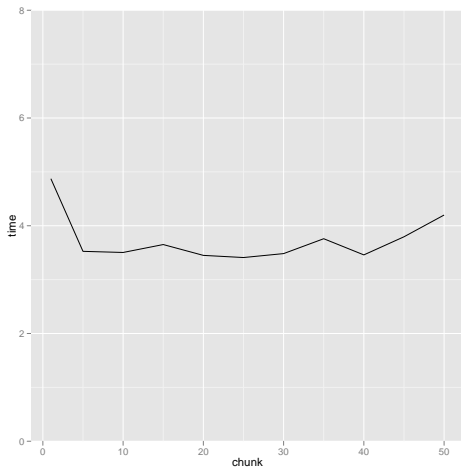
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- 10,000
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- $k = 4$ (i.e.
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- 2 procs.,
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- chunk sizes
1,5,10,...,50;
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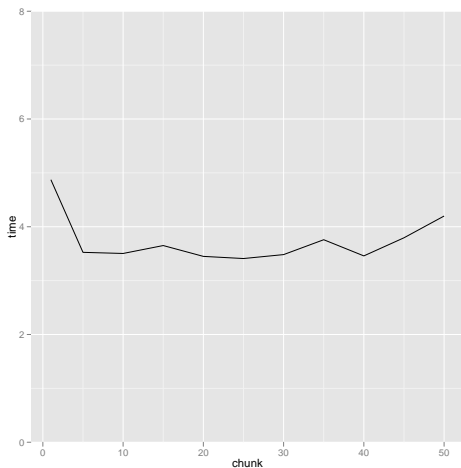
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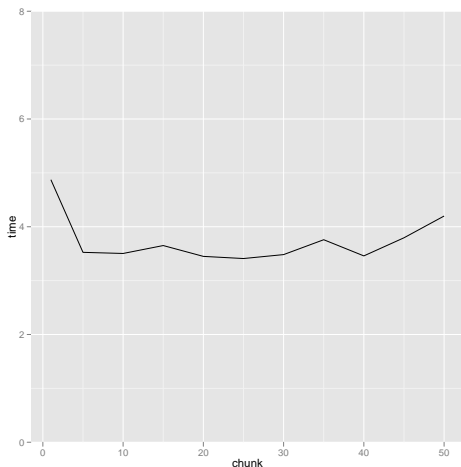
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Chunks too large \Rightarrow load balance problem.

Network Platform

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Same setting, but on a network platform.

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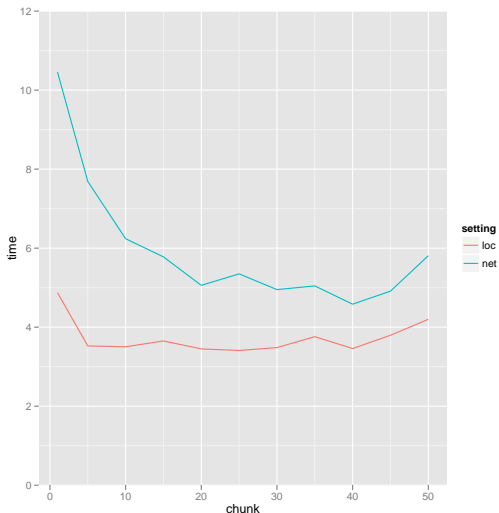
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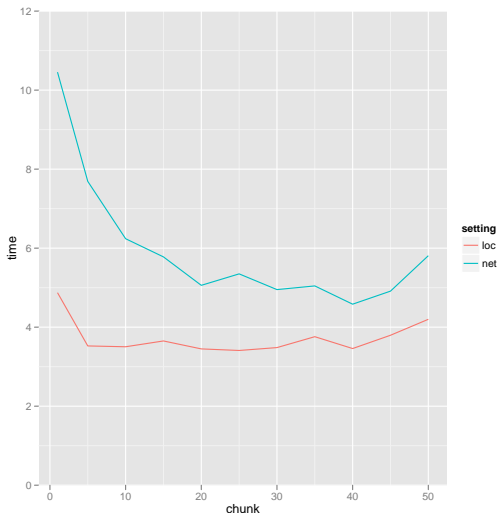
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Again, random method only asymp. optimal, but good choice if don't want to spend time tweaking the chunk size.

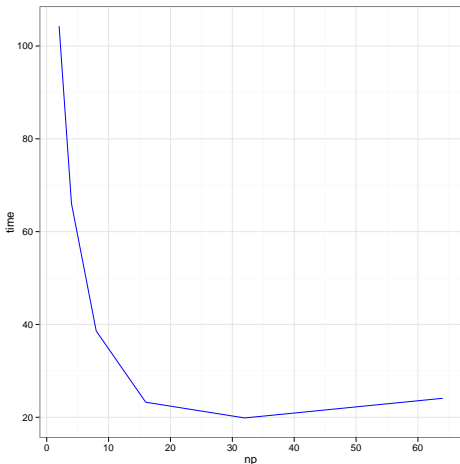
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- Random sched.
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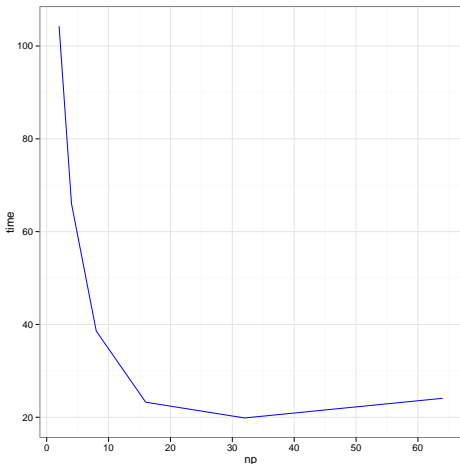
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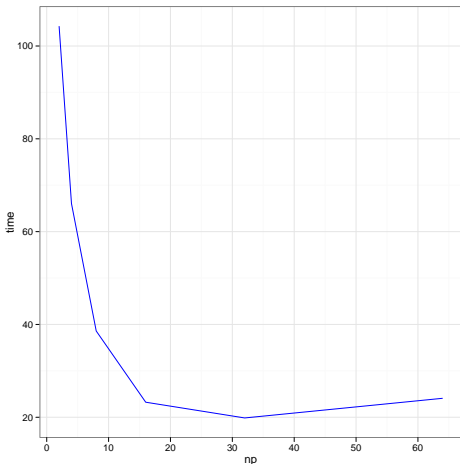
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Overhead \Rightarrow diminishing returns

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Overhead \Rightarrow diminishing returns—eventually negative.

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- Scheduling may be rather intricate.

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Slides available at

<http://heather.cs.ucdavis.edu/RiceSlides.pdf>

To learn about parallel programming, see my open source book
at <http://heather.cs.ucdavis.edu/parprocbook>.