Efficient R Parallel Loops on Long-Latency Platforms

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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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- Proposal of a new loop scheduling method, shown "optimal."
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- Discussion of a possible algorithmic shortcut.

Research Literature

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- 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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  - **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 obs., 8 predictors
- k = 4 (i.e. up to 4 preds.)
- 2 procs., same machine
- chunk sizes 1,5,10,...,50; 5 reps. each

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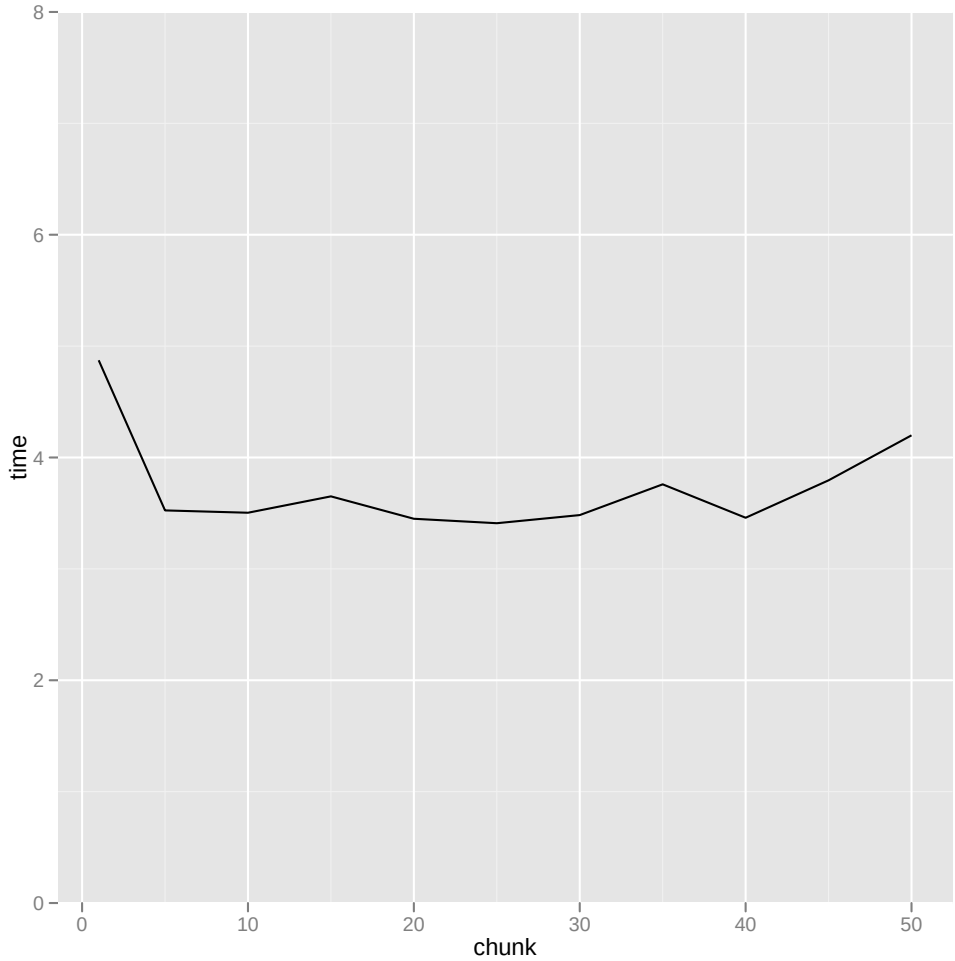

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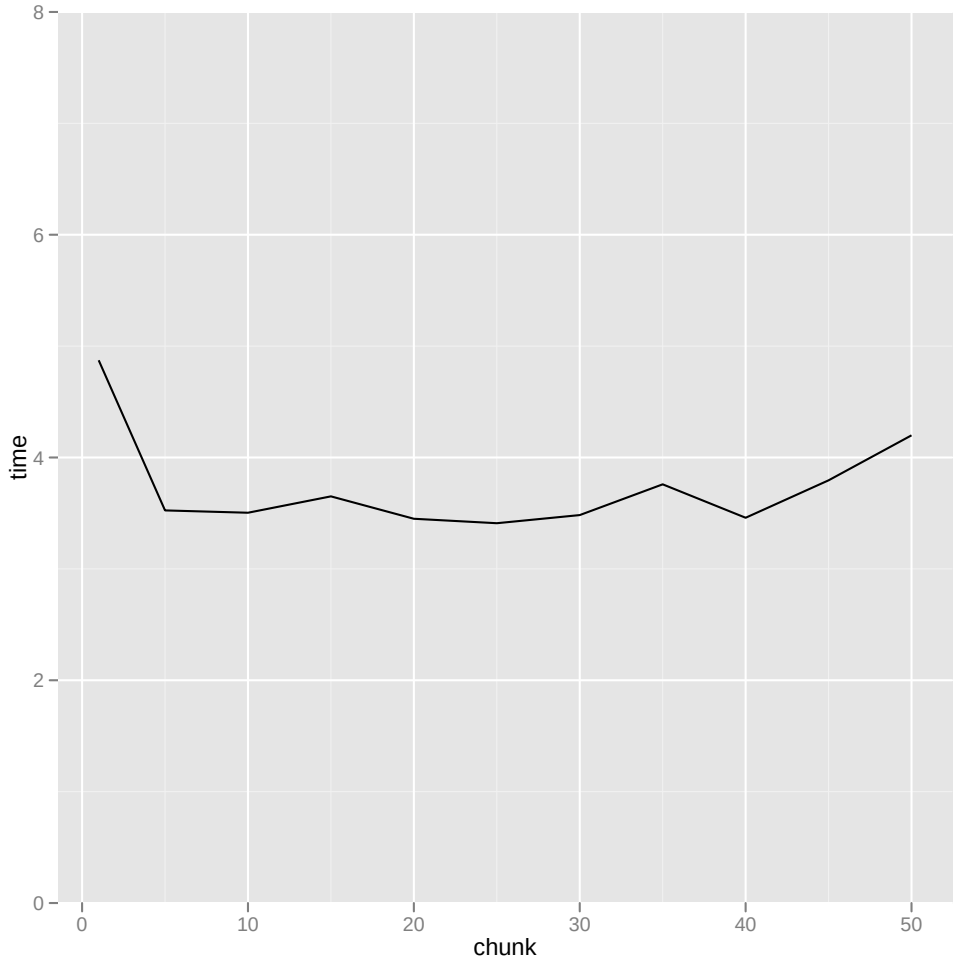

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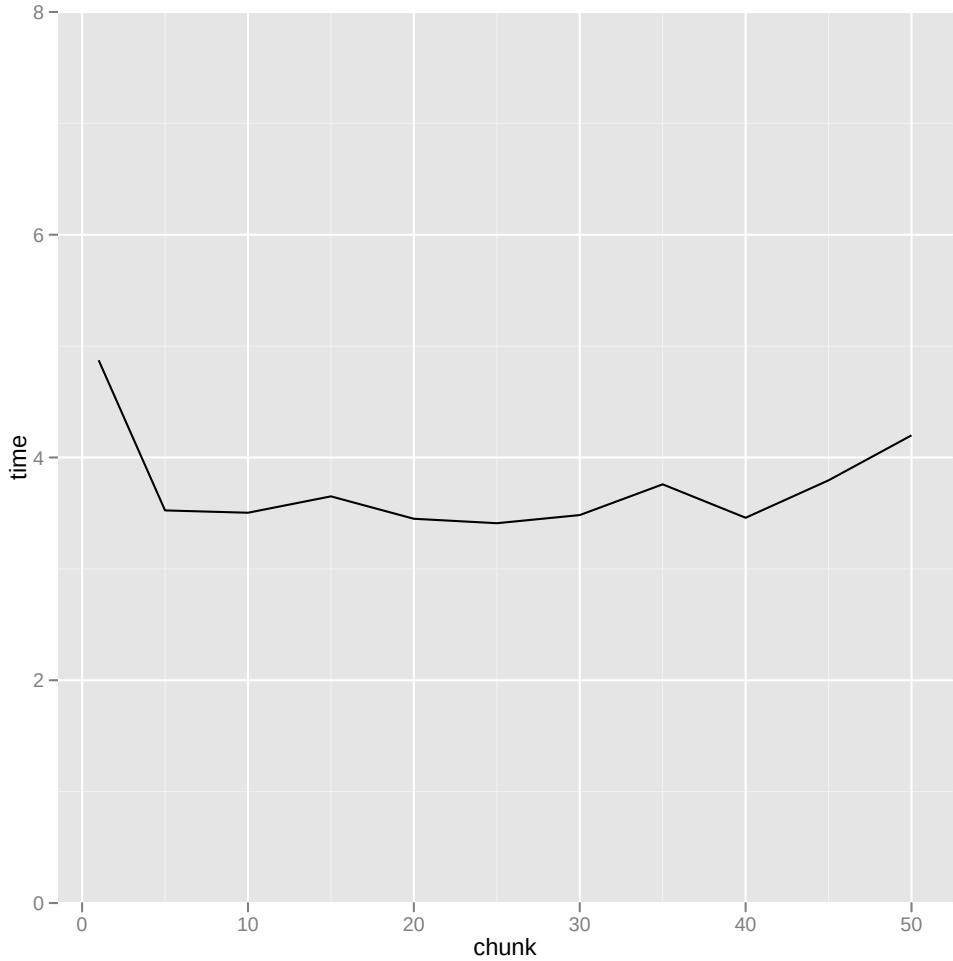

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Chunks too large ⇒ load balance problem.

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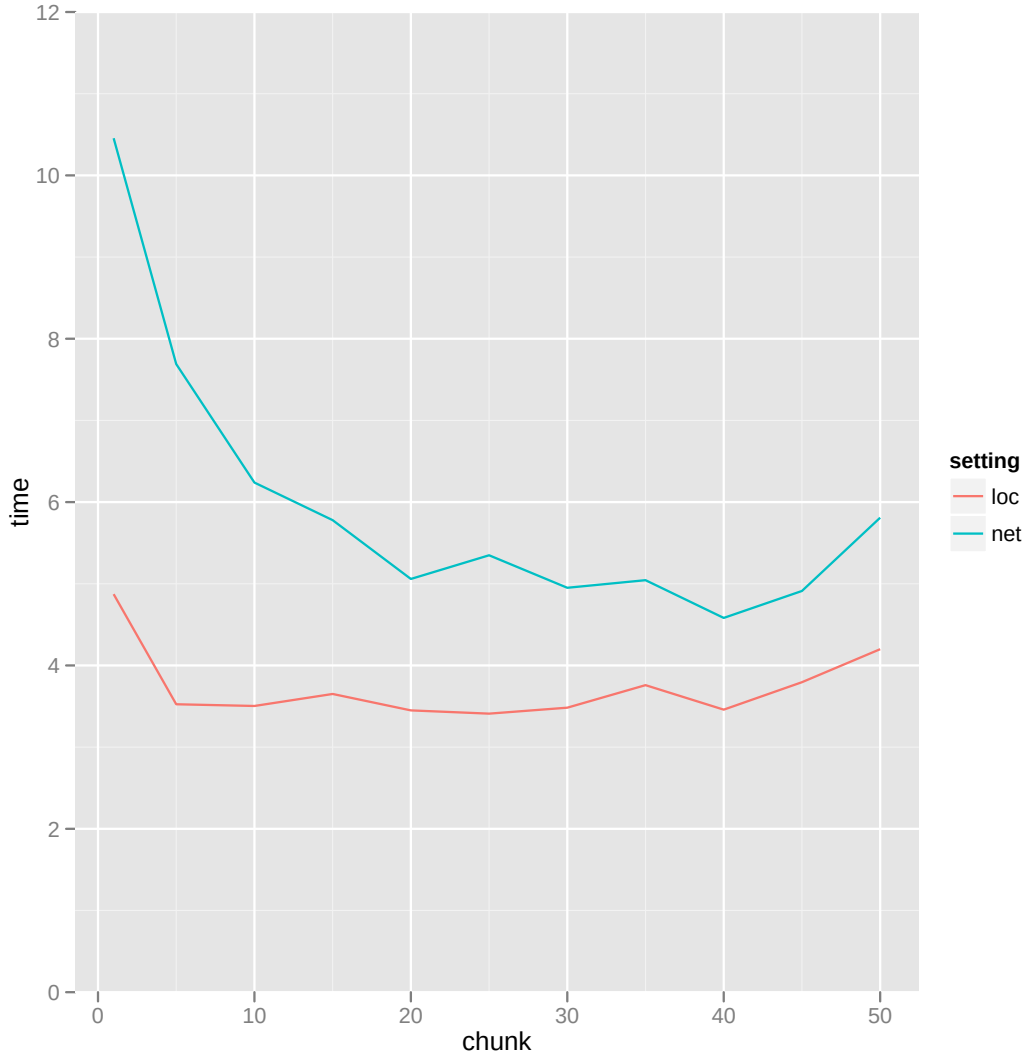

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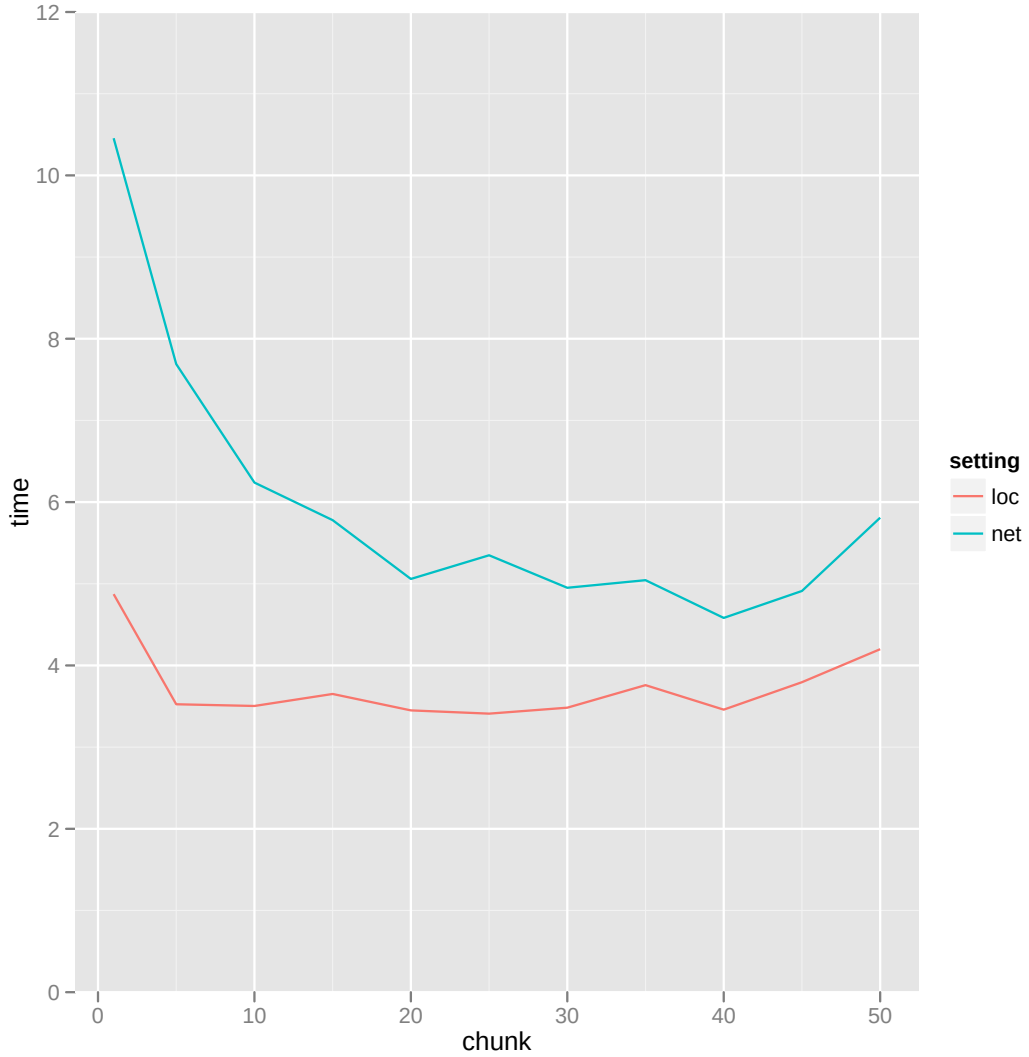

Impact of choice of chunk size more dramatic here.

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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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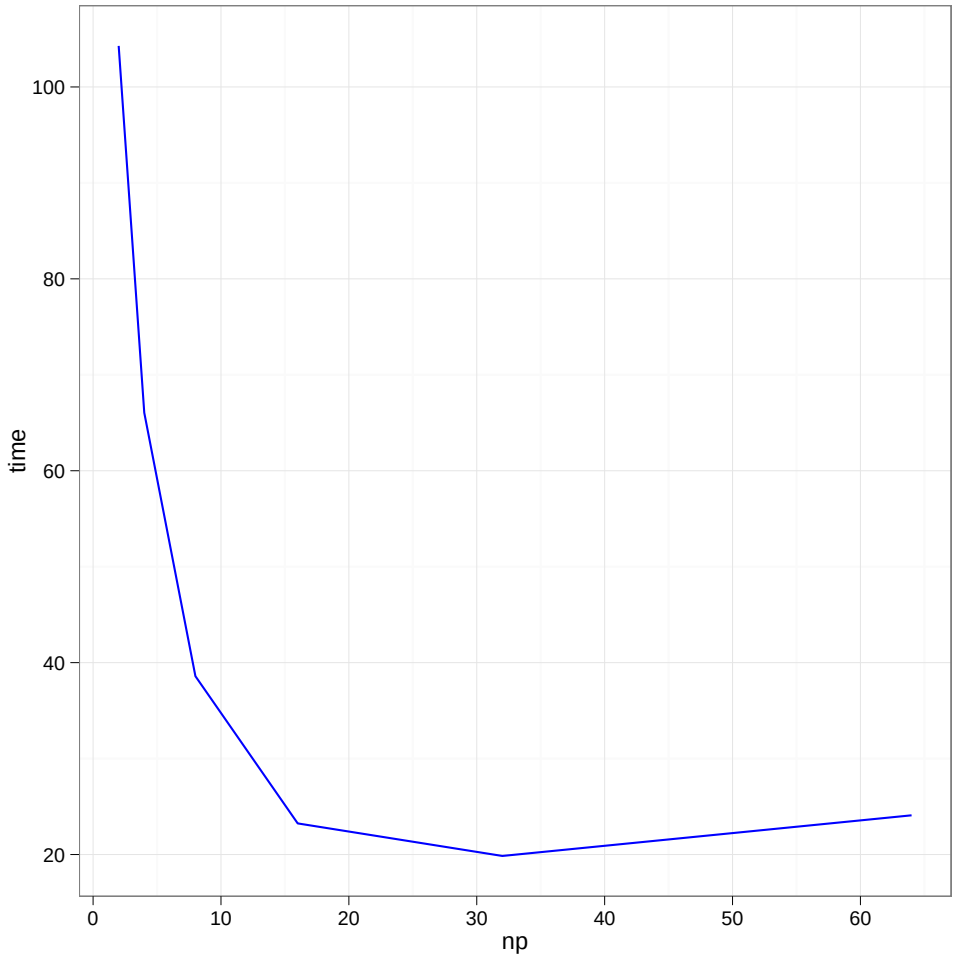

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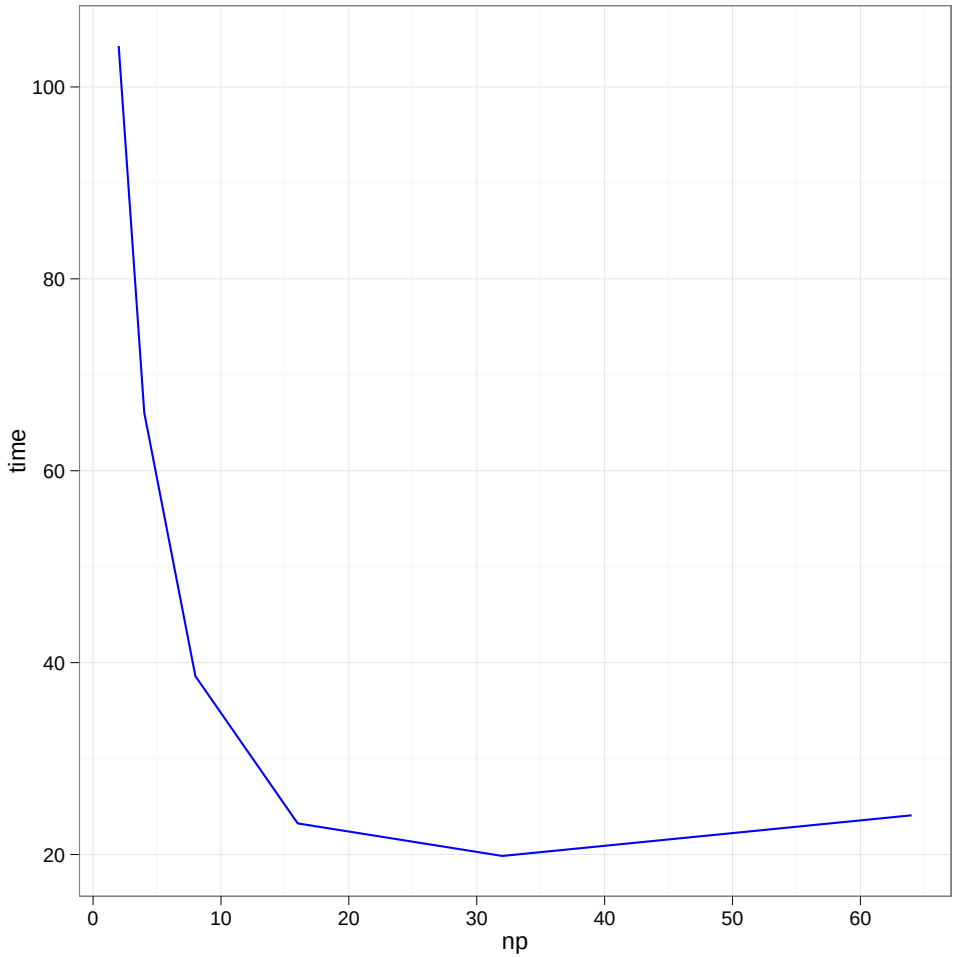

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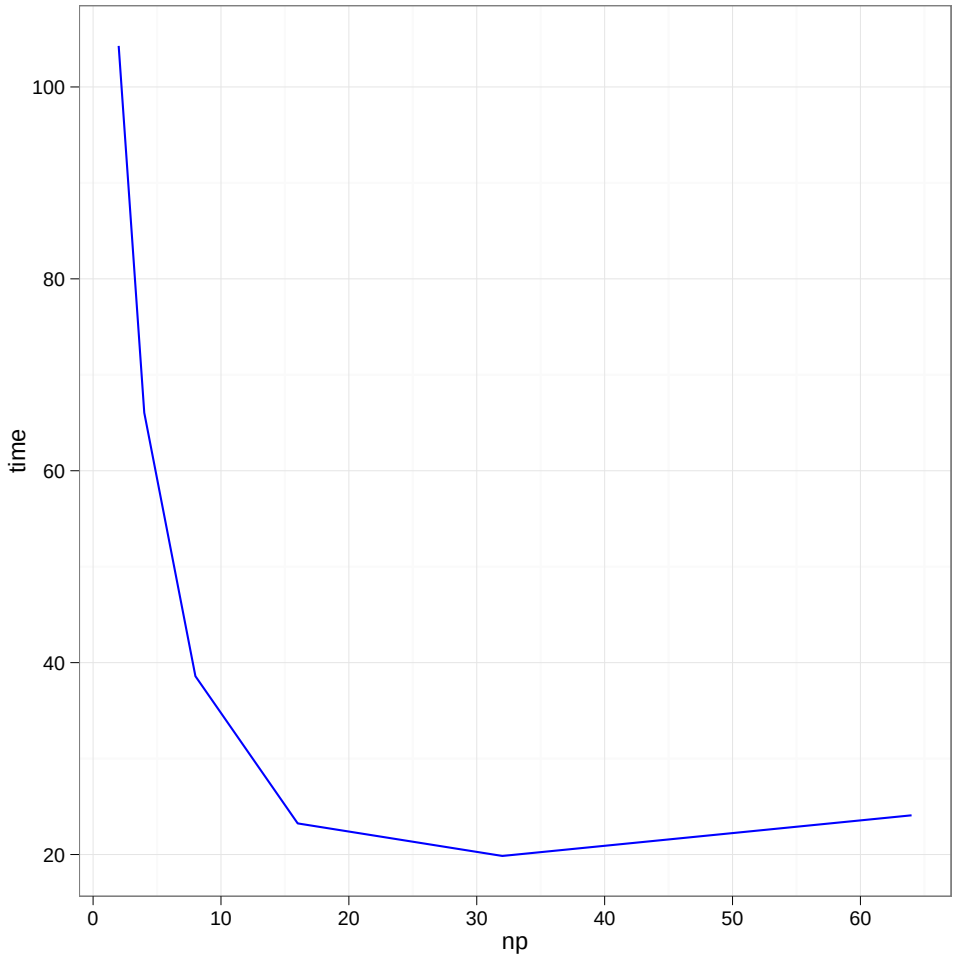

Overhead ⇒ diminishing returns—eventually negative.

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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`.