

Cluster basics

PARALLEL PROGRAMMING IN R

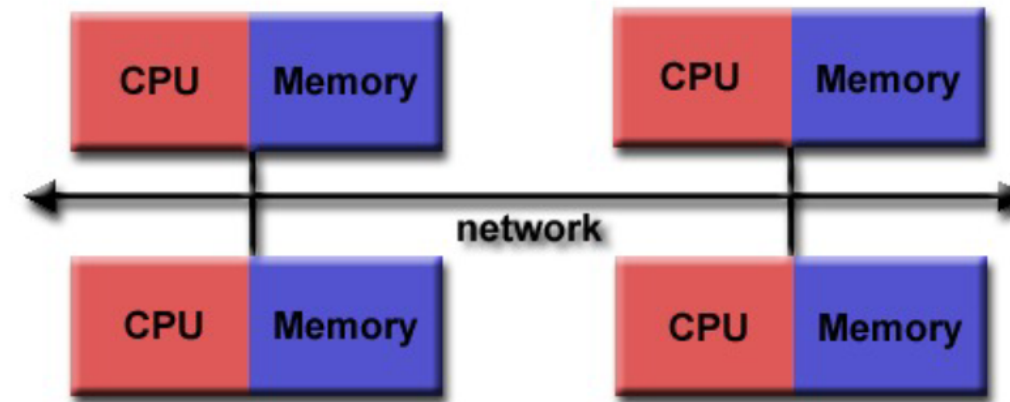


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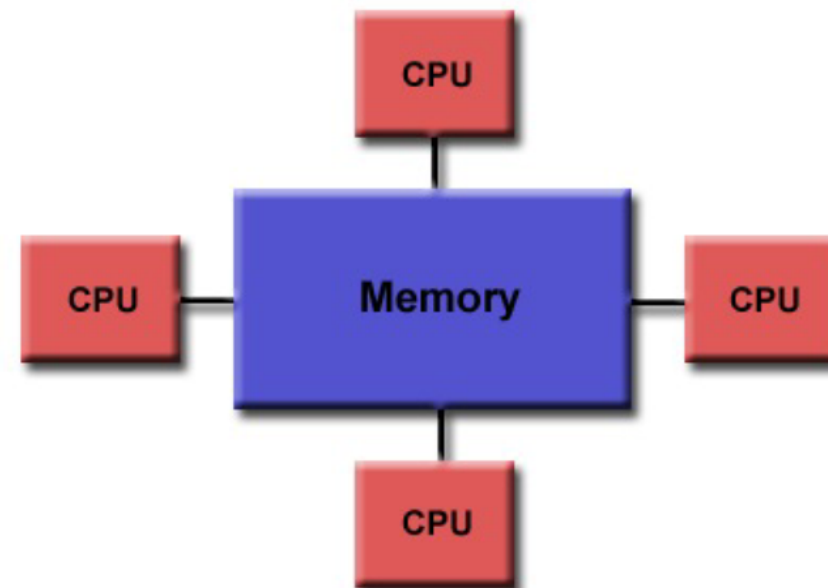
parallel

snow
(L. Tierney et al)



all OS

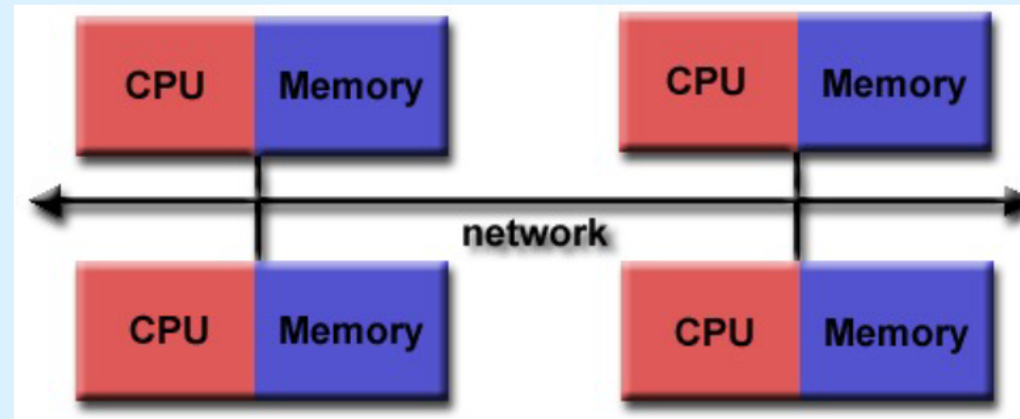
multicore
(S. Urbanek)



all OS
except Windows

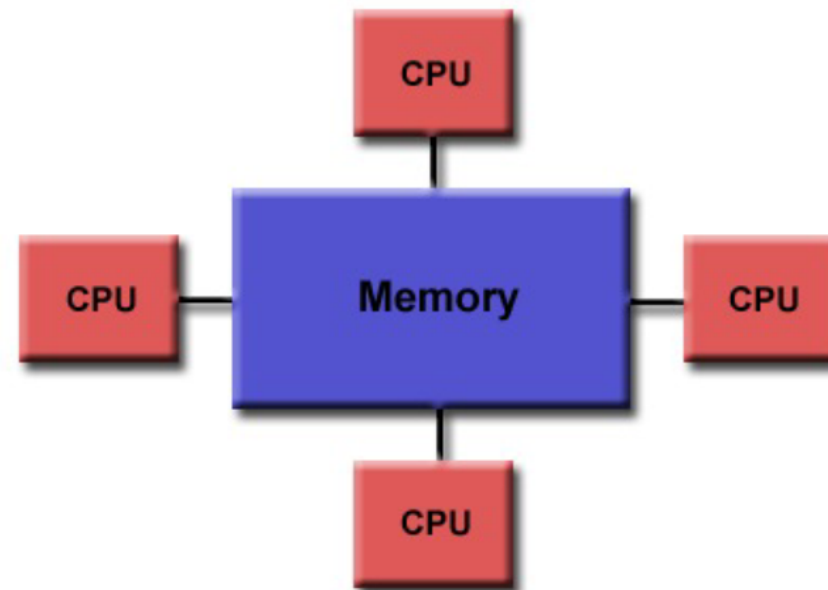
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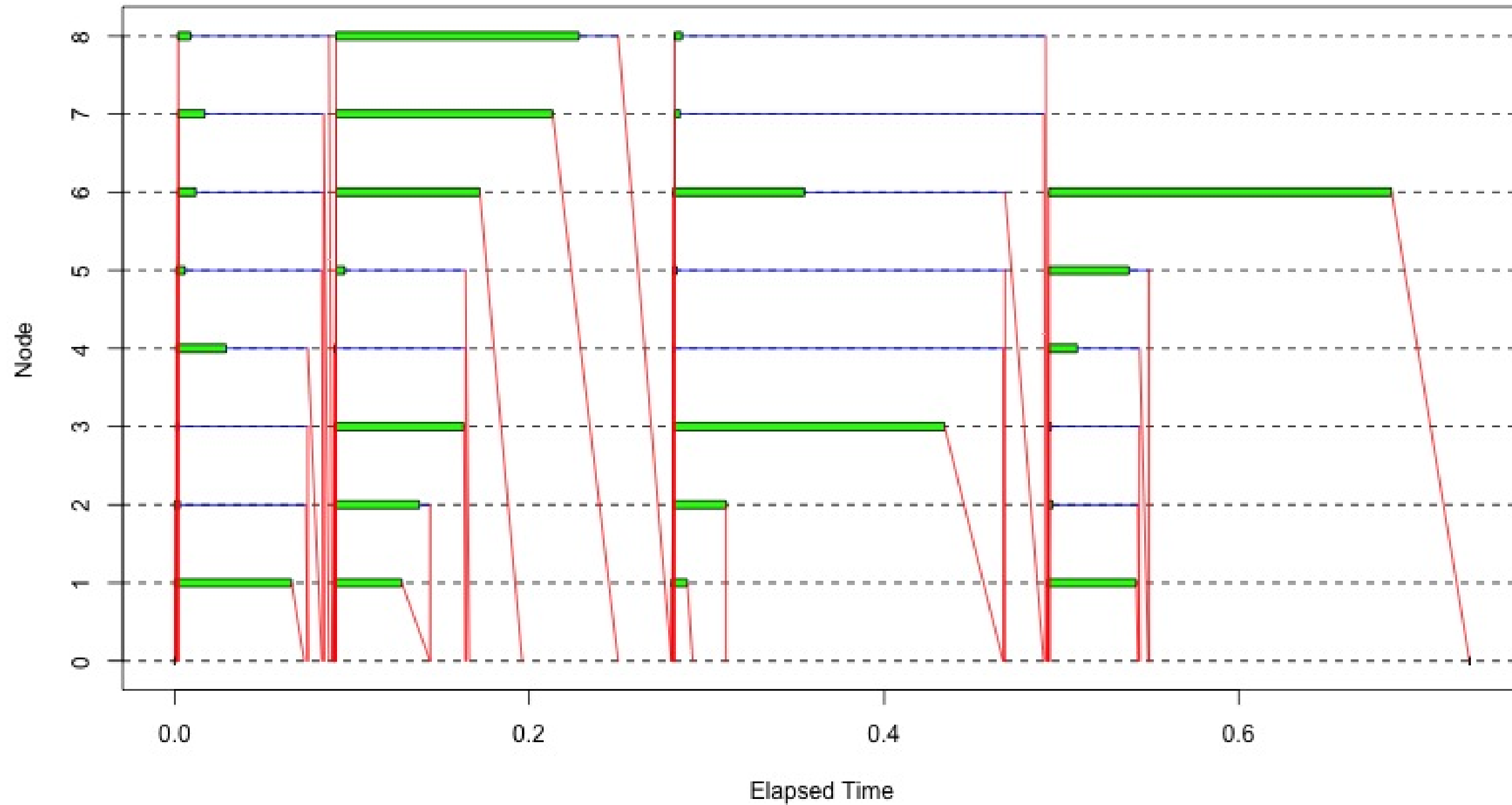
all OS

multicore
(S. Urbanek)



all OS
except Windows
mclapply, mcmapply,
mcMap

Usage with clusterApply



Supported backends

Socket communication (default, all OS platforms)

```
cl <- makeCluster(ncores, type = "PSOCK")
```

- Workers start with an empty environment (i.e. new R process).

Supported backends

Forking (not available for Windows)

```
cl <- makeCluster(ncores, type = "FORK")
```

- Workers are complete copies of the master process.

Supported backends

Using the **MPI** library (uses Rmpi)

```
cl <- makeCluster(ncores, type = "MPI")
```

Let's practice!
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The core of parallel

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Core functions

Main processing functions:

- `clusterApply()`
- `clusterApplyLB()`

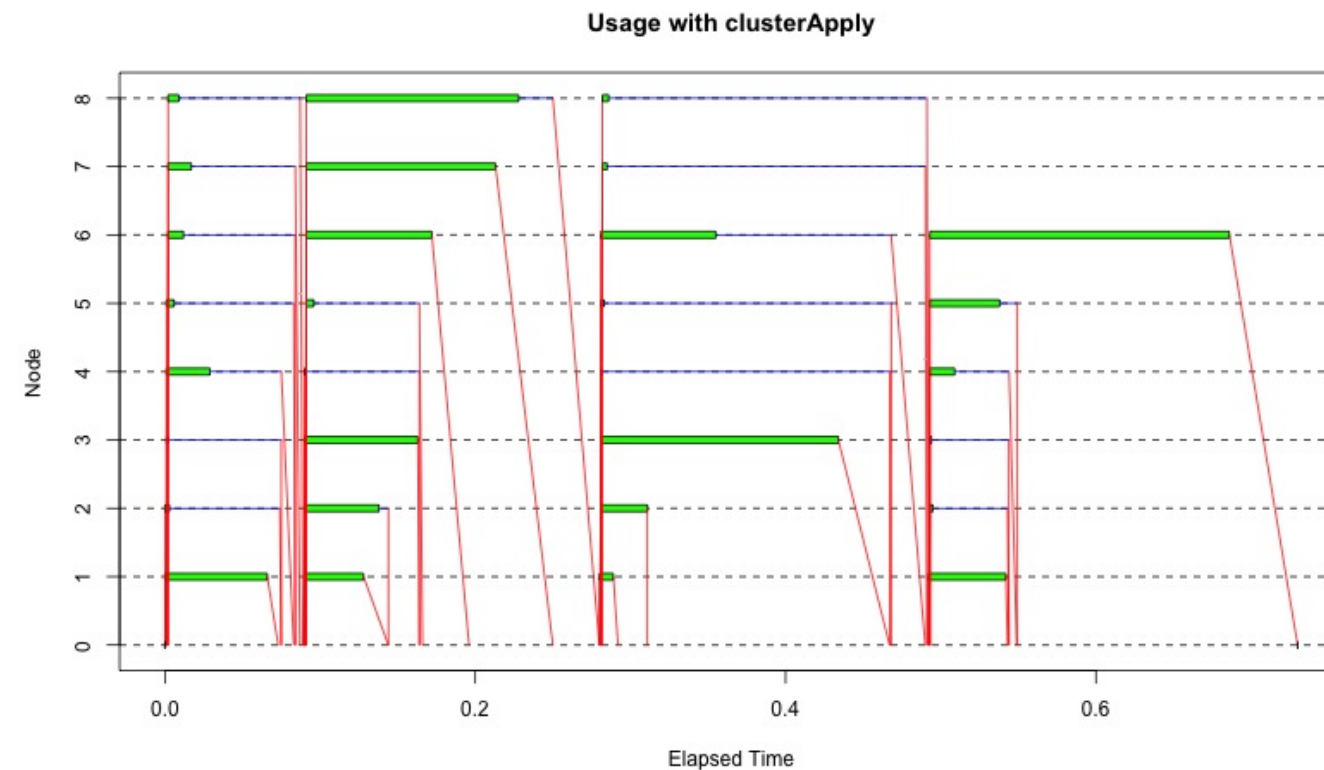
Wrappers:

- `parApply()` , `parLapply()` , `parSapply()`
- `parRapply()` , `parCapply()`
- `parLapplyLB()` , `parSapplyLB()`

clusterApply(): Number of tasks

```
clusterApply(cl, x = arg.sequence, fun = myfunc)
```

`length(arg.sequence)` = number of tasks (green bars)



Parallel vs. sequential

Not all embarrassingly parallel applications are suited for parallel processing.

Processing overhead:

- Starting/stopping cluster
- Number of messages sent between nodes and master
- Size of messages (sending big data is expensive)

Things to consider:

- How big is a single task (green bar)
- How much data need to be sent
- How much gain is there by running it in parallel → **benchmark**

Let's practice!
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Initialization of nodes

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Why initialize?

- Each cluster node starts with an empty environment (no libraries loaded).
- Repeated communication with the master is expensive.
- Example:

```
clusterApply(cl, rep(1000, n), rnorm, sd = 1:1000)
```

- Master sends a vector of `1:1000` to all `n` tasks (`n` can be very large).
- Good practice: Master initializes workers at the beginning with everything that stays constant or/and is time consuming. Examples:
 - Sending static data
 - Loading libraries
 - Evaluating global functions

clusterCall()

- Evaluates the same function with the same arguments on all nodes.

Example:

```
cl <- makeCluster(2)
clusterCall(cl, function() library(jane austenr))
clusterCall(cl, function(i) emma[i], 20)
```

```
[[1]]
[1] "She was the youngest of the two daughters of a most affectionate,"

[[2]]
[1] "She was the youngest of the two daughters of a most affectionate,"
```


clusterEvalQ()

- Evaluates a literal expression on all nodes (equivalent to `evalq()`)

Example:

```
cl <- makeCluster(2)
clusterEvalQ(cl, {library(janeaustenr)
                  library(stringr)
                  get_books <- function() austen_books()$book %>% unique %>% as.character })
clusterCall(cl, function(i) get_books()[i], 1:3)
```

```
[[1]]
[1] "Sense & Sensibility" "Pride & Prejudice"   "Mansfield Park"

[[2]]
[1] "Sense & Sensibility" "Pride & Prejudice"   "Mansfield Park"
```

clusterExport()

- Exports given objects from master to workers.

Example:

```
books <- get_books()
cl <- makeCluster(2)
clusterExport(cl, "books")
clusterCall(cl, function() print(books))
```

```
[[1]]
[1] "Sense & Sensibility" "Pride & Prejudice"  "Mansfield Park"
[4] "Emma"                "Northanger Abbey"  "Persuasion"

[[2]]
[1] "Sense & Sensibility" "Pride & Prejudice"  "Mansfield Park"
[4] "Emma"                "Northanger Abbey"  "Persuasion"
```

Let's practice!
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Subsetting data

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Data chunks

- Each task applied to different data (data chunk)
- Data chunks are passed to workers as follows:
 1. Random numbers generated on the fly
 2. Passing chunks of data as argument
 3. Chunking on workers' side

Data chunk as random numbers

```
myfunc <- function(n, ...) mean(rnorm(n, ...))  
  
clusterApply(cl, rep(1000, 20), myfunc, sd = 6)
```

Data chunk as argument (1)

- Dataset is chunked into several blocks on master
- Each block passed to worker via an argument
- Incorporated into higher level functions (`parApply()` etc)

```
cl <- makeCluster(4)
mat <- matrix(rnorm(12), ncol=4)
```

```
      [,1]      [,2]      [,3]      [,4]
[1,]  1.1540263 -2.180922  0.5322614  0.5578128
[2,] -1.8763588 -1.625226  0.4058091 -0.5532732
[3,] -0.1685597 -1.089104  0.1770636  0.5483025
```

Data chunk as argument (2)

Sum of columns (`colSums(mat)`):

```
parCapply(cl, mat, sum)
unlist(clusterApply(cl, as.data.frame(mat), sum))
```

- Sends each worker a column of `mat`

Chunking on workers' end

Example of matrix multiplication $M \times M$:

```
n <- 100  
M <- matrix(rnorm(n * n), ncol = n)  
clusterExport(cl, "M")
```

```
mult_row <- function(id) apply(M, 2, function(col) sum(M[id,] * col))
```

```
clusterApply(cl, 1:n, mult_row) %>% do.call(rbind, .)
```

Let's practice!
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