

# pbdR: Input, PCA, and Movies

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# The pbdR Core Team

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# Contents

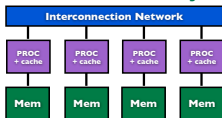
- 1 Hardware and Software Landscape
- 2 Data Input
- 3 Principal Components Analysis For Spatio-Temporal Data
- 4 Plot Ensembles in Parallel
- 5 Rearranging ddmatrix Data

# Contents

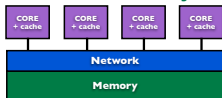
- 1 Hardware and Software Landscape
  - Quick Overview of Parallel Hardware
  - A Quick Overview of Parallel Software
  - pbdR Connects R to HPC Libraries

## Three Basic Flavors of Hardware

### Distributed Memory



### Shared Memory



### Co-Processor

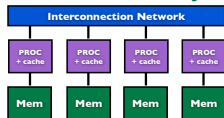


GPU: Graphical Processing Unit

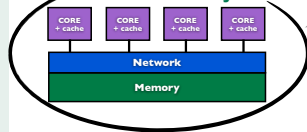
MIC: Many Integrated Core

## Your Laptop or Desktop

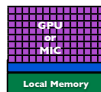
### Distributed Memory



### Shared Memory



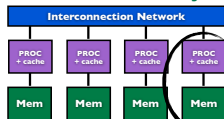
### Co-Processor



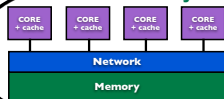
GPU: Graphical Processing Unit  
MIC: Many Integrated Core

## A Server or Cluster

### Distributed Memory



### Shared Memory



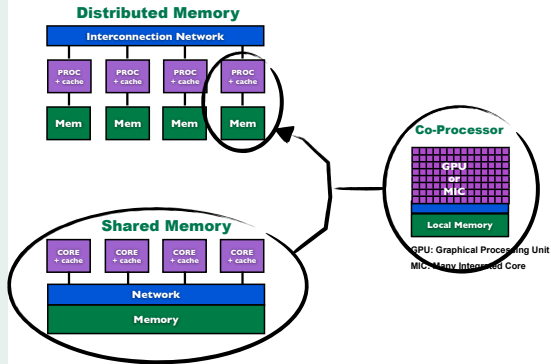
### Co-Processor



GPU: Graphical Processing Unit  
MIC: Many Integrated Core

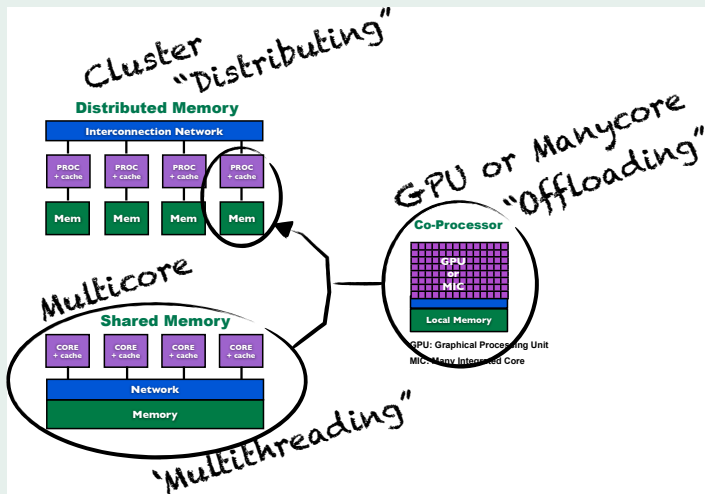
## Quick Overview of Parallel Hardware

## Server to Supercomputer

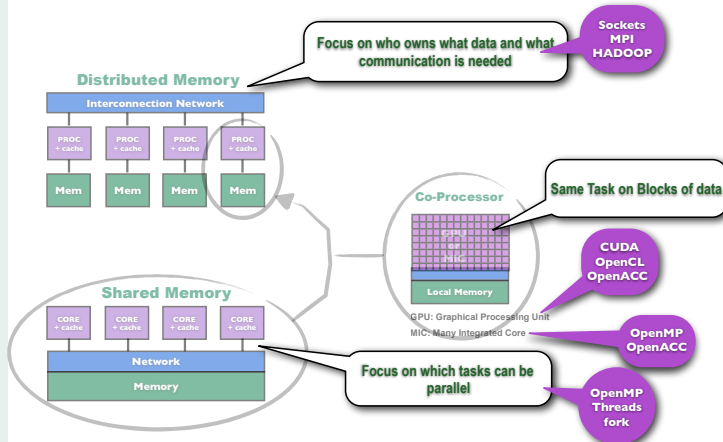




## Knowing the Right Words

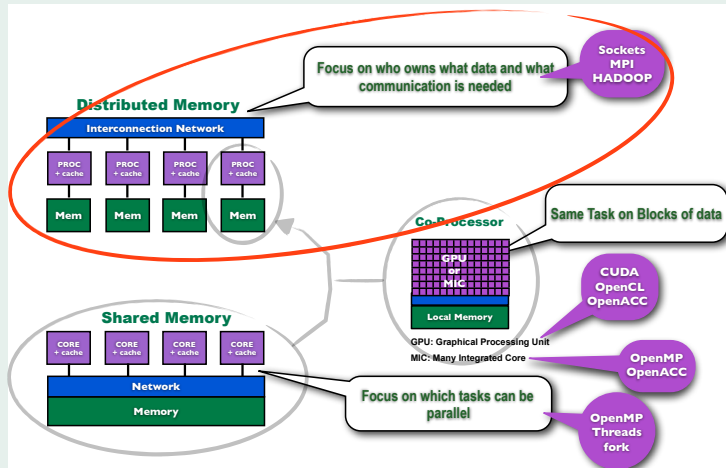


## “Native” Programming Models and Tools

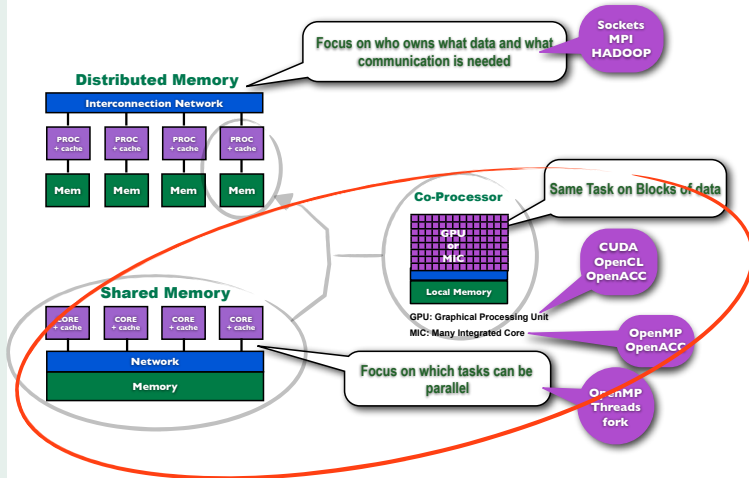


## A Quick Overview of Parallel Software

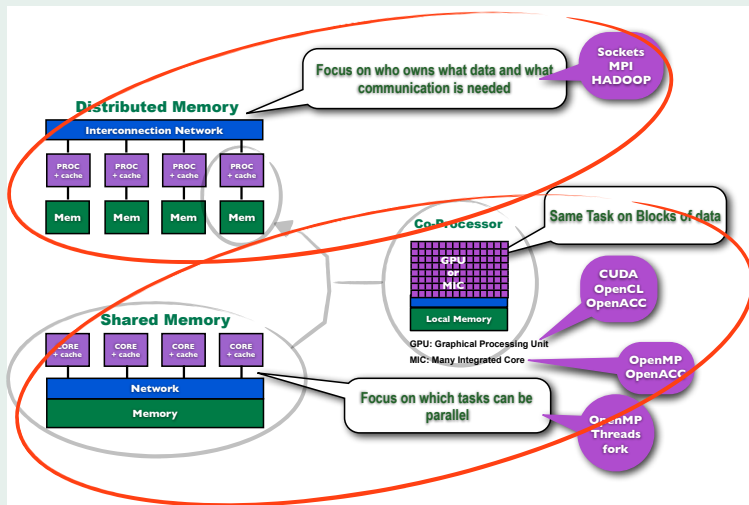
## 30+ Years of Parallel Computing Research



## Last 10 years of Advances

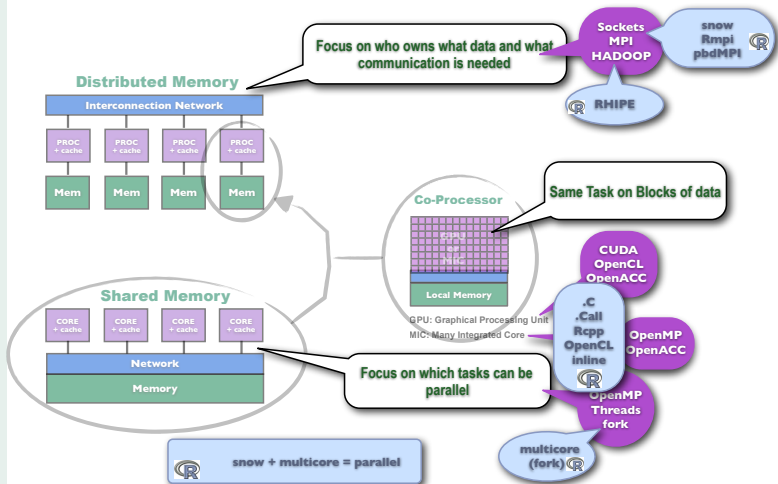


## Putting It All Together Challenge

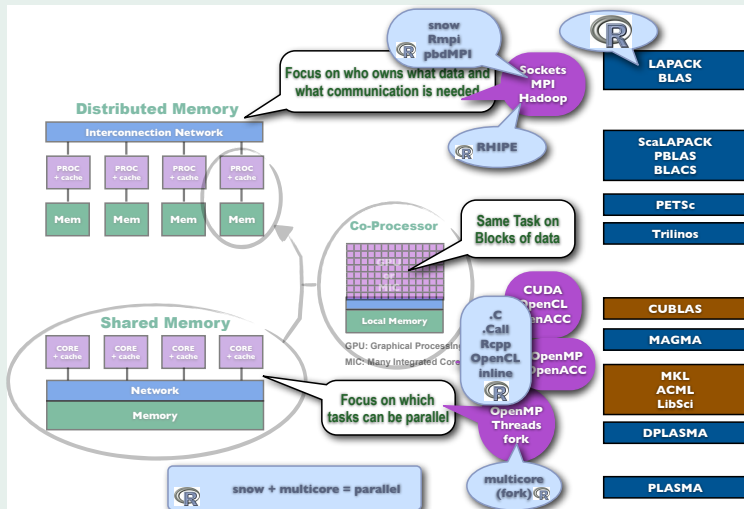


## A Quick Overview of Parallel Software

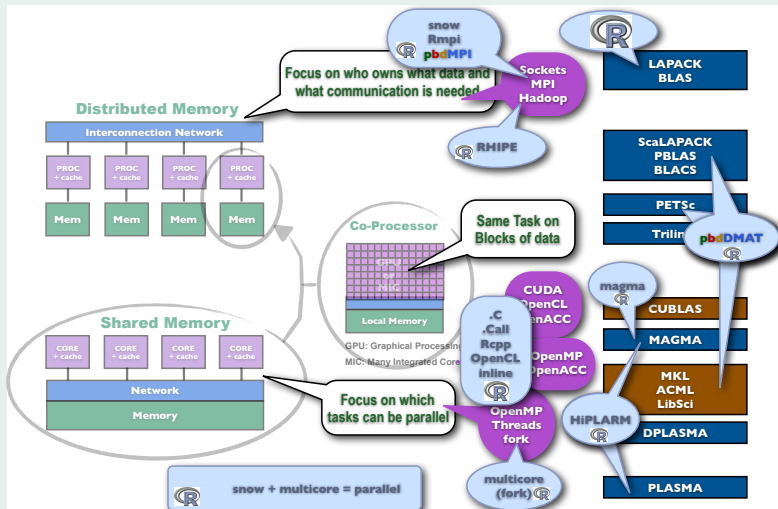
## R Interfaces to Native Tools



# HPC Libraries

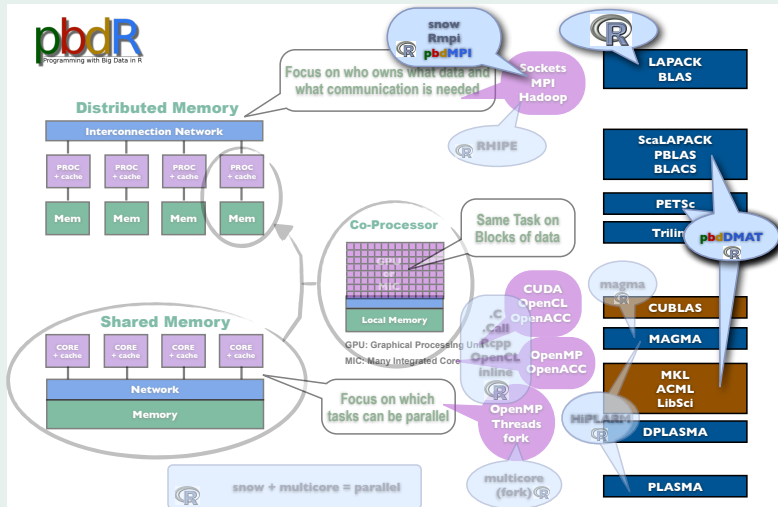


## R Interfaces to Scalable HPC Libraries





## pbdR Interfaces to Scalable HPC Libraries



# Contents

- 2 Data Input
  - Serial Data Input
  - Parallel Data Input

## Serial Data Input

I/O has a separate manual: <http://r-project.org/>

- `scan()`
- `read.table()`
- `read.csv()`
- ...
- `readBin()`
- `ncvar_get()`
- `readSocket()`

## No parallel file system: Read Serial then Distribute

read.csv()

```
1 library(pbdDMAT)
2 if(comm.rank() == 0) { # only read on process 0
3   x <- read.csv("myfile.csv")
4 } else {
5   x <- NULL
6 }
7
8 dx <- as.ddmatrix(x)
```

## New Issues

- How to read in parallel?
- CSV, SQL, NetCDF4, HDF, ADIOS, custom binary
- How to partition data across nodes?
- How to structure for scalable libraries?
- Read directly into form needed or restructure?
- ...
- Currently very “hands on”
- A lot of work needed here!

## CSV Data

### Serial Code

```
1 d <- read.csv('x.csv')
```

### Parallel Code 0\_readcsv.r

```
1 library(pbdDEMO, quiet = TRUE)
2 init.grid()
3 dx <- read.csv.ddmatrix("x.csv", header=TRUE,
4     sep=',', nrow=10, ncol=10,
5     num.rdrs=2, ICTXT=0)
6 comm.print(dx)
7 finalize()
```

## NetCDF4 Data

### Parallel Read

```
1 ### Must determine who will read what portion(s) and how  
  to assemble them before reading  
2  
3 ### parallel read after determining st and co  
4 nc <- nc_open_par(file.name)  
5  
6 nc_var_par_access(nc, "TREFHT")  
7 new.X.gbdc <- ncvar_get(nc, "TREFHT", start = st, count  
  = co)  
8 nc_close(nc)  
9  
10 finalize()
```



## Parallel Data Input

## Binary Data

## Read subcube

```

1 library(pbdDMAT, quiet = TRUE)
2 init.grid()
3
4 data.dim <- c(2048, 2048, 2048) # full data dimension
5 g.start <- c(1, 1, 513)        # global subcube corner
6 g.dim <- c(64, 64, 1024)       # global subcube extent
7
8 my.start <- g.start + c(0, 0, comm.rank()*my.dim[3])
9 my.dim <- g.dim / c(1, 1, comm.size())
10
11 size <- 4 # file is single precision floats
12
13 vx <- block3d.read('filename', data.dim, my.start,
14                   my.dim, size)
15
16 ## local reshape dimensions
17 my.nrow <- prod(my.dim[1:2])
18 my.ncol <- my.dim[3]
19 ldim <- c(my.nrow, my.ncol)
20
21 ## global reshape dimensions
22 g.nrow <- prod(g.dim[1:2])
23 g.ncol <- g.dim[3]
24 gdim <- c(g.nrow, g.ncol)
25
26 ## reshape local
27 X <- matrix(vx, nrow=my.nrow, ncol=my.ncol, byrow=FALSE)
28
29 ## glue local pieces into a ddmatrix
30 X <- new("ddmatrix", Data=X, dim=gdim, ldim=ldim,
31         bldim=ldim, ICTXT=1)
32
33 ## transform to 2d block cyclic
34 X <- redistribute(X, bldim=c(8,8), ICTXT=0)

```



## Parallel Data Input

## Binary Data

## 3d Block Binary Reader

```

1 block3d.read <- function(file, data.dim, my.start,
  my.dim, size=4) {
2   con.x <- file(file, "rb", blocking=TRUE)
3
4   start <- sum((my.start - 1) * c(1,
     cumprod(data.dim)[-length(data.dim)]))
5
6   x <- rep(NA, prod(my.dim))
7
8   block <- 1:my.dim[1]
9
10  for(j in 1:my.dim[3]) {
11    sofar <- 0
12    for(i in 1:my.dim[2]) {
13      seek(con.x, where=start, rw="read", origin="start")
14      x[block] <- readBin(con=con.x, what="numeric",
        n=my.dim[1], size=size)
15      block <- block + my.dim[1]
16
17      start <- start + data.dim[1]*size
18      sofar <- sofar + data.dim[1]*size
19    }
20    start <- start - sofar + data.dim[1]*data.dim[2]*size
21  }
22
23  close(con.x)
24  x
25 }

```

# Contents

- 3 Principal Components Analysis For Spatio-Temporal Data
  - Empirical Orthogonal Functions
  - Principal Components Analysis

## The Math

$m \times n$  matrix  $X$ : Measurements on  $n$  spatial locations at  $m$  times

Center the matrix:  $X_c$  is the column centered  $X$

Singular value decomposition:  $X_c = VDU^T$

$n$  time series: columns of  $VD = X_c U$

$m$  images: columns of  $UD = X_c^T V$

Note that  $VD$  and  $UD$  have same units as  $X$

## Empirical Orthogonal Functions in Climate Analysis

- Computation and volume rendering of large-scale EOF coherent modes in rotating turbulent flow data, AGU Fall Meeting, December 2013

## Principal Components Analysis

## Coherent Modes in Turbulent Flow

Get and Redistribute the Data

```

1 library(pbdDMAT, quiet = TRUE)
2 init.grid()
3
4 ## load local data (file assumes 4 processors!)
5 g.dim <- c(64, 64, 1024)
6 my.dim <- g.dim / c(1, 1, comm.size())
7 save.file <- paste("xyz.RData", comm.rank(), sep="") #
8   assumes 4 processors!
9 load(save.file)
10
11 ## reshape 3d array into a matrix for PCA (EOF)
12   computation
13   ## first two dimensions become rows and third becomes
14   columns
15 ## local reshape dimensions
16 my.nrow <- prod(my.dim[1:2])
17 my.ncol <- my.dim[3]
18 ldim <- c(my.nrow, my.ncol)
19
20 ## global reshape dimensions
21 g.nrow <- prod(g.dim[1:2])
22 g.ncol <- g.dim[3]
23 gdim <- c(g.nrow, g.ncol)
24
25 ## now reshape local
26 X <- matrix(vx, nrow=my.nrow, ncol=my.ncol, byrow=FALSE)
27 Y <- matrix(vy, nrow=my.nrow, ncol=my.ncol, byrow=FALSE)
28 Z <- matrix(vz, nrow=my.nrow, ncol=my.ncol, byrow=FALSE)
29
30 ## glue local pieces into a ddmatrix
31 X <- new("ddmatrix", Data=X, dim=gdim, ldim=ldim,
32   bldim=ldim, ICTXT=1)
33 Y <- new("ddmatrix", Data=Y, dim=gdim, ldim=ldim,
34   bldim=ldim, ICTXT=1)
35 Z <- new("ddmatrix", Data=Z, dim=gdim, ldim=ldim,
36   bldim=ldim, ICTXT=1)
37
38 ## transform to 2d block cyclic
39 X <- redistribute(X, bldim=c(8,8), ICTXT=0)
40 Y <- redistribute(Y, bldim=c(8,8), ICTXT=0)
41 Z <- redistribute(Z, bldim=c(8,8), ICTXT=0)

```

## Coherent Modes in Turbulent Flow

### Compute PCA and do Scree Plot (0\_pca.r)

```

1 E <- sqrt(X^2 + Y^2 + Z^2) # energy from velocity
2 E.pca <- prcomp(x=E, retx=TRUE, scale=FALSE)
3
4 # plot using one process
5 if(comm.rank() == 0)
6 {
7     ## scree plot for first 50 components
8     variance <- E.pca$sdev^2 # note: all own sdev
9     proportion <- variance[1:50]/sum(variance)
10    cumulative <- cumsum(proportion)
11    component <- 1:length(proportion)
12    png("scree.png")
13    plot(component, cumulative, ylim=c(0,1))
14    points(component, proportion, type="h", col="blue")
15    dev.off()
16 }
17
18 finalize()

```

# Contents

- 4 Plot Ensembles in Parallel
  - Parallel Plot Ensembles

## Parallel Plot Ensembles

## How can we plot in parallel?

- Several plots, one or more on each processor (can do now)
- One plot by several processors (need to rewrite graphics)



## Parallel Plot Ensembles

## Plots in parallel

## png.slice

```

1 png.slice <- function(x, g.dim, lab="slice", title=lab,
  work.dir="", zero.center=TRUE, most.positive=TRUE)
2 {
3   X <- array(as.vector(x), dim=g.dim)
4
5   ## prepare zero centered topo.colors
6   if(zero.center)
7   {
8     . . .
9   }
10  else
11    zlim <- range(X)
12
13  ## set most positive (for unique up to sign)
14  if(most.positive)
15  {
16    . . .
17  }
18
19  ## make png file
20  file <- paste(work.dir, lab, "-r", comm.rank(),
21    ".png", sep="")
22  png(file)
23  image(x=1:g.dim[1], y=1:g.dim[2], z=X,
24    col=topo.colors(40), useRaster=TRUE, asp=1,
25    xlim=c(1, g.dim[1] + 1), ylim=c(1, g.dim[2] + 1),
26    zlim=zlim)
27  title(title)
28  ret <- dev.off()
29  invisible(ret)
30 }

```

## Parallel Plot Ensembles

## Plots in parallel

## Get and Redistribute the Data

```

1 library(pbdDMAT, quiet = TRUE)
2 init.grid()
3
4 ## set global and local dimensions
5 g.dim <- c(64, 64, 1024)
6 my.dim <- g.dim / c(1, 1, comm.size())
7
8 save.file <- paste("xyz.RData", comm.rank(), sep="")
9 load(save.file) # gets vx vector
10
11 ## reshape 3d array into a matrix
12 ## first two dimensions become rows and third becomes
   columns
13
14 ## local reshape dimensions
15 my.nrow <- prod(my.dim[1:2])
16 my.ncol <- my.dim[3]
17 ldim <- c(my.nrow, my.ncol)
18
19 ## global reshape dimensions
20 g.nrow <- prod(g.dim[1:2])
21 g.ncol <- g.dim[3]
22 gdim <- c(g.nrow, g.ncol)
23
24 ## now reshape local
25 X <- matrix(vx, nrow=my.nrow, ncol=my.ncol, byrow=FALSE)
26
27 ## glue local pieces into a ddmatrix
28 X <- new("ddmatrix", Data=X, dim=gdim, ldim=ldim,
   bldim=ldim, ICTXT=1)
29
30 ## transform to 2d block cyclic
31 X <- redistribute(X, bldim=c(8,8), ICTXT=0)
32
33 ## Plot few columns in parallel
34 . . .
35 finalize()

```

## Plots in parallel

Make comm.size() plots in parallel

```

1  step <- 5
2  max.plots <- min(20, ncol(X) %/% step)
3  last.plot <- 1 - step
4  time <- comm.timer(
5  for(i in 1:max.plots)
6    {
7      now.plots <- last.plot + step*(1:comm.size())
8      my.col <- gather.col(X[, now.plots])
9      lab <- paste("col", lead0(now.plots[comm.rank()
10        + 1]), sep="")
11      png.slice(my.col, g.dim[1:2], lab)
12      last.plot <- now.plots[length(now.plots)]
13    }
14 )

```

## Plots in parallel

### gather.col (3\_plot.r)

```

1 gather.col <- function(x, num=min(ncol(x), comm.size()))
2 {
3   ## gather complete columns of a global array to
4     different ranks
5   x.num <- x[, 1:num]
6   x.num <- as.colblock(x.num)
7
8   ## ScaLAPACK fix (a future release will automate)
9   if(ownany(x.num))
10     ret <- as.vector(submatrix(x.num))
11   else
12     ret <- NULL
13   ret
14 }

```

## Plots in parallel

Now Plot the PCA Components (4\_plot.r)

```

1 E <- sqrt(X^2 + Y^2 + Z^2)
2
3 E.pca <- prcomp(x=E, retx=TRUE, scale=FALSE)
4
5 ## Use ranks 1 to n.pca to plot individual components in
   parallel
6 n.pca <- min(comm.size(), g.nrow)
7 my.col <- gather.col(E.pca$x, num=n.pca)
8
9 if(!is.null(my.col))
10 {
11     ## component plots on rank 1 to n.pca
12     lab <- paste("pc", comm.rank(), sep=" ")
13     title <- paste(lab, "sigma^2 =",
14                     variance[comm.rank() + 1])
15     png.slice(my.col, g.dim[1:2], lab, title=title,
16               work.dir=work.dir)
17 }
```

## Parallel Plot Ensembles

Exercise: `scripts/pbdDMAT/dmat_app`

- Experiment with scripts `0_pca.r`, `1_plot.r`, `2_plot.r`, `3_plot.r`, `4_plot.r`

# Contents

- 5 Rearranging ddmatrix Data
  - Rearranging Data

## Simple Redistributions

- `as.block(dx, square.bldim = TRUE)`
- `as.rowblock(dx)`
- `as.colblock(dx)`
- `as.rowcyclic(dx, bldim = .BLDIM)`
- `as.colcyclic(dx, bldim = .BLDIM)`
- `as.blockcyclic(dx, bldim = .BLDIM)`

## BLACS context (Processor Grid)

- `init.grid(P,Q)`
- `.ICTXT = 0` gives  $P \times Q$
- `.ICTXT = 1` gives  $PQ \times 1$
- `.ICTXT = 2` gives  $1 \times PQ$



## Rearranging Data

## Exercise: scripts/pbdDMAT/dmat\_app

- Experiment with scripts 5ictxt.r, 6\_ictxt.r, and 7\_ictxt.r
- Experiment with other redistributions

## The pbdR Project

- Our website: <http://r-pbd.org/>
- Email us at: [RBigData@gmail.com](mailto:RBigData@gmail.com)
- Our google group: <http://group.r-pbd.org/>

## Where to begin?

- The **pbdDEMO** package  
<http://cran.r-project.org/web/packages/pbdDEMO/>
- The **pbdDEMO** Vignette: <http://goo.gl/HZkRt>

Thanks for coming!

# Questions?



<http://r-pbd.org/>