# *pR*: Introduction to Parallel R for Statistical Computing

## for people with little knowledge but infinite intelligence

CScADS Scientific Data and Analytics for Petascale Computing Workshop

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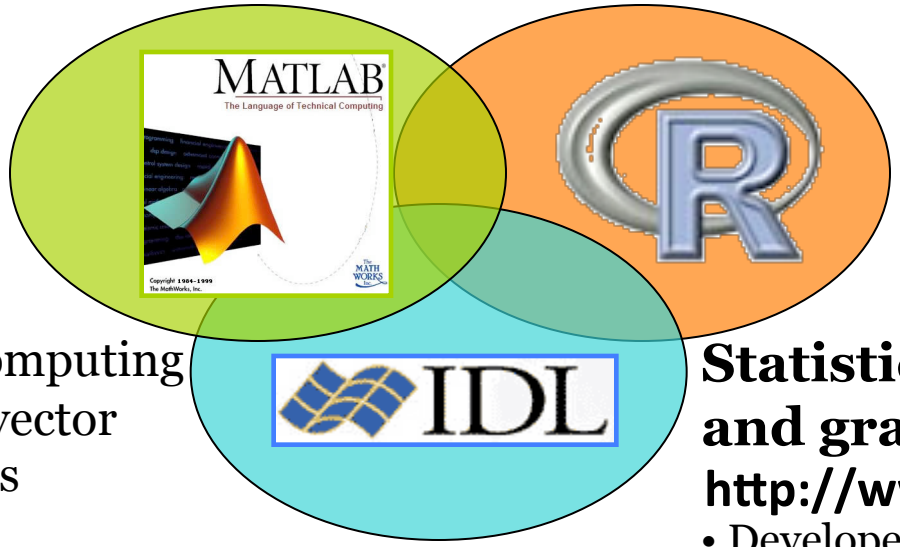
# Why R?




- Technical computing
- Matrix and vector formulations

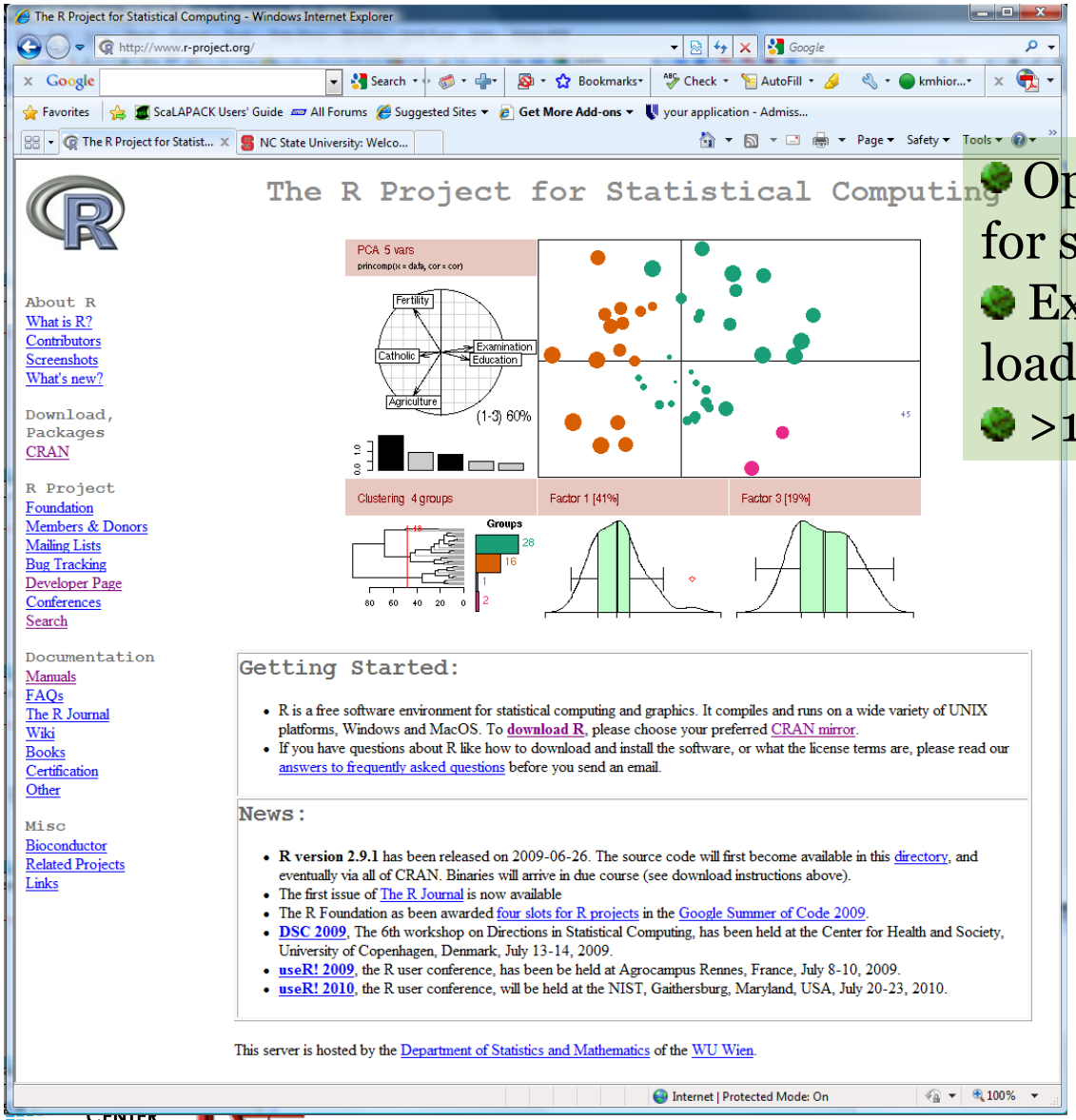
- Data Visualization and analysis platform
- Image processing, vector computing

**Statistical computing and graphics**

**http://www.r-project.org**

- Developed by **R**. Gentleman & **R**. Ihaka
- Expanded by community as open source
- Statistically rich

# Statistical Computing with *R* – http://www.r-project.org




- Open source, most widely used for statistical analysis and graphics
- Extensible via dynamically loadable add-on packages
- >1,800 packages on CRAN

```
> library (stats)
> pca = prcomp (data)
> summary (pca)
> …
> dyn.load( “foo.so”)
> .C( “foobar” )
> dyn.unload( “foo.so” )
```

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# How to Get Started with R?

- Step 1: **Download R** (under Linux):
  - mkdir for RHOME; cd $RHOME
  - wget http://cran.cnr.berkeley.edu/src/base/R-2/R-2.9.1.tar.gz
- Step 2: **Install R** (under Linux):
  - tar –zxvf  R-2.9.1.tar.g
  - ./configure *--prefix=<RHOME>  --enable-R-shlib*
  - make
  - make install
- Step 3: **Run R** (under Linux):
  - Update env. variables in $HOME/.bash_profile:
    - *export PATH=<RHOME>/bin:$PATH*
    - *export R_HOME=<RHOME>*
  - R

# Session 1: Vectors and vector operations

To create a vector:

```
# c() command to create vector x
x=c(12,32,54,33,21,65)
# c() to add elements to vector x
x=c(x,55,32)
```

```
# seq() command to create
sequence of number
years=seq(1990,2003)
# to contain in steps of .5
a=seq(3,5,.5)
```

```
# rep() command to create data
that follow a regular pattern
b=rep(1,5)
c=rep(1:2,4)
```

To access vector elements:

```
# 2nd element of x
x[2]
# first five elements of x
x[1:5]
# all but the 3rd element of x
x[-3]
# values of x that are < 40
x[x<40]
# values of y such that x is < 40
y[x<40]
```

To perform operations:

```
# mathematical operations on vectors
y=c(3,2,4,3,7,6,1,1)
x+y; 2*y;  x*y;  x/y;  y^2
```

# Session 2: Matrices & matrix operations

To create a matrix:

```
# matrix() command to create matrix A with rows and cols
A=matrix(c(54,49,49,41,26,43,49,50,58,71),nrow=5,ncol=2))
```

To access matrix element:

```
# matrix_name[row_no, col_no]
 A[2,1] # 2nd row, 1st column element
 A[3,]  # 3rd row
 A[,2]  # 2nd column of the matrix
 A[2:4,1]  # submatrix of 2nd-4th elements
of the 1st column
 A["KC",] # access row by name, "KC"
```

Statistical operations:

```
 rowSums(A)
 colSums(A)
 rowMeans(A)
 colMeans(A)
# max of each columns
 apply(A,2,max)
# min of each row
 apply(A,1,min)
```

To perform element by element ops:

```
2*A+3; A+B; A*B; A/B;
```

# Help in R

- **At the package level**:
  - help (package=pkg_name) (e.g. help (package=stats))
  - pkg_name::<TAB><TAB> (stats:: )
  - CRAN Search:
  - CRAN Task Views: http://cran.cnr.berkeley.edu/web/views/
  - From R GUI: Help → Search help…
- **At the function level**:
  - help (function_name) (e.g. help(prcomp))
  - ?function_name (e.g.: ?prcomp)
  - ??function_name

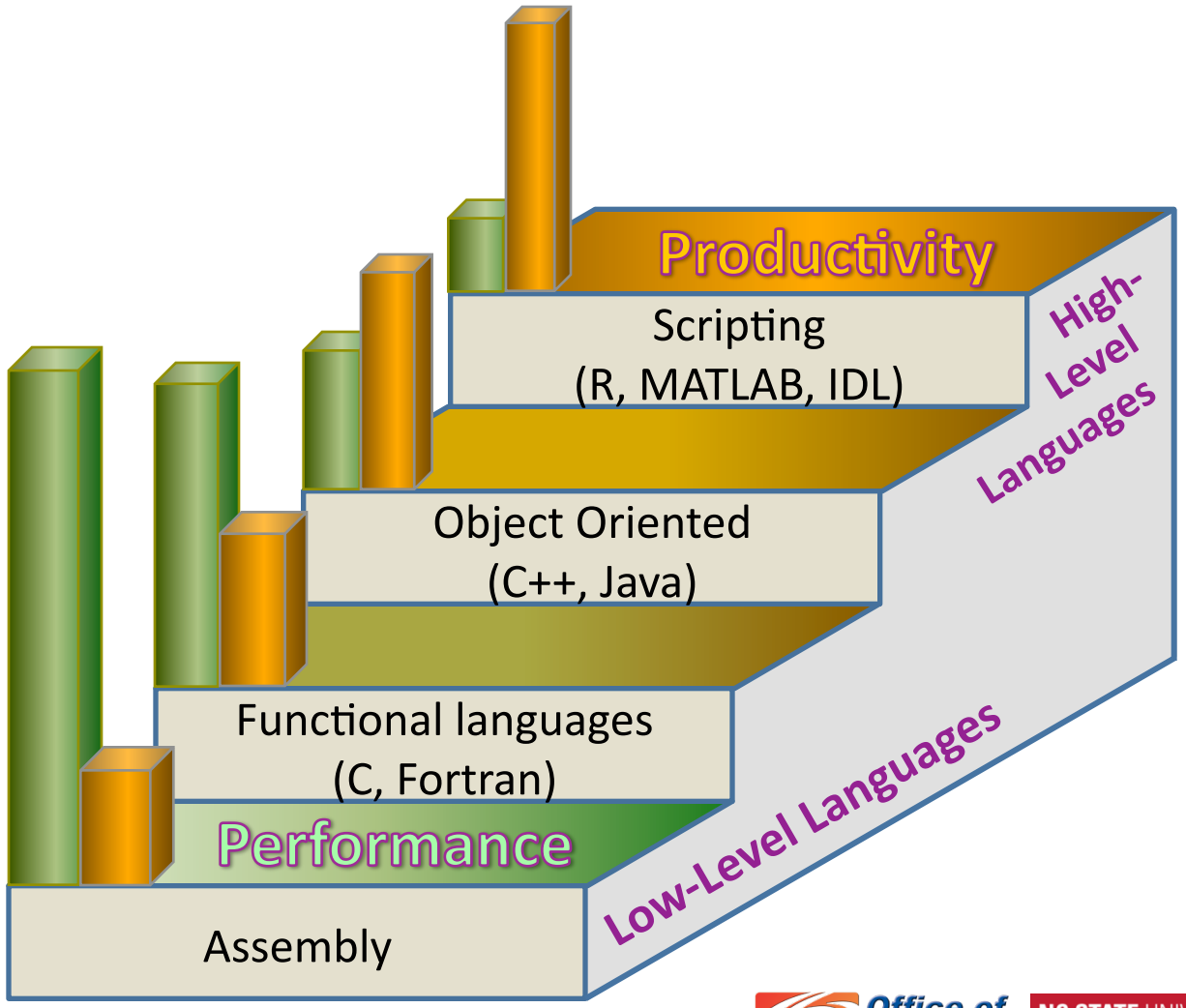
# How to Add a Package?

- From R prompt:
  - install.packages(“pkg_name") (install.packages(“ctv”)
- From R GUI:
  - Packages → Install package(s)…
- From Command Line:
  - R CMD INSTALL pkg_name.version.tar.gz

# Useful R Links

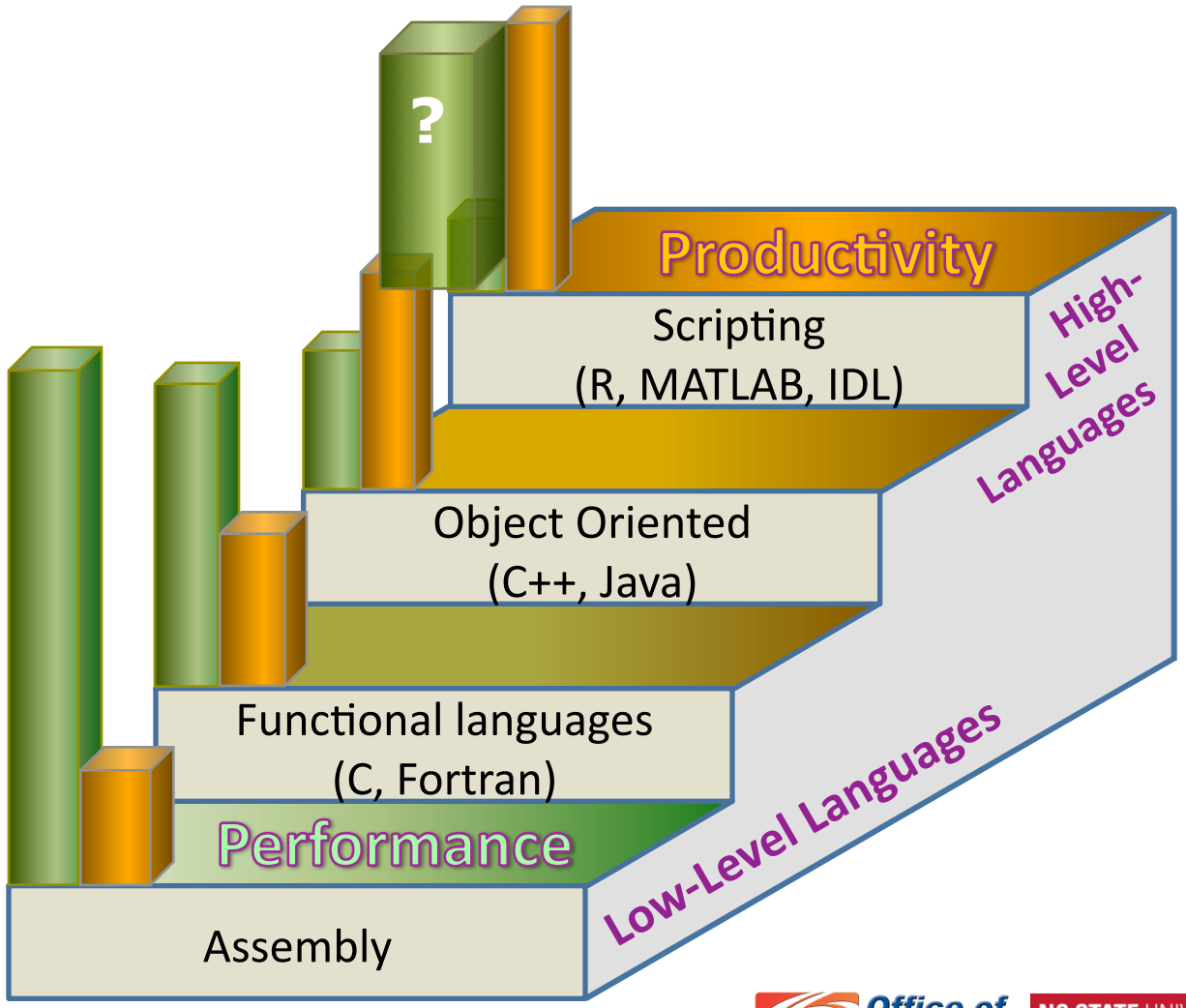
- R Home: http://www.r-project.org/
- R's CRAN package distribution: http://cran.cnr.berkeley.edu/
- Introduction to R manual: http://cran.cnr.berkeley.edu/doc/manuals/R-intro.pdf
- Writing R extensions: http://cran.cnr.berkeley.edu/doc/manuals/R-exts.pdf
- Other R documentation: http://cran.cnr.berkeley.edu/manuals.html

# The Programmer's Dilemma



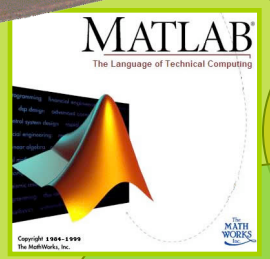
# Towards High-Performance High-Level Languages

## How do we get there? – Parallelization



# One Hat Does NOT Fit All

## Parallel R for Data Intensive Statistical Computing





**Data Intensive Statistical Computing**

- Technical computing
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**Statistical computing and graphics**

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# Towards Enabling Parallel Computing in *R*

http://cran.cnr.berkeley.edu/web/views/HighPerformanceComputing.html

- ***snow*** (Luke Tierney): general API on top of message passing routines to provide high-level (*parallel apply*) commands; mostly demonstrated for ***embarrassingly parallel*** applications.

| ***snow* API** | *High Level Routines* |
|---|---|
| `parLapply` | parallel `lapply` |
| `parSapply` | parallel `sapply` |
| `parApply` | parallel `apply` |
| | *Basic Routines* |
| `clusterExport` | export variables to nodes |
| `clusterCall` | call function on each node |
| `clusterApply` | apply function to arguments on nodes |
| `clusterApplyLB` | load balanced `clusterApply` |
| `clusterEvalQ` | evaluate explicit expression on nodes |
| `clusterSplit` | split vector into pieces for nodes |
| | *Administrative Routines* |
| `makeCluster` | create a new cluster of nodes |

- ***Rmpi*** (Hao Yu): ***R*** interface to ***MPI***.
- ***rpvm*** (Na Li and Tony Rossini): ***R*** interface to ***PVM***; requires knowledge of parallel programming.

```
> library (rpvm)
> .PVM.start.pvmd ()
> .PVM.addhosts (...)
> .PVM.config ()
```

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# Lessons Learned from R/Matlab Parallelization

## Interactivity and High-Level: Curse & Blessing

high

Abstraction
Interactivity
Productivity

low

**Back-end approach**
- **data parallelism**
- **C/C++/Fortran with MPI**
- **RScaLAPACK** (Samatova et al, 2005)

**Automatic parallelization**
- **task parallelism**
- **task-pR** (Samatova et al, 2004)

**Embarrassing parallelism**
- **data parallelism**
- **snow** (Tierney, Rossini, Li, Sevcikova, 2006)

**Manual parallelization**
- **message passing**
- **Rmpi** (Hao Yu, 2006)
- **rpvm** (Na Li & Tony Rossini, 2006)

**Compiled approach**
- **Matlab→C→automatic parallelization**

**pR**

Packages: http://cran.r-project.org/

**Parallel Performance**

high

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# Types of Users

- **R end-user**:
  - Use R scripting language for statistical analysis tasks
- **R contributor**:
  - Contribute R packages
  - Use R (sometimes serial C/C++, Fortran)
- **HPC developer**:
  - MPI C/C++/Fortran codes
  - Linear algebra routines that underlie data analysis *f*()
  - Parallel machine learning and data mining algorithms:
    - Unsupervised learning: clustering, association rule mining,…
    - Supervised learning: SVM, NN, Decision Trees, Bayesian networks

# Our Philosophy

- From R end user's perspective:
  - Require ***NO*** (very trivial) changes to serial R code
  - Yet deliver HPC performance

- From HPC developer's perspective:
  - Provide ***native*** to HPC developer interface to R internals
  - With NO (constantly small) overhead

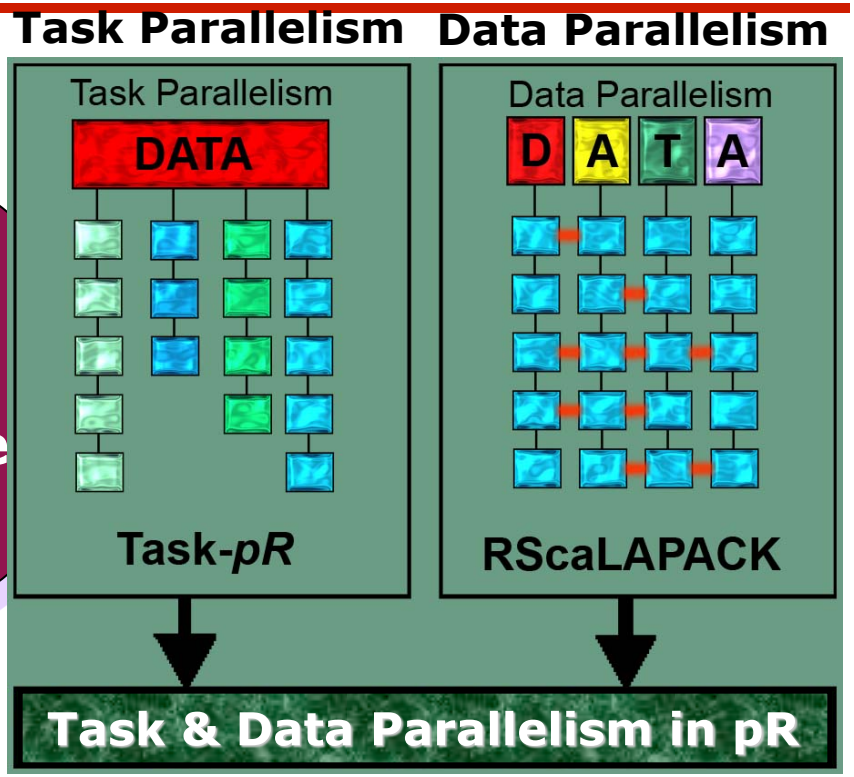
# Task and Data Parallelism in pR

**Goal: Parallel R (*pR*) aims:**

**(1) to automatically detect and execute *task-parallel* analyses;**

**(2) to easily plug-in *data-parallel* MPI-based C/C++/Fortran code**

**(3) to retain high-level of *interactivity, productivity* and *abstraction***




**Embarrassingly-parallel:**

- Likelihood Maximization
- Sampling: Bootstrap, Jackknife
- Markov Chain Monte Carlo
- Animations

**Data-parallel:**

- k-means clustering
- Principal Component Analysis
- Hierarchical clustering
- Distance matrix, histogram

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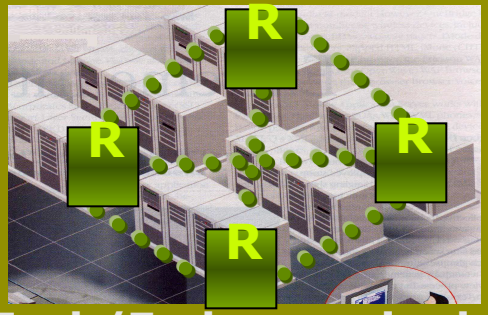
# *pR* Multi-tiered Architecture

**Interactive R Client**

**Loosely Coupled**

**R Servers**



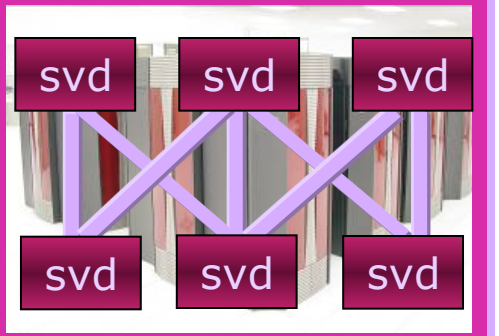

**Task/Embarrassingly parallel jobs**

A

S

**Tightly Coupled**

**MPI Servers**




**Data parallel jobs**

```
A ← matrix (1:10000, 100,100)
library (pR)

S ← sla.svd(A)        Data parallel
b ← list ()
for (k in 1:dim (A) [ 1 ] ) {
    b [ k ] ← sum ( A [ k, ] )
}          Embarrassingly parallel
m ← mean ( A )
d ← sum ( A )          Task parallel
```

getValue()

putValue()

**Data Bank Server(s)**

**Memory & I/O Management**

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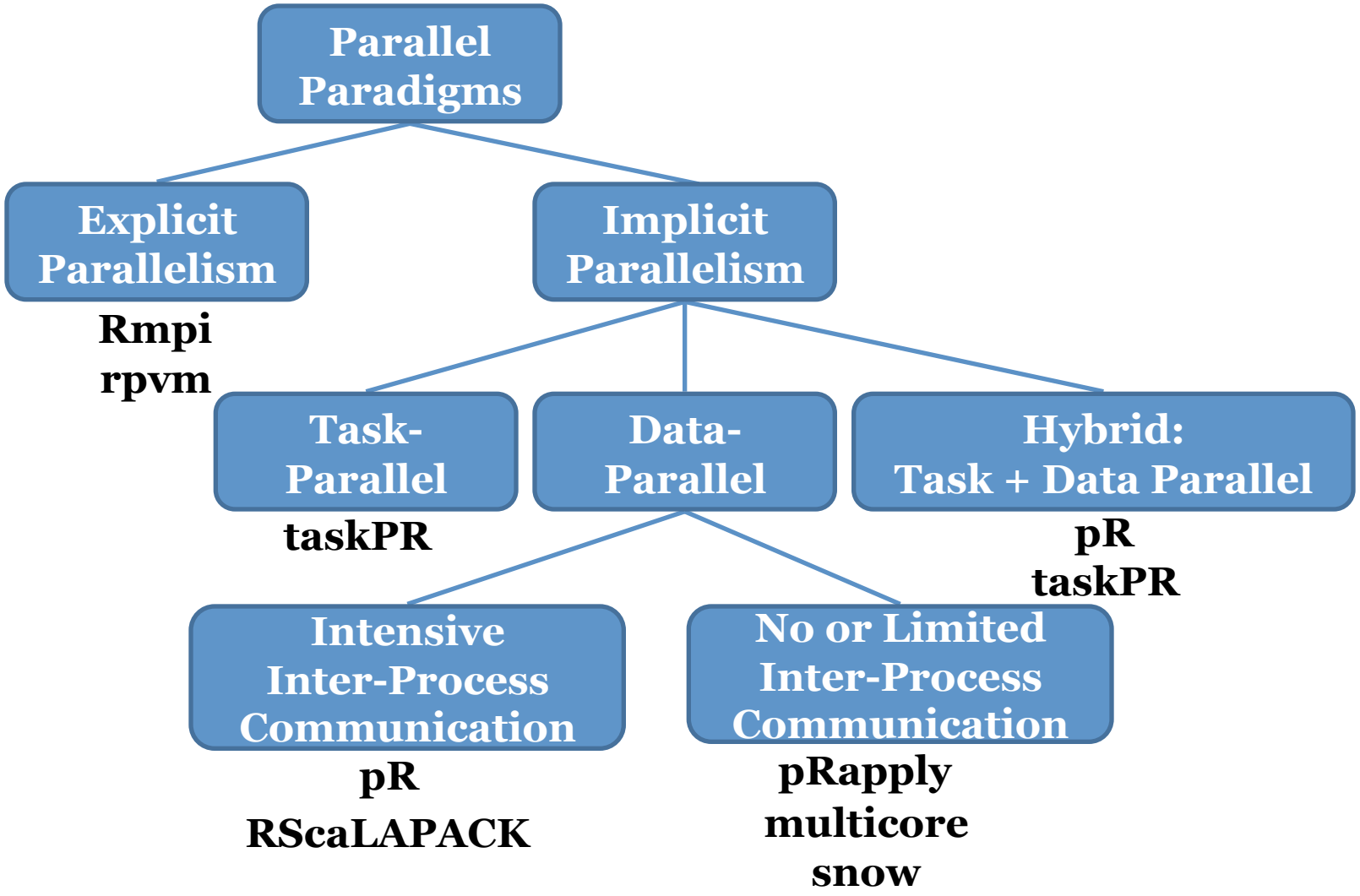
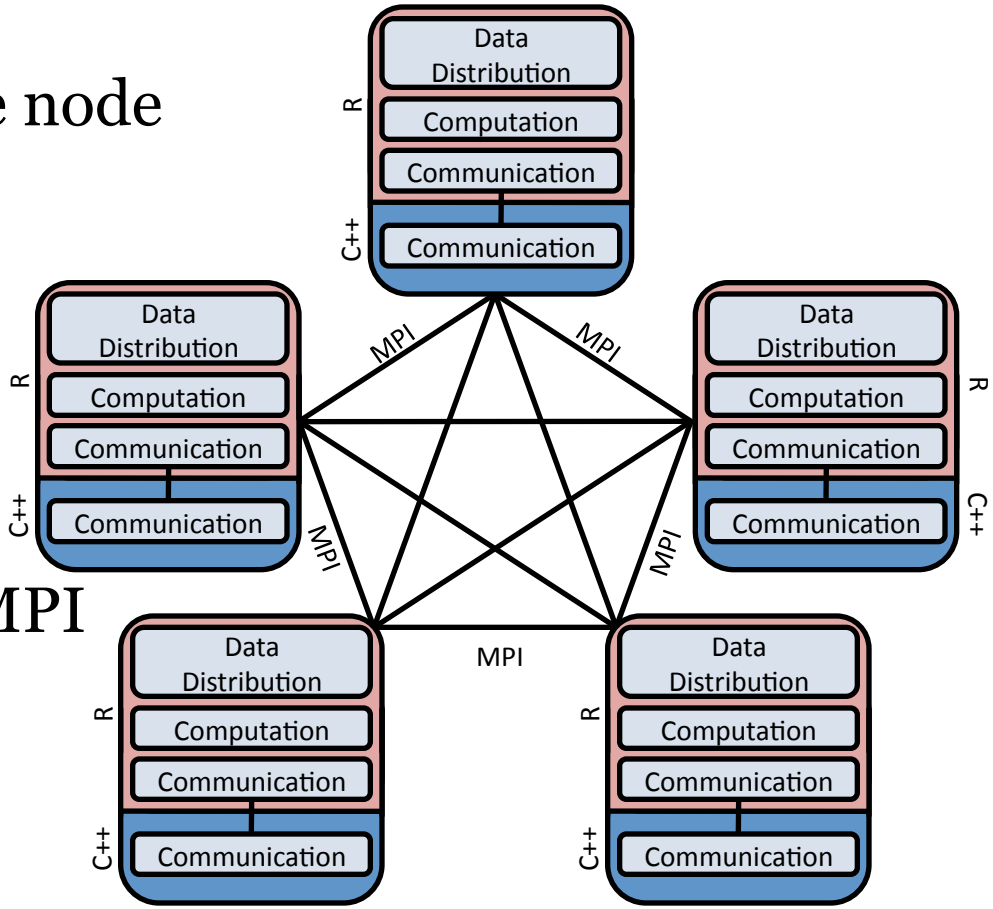
# Parallel Paradigm Hierarchy



# Rmpi May Not Be Ideal for All End-Users

- R-wrapper around MPI
- R is required at each compute node
- Executed as interpreted code, which introduces noticeable overhead
- Supports ~40 of >200 MPI-2 functions
- Users must be familiar with MPI details
- Can be especially useful for prototyping



# Rmpi Matrix Multiplication Requires Parallel Programming Knowledge and is Rmpi Specific

```
mm_Rmpi <- function(A, B, n_cpu = 1) {
  da <- dim(A) ## dimensions of matrix A
  db <- dim(B) ## dimensions of matrix B

  ## Input validation
  matrix_mult_validate( A, B, da, db )
  if( n_cpu == 1 )
    return(A %*% B)

  ## spawn R workers
  mpi.spawn.Rslaves( nslaves = n_cpu )

  ## broadcast data and functions
  mpi.bcast.Robj2slave( A )
  mpi.bcast.Robj2slave( B )
  mpi.bcast.Robj2slave( n_cpu )

  ## how many rows on workers ?
  nrows_workers <- ceiling( da[ 1 ] / n_cpu )
  nrows_last <- da[ 1 ] - ( n_cpu - 1 ) *
    nrows_workers

  ## broadcast number of rows and foo to apply
  mpi.bcast.Robj2slave( nrows_workers )
  mpi.bcast.Robj2slave( nrows_last )
  mpi.bcast.Robj2slave( mm_Rmpi_worker )

  ## start partial matrix multiplication
  mpi.bcast.cmd( mm_Rmpi_worker() )

  ## gather partial results from workers
  local_results <- NULL
  results <- mpi.gather.Robj(local_results)
  C <- NULL

  ## Rmpi returns a list
  for(i in 1:n_cpu)
    C <- rbind(C, results[[ i + 1 ]])

  mpi.close.Rslaves()
  C
}
```

Worker

```
mm_Rmpi_worker <- function(){
  commrank <- mpi.comm.rank() - 1
  if(commrank == ( n_cpu - 1 ))
    local_results <- A[ (nrows_workers * commrank + 1): (nrows_workers * commrank + nrows_last),] %*% B
  else
    local_results <- A[ (nrows_workers * commrank + 1): (nrows_workers * commrank + nrows_workers),] %*% B

  mpi.gather.Robj(local_results, root = 0, comm = 1)
}
```

# pR Matrix Multiplication

pR example:

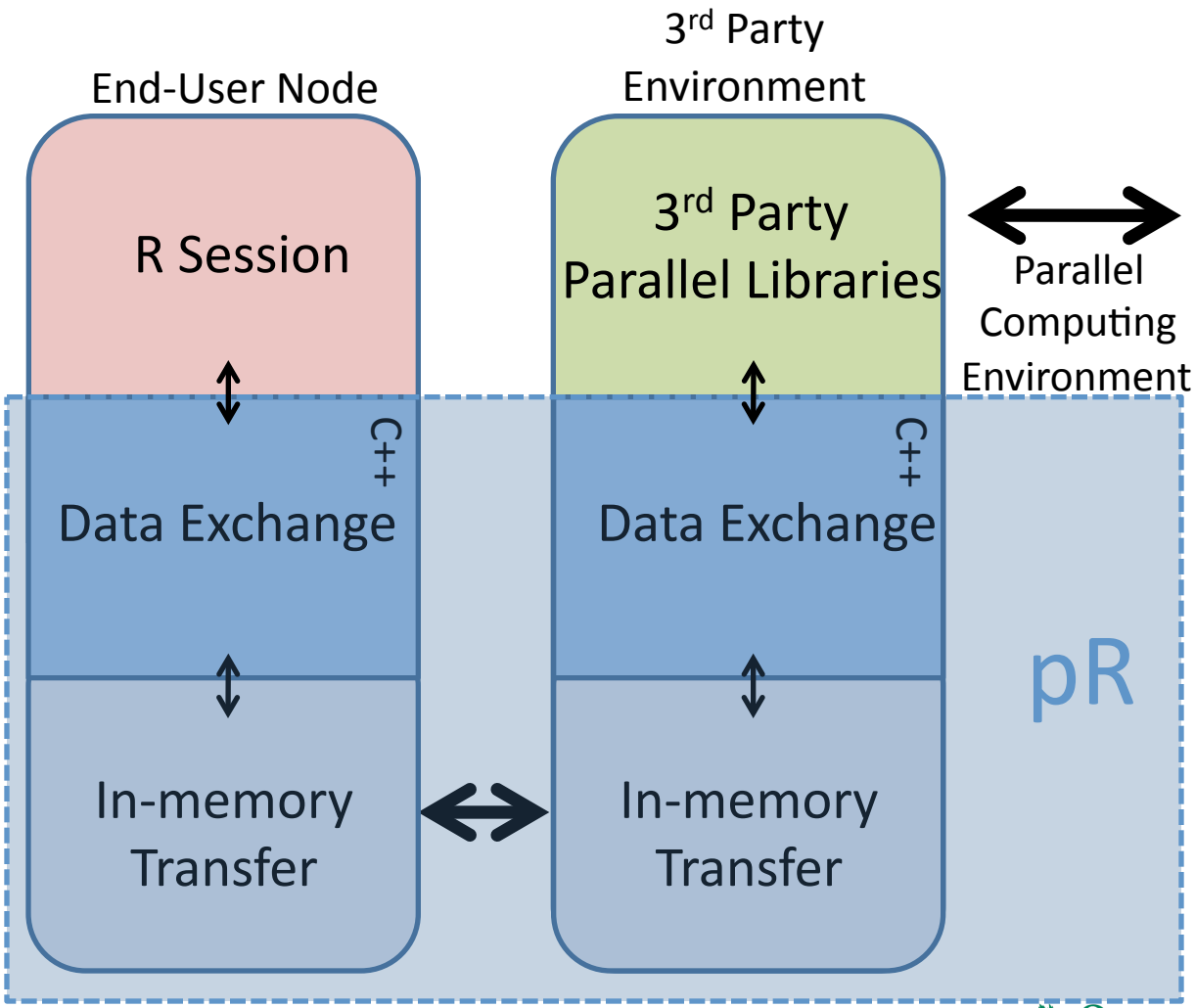
```
library (RScaLAPACK)
A = matrix (c(1:256),16,16)
B = matrix (c(1:256),16,16)
C = sla.multiply (A, B)
```

Using R:

```
A = matrix (c(1:256),16,16)
B = matrix (c(1:256),16,16)
C = A % * % B
```

# pR Parallel Plugin: Goals & Software Stack

- Couple general parallel computation capabilities within R
- Shield end-users from the complexities of parallel computing
- Enable execution of compiled and scripting codes together



# pR Example: Do it Yourself

R End-User

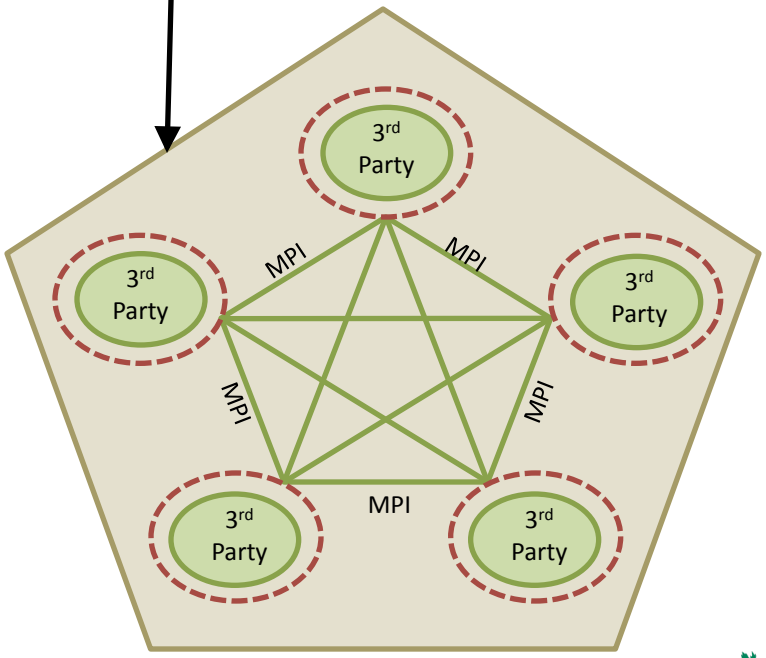
```
A = matrix(c(1:256),16,16)
B = matrix(c(1:256),16,16)
C = mm(A, B)
```

pR glue code

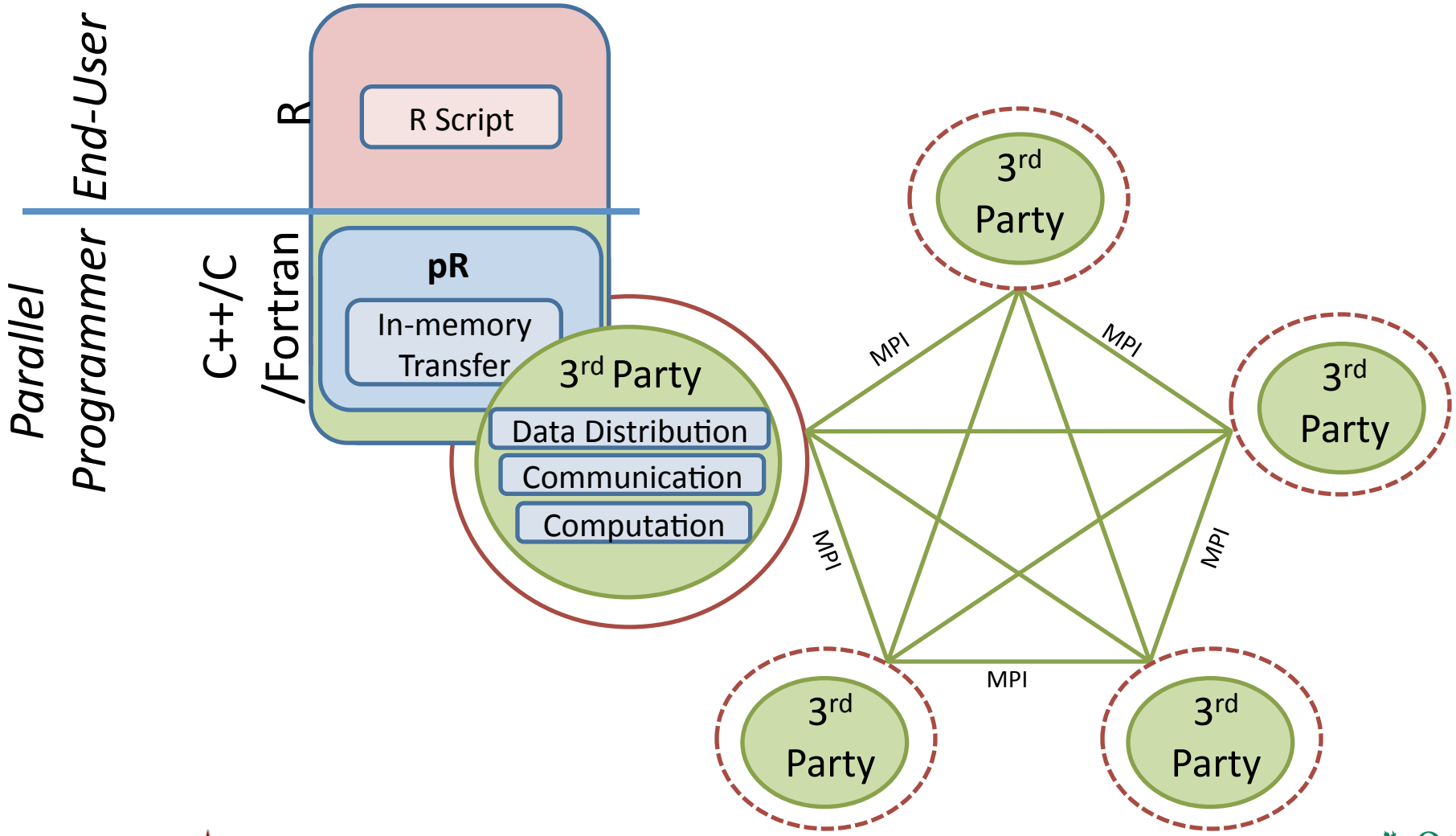
```
mm(SEXP args) {
  double *a, *b;
  a = args.getPointer();
  b = args.getPointer();
  c = matrix_multiply(a,b);
  return c.getRObject();
}
```

3rd Party Code: HPC MPI code

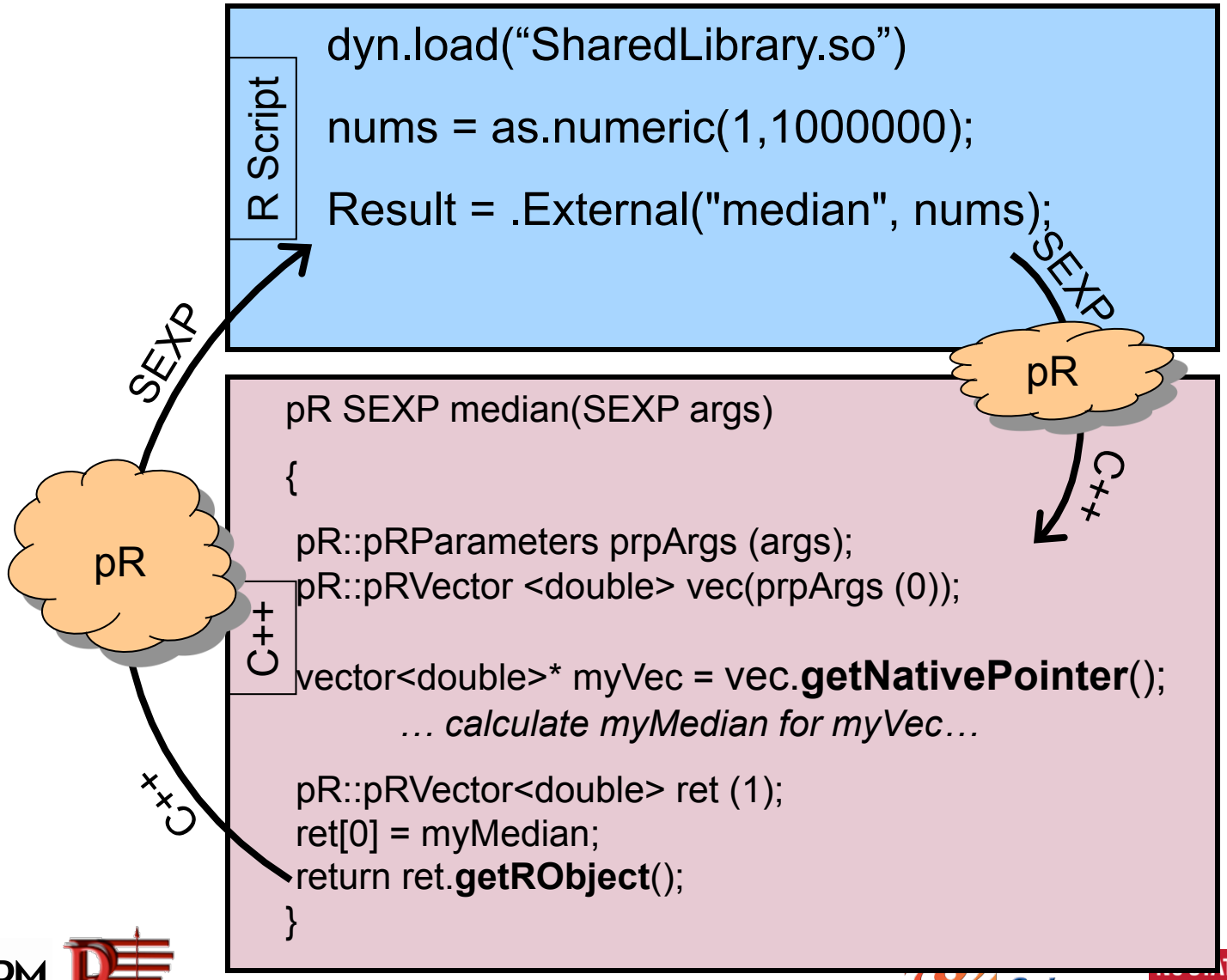
```
matrix_multiply(a,b) {
  ...
  return c;
}
```



# pR Overview


End-User
Parallel Programmer
R
R Script
C++/C /Fortran
pR
In-memory Transfer
3rd Party
Data Distribution
Communication
Computation
MPI
MPI
MPI
MPI
MPI
3rd Party
3rd Party
3rd Party
3rd Party

# C/C++/Fortran Plug-in to pR



# Serial pR Performance over Python and R

| Method | Python | R | pR | pR Improv. over Python | pR Improv. over R |
|---|---|---|---|---|---|
| Median | 0.300 | 0.108 | 0.030 | 10.0 | 3.6 |
| Geometric Mean | 0.323 | N/A | 0.128 | 2.9 | N/A |
| Average | 0.071 | 0.049 | 0.012 | 5.9 | 4.1 |
| Standard Deviation | 0.420 | 0.020 | 0.019 | 22.1 | 1.1 |
| **Average** | | | | 18.1 | 2.8 |

| Method | C++ | R | pR | R Overhead | pR Overhead | Times Imrov. over R |
|---|---|---|---|---|---|---|
| ddot | 0.003 | 0.131 | 0.003 | 0.128 | 0.001 | 43.7 |
| dnrm2 | 0.024 | 0.044 | 0.026 | 0.014 | 0.000 | 1.7 |
| dchdc | N/A | 0.001 | 0.001 | 0.001 | 0.000 | 1.0 |
| dsvdc | N/A | 0.661 | 3.864 | 0.026 | 0.000 | 0.2 |
| dgeev | 0.002 | 0.557 | 0.004 | 0.027 | 0.002 | 139.3 |
| **Average** | | | | | | 37.2 |

# pR Often Lowers Overhead Compared to R

| Method | C++ | *R* | pR | *R* Overhead | pR Overhead | Times Imrov. over *R* |
|---|---|---|---|---|---|---|
| ddot | 0.003 | 0.131 | 0.003 | 0.128 | 0.001 | 43.7 |
| dnrm2 | 0.024 | 0.044 | 0.026 | 0.014 | 0.000 | 1.7 |
| dchdc | N/A | 0.001 | 0.001 | 0.001 | 0.000 | 1.0 |
| dsvdc | N/A | 0.661 | 0.516 | 0.026 | 0.000 | 1.3 |
| dgeev | 0.002 | 0.557 | 0.004 | 0.027 | 0.002 | 139.3 |
| Average | | | | | | 37.2 |

Comparing C++, R and BridgeR External Method Calls in Seconds

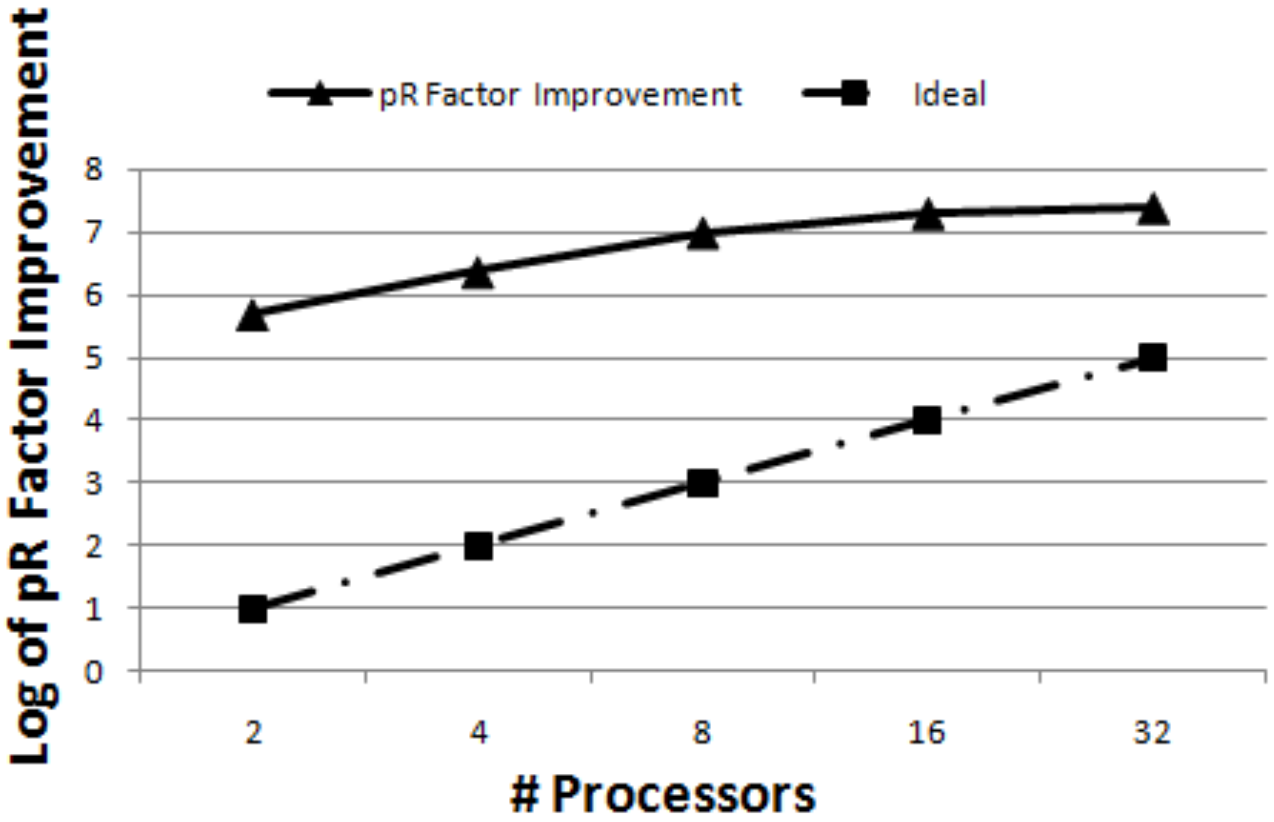
# pR to R Performance Comparison

| Matrix Size | $R$ (sec) | $pR$ (sec) | $pR$ Factor Improvement |
|---|---|---|---|
| 32 | $< 1 \cdot 10^{-3}$ | $1 \cdot 10^{-3}$ | 0.0 |
| 64 | $1 \cdot 10^{-3}$ | $8 \cdot 10^{-3}$ | 0.01 |
| 128 | $1 \cdot 10^{-3}$ | $8 \cdot 10^{-2}$ | 0.07 |
| 256 | $5 \cdot 10^{-2}$ | $1 \cdot 10^{-1}$ | 0.41 |
| 512 | $8 \cdot 10^{-1}$ | $2 \cdot 10^{-1}$ | 5.63 |
| 1024 | $1 \cdot 10^{1}$ | $6 \cdot 10^{-1}$ | 17.18 |
| 2048 | $9 \cdot 10^{1}$ | $4 \cdot 10^{0}$ | 19.78 |
| 4096 | $7 \cdot 10^{2}$ | $2 \cdot 10^{1}$ | 28.32 |

Single processor matrix-multiplication testcase.

System: 32 node Intel-based Infiniband cluster running Linux. Each node contains two 3.4 GHz Pentium IV processors and 6GB of memory.

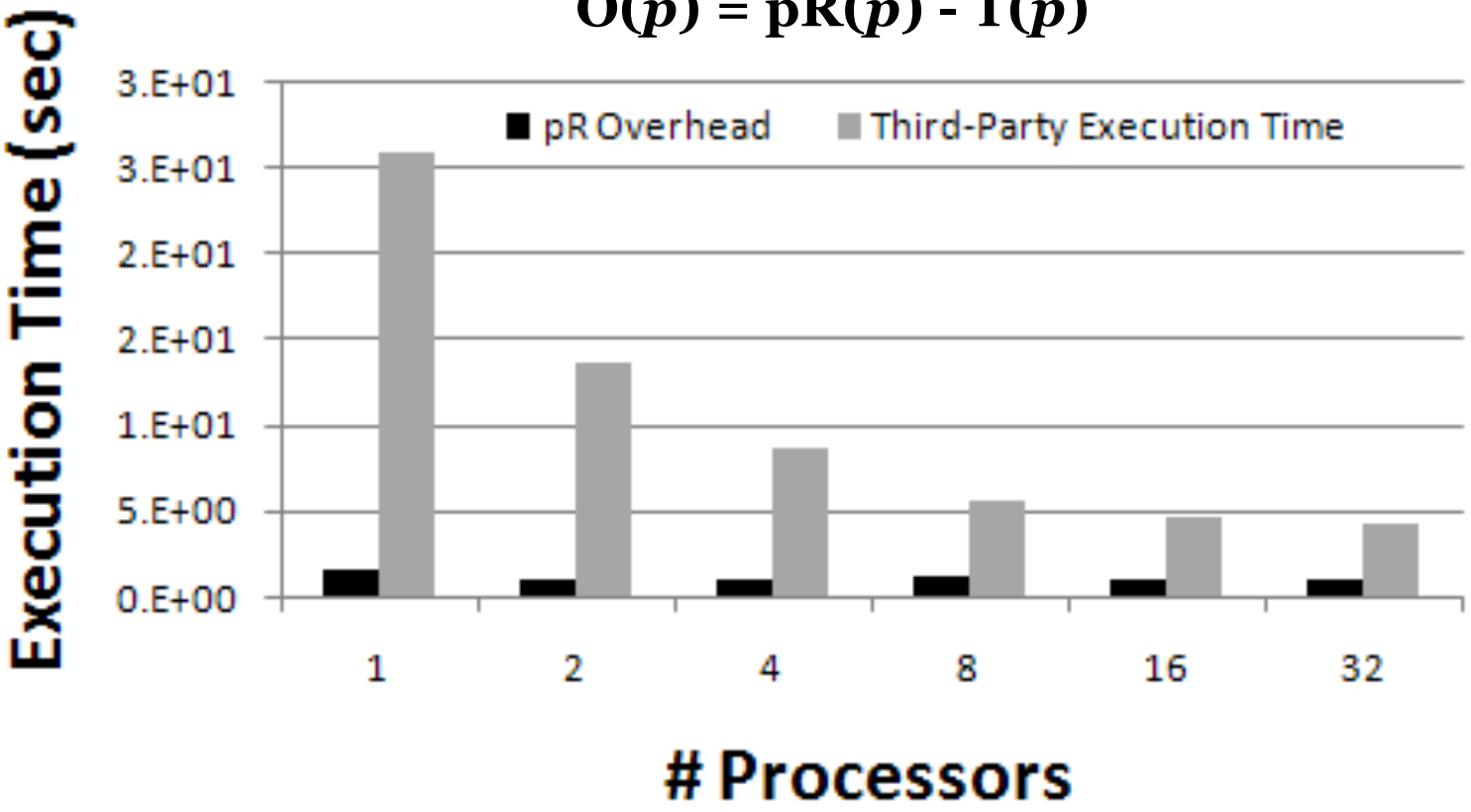
# pR Achieves Superlinear Speedup vs. Serial R




Using a matrix-multiplication testcase on 4096x4096 matrices.

# pR Overhead is ~Constant and Small

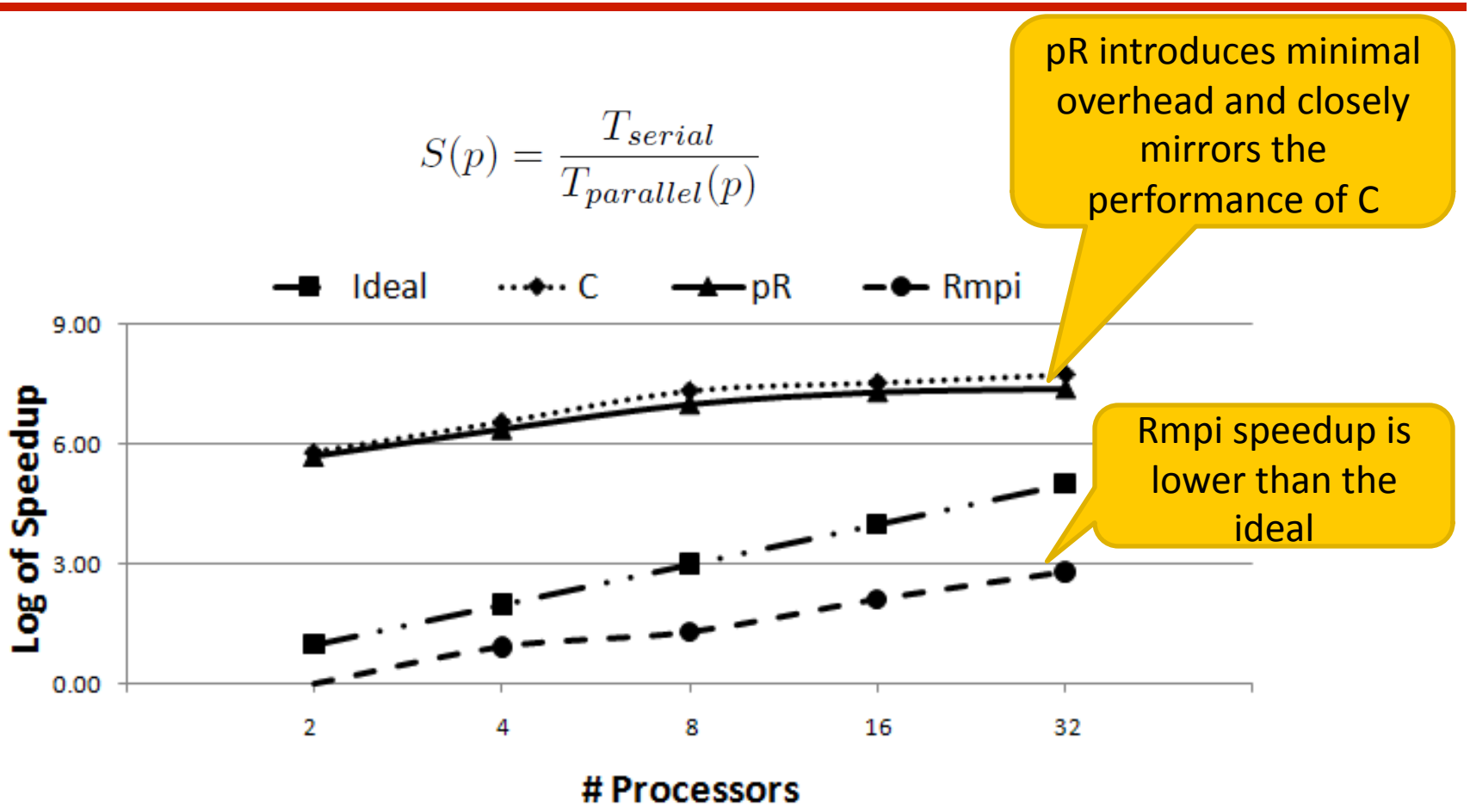
$$O(p) = pR(p) - T(p)$$




Matrix-multiplication testcase on 4096x4096 matrices

# pR Offers Parallel *Scripting* Computing with the Same Performance as Parallel *Compiled* Codes

$$S(p) = \frac{T_{serial}}{T_{parallel}(p)}$$

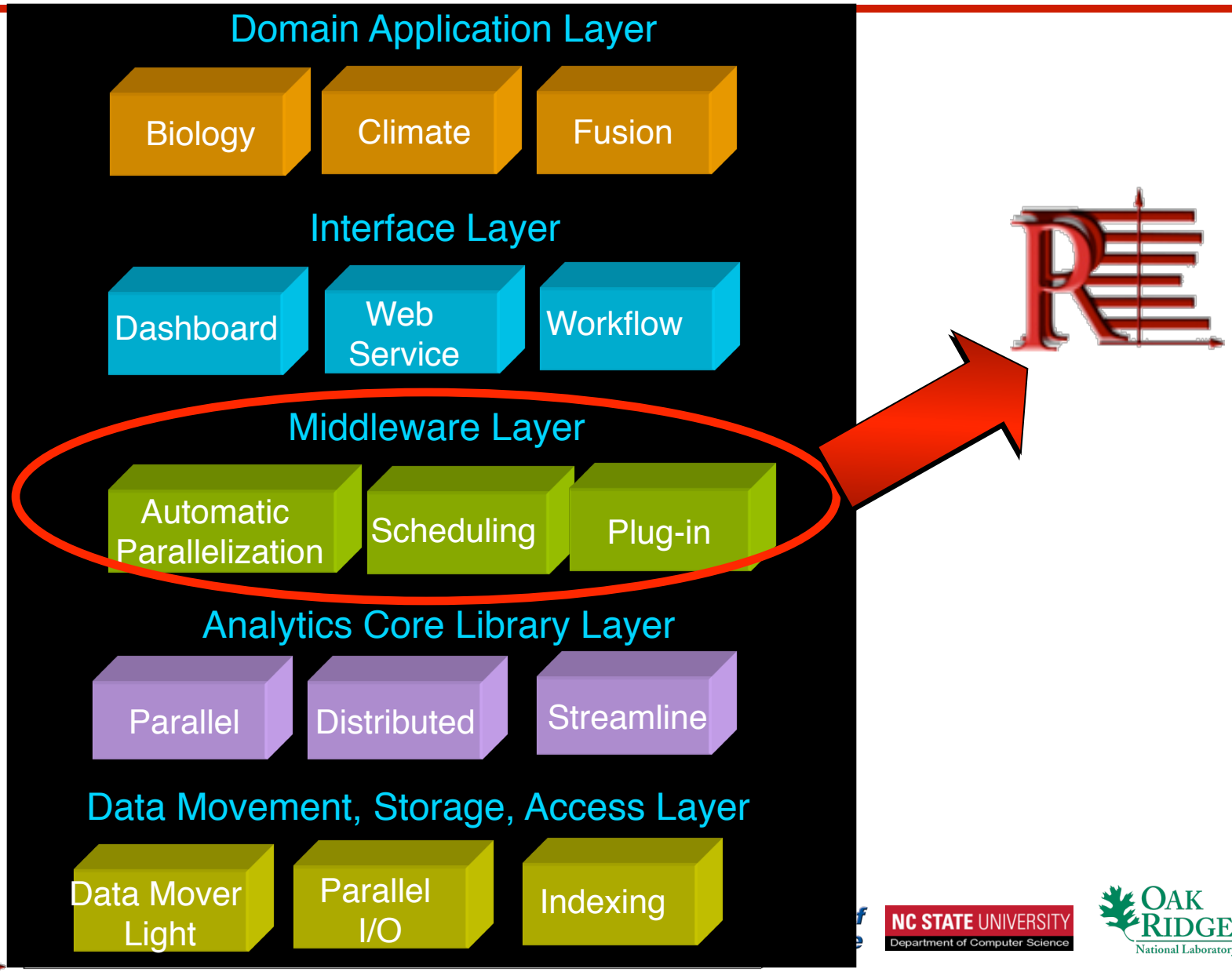



Using a matrix-multiplication testcase on 4096 x 4096 matrices, and comparing against a serial R implementation.

# pR Provides Simple, Efficient Third-Party Access to R

- Tightly-Coupled R Interface Between R and Third-Party Code
- Bidirectional Translation of Data Objects
- Memory Management: Direct Memory Access to R objects
- Compared to R: Average Speedup of 37x (with large variability)
- Compared to C: Negligible Overhead Induced

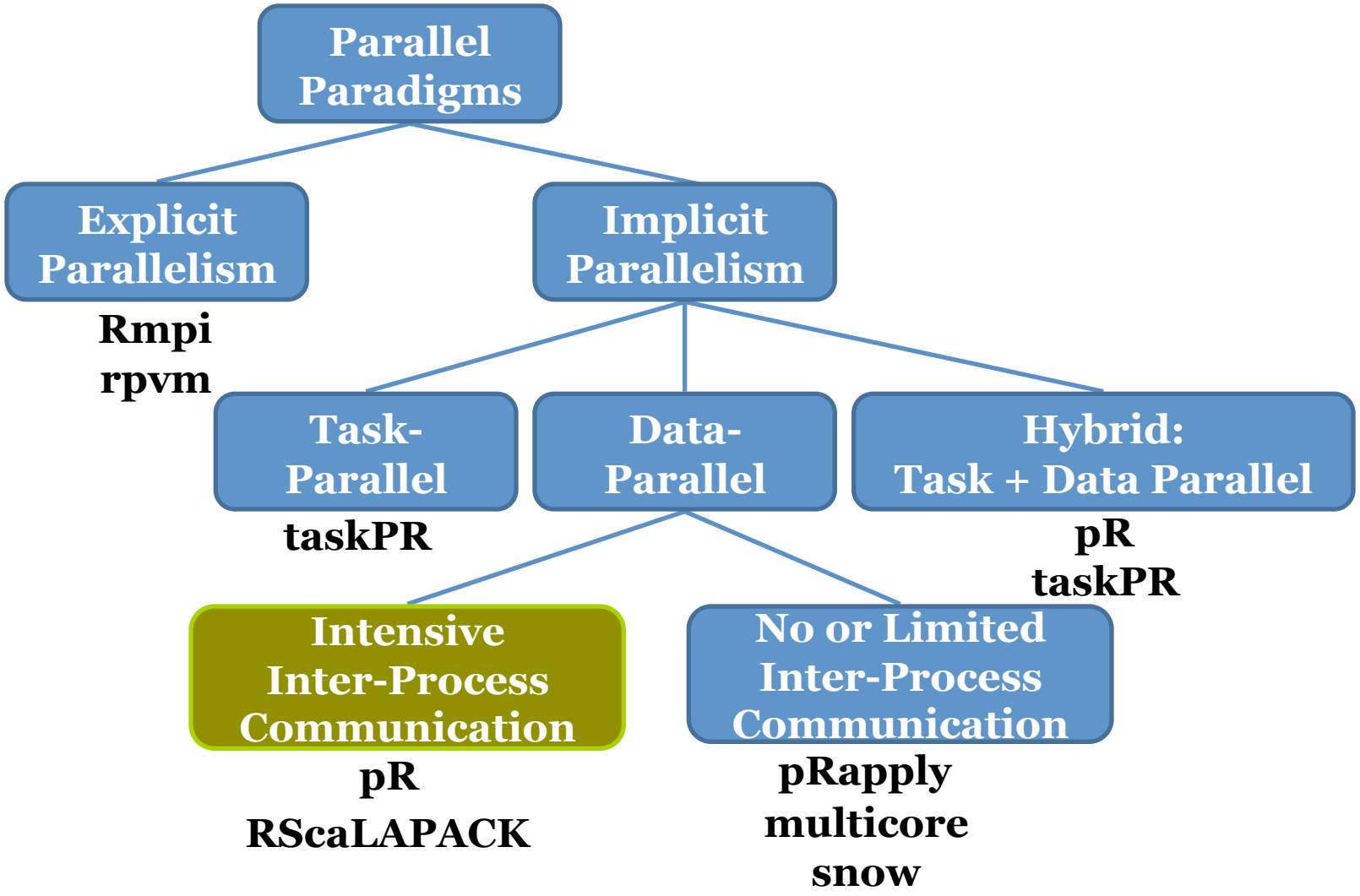
# End-to-End Data Analytics



# pR

- Lightweight middleware to bridge 3rd party codes
- pR-based packages:
  - RScaLAPACK
  - pRapply
  - pRstats
  - ….
- You can add your own libraries using pR

# Parallel Paradigm Hierarchy



# What is RScaLAPACK?

- Motivation:
  - Many data analysis routines call linear algebra functions
  - In R, they are built on top of **serial** LAPACK library: http://www.netlib. org/lapack

- ScaLAPACK:
  - **parallel** LAPACK: http://www.netlib. org/scalapack

- RScaLAPACK is a wrapper library to ScaLAPACK:
  - Also allows to link with ATLAS: http://www.netlib.org/atlas

# Ex: RScaLAPACK Examples

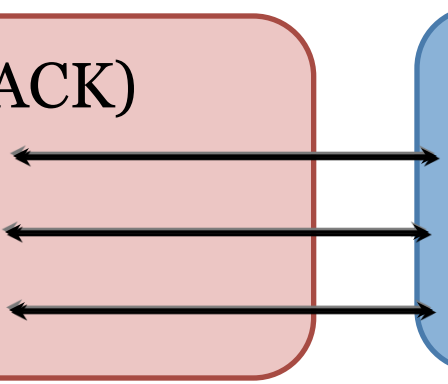
```
A = matrix(rnorm(256),16,16)
b = as.vector(rnorm(16))
```

Using RScaLAPACK:

```
library (RScaLAPACK)
sla.solve (A,b)
sla.svd (A)
sla.prcomp (A)
```

Using R:

```
solve (A,b)
La.svd (A)
prcomp (A)
```



# RScaLAPACK Functions

- library (RScaLAPACK)
- help (package=RScaLAPACK)
- help (sla.solve)  or ?sla.solve
- example (sla.solve)
- demo (RScaLAPACK)

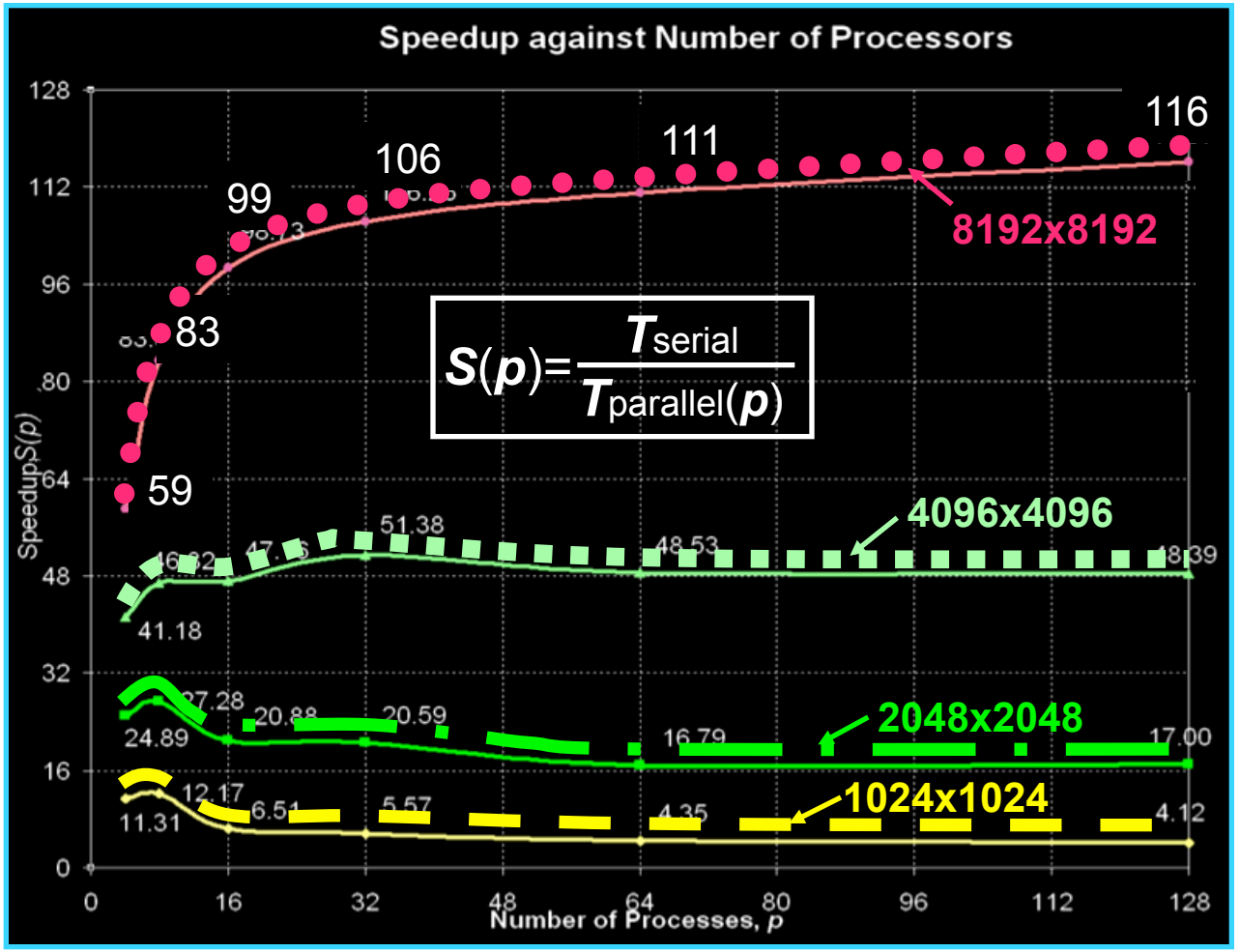
# Currently Supported Functions

| Serial R Functions | Parallel RScaLAPACK | RScaLAPACK Function Description |
|---|---|---|
| **svd** | **sla.svd** | **Compute a singular value decomposition of a rectangular matrix** |
| **eigen** | **sla.eigen** | **Computes the Eigen values and Eigen vectors of symmetric square matrix** |
| **chol** | **sla.chol** | **Computes the Choleski factorization of a real symmetric positive definite square matrix** |
| **chol2inv** | **sla.chol2inv** | **Invert a symmetric, positive definite, square matrix from its Choleski decomposition** |
| **solve** | **sla.solve** | **This generic function solves the equation a*x=b for x** |
| **qr** | **sla.qr** | **computes the QR decomposition of a matrix** |
| **factanal** | **sla.factanal** | **Perform maximum-likelihood factor analysis on a covariance matrix or data matrix using RScaLAPACK functions** |
| **factanal.fit.mle** | **sla.factanal.fit.mle** | **Perform maximum-likelihood factor analysis on a covariance matrix or data matrix using RScaLAPACK functions** |
| **prcomp** | **sla.prcomp** | **performs a principal components analysis on the given data matrix using RScaLAPACK functions** |
| **princomp** | **sla.princomp** | **performs a principal components analysis on the given data matrix using RScaLAPACK functions** |
| **varimax** | **sla.varimax** | **These functions rotate loading matrices in factor analysis using RScaLAPACK functions** |
| **promax** | **sla.promax** | **These functions rotate loading matrices in factor analysis using RScaLAPACK** |

# Scalability of *pR: RScaLAPACK*

***R> solve (A,B)*** ***pR> sla.solve (A, B, NPROWS, NPCOLS, MB)***

***A, B*** are input matrices; ***NPROWS*** and ***NPCOLS*** *are process grid specs;* ***MB*** is block size




Architecture: SGI Altix at CCS of ORNL with **256 Intel Itanium2 processors** at **1.5 GHz**; 8 GB of memory per processor (**2 TB** system memory); 64-bit Linux OS; 1.5 TeraFLOPs/s theoretical total peak performance.

# Changing the Processor Grid in RScaLAPACK

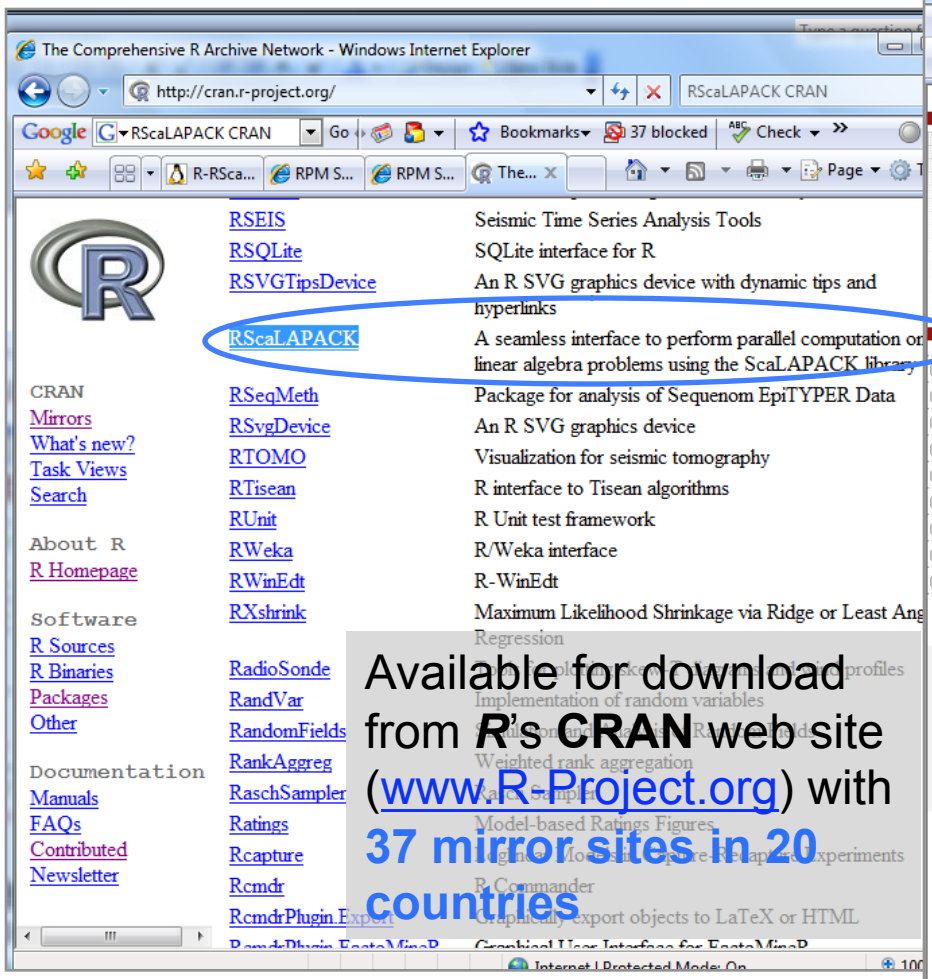
```
library (RScaLAPACK)
A = matrix(rnorm(128*128),128,128)
?sla.gridInit
```

Changing processor grid:

```
sla.gridInit(NPROCS=8)
x = sla.solve (A, NPROWS=4)
sla.gridExit()
```

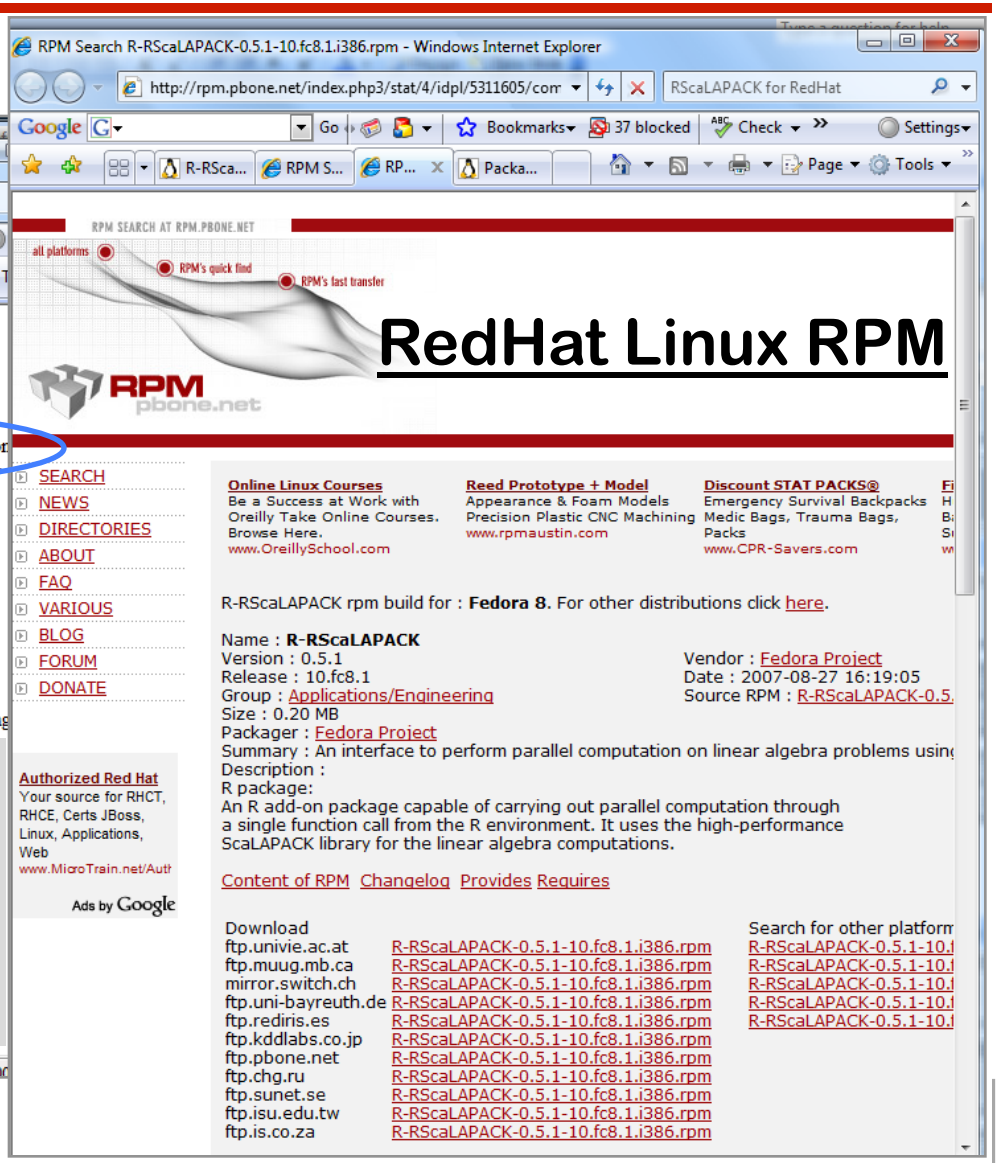
# RedHat and CRAN Distribution

## CRAN R-Project




Available for download from ***R***'s **CRAN** web site (www.R-Project.org) with **37 mirror sites in 20 countries**

http://cran.r-project.org/web/packages/RScaLAPACK/index.html



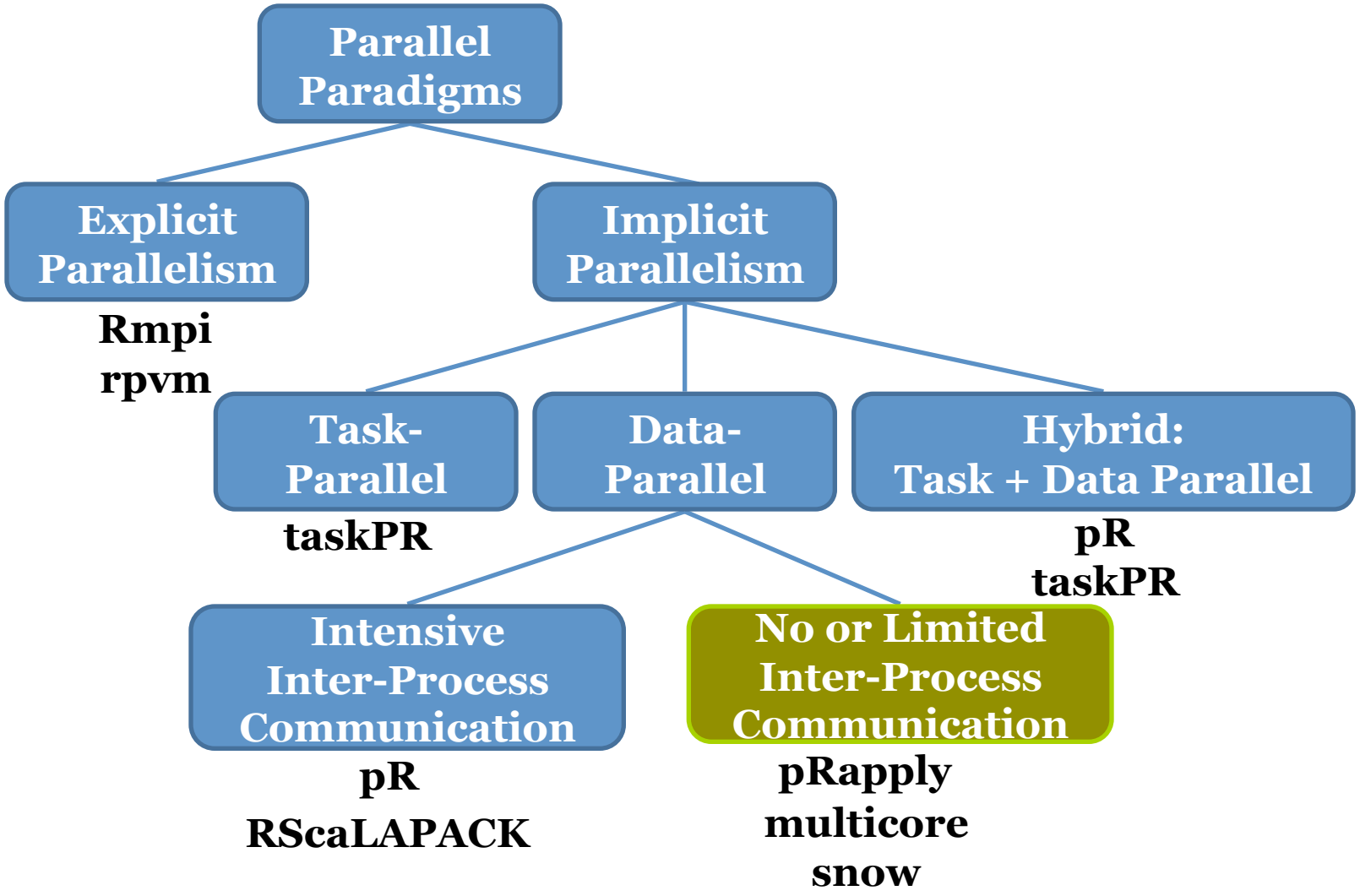

http://rpmfind.net/linux/RPM/RByName.html

# RScaLAPACK Installation

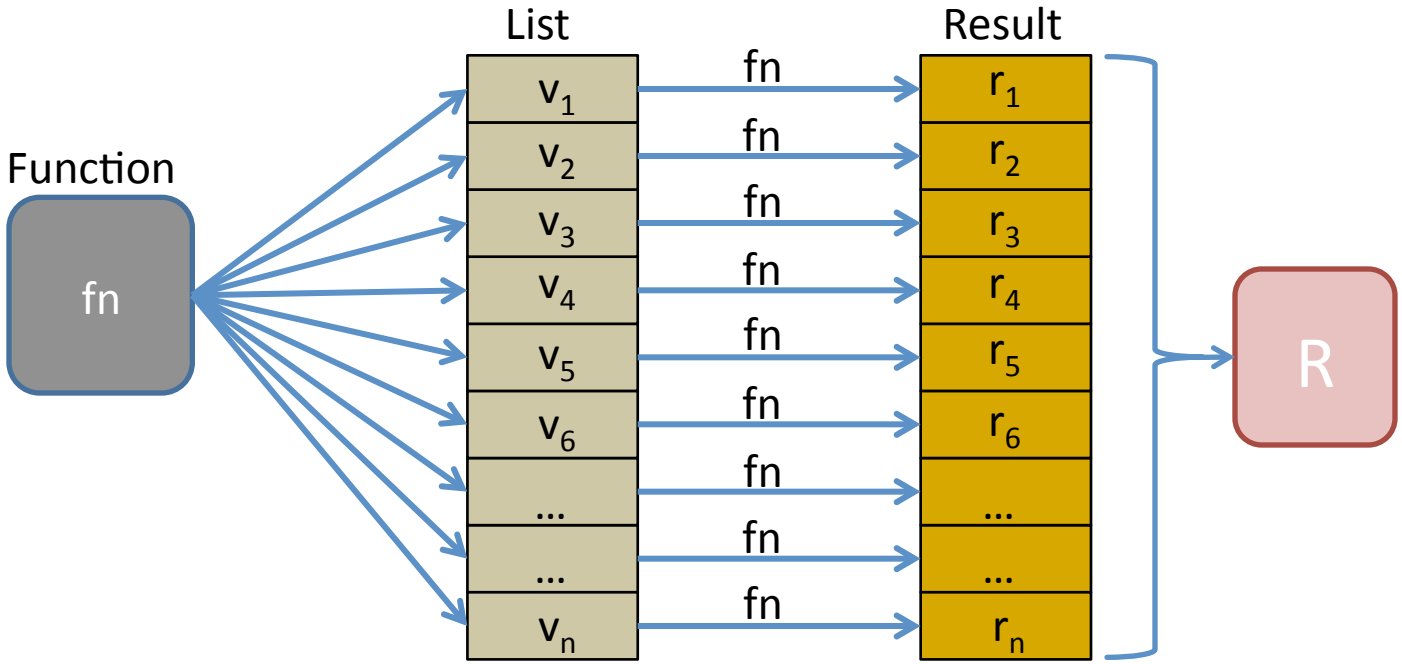
- **Download** RscaLAPACK from R's CRAN web-site
- **Install dependency packages**:
  - Install R
  - MPI (Open MPI, MPICH, LAM MPI)
  - ScaLAPACK (with the proper MPI distribution)
  - Setup environment variables

    *export LD_LIBRARY_PATH=<path2deps>/lib:$LD_LIBRARY_PATH*
- **Install RScaLAPACK**:
  - R CMD INSTALL *--configure-args="--with-f77 --with-mpi=<MPI install home directory> --with-blacs=<blacs build>/lib --with-blas=<blas build>/lib --with-lapack=<lapack build>/lib --with-scalapack=<scalapack build>/lib" RScaLAPACK_0.6.1.tar.gz*

# Parallel Paradigm Hierarchy



# R's *lapply* Method is a Natural Candidate for Automatic Parallelization




- Examples: Bootstrapping, Monte Carlo, etc.

# Existing R Packages with Parallel *lapply*

- multicore
  - Limited to single-node execution
  - *mclapply*

- snow
  - Built on Rmpi – uses MPI for communication
  - Requires users to explicitly manage R dependencies (libraries, variables, functions)
  - *clusterApply*

# snow Example

R End-User

```
1  library(snow);
2  library(abind);
3  x = as.list(1:16);
4  axis=0;
5  y = matrix(1:12,3,4);
6  fn <- function(){
7     z = y+100;
8     b = dim(abind(y,z,along=axis))
9  }
10
11 cl = makeCluster(numProcs, type = "MPI")
12 clusterApply(cl, x, fn);
13 stopCluster(c1);
```

Explicitly send libraries, functions, and variables

```
1 clusterExport(cl, list(axis, y));
2 clusterEvalQ(cl, library(abind));
```

# pRapply Example

**pRlapply (list, fn, procs=2, cores=2)**

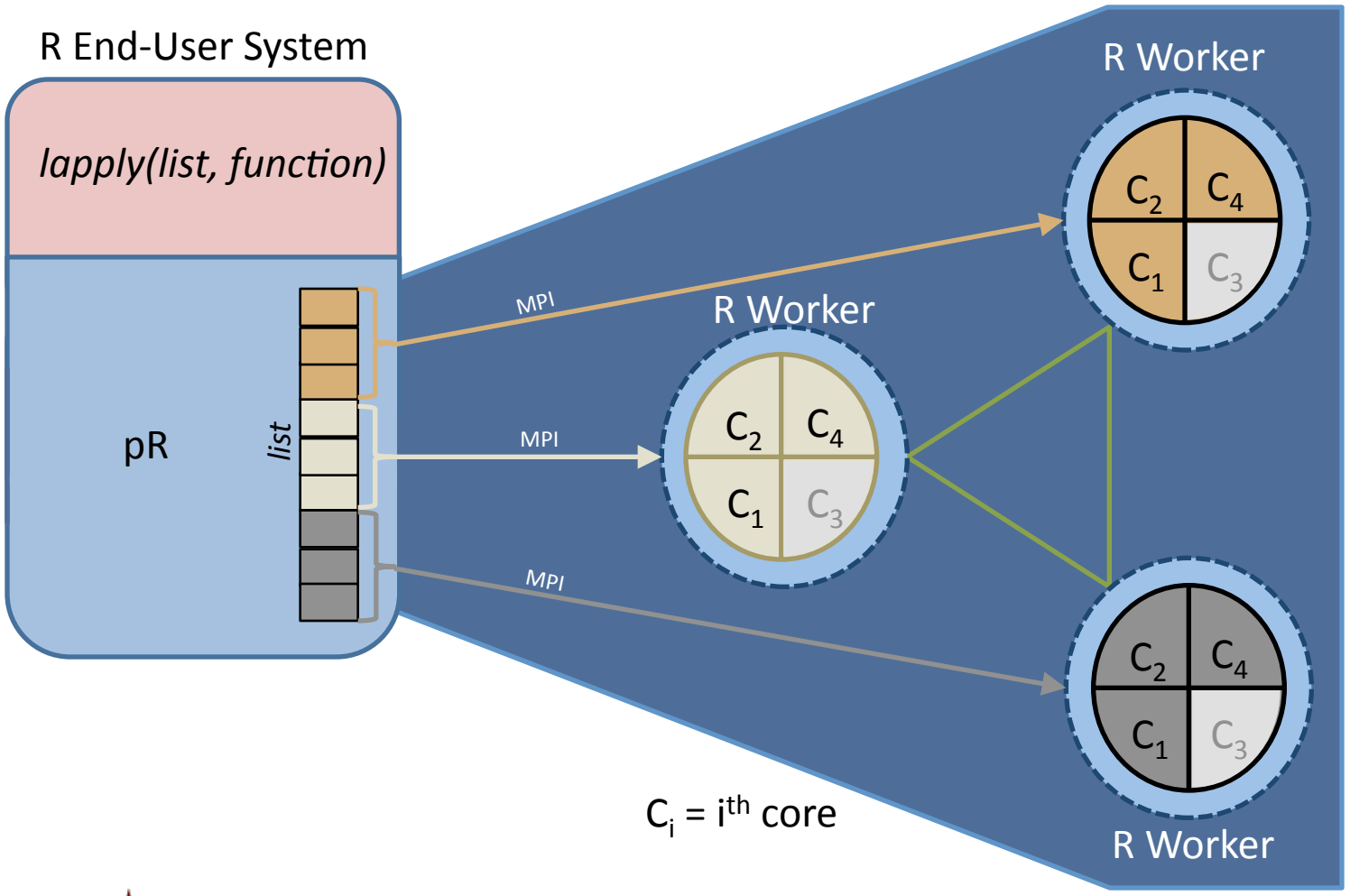
Using pRapply:

```
1  library(pRapply);
2  library(abind);
3  x = as.list(1:16);
4  axis=0;
5  y = matrix(1:12,3,4);
6  fn <- function(){
7     z = y+100;
8     b = dim(abind(y,z,along=axis))
9  }
10
11 pRlapply(x, fn)
```

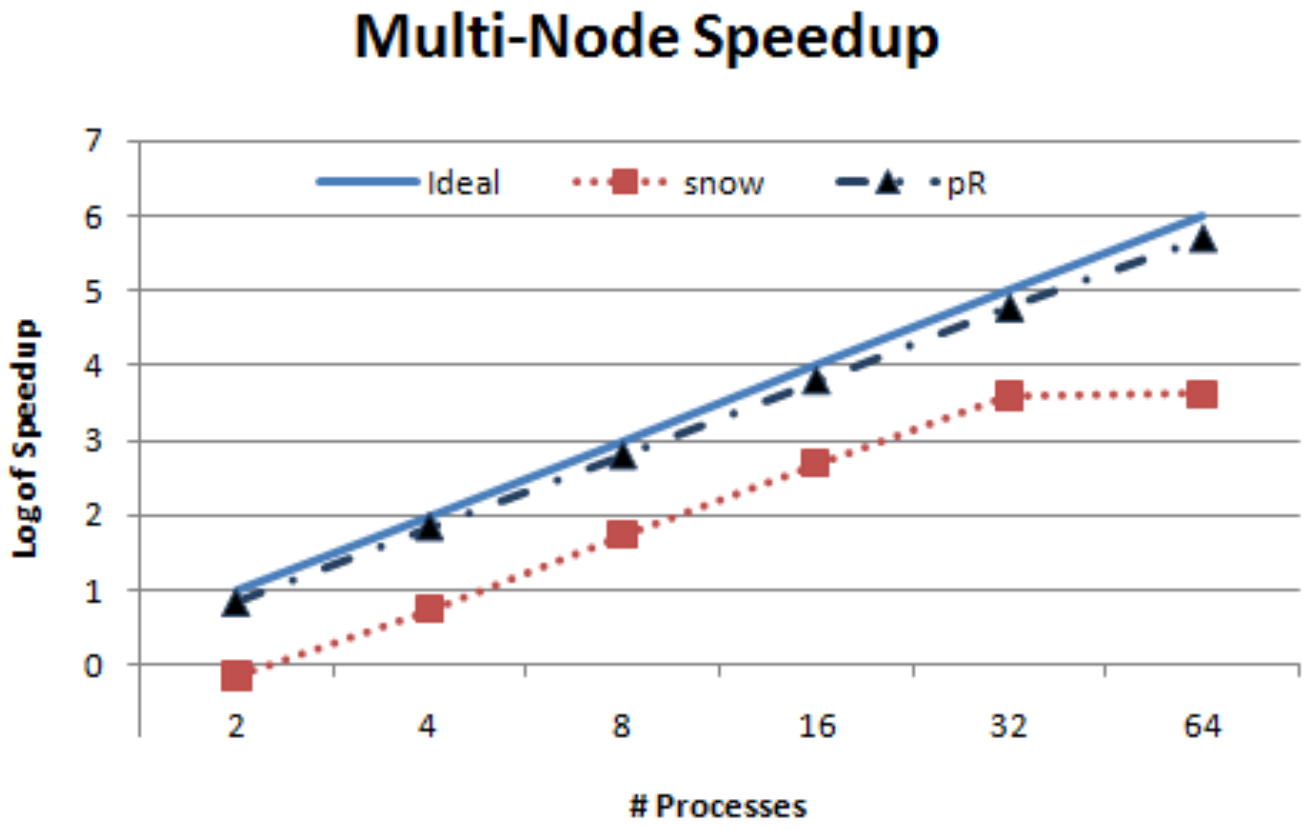
Using R:

```
1
2  library(abind);
3  x = as.list(1:16);
4  axis=0;
5  y = matrix(1:12,3,4);
6  fn <- function(){
7     z = y+100;
8     b = dim(abind(y,z,along=axis))
9  }
10
11 lapply(x, fn)
```

# pR Automatic Parallelization Uses a 2-Tier Execution Strategy



# pRapply: ~Ideal Speedup vs. snow




Multi-node speedup for pR and snow compared to the serial R implementation using a testcase that sums 4096 vectors, each of size $2^{24}$.

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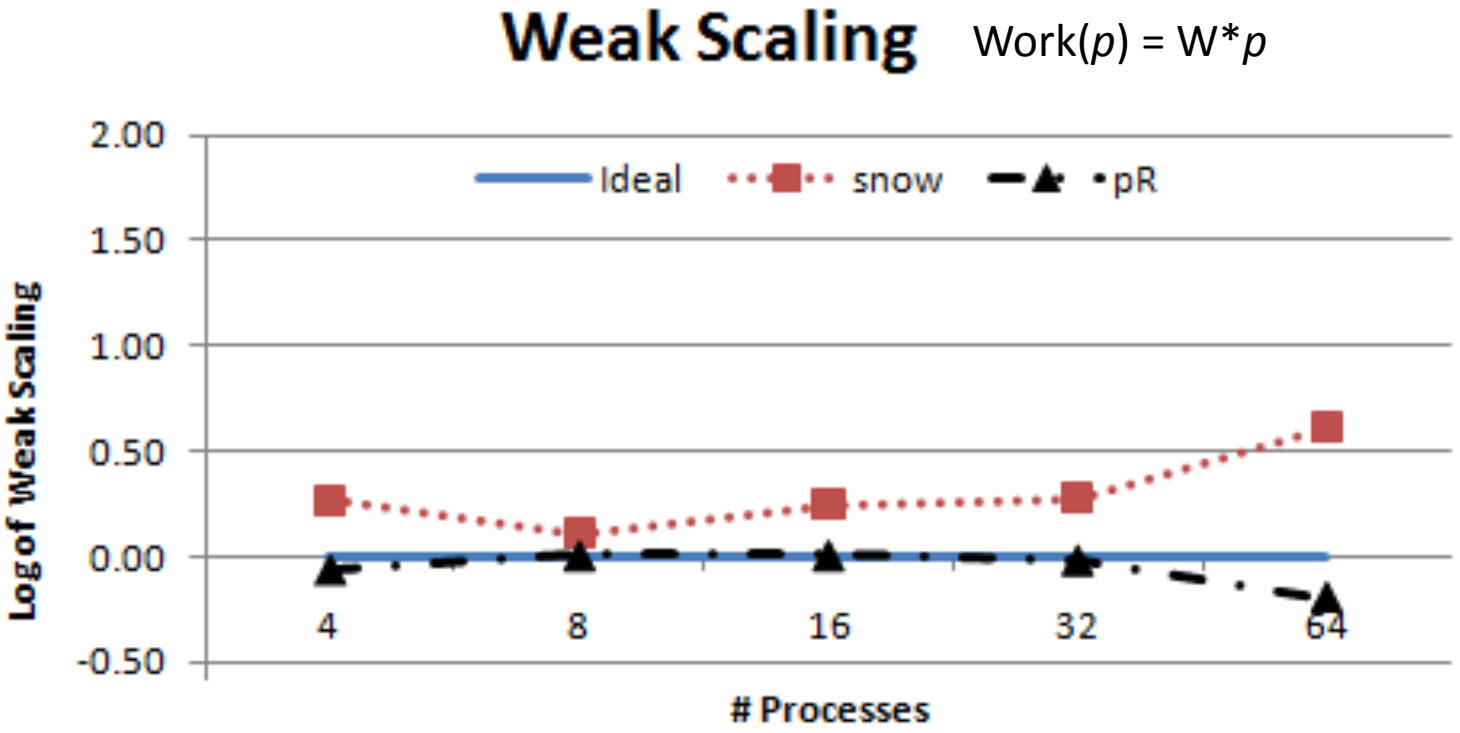
# pRapply: Ideal or Better Weak Scaling




Weak scaling comparison of snow and pR in a 64-node hybrid multi-node multi-core environment; each process sums a $2^{24}$ element vector.

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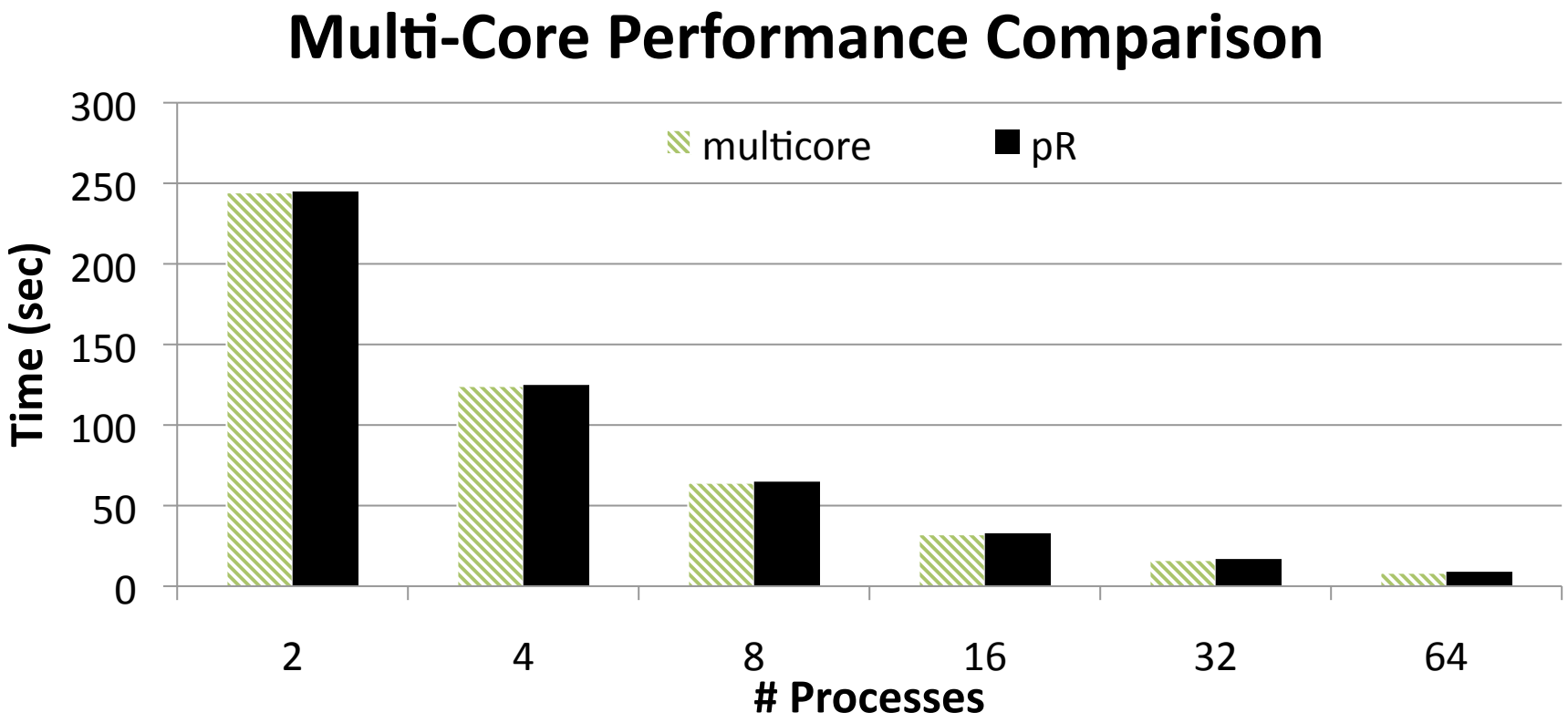
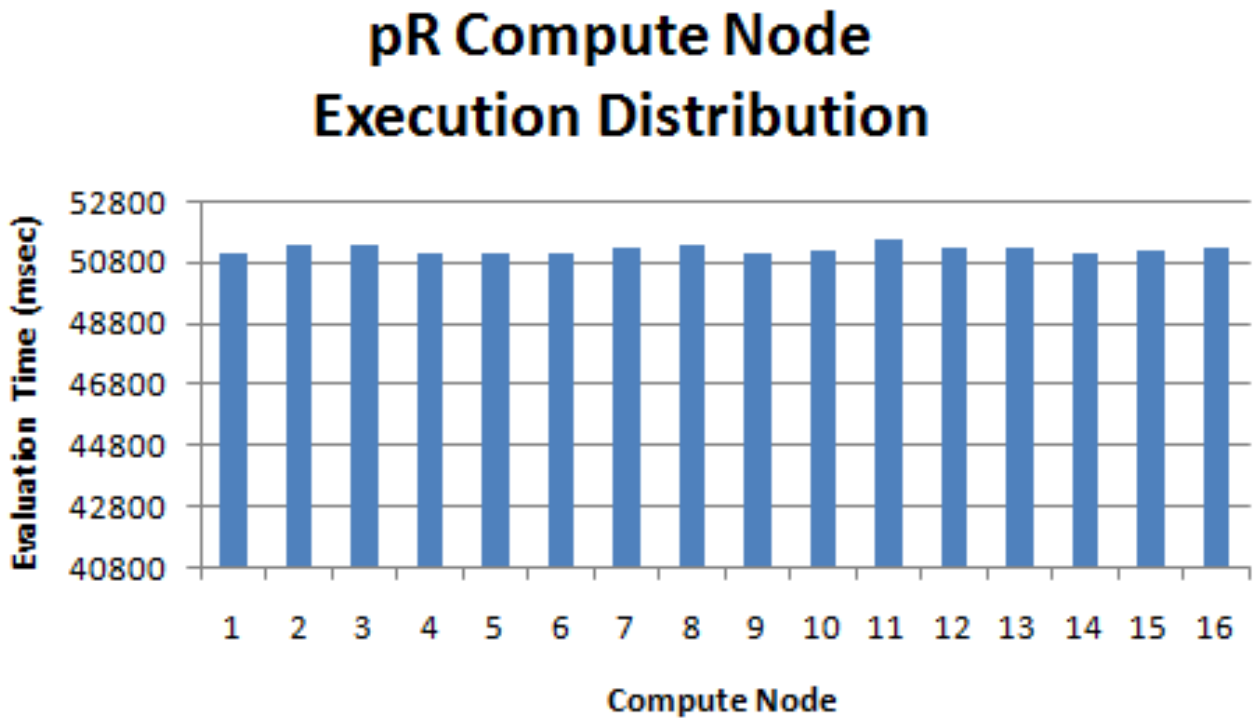
# pRapply: Like *multicore*, but Supports Hybrid Multi-Node, Multi-Core Execution




The pR overhead and total execution time compared to the multicore package over powers of two processes (1-64) using a testcase that *sleeps* 120 times for 4 seconds.

# pR Achieves Load-Balanced Performance




pR compute node execution heterogeneity in a hybrid multi-node multi-core Environment using 16 nodes to each sum a $2^{24}$ element vector.

# pR Major Contributions

- Enables integrating efficient serial codes into R using in-memory data transfers
- Provides parallel computing capabilities within R
- Enables automatic parallelization of data-parallel codes in hybrid multi-core and multi-node environments

# Acknowldgements


- Guruprasad Kora, ORNL
- Paul Breimyer, Lincoln Lab
- Srikanth Yoginath, ORNL
- David Bauer, GA Tech

# Publications


1. *pR: Efficient and Scalable Parallel R for High-Performance Statistical Computing;* The International Conference on Information and Knowledge Engineering (IKE) 2009; Paul Breimyer, Guruprasad Kora, William Hendrix, Nagiza F. Samatova
2. *Parallel R for High Performance Analytics: Applications to Biology*; Scientific Data Management (Book In Press), 2008; Nagiza F. Samatova, Paul Breimyer, Guruprasad Kora, Chongle Pan, Srikanth Yoginath; Editors: Arie Shoshani, Doron Rotem, Chandrika Kamath
3. *pR: Automatic Parallelization of Data-Parallel Statistical Computing Codes for R in Hybrid Multi-Node and Multi-Core Environments*; International Association for Development of Information Society (IADIS) 2009; Paul Breimyer, Guruprasad Kora, William Hendrix, Nagiza F. Samatova
4. RScaLAPACK on CRAN: http://cran.r-project.org/mirrors.html
5. *High performance statistical computing with parallel R: applications to biology and climate modelling,* Journal of Physics: Conference Series 46 (2006) 505–509; Samatova NF, Branstetter M, Ganguly AR, Hettich R, Khan S, Kora G, Li J, Ma X, Pan C, Shoshani A, Yoginath S,
6. *RScaLAPACK: High-performance parallel statistical computing with R and ScaLAPACK.* Proceedings of the 18th International Conference on Parallel and Distributed Computing Systems (PDCS-2005), Sep 12-14, 2005, Las Vegas, Nevada; Yoginath S, Samatova NF, Bauer D, Kora G, Fann G, Geist A.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# Session 2: Input and Output

## To input data:

```
# scan() command to scan data
 x=scan()
# enter numbers, one or more on a
line, and type a blank line to end
```

```
# read.table() command to read
data from file
 y=read.table("myfile")
```

```
 # rep() command to create data
that follow a regular pattern
 b=rep(1,5)
 c=rep(1:2,4)
```

## To access vector elements:

```
# 2nd element of x
 x[2]
# first five elements of x
 x[1:5]
# all but the 3rd element of x
 x[-3]
 # values of x that are < 40
 x[x<40]
# values of y such that x is < 40
 y[x<40]
```

## To perform operations:

```
 # mathematical operations on vectors
y=c(3,2,4,3,7,6,1,1)
 x+y; 2*y;  x*y;  x/y;  y^2
```

# Session 4: Plotting in R

- To create a vector:
  - x=c(12,32,54,33,21,65) # help (c)