bigmemory: bigger, better, and platform-independent

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Abstract

The newly re-engineered package bigmemory uses the Boost Interprocess C++ library to provide platform independent support for massive matrices. These matrices may be allocated to shared memory with transparent read and write locking. In addition, bigmemory now supports file-backed matrices, ideal for applications exceeding available RAM.

Not all of the following slides will be presented during the talk, but we wanted to make them available online.

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ASA 2009 Data Expo: Airline on-time performance

http://stat-computing.org/dataexpo/2009/

- Flight arrival and departure details for all* commercial flights within the USA, from October 1987 to April 2008.
- Nearly 120 million records, 29 variables (mostly integer-valued)
- We preprocessed the data, creating a single CSV file, recoding the carrier code, plane tail number, and airport codes as integers.

* Not really. Only for carriers with at least 1% of domestic flights in a given year.

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Hardware used in the examples

Yale's "Bulldogi" cluster:

- 170 Dell Poweredge 1955 nodes
- 2 dual-core 3.0 Ghz 64-bit EM64T CPUs
- 16 GB RAM each node
- Gigabit ethernet with both NFS and a Lustre filesystem
- Managed via PBS

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This laptop (it ain't light):

- Dell Precision M6400
- Intel Core 2 Duo Extreme Edition
- 4 GB RAM (a deliberate choice)
- Plain-vanilla primary hard drive
- 64 GB solid state secondary drive

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ASA 2009 Data Expo: Airline on-time performance

120 million flights by 29 variables ~ 3.5 billion elements. Too big for an R matrix (limited to 2^31 – 1 ~ 2.1 billion elements and likely to exceed available RAM, anyway).

Hadley Wickham's recommended approach: ***sqlite***

Upcoming alternative: ***ff***

- We used version 2.1.0 (beta)
- ***ff*** matrix limited to 2^31-1 elements;
- ***ffdf*** data frame works, though.

Others: ***BufferedMatrix***, ***filehash***,

- many database interface packages;
- ***R.huge*** will no longer be supported.

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Airline on-time performance via *bigmemory*

Via *bigmemory* (on CRAN): creating the filebacked big.matrix

Note: as part of the creation, I add an extra column that will be used for the calculated age of the aircraft at the time of the flight.

```
> x <- read.big.matrix("AirlineDataAllFormatted.csv",
                       header=TRUE, type="integer",
                       backingfile="airline.bin",
                       descriptorfile="airline.desc",
                       extraCols="age")
```

~ 25 minutes

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Airline on-time performance via *sqlite*

Via *sqlite* (http://sqlite.org/): preparing the database

```
Revo$ sqlite3 ontime.sqlite3
SQLite Version 3.6.10 …
sqlite> create table ontime (Year int, Month int,
              …, origin int, …, LateAircraftDelay int);
sqlite> .separator ,
sqlite> .import AirlineDataAllFormatted.csv ontime
sqlite> delete from ontime where typeof(year)==“text”;
sqlite> create index origin on ontime(origin);
sqlite> .quit
Revo$
```

~ 75 minutes excluding the **`create index`**.

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A first comparison: *bigmemory* vs *RSQLite*

Via *RSQLite* and *bigmemory*, a column minimum?

The result: *bigmemory* wins.

```
> library(bigmemory)
> x <- attach.big.matrix(
         dget("airline.desc") )
> system.time(colmin(x, 1))
   user  system elapsed
  0.236   0.372   7.564
> system.time(a <- x[,1])
   user  system elapsed
  0.852   1.060   1.910
> system.time(a <- x[,2])
   user  system elapsed
  0.800   1.508   9.246
```

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```
> library(RSQLite)
> x <- attach.big.matrix(
+                 dget("airline.desc") )
> ontime <- dbConnect("SQLite",
+                dbname="ontime.sqlite3")
> from_db <- function(sql) {
+                dbGetQuery(ontime, sql)
+             }
> system.time(from_db(
+       "select min(year) from ontime"))
    user  system elapsed
  45.722  14.672 129.098
> system.time(a <-
+   from_db("select year from ontime"))
    user  system elapsed
  59.208  20.322 138.132
```

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Airline on-time performance via *ff*

Example: *ff* (Dan Adler et.al., Beta version 2.1.0)

```
> library(bigmemory)
> library(filehash)
> x <- attach.big.matrix(dget("airline.desc"))
> y1 <- ff(x[,1], filename="ff1")
> y2 <- ff(x[,2], filename="ff2")
…
> y30 <- ff(x[,30], filename="ff30")
> z <- ffdf(y1,y2,y3,y4,y5,y6,y7,y8,y9,y10,
+           y11,y12,y13,y14,y15,y16,y17,y18,y19,y20,
+           y21,y22,y23,y24,y25,y26,y27,y28,y29,y30)
```

With apologies to Adler et.al, we couldn't figure out how to do this more elegantly, but it worked (and, more quickly – 7 minutes, above – than you'll see with the subsequent two examples with other packages). As we noted last year at UseR!, an function like ***read.big.matrix()*** would greatly benefit ***ff***.

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Airline on-time performance via *ff*

Example: *ff* (Dan Adler et.al., Beta version 2.1.0)

The challenge: R's *min()* on extracted first column; caching.

The result: they're about the same.

```
# With ff:
> system.time(min(z[,1], na.rm=TRUE))
   user  system elapsed
  2.188   1.360  10.697
> system.time(min(z[,1], na.rm=TRUE))
   user  system elapsed
  1.504   0.820   2.323
```

```
> # With bigmemory:
> system.time(min(x[,1], na.rm=TRUE))
   user  system elapsed
  1.224   1.556  10.101
> system.time(min(x[,1], na.rm=TRUE))
   user  system elapsed
  1.016   0.988   2.001
```

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Airline on-time performance via *ff*

Example: *ff* (Dan Adler et.al., Beta version 2.1.0)

The challenge: alternating *min()* on first and last rows.

The result: maybe an edge to *bigmemory*, but do we care?

```
> # With bigmemory:
> system.time(min(x[1,],na.rm=TRUE))
   user  system elapsed
  0.004   0.000   0.071
> system.time(min(x[nrow(x),],
                  na.rm=TRUE))
   user  system elapsed
  0.000   0.000   0.001
> system.time(min(x[1,],na.rm=TRUE))
   user  system elapsed
  0.000   0.000   0.001
> system.time(min(x[nrow(x),],
                  na.rm=TRUE))
   user  system elapsed
  0.000   0.000   0.001
```

```
> # With ff:
> system.time(min(z[1,],na.rm=TRUE))
   user  system elapsed
  0.040   0.000   0.115
> system.time(min(z[nrow(z),],
+                  na.rm=TRUE))
   user  system elapsed
  0.032   0.000   0.099
> system.time(min(z[1,],na.rm=TRUE))
   user  system elapsed
  0.020   0.000   0.024
> system.time(min(z[nrow(z),],
                  na.rm=TRUE))
   user  system elapsed
  0.036   0.000   0.080
```

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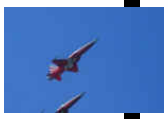
Airline on-time performance via *ff*

Example: *ff* (Dan Adler et.al., Beta version 2.1.0)

The challenge: random extractions, two runs (time two):

```
> theserows <- sample(nrow(x), 10000)
> thesecols <- sample(ncol(x), 10)
>
> # With ff:
> system.time(a <- z[theserows,
+                    thesecols])
   user  system elapsed
  0.092   1.796  60.574
> system.time(a <- z[theserows,
+                    thesecols])
   user  system elapsed
  0.040   0.384   4.069

> # With bigmemory:
> system.time(a <- x[theserows,
+                    thesecols])
   user  system elapsed
  0.020   1.612  64.136
> system.time(a <- x[theserows,
+                    thesecols])
   user  system elapsed
  0.020   0.024   1.323
```



```
> theserows <- sample(nrow(x), 100000)
> thesecols <- sample(ncol(x), 10)
>
> # With ff:
> system.time(a <- z[theserows,
+                    thesecols])
   user  system elapsed
  0.352   3.305  78.161
> system.time(a <- z[theserows,
+                    thesecols])
   user  system elapsed
  0.340   3.156  77.623

> # With bigmemory:
> system.time(a <- x[theserows,
+                    thesecols])
   user  system elapsed
  0.248   2.752  78.935
> system.time(a <- x[theserows,
+                    thesecols])
   user  system elapsed
  0.248   2.676  78.973
```

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Airline on-time performance via *filehash*

Example: *filehash* (Roger Peng, on CRAN)

```
> library(bigmemory)
> library(filehash)
> x <- attach.big.matrix(dget("airline.desc"))
> dbCreate("filehashairline", type="RDS")
> fhdb <- dbInit("filehashairline", type="RDS")
> for (i in 1:ncol(x))
+   dbInsert(fhdb, colnames(x)[i], x[,i])   # About 15 minutes.
```

```
> system.time(min(fhdb$Year))
   user  system elapsed
 11.317   0.236  11.584
> system.time(min(fhdb$Year))
   user  system elapsed
 11.744   0.236  11.987
```

```
> system.time(min(x[,"Year"]))
   user  system elapsed
  1.128   1.616   9.758
> system.time(min(x[,"Year"]))
   user  system elapsed
  0.900   0.984   1.891
> system.time(colmin(x, "Year"))
   user  system elapsed
  0.184   0.000   0.183
```

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***filehash* is quite memory-efficient on disk!**

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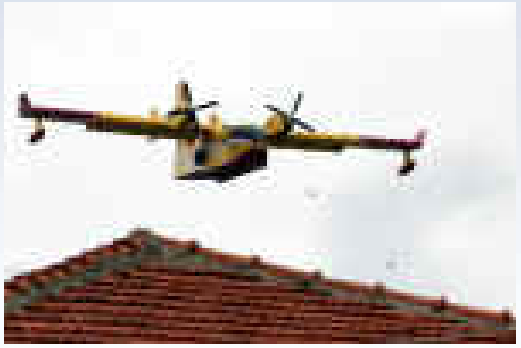
Airline on-time performance via *BufferedMatrix*

Example: *BufferedMatrix* (Ben Bolstad, on BioConductor)

```
> library(bigmemory)
> library(BufferedMatrix)
> x <- attach.big.matrix(dget("airline.desc"))
> y <- createBufferedMatrix(nrow(x), ncol(x))
> for (i in 1:ncol(x)) y[,i] <- x[,i]
```



More than 90 minutes to fill the *BufferedMatrix*; inefficient (only 8-byte numeric is supported); not persistent.

```
> system.time(colmin(x))
   user  system elapsed
  4.576   4.560 113.289
> system.time(colMin(y))
   user  system elapsed
 20.926  71.492 966.952
```

```
> system.time(colmin(x, na.rm=TRUE))
   user  system elapsed
 11.264   9.645 256.911
> system.time(colMin(y, na.rm=TRUE))
   user  system elapsed
 39.515  70.436 941.229
```

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More basics of *bigmemory*

```
> library(bigmemory)
> xdesc <- dget("airline.desc")
> x <- attach.big.matrix(xdesc)
> dim(x)
[1] 118914458        30
> colnames(x)
 [1] "Year"              "Month"             "DayofMonth"
 [4] "DayOfWeek"         "DepTime"           "CRSDepTime"
 [7] "ArrTime"           "CRSArrTime"        "UniqueCarrier"
[10] "FlightNum"         "TailNum"           "ActualElapsedTime"
[13] "CRSElapsedTime"    "AirTime"           "ArrDelay"
[16] "DepDelay"          "Origin"            "Dest"
… (rows omitted for this slide)
> tail(x, 1)
             Year             Month        DayofMonth         DayOfWeek
             2008                 4                17                 4
          DepTime       CRSDepTime           ArrTime       CRSArrTime
              381               375               472               754
    UniqueCarrier         FlightNum           TailNum ActualElapsedTime
               11              1211              2057                91
   CRSElapsedTime           AirTime          ArrDelay          DepDelay
               99                64                -2                 6
           Origin              Dest          Distance            TaxiIn
               63                35               430                15
… (rows omitted for this slide)
```

A ***big.matrix*** is a lot like a ***matrix***...

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More basics of *bigmemory*

```
> ###################################################
> # Can we get all flights from JFK to SFO?  Sure!
>
> a <- read.csv("AirportCodes.csv")
> a <- na.omit(a)
> JFK <- a$index[a$airport=="JFK"]
> SFO <- a$index[a$airport=="SFO"]
>
> gc(reset=TRUE)
         used (Mb) gc trigger  (Mb) max used (Mb)
Ncells 214256 11.5     407500  21.8   214256 11.5
Vcells 169064  1.3   29629238 226.1   169064  1.3
> system.time(
+   y <- x[x[,"Origin"]==JFK & x[,"Dest"]==SFO,]
+ )
   user  system elapsed
   6.50    5.23   11.74
> dim(y)
[1] 99867    30
> gc()
          used (Mb) gc trigger   (Mb)  max used   (Mb)
Ncells  214242 11.5     407500   21.8    220478   11.8
Vcells 1667071 12.8  220757362 1684.3 241395930 1841.8
> rm(y)
```

Slower and less memory-efficient than our alternative: ***mwhich()***, coming up next...

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mwhich()

```
> ################################################
> # mwhich() for fast, no-overhead "multi-which"
>
> gc(reset=TRUE)
         used (Mb) gc trigger   (Mb) max used (Mb)
Ncells 214238 11.5     407500   21.8   214238 11.5
Vcells 169034  1.3  176605889 1347.4   169034  1.3
> system.time(
+   y <- x[mwhich(x, cols=c("Origin", "Dest"),
+                    vals=list(JFK, SFO),
+                    comps="eq",
+                    op="AND"), ]
+ )
   user  system elapsed
  5.270   0.020   5.308
> dim(y)
[1] 99867    30
> gc()
          used (Mb) gc trigger  (Mb) max used (Mb)
Ncells  214277 11.5     407500  21.8   235659 12.6
Vcells 1667109 12.8  113027768 862.4  3271422 25.0
> rm(y)
```

Fast, no memory overhead!

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mwhich(): useful with R matrices, too!

```
> ###################################################
> # mwhich() works on a matrix, too, but I can't
> # hold all the data as an R matrix, even if I had
> # the RAM (see earlier comment on size). On a subset:
>
> xx <- x[,15:18]
> gc(reset=TRUE)
            used   (Mb) gc trigger   (Mb)  max used   (Mb)
Ncells    203561   10.9     407500   21.8    203561   10.9
Vcells 237996106 1815.8  499861463 3813.7 237996106 1815.8
> system.time(
+   y <- xx[mwhich(x, cols=c("Origin", "Dest"),
+                  vals=list(JFK, SFO),
+                  comps="eq",
+                  op="AND"), ]
+ )
   user  system elapsed
  5.220   0.000   5.219
> dim(y)
[1] 99867     4
> gc()
            used   (Mb) gc trigger   (Mb)  max used   (Mb)
Ncells    203566   10.9     407500   21.8    213419   11.4
Vcells 238195846 1817.3  499861463 3813.7 238448239 1819.3
```

Just as fast as with a ***big.matrix***, with no memory overhead beyond the ***matrix*** itself.

Airline on-time performance: solving a problem

For each plane in the data set, what was the first month (in months A.D.) of service?

```
> date()
[1] "Fri Jun 19 13:27:23 2009"
> library(bigmemory)
> xdesc <- dget("airline.desc")
> x <- attach.big.matrix(xdesc)
> numplanes <- length(unique(x[,"TailNum"])) - 1
> planeStart <- rep(0, numplanes)
> for (i in 1:numplanes) {
+   y <- x[mwhich(x, "TailNum", i, 'eq'),
+          c("Year", "Month"), drop=FALSE]  # Note this.
+   minYear <- min(y[,"Year"], na.rm=TRUE)
+   these <- which(y[,"Year"]==minYear)
+   minMonth <- min(y[these,"Month"], na.rm=TRUE)
+   planeStart[i] <- 12*minYear + minMonth
+ }
> date()
[1] "Fri Jun 19 22:27:36 2009"
```

No surprises... yet.

~ 9 hours

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Introducing *foreach, iterators, doMC, doSNOW, doNWS*

- Brand new, coming out of REvolution Computing
- The brainchildren of Steve Weston (who produced a subset of the slides immediately following this one)
- The following are called "parallel backends":
  - ***doMC*** makes use of ***multicore*** (Simon Urbanek)
  - ***doSNOW*** makes use of ***snow*** (Luke Tierney, A.J. Rossini, Na Li, and H. Sevcikova)
  - ***doNWS*** makes use of NetWorkSpaces (***nws***, REvolution Computing following from Scientific Computing Associates)

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foreach, iterators

```
> library(foreach)
Loading required package: iterators
Loading required package: codetools
> foreach (i=1:3) %do% { sqrt(i) }
[[1]]
[1] 1

[[2]]
[1] 1.414214

[[3]]
[1] 1.732051

> foreach (i=1:3, .combine=c) %do% { sqrt(i) }
[1] 1.000000 1.414214 1.732051
> foreach (i=1:3, .combine='+') %do% { sqrt(i) }
[1] 4.146264
```

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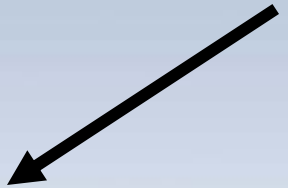
foreach on SMP via *doMC* (master plus 4 workers)

```
> date()
[1] "Thu Jun 18 21:39:09 2009"
> library(bigmemory)
> library(doMC)
Loading required package: foreach
Loading required package: iterators
Loading required package: codetools
Loading required package: multicore
> registerDoMC()
> xdesc <- dget("airline.desc")
> x <- attach.big.matrix(xdesc)
> numplanes <- length(unique(x[,"TailNum"])) - 1
> planeStart <- foreach(i=1:numplanes, .combine=c) %dopar% {
+   require(bigmemory)
+   x <- attach.big.matrix(xdesc)
+   y <- x[mwhich(x, "TailNum", i, 'eq'),
+          c("Year", "Month"), drop=FALSE]
+   minYear <- min(y[,"Year"], na.rm=TRUE)
+   these <- which(y[,"Year"]==minYear)
+   minMonth <- min(y[these,"Month"], na.rm=TRUE)
+   12*minYear + minMonth
+ }
> date()
[1] "Fri Jun 19 00:14:36 2009"
```

VERY NEW!



- ~ 2.5 hours
- A new type of loop structure
- Some initialization

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Package ***multicore*** by Simon Urbanek

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foreach on SMP via *doSNOW* (master plus 3 workers)

```
> date()
[1] "Fri Jun 19 09:10:22 2009"
> library(bigmemory)
> library(doSNOW)
Loading required package: foreach
Loading required package: iterators
Loading required package: codetools
Loading required package: snow
> cl <- makeSOCKcluster(3)
> registerDoSNOW(cl)
> xdesc <- dget("airline.desc")
> x <- attach.big.matrix(xdesc)
> numplanes <- length(unique(x[,"TailNum"])) - 1
> planeStart <- foreach(i=1:numplanes, .combine=c) %dopar% {
+   require(bigmemory)
+   x <- attach.big.matrix(xdesc)
+   y <- x[mwhich(x, "TailNum", i, 'eq'),
+          c("Year", "Month"), drop=FALSE]
+   minYear <- min(y[,"Year"], na.rm=TRUE)
+   these <- which(y[,"Year"]==minYear)
+   minMonth <- min(y[these,"Month"], na.rm=TRUE)
+   12*minYear + minMonth
+ }
> date()
[1] "Fri Jun 19 12:38:33 2009"
```

- ~ 3.5 hours
- Different parallel backend setup and registration
- Otherwise identical code to the ***doMC*** SMP version

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Package ***snow*** by Luke Tierney, A.J. Rossini, Na Li, and H. Sevcikova

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foreach on SMP via *doNWS* (master plus 3 workers)

```
> date()
[1] "Thu Jun 18 17:42:52 2009"
> library(bigmemory)
> library(doNWS)
Loading required package: foreach
Loading required package: iterators
Loading required package: codetools
Loading required package: nws
> sl <- sleigh(workerCount=3)
> registerDoNWS(sl)
> xdesc <- dget("airline.desc")
> x <- attach.big.matrix(xdesc)
> numplanes <- length(unique(x[,"TailNum"])) - 1
> planeStart <- foreach(i=1:numplanes, .combine=c) %dopar% {
+   require(bigmemory)
+   x <- attach.big.matrix(xdesc)
+   y <- x[mwhich(x, "TailNum", i, 'eq'),
+          c("Year", "Month"), drop=FALSE]
+   minYear <- min(y[,"Year"], na.rm=TRUE)
+   these <- which(y[,"Year"]==minYear)
+   minMonth <- min(y[these,"Month"], na.rm=TRUE)
+   12*minYear + minMonth
+ }
> date()
[1] "Thu Jun 18 21:12:45 2009"
```

- ~ 3.5 hours
- A different parallel backend setup and registration
- Otherwise identical code to the ***doMC*** and ***doSNOW*** SMP versions

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foreach on cluster via *doNWS* (10 nodes by 3 processors)

```
> date()
[1] "Thu Jun 18 18:10:37 2009"
> library(bigmemory)
> library(doNWS)
Loading required package: foreach
Loading required package: iterators
Loading required package: codetools
Loading required package: nws
> nodes <- pbsNodeList()[-1]
> sl <- sleigh(nodeList=nodes, launch=sshcmd)
> registerDoNWS(sl)
> xdesc <- dget("airline.desc")
> x <- attach.big.matrix(xdesc)
> numplanes <- length(unique(x[,"TailNum"])) - 1
> planeStart <- foreach(i=1:numplanes, .combine=c) %dopar% {
+   require(bigmemory)
+   x <- attach.big.matrix(xdesc)
+   y <- x[mwhich(x, "TailNum", i, 'eq'),
+          c("Year", "Month"), drop=FALSE]
+   minYear <- min(y[,"Year"], na.rm=TRUE)
+   these <- which(y[,"Year"]==minYear)
+   minMonth <- min(y[these,"Month"], na.rm=TRUE)
+   12*minYear + minMonth
+ }
> dput(planeStart, "planeStart30NWS.txt")
> date()
[1] "Thu Jun 18 18:51:23 2009"
```

```
# Cluster Setup:
# qsub -I -l nodes=10:ppn=3 -q sandbox
# Once launched, fire up R on master.
```

- ~ 40 minutes (slower than expected – why?)
- No substantive code changes from the SMP version
- Different ***sleigh()*** (NetWorkSpaces) setup for cluster

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Big ***big.matrix***: no 2^31 row limitation

```
> R <- 3e9              # 3 billion rows
> C <- 2                # 2 columns
>
> R*C*8                 # 48 GB total size
[1] 4.8e+10
>
> date()
[1] "Thu Jun 18 20:11:49 2009"
> x <- filebacked.big.matrix(R, C, type='double',
+                            backingfile='test.bin',
+                            descriptorfile='test.desc')
> x[1,] <- rnorm(C)
> x[nrow(x),] <- runif(C)
> summary(x[1,])
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-1.7510 -1.2640 -0.7777 -0.7777 -0.2912  0.1953
> summary(x[nrow(x),])
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.04232 0.21080 0.37930 0.37930 0.54780 0.71630
> date()
[1] "Thu Jun 18 20:11:49 2009"
```

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REvolution computing

The new package ***synchronicity***

- Locking has been removed from ***bigmemory*** itself (upcoming version 4.0 and onwards) so that packages can take advantage of synchronization mechanisms without having to install bigmemory.
  - exclusive locks
  - shared locks
  - timed locks
  - conditional locking
- Allows for the creation of Universal Unique Identifiers
- The following locking schemes have been implemented for use in ***bigmemory*** (version 4.0 and onwards).
  - no locking
  - read only (allows a ***big.matrix*** object to be read only)
  - column locking
  - row locking
- The architecture is flexible enough to allow a user to define his own mutex scheme for a ***big.matrix*** object.

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Supporting linear algebra routines with ***bigalgebra***

- ***bigalgebra*** (currently in development) suports linear algebra operations on ***R*** matrices as well as ***big.matrix*** objects (including various combinations) for the following operations:
  - matrix copy
  - scalar multiply
  - matrix addition
  - matrix multiplication
  - SVD
  - eigenvalues and eigenvectors
  - Cholesky fatorization
  - QR factorization
  - others?
- The routines are implemented in BLAS and LAPACK libraries

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In summary: ***bigmemory*** and more

- **User-friendly, familiar interface (less user overhead than the other alternatives)**
- **Memory-efficient externalities (e.g. `mwhich`() cleverness)**
- **Shared memory will full mutexes (SMP)**
- **Distributed memory (locking to be supported via NetWorkSpaces soon; currently no mutexes)**
- **A developer tool, with access to pointers in C++ allowing integration with existing libraries (e.g. linear algebra routines).**

- ***foreach*/*iterators* plus *bigmemory*: a winning combination for massive data concurrent programming**

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Supplemental Slides: ***mwhich()*** and ***bigmemory*** for developers

The following includes C++ templates, but there isn't much to learn if you want to develop analytics to be used with R matrices as well as *big.matrix* objects.

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bigmemory for developers

```
template<typename T, typename MatrixType>
SEXP MWhichMatrix(MatrixType mat, long nrow, SEXP selectColumn,
                  SEXP minVal, SEXP maxVal, SEXP chkMin, SEXP chkMax,
                  SEXP opVal, double C_NA)
{
  long numSc = GET_LENGTH(selectColumn);
  double *sc = NUMERIC_DATA(selectColumn);
  double *min = NUMERIC_DATA(minVal);
  double *max = NUMERIC_DATA(maxVal);
  int *chkmin = INTEGER_DATA(chkMin);
  int *chkmax = INTEGER_DATA(chkMax);

  double minV, maxV;
  int ov = INTEGER_VALUE(opVal);
  long count = 0;
  long i,j;
  double val;
  for (i=0; i < nrow; ++i) {
    for (j=0; j < numSc; ++j)  {
      // …
      val = (double) mat[(long)sc[j]-1][i];
      // …
```

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bigmemory for developers

```
SEXP MWhichBigMatrix(SEXP bigMatAddr, SEXP selectColumn, SEXP minVal,
                     SEXP maxVal, SEXP chkMin, SEXP chkMax, SEXP opVal)
{
  BigMatrix *pMat =
    reinterpret_cast<BigMatrix*>(R_ExternalPtrAddr(bigMatAddr));
  if (pMat->separated_columns())
  {
    switch (pMat->matrix_type())
    {
      case 1:
        SepBigMatrixAccessor<char> mat(*pMat);
        return MWhichMatrix<char>(mat, pMat->nrow(), selectColumn,
          minVal, maxVal, chkMin, chkMax, opVal, NA_CHAR);
      //… (cases 2 and 4 omitted here)
      case 8:
        SepBigMatrixAccessor<double> mat(*pMat);
        return MWhichMatrix<double>(mat, pMat->nrow(), selectColumn,
          minVal, maxVal, chkMin, chkMax, opVal, NA_REAL);
    }
  } else // Same type of code, but with BigMatrixAccessor
```

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bigmemory for developers

```
SEXP MWhichRIntMatrix(SEXP matrixVector, SEXP nrow, SEXP selectColumn,
  SEXP minVal, SEXP maxVal, SEXP chkMin, SEXP chkMax, SEXP opVal)
{
  long numRows = static_cast<long>(INTEGER_VALUE(nrow));
  BigMatrixAccessor<int> mat(INTEGER_DATA(matrixVector), numRows);

  return MWhichMatrix<int>(mat, numRows, selectColumn, minVal, maxVal,
    chkMin, chkMax, opVal, NA_INTEGER);
}

SEXP MWhichRNumericMatrix(SEXP matrixVector, SEXP nrow, SEXP selectColumn,
  SEXP minVal, SEXP maxVal, SEXP chkMin, SEXP chkMax, SEXP opVal)
{
  long numRows = static_cast<long>(INTEGER_VALUE(nrow));
  BigMatrixAccessor<double> mat(NUMERIC_DATA(matrixVector), numRows);

  return MWhichMatrix<double>(mat, numRows, selectColumn, minVal, maxVal,
    chkMin, chkMax, opVal, NA_REAL);
}
```

(Yes, these could have been a single function with a switch statement.)

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bigmemory for developers

```
template<typename T>
class SepBigMatrixAccessor
{
  public:
    SepBigMatrixAccessor( BigMatrix &bm)
    {
      _ppMat = reinterpret_cast<T**>(bm.matrix());
    }

    inline T* operator[](const unsigned long col) {
      return _ppMat[col];
    }
  protected:
    T **_ppMat;
};
```

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REvolution computing

bigmemory for developers

```
template<typename T>
class BigMatrixAccessor    // We'll rename this MatrixAccessor
{
  public:
    BigMatrixAccessor( T* pData, const unsigned long nrow)
    {
      _pMat = pData;
      _nrow = nrow;
    }
    BigMatrixAccessor( BigMatrix &bm )
    {
      _pMat = reinterpret_cast<T*>(bm.matrix());
      _nrow = bm.num_rows();
    }
    inline T* operator[](const unsigned long col) {
      return _pMat+_nrow*col;
    }
  protected:
    T *_pMat;
    long _nrow;
};
```

For handling an R **`matrix`**

For handling a **`big.matrix`**

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