

Your Best Next Business Solution

Big Data In R

Big Data In R

- R Works on RAM
- Causing Scalability issues
- Maximum length of an object is 2^31-1
- Some packages developed to help overcome this problem





Big Data In R

- RODBC Package
- biglm Package
- ff Package
- bigmemory package
- snow package





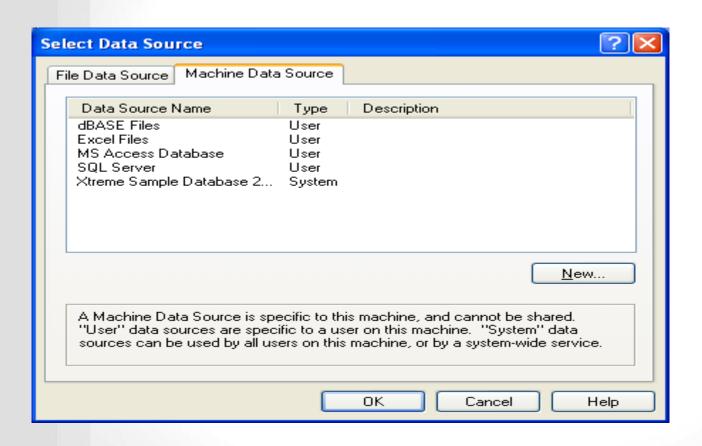
- Connecting to external DB from R to retrieve and handle data stored in the DB
- RODBC package support connection to SQL-based database (DBMS)
 such as: Oracle, SQL Server, SQLite, MySQL and more
- Require an ODBC driver which usually comes with the DBMS
- Windows offer an ODBC driver to flat files and Excel
- Supports client-server architecture





Defining DSN:

> odbcDriverConnect()

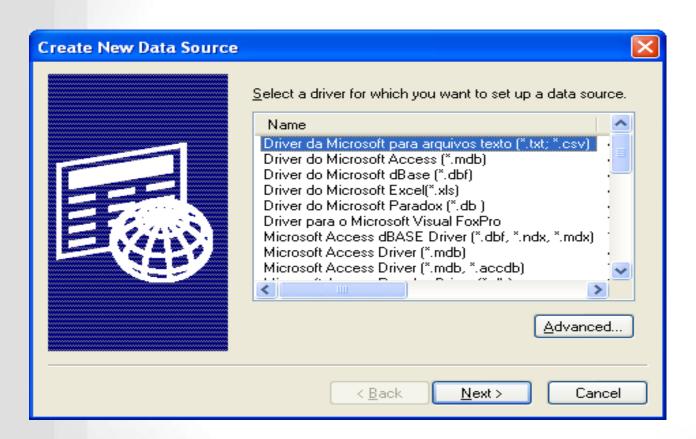






Defining DSN:

> odbcDriverConnect()







```
# Main Commands:
odbcConnect(dsn, uid = "", pwd = "", ...)
odbcGetInfo(channel)
sqlColumns(channel, sqtable, ...)
sqlFetch(channel, sqtable, ..., colnames = FALSE, rownames = TRUE)
sqlQuery(channel, query, errors = TRUE, ..., rows_at_time)
```



```
# Open connection:
   > xf <- odbcConnect(dsn="SQL Server")</pre>
# Read table:
   > go<-sqlFetch(xf,sqtable="adult",colnames=T)
   > str(go)
   data.frame': 32560 obs. of 15 variables:....
# Alternatively:
   > go1 <- sqlQuery(xf, "select * from samples.dbo.adult")</p>
   > str(go1)
   data.frame': 32560 obs. of 15 variables:....
```





This allow you to run any SQL command on the database

- > sqlQuery(xf, "CREATE TABLE Rdemo (id INT IDENTITY,x1 float,x2 float)") character(0)
- > sqlColumns(xf,"RDemo")


```
1 Samples dbo RDemo Id 4 int identity
2 Samples dbo RDemo x1 6 float
```

3 Samples dbo RDemo x2 6 float



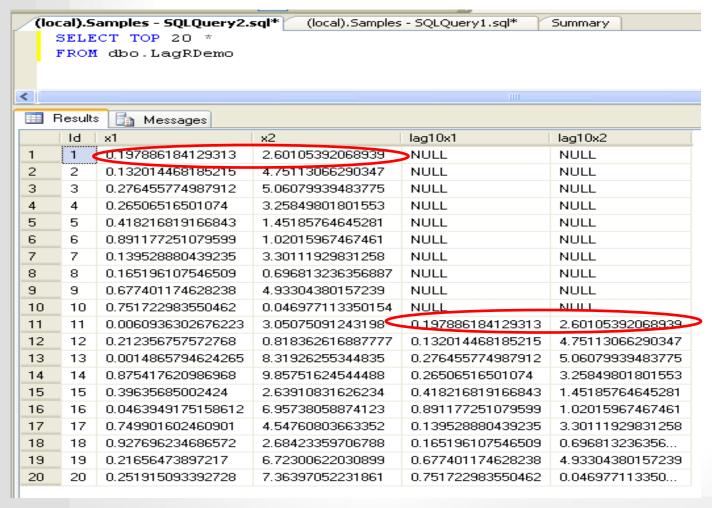


We can use R to run processes which are difficult or impossible in DBMS Example: calculate lag values





Example: calculate lag values







BigIm Package

Building Generalized linear models on big data

- Loading data into memory in chunks
- Processing the last chunk and updating the sufficient statistic required for the model
- Disposes the last chunk and loading the next chunk
- Repeats until end of file





BigIm Package

```
library(biglm)
make.data<-function(filename, chunksize,...){
   conn<-NULL
   function(reset=FALSE){
        if(reset){
        if(!is.null(conn)) close(conn)
        conn<<- file (description=filename, open="r")
        } else{
   rval<-read.csv(conn, nrows=chunksize,...)
   if (nrow(rval)==0) {
   close(conn)
   conn<<-NULL
   rval<-NULL
return(rval)
}}}
```





BigIm Package

```
> airpoll<-make.data("c:\\Rdemo.txt",chunksize=100000
   ,colClasses = list ("numeric","numeric","numeric")
   ,col.names = c("ld","x1","x2"))
> ImRDemo <-biggIm(Id~x1+x2,data=airpoll)
>summary(ImRDemo)
Large data regression model: bigglm(Id \sim x1 + x2, data = airpoll)
Sample size = 1e+06
                 (95% CI)
                                SE p
         Coef
(Intercept) 499583.8466 498055.6924 501112.0007 764.0771 0.0000
x1
        -603.1151 -2602.7075 1396.4774 999.7962 0.5464
x2
        143.6304 -56.2982 343.5591 99.9643 0.1508
```





- One of the main problems when dealing with large data set in R is memory limitations
 - On 32-bit OS the maximum amount of memory (i.e. virtual memory space) is limited to 2-4 GB
 - Therefore, one cannot store larger data into memory
 - It is impracticable to handle data that is larger than the available
 RAM for it drastically slows down performance.





- The ff package offers file-based access to data sets that are too large to be loaded into memory, along with a number of higher-level functions.
- It provides Memory-efficient storage of large data on disk and fast access functions.
- The ff package provides data structures that are stored on disk but behave as if they were in RAM by transparently mapping only a section (pagesize) in main memory
- A solution to the memory limitation problem is given by considering only
 parts of the data at a time, i.e. instead of loading the entire data set into
 memory only chunks thereof are loaded upon request





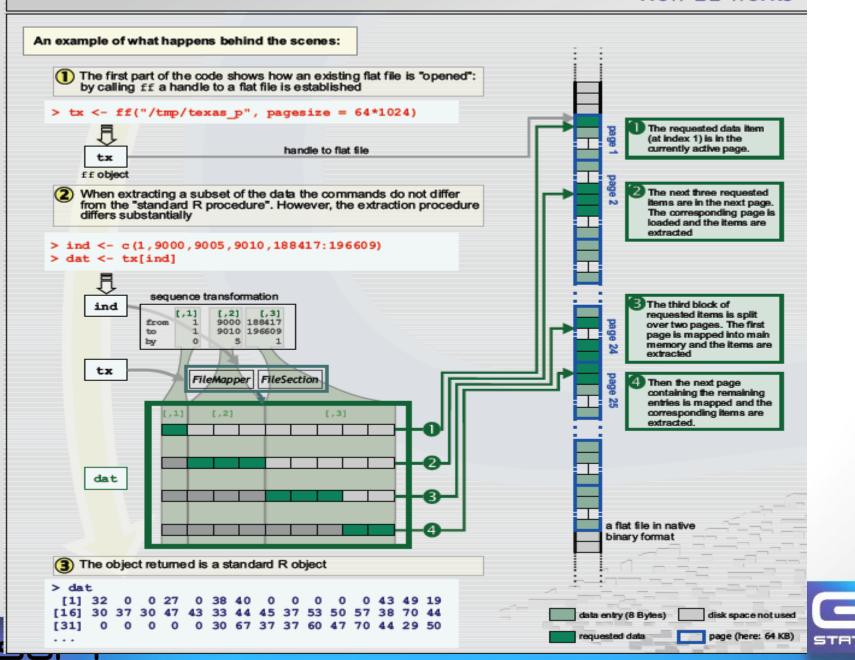
Comparison between ff and standard R objects How the creation of n values effects the run-time virtual memory address space: native R vector: ff object: > ffOb <- ff("foo",8000000) > rObj <- numeric(8000000) > aVal <- ff0b[1:2000000] > aVal <- robj[1:2000000] Data storage Data storage (reduced due to memorymapped pages of flat files) Virtual Memory Address Space Indices storage Indices storage (reduced due to packing (temporary) of index sequences) Resulting vector Resulting vector storage storage The amout of memory required The amout of memory required by an ff object. by a native R vector object. 512 kilobytes





Source: www.r-project.org

How ff works



```
> library (ff)
> N <- 1,000 # sample size #
> n <- 100 # chunk size #
> years <- 2000 : 2009
> types <- factor ( c ( "A " , "B " , " C " ) )
# Creating a (one-dimensional) flat file:
> Year <- ff (years, vmode = 'ushort', length = N, update = FALSE,
+ filename = "d:/tmp/Year.ff", finalizer = "close")
> Year
ff (open) ushort length=1000 (1000)
      [2] [3] [4] [5] [996] [997] [998] [999] [1000]
  0
      0
           0
               0 0: 0 0
                                    0
                                         0
                                                0
```





Modifying data: > for (i in chunk (1, N, n)) + Year [i] <- sample (years , sum (i) , TRUE)</pre>

> Year

```
ff (open) ushort length=1000 (1000)
[1] [2] [3] [4] [996] [997] [998] [999] [1000]
2001 2006 2007 2003 : 2002 2008 2007 2005 2003
```





```
# And the same for : Type
> Type <- ff (types, vmode = 'quad', length = N, update = FALSE,
+ filename = "d:/tmp/Type.ff", finalizer = "close")
> for ( i in chunk ( 1, N, n ) )
+ Type [i] <- sample (types, sum (i), TRUE)
> Type
ff (open) quad length=1000 (1000) levels: A B C
 [1]
        [3] [4] [996] [997] [998] [999] [1000]
         BB: CCBAC
```





```
# create a data.frame #
> x <- ffdf (Year = Year, Type = Type)
> X
ffdf (all open) dim=c(1000,2), dimorder=c(1,2) row.names=NULL
ffdf data
    Year Type
     2001 A
    2006 A
3
    2007 B
4
  2003 B
996
    2002 C
997 2008 C
998
    2007 B
999 2005 A
1000 2003 C
```





• The data used:

ASA 2009 Data Expo: Airline on-time performance http://stat-computing.org/dataexpo/2009/

- The data consisted of details of flight arrival and departure for all commercial flights within the USA, from October 1987 to April 2008.
- Nearly 120 million records, 29 variables (mostly integer-valued)

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



The challenge: find min() on extracted first column;

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





The challenge: random extractions

- > theserows <- sample(nrow(x), 10000)</pre>
- > thesecols <- sample(ncol(x), 10)</pre>

With ff:

> system.time(a <- z[theserows, thesecols])
user system elapsed

0.092 1.796 60.574

With bigmemory:

> system.time(a <- x[theserows, thesecols])</pre>

user system elapsed

0.020 1.612 64.136





- An R package which allows powerful and memory-efficient parallel analyses and data mining of massive data sets.
- Permits storing large objects (matrices etc.) in memory (on the RAM) using external pointer objects to refer to them.
- The data sets may also be file-backed, to easily manage and analyze data sets larger than available RAM.
- Several R processes on the same computer can also share big memory objects.





- BigMemory creates a variable X <- big.martix , such that X is a pointer to the dataset that is saved in the RAM or on the hard drive.
- When a big.matrix, X, is passed as an argument to a function, it is essentially providing call-byreference rather than call-by-value behavior
- Backingfile is the root name for the file(s) for the cache of X.
- Descriptorfile the name of the file to hold the filebacked description, for subsequent use with attach.big.matrix
- attach.big.matrix creates a new big.matrix object which references previously allocated shared memory or file-backed matrices.





- The default big.matrix is not shared across processes and is limited to available RAM.
- A shared big.matrix has identical size constraints as the basic big.matrix, but may be shared across separate
- A file-backed big.matrix may exceed available RAM by using hard drive space, and may also be shared across processes.
 - big.matrix (nrow, ncol, type = "integer",)
 - shared.big.matrix (nrow, ncol, type = "integer",)
 - filedbacked.big.matrix (nrow, ncol, type = "integer",)
 - read.big.matrix (filename, sep=,)





```
> library (bigmemory)
# Creating A new BigMemory object
> X <- read.big.matrix ("BigMem.csv", type = "double", backingfile =
"BigMem.bin", descriptorfile = "BigMem.desc", shared = TRUE)
> X
An object of class "big.matrix"
Slot "address":
<pointer: 0x0196d058>
```





```
> X [1:4,1:4]
    [,1] [,2] [,3] [,4]
[1,] 100 200 300 400
[2,] 100 200 300 400
[3,] 100 200 300 400
[4,] 100 200 300 400
# Creating an existing BigMemory object on a different machine
> Y <- attach.big.matrix ( "BigMem.desc" )
> Y
An object of class "big.matrix"
Slot "address":
<pointer: 0x01972b18>
```





```
> X [1,1] = 1111
> X [ 1:4, 1:4]
    [,1] [,2] [,3] [,4]
[1,] 1111 200 300 400
[2,] 100 200 300 400
[3,] 100 200 300 400
[4,] 100 200 300 400
# On different R:
> Y [ 1:4, 1:4]
    [,1] [,2] [,3] [,4]
[1,] 1111 200 300 400
[2,] 100 200 300 400
[3,] 100 200 300 400
[4,] 100 200 300 400
```



```
> Z <- shared.big.matrix (1000,70, type = "double")
> describe( Z )
$sharedType
[1] "SharedMemory"
$sharedName
[1] "d177ab0c-348c-484e-864f-53025015656e"
$nrow
[1] 1000
$ncol
[1] 70
$rowNames
NULL
$colNames
NULL
$type
[1] "double"
```





- Simple Network of Workstations
- An R package which supports simple parallel computing.
- The package provides high-level interface for using a workstation cluster for parallel computations in R.
- Snow relies on the Master/Slave model of communication:
- One device (master) controls one or more other devices (slaves)
- Note: communication is orders of magnitude slower than computation. For efficient parallel computing a dedicated high-speed network is needed.





Starting and Stopping clusters:

The way to Initialize slave R processes depends on system configuration, for example:

- > cl <- makeCluster(2, type = "SOCK")</pre>
- # Shut down the cluster and clean up any remaining connections between machines:
- > stopCluster (cl)





```
clusterCall (cl, fun,...)
```

clusterCall calls a specified function with identical arguments on each node in the cluster.

The arguments to clusterCall are evaluated on the master, their values transmitted to the slave nodes which execute the function call.

```
> myfunc <- function ( x) { x + 1 }
> myfunc_argument <- 5
> clusterCall ( cl, myfunc, myfunc_argument )
        [[1]]
        [1] 6
[[2]]
      [1] 6
```





```
Example: simulate random numbers
> clusterApply(cl,c(4,2),runif)
[[1]]
0.90365799 0.03189395 0.59713787 0.33039294 [1]
[[2]]
0.6620030 0.8329455 [1]
> system.time(clusterApply(cl,c(6000000,9000000),runif))
user system elapsed
 5.03 0.94 11.31
> system.time(runif(15000000))
user system elapsed
5.11 0.12 5.47
```



