### R Programming and Data Analysis Intermediate R Programming

### Introduction

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() Intermediate R Programming Introduction

# **Numerical Tools**

### **Numerical Tools**

... Demonstration ...

(See numerical.Rmd)

- Debugging is an integral part of writing nontrivial programs.
- It is rare to write a perfect program on the first attempt.
- When running a new program, we might see
  - a. errors or warnings.
  - b. an obviously incorrect result (e.g. NA or a negative probability).
  - c. a subtly incorrect result.
  - d. a result whose correctness we are not certain of.
  - e. problems only for certain inputs or random draws.
- Some basic debugging techniques can help us track down the sources of these issues.

() Intermediate R Programming Debugging 6

- Develop code "interactively".
  - a. Write a few lines of code, run them, and examine the output.
  - b. Prevents some obvious errors, and quickly get a working program.
- Use print statements to report important values.
  - a. Especially useful for longer programs that cannot be run interactively.
  - b. For example, to see how an optimization is working, we can print the result before returning it.

```
f <- function(x) {
    fx <- 1 - sum(x^2)
    cat("x = (", paste(round(x, 4), collapse = ","), "),
        fx =", fx, "\n")
    return(fx)
}

> x0 <- rep(0, 5)
> res <- optim(x0, f, control = list(fnscale = -1))
...
x = ( 0.005,0.051,0.011,0.011,0.011 ), fx = 0.997011
x = ( 0.022,0.0244,-0.0916,0.0484,0.0484 ), fx = 0.985845
x = ( 0.0055,0.0061,0.0521,0.0121,0.0121 ), fx = 0.9969253
...</pre>
```

- Sometimes it is helpful to leave print statements in program after debugging is complete.
- These functions are useful for basic logging

> logger("Starting %d reps of MCMC\n", R)
2016-07-25 15:55:01 - Starting 1000 reps of MCMC

printf <- function (msg, ...) {

```
cat(sprintf(msg, ...))
}
logger <- function (msg, ...) {
    sys.time <- as.character(Sys.time())
    cat(sys.time, "-", sprintf(msg, ...))
}
> printf("Convergence Status: %d\n", res$convergence)
Convergence Status: 0
```

• The log4r package is a bit more sophisticated. Supports multiple logging levels (INFO, WARN, ERROR, etc).

() Intermediate R Programming Debugging 8/1

- R has an interactive debugger to step through running programs.
- Can ask R to start debugger when a particular function is called in the current session. This can be any function in R, not only ours.

```
> debug(optim)
> x0 <- rep(0, 5)
> res <- optim(x0, f, control = list(fnscale = -1))
debugging in: optim(x0, f, control = list(fnscale = -1))
debug: {
... [optim function contents are shown] ...
}</pre>
```

• Now program is paused and we can use regular R commands.

```
Browse[2]> ls()
[1] "control" "fn" "gr" "hessian" "lower" "method" "par" "upper"
Browse[2]> print(control)
$fnscale
[1] -1
Browse[2]>
```

- Can step to the next line, the next breakpoint, or stop debugger.
- Changes made to workspace may be discarded after exiting debugger.
- Use undebug(optim) to stop watching optim calls.

 Another way to invoke the debugger is to put a browser call in your program. R starts the debugger when it encounters this statement.

```
f <- function(x) {
    z < -t(x) %*% x
    browser()
    return(z)
> x < -c(1,2,3)
> f(x)
Called from: f(x)
Browse[1] > ls()
[1] "x" "z"
Browse[1]> x
[1] 1 2 3
Browse[1]> z
     [.1]
[1,] 14
Browse[1]> 0
```

• For more information about debugging in R, see www.stats.uwo.ca/faculty/murdoch/software/debuggingR.

# **Reading and Writing Data**

### **Objects and the Workspace**

- The entities that R creates and manipulates are known as objects.
- These may be variables, arrays of numbers, character strings, functions, or more general structures built from such components.
- The collection of objects currently stored in R is called the workspace.
- The workspace can be saved to disk, and loaded back into R in a new or existing session.
- Workspace does not store packages that were loaded we have to reload them ourself.

### **Objects and the Workspace**

- The commands object or 1s can be used to display the objects currently loaded in R.
- Use the function rm to remove objects from your workspace.

```
> x <- rnorm(5)
> x
[1] -0.8287666  0.8377261 -0.3695485  1.3661922  1.8287291
> y <- x + 10
> y
[1]  9.171233  10.837726  9.630451  11.366192  11.828729
> objects()
[1]  "x" "y"
> ls()
[1]  "x" "y"
> rm(list = ls(all = TRUE))
> ls()
character(0)
```

Note that character(0) represents a string vector of length zero.

### Saving the Workspace

• R designates a directory on the computer to be the "current working directory". This is where output files will be written by default.

```
> getwd()
[1] "/path/to/here"
```

• To get/set the working directory with getwd/setwd

```
> setwd("/path/to/here")
> getwd()
[1] "/path/to/here"
```

- When we exit a session, R asks if we wish to save the workspace.
  - If we say "yes", a binary file .RData will be created; this contains all the objects in our workspace (therefore file might be large).
  - ► A text file .Rhistory may be also be created; contains our history of commands
  - ► Next time we launch R from that directory, our workspace will return to the same state
  - ► We can also load the state files manually.

### Saving the Workspace

We can save the workspace at any time (not just when quitting), and using any filename we wish, using save.image.

```
> x <- c(1,2,3)
> A <- matrix(1:9, nrow = 3, ncol = 3)
> B <- diag(10)
> ls()
[1] "A" "B" "x"
> save.image(file = "myworkspace.Rdata")
```

We can also save specific objects from the workspace using save.

```
> ls()
character(0)
> x <- 10
> y <- 11
> z <- 12
> save(list = c("x","y"), file = "myvariables.Rdata")
```

## **Loading the Workspace**

Saved R data can be loaded at any time using load. Be aware that objects in your current environment may be overwritten.

```
> x <- 55
> y <- 77
> load("myworkspace.Rdata")
> ls()
[1] "A" "B" "x" "y"
> x
[1] 1 2 3
> y
[1] 77
```

#### **CSV** Files

Recall the CO2 dataset.

```
> CO2
Plant Type Treatment conc uptake
1 Qn1 Quebec nonchilled 95 16.0
2 Qn1 Quebec nonchilled 175 30.4
...
83 Mc3 Mississippi chilled 675 18.9
84 Mc3 Mississippi chilled 1000 19.9
```

Write it to a CSV file.

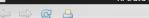
```
> write.table(CO2, file = "CO2.csv", sep = ",")
> getwd()
[1] "/path/to/file"
```

Check contents of the file.

```
[username@localhost ~]$ cat /path/to/file/C02.csv
"Plant","Type","Treatment","conc","uptake"
"1","Qn1","Quebec","nonchilled",95,16
"2","Qn1","Quebec","nonchilled",175,30.4
...
"83","Mc3","Mississippi","chilled",675,18.9
"84","Mc3","Mississippi","chilled",1000,19.9
```

#### **CSV** Files

#### • Read the file into R



read.table {utils}

R Documentation

↑ \_ □ X

#### Data Input

#### Description

Reads a file in table format and creates a data frame from it, with cases corresponding to lines and variables to fields in the file.

#### Usage

```
read.table(file, header = FALSE, sep = "", quote = "\"'",
          dec = ".", numerals = c("allow_loss", "warn.loss", "no.loss"),
           row.names. col.names. as.is = stringsAsFactors.
          na.strings = "NA", colClasses = NA, nrows = -1,
          skip = 0. check.names = TRUE. fill = !blank.lines.skip.
          strip.white = FALSE, blank.lines.skip = TRUE,
          comment.char = "#".
          allowEscapes = FALSE, flush = FALSE,
          stringsAsFactors = default.stringsAsFactors(),
          fileEncoding = "", encoding = "unknown", text, skipNul = FALSE)
read.csv(file, header = TRUE, sep = ".", quote = "\"".
         dec = ".". fill = TRUE. comment.char = "". ...)
read.csv2(file, header = TRUE, sep = ":", quote = "\"".
          dec = ",", fill = TRUE, comment.char = "", ...)
read.delim(file, header = TRUE, sep = "\t", quote = "\"",
          dec = ".", fill = TRUE, comment.char = "", ...)
```

#### **CSV** Files

- The readr package provides more sophisticated file parsing tools.
   Often faster than the usual read.table, read.csv, etc.
- We will generate a large CSV to demonstrate.

• This produces a ~124 MB file.

#### **CSV** Files

```
> system.time(dat1 <- read.csv("mydata.dat"))
  user system elapsed
31.166 8.792 46.799
> head(dat1, 3)
1 2.4157666 NO 5
2 -0.1859725 NO 8
3 -0.3424828 YES 7
> system.time(dat2 <- read_csv("mydata.dat"))</pre>
Parsed with column specification:
cols(
 x = col_double(),
 y = col character(),
 z = col integer()
                  ======= | 100% 123 MB
  user system elapsed
 7.890 1.702 10.677
> head(dat2, 3)
# A tibble: 6 x 3
      <dbl> <chr> <int>
1 2.4157666 NO
2 -0.1859725 NO
3 -0.3424828 YES
                     7
```

### **HDF5** Files

- HDF5 (www.hdfgroup.org/HDF5) flexible library for storing and managing data.
- Portable file format with interfaces in C/C++, Fortran, Python, R, and others.
- An HDF5 file has a hierarchical format like a filesystem.
  - 1. Groups are like directories.
  - 2. Datasets are like files, but have a well-defined structure.
  - 3. Attributes are metadata which can be attached to groups and datasets.
- rhdf5 is an R package for manipulating HDF5 files.

```
source("https://bioconductor.org/biocLite.R")
biocLite("rhdf5")
```

### **HDF5** Files

```
library(rhdf5)
h5createFile("mydata.h5")

y <- mtcars$mpg
X <- model.matrix(~ cyl + disp + hp, data = mtcars)
h5createGroup("mydata.h5","mtcars")
h5write(mtcars, "mydata.h5","mtcars/mtcars")
h5write(y, "mydata.h5","mtcars/y")
h5write(X, "mydata.h5","mtcars/X")

y <- CO2$conc
X <- model.matrix(~ Plant + Type + Treatment + uptake, data = CO2)
h5createGroup("mydata.h5","CO2")
h5write(mtcars, "mydata.h5","CO2/CO2")
h5write(y, "mydata.h5","CO2/Y")
h5write(X, "mydata.h5","CO2/X")</pre>
```

```
> h51s("mydata.h5")
                       dclass
                                 dim
   group name
                  otype
     / CO2 H5I GROUP
0
 /CO2 CO2 H5I_DATASET COMPOUND 32
2
 /CO2 X H5I_DATASET FLOAT 84 x 15
3 /CO2 y H5I_DATASET FLOAT 84
      / mtcars
               H5I GROUP
5 /mtcars X H5I DATASET FLOAT 32 x 4
6 /mtcars mtcars H5I DATASET COMPOUND 32
7 /mtcars v H5I DATASET FLOAT
                                  32
> H5close()
```

### **HDF5** Files

```
> library(rhdf5)
> h5read("mydata.h5","mtcars/y")
 [1] 21.0 21.0 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 17.8
[12] 16.4 17.3 15.2 10.4 10.4 14.7 32.4 30.4 33.9 21.5 15.5
[23] 15.2 13.3 19.2 27.3 26.0 30.4 15.8 19.7 15.0 21.4
> h5read("mydata.h5","mtcars/mtcars")
    mpg cyl disp hp drat wt qsec vs am gear carb
1 21.0 6 160.0 110 3.90 2.620 16.46 0 1
2 21.0 6 160.0 110 3.90 2.875 17.02 0 1 4
31 15.0 8 301.0 335 3.54 3.570 14.60 0 1 5 32 21.4 4 121.0 109 4.11 2.780 18.60 1 1 4
> h5read("mydata.h5","mtcars/X")
      [,1] [,2] [,3] [,4]
 [1,] 1 6 160.0 110
 [2,] 1 6 160.0 110
. . .
[31,] 1 8 301.0 335
[32.] 1 4 121.0 109
> h5read("mydata.h5","mtcars/X", index=list(1:5,1:3))
     [,1] [,2] [,3]
[1,] 1 6 160
[2,] 1 6 160
[3,] 1 4 108
[4,] 1 6 258
[5.]
                360
```

()

#### **SAS** Files

- SAS is a commercial software suite which is popular with data analysts, corporations, and government agencies.
- The main format for SAS files is a proprietary sas7bdat format.
  - The foreign and Hmisc packages can read them, but require SAS installed on the computer.
  - 2. The sas7bdat and haven packages can read them without SAS.
- The XPORT format is intended to be more interoperable.
  - 1. Can be read by the foreign package.
- The foreign package can also read/write data for statistical packages such as Minitab, S, SAS, SPSS, Stata, Systat.

#### **SAS** Files

```
> library(haven)
> url1 <- "http://www.principlesofeconometrics.com/sas/yield.sas7bdat"
> yield <- read sas(url1)
> class(yield)
[1] "tbl df"
                "tbl"
                             "data frame"
> tail(yield)
# A tibble: 6 x 5
    YIELD T
                   GROW
                            GERM
                                   FLOWER
    <dbl> <dbl> <dbl>
                            <dbl>
                                     <dbl>
1 1.080829
             34 1.354559 1.155823 1.208213
2 1.831250
             35 1.005840 0.991480 0.939275
3 1.028031
             36 1.288040 0.366613 0.810828
4 1.465217
             37 0.828458 1.385182 0.698436
5 1.706897
6 1.988593
             38 0.772018 0.837972 0.586044
             39 1.052202 0.895763 1.111877
> url2 <- "http://www.principlesofeconometrics.com/sas/vote.sas7bdat"
> vote <- read sas(url2)
> tail(vote)
# A tibble: 6 x 7
        STATE VOTE INCOME SCHOOL URBAN NORTHEAST SOUTHEAST
        <chr> <dbl> <dbl> <dbl> <dbl> <
                                            < 1db>>
                                                      <dbl>
                  0 12.415 12.5 0.0
      Vermont
                                                          0
      Virginia
                  0 14.579 12.4 65.6
3
    Washington
                  0 14.962 12.7 71.1
                                                O
                  1 12.007 12.1 36.1
1 15.064 12.5 63.0
 WestVirginia
                                                          0
5
    Wisconsin
                                                O
6
       Wyoming
                  0 14.784 12.6 0.0
```

#### **SAS** Files

```
> library(sas7bdat)
> yield <- read.sas7bdat(url1)
> at <- attributes(yield)
> names(at)
 [1] "names" "row.names" "class" "pkg.version"
[5] "column.info" "date.created" "date.modified" "SAS.release"
 [9] "SAS.host"
                   "OS.version" "OS.maker" "OS.name"
[13] "endian"
                    "winunix"
> at$SAS.host
[1] "WIN"
> at$SAS.release
[1] "9.0000MO"
> at$date.created
[1] "2008-05-13 17:02:32 EDT"
> at$date.modified
[1] "2008-05-13 17:02:32 EDT"
> str(at$column.info[[1]])
List of 11
$ name : chr "YIELD"
$ offset: int 0
$ length: int 8
$ type : chr "numeric"
$ fhdr : int 0
$ foff : int 0
$ flen : int 0
$ label : chr "wheat yield, tonnes per hectare"
$ lhdr : int 0
$ loff : int 36
$ 11en : int 31
```

#### **Databases**

 R can interact with both SQL databases (DBs) and NoSQL DBs by using appropriate packages.

#### SQL DBs

- ► Store data in a highly structured relational DB
- ► Tables are optimized for storage and efficient merging. This usually requires careful planning.
- ► Use SQL (Structured Query Language) to query and modify the DB.
- Examples include MySQL, Oracle, PostgreSQL, SQLite, and SQLServer.

#### NoSQL DBs

- Less structured than relational DBs (e.g. key-value pairs), but more flexible.
- ► Use an alternative query language to SQL.
- ► Examples include MongoDB and Google BigTable.

#### **Databases**

- We will focus on SQL databases.
- The DBI package provides a generic interface to SQL DBs.
- Other packages build on DBI for specific database implementations. For example, RMySQL, ROracle, RPostgreSQL, RSQLite, RSQLServer.
- SQLite
  - A "self-contained, serverless, zero-configuration, transactional SQL database engine".
  - ► Databases are stored in ordinary files.
  - ► Good for local storage in an application (e.g. storing website cookies in Firefox).

### **SQL** Databases

```
> library(DBI)
> con <- dbConnect(RSQLite::SQLite(), "mydata.sqlite")</pre>
> dbListTables(con)
character (0)
> dbWriteTable(con, "mtcars", mtcars)
[1] TRUE
> dbListTables(con)
[1] "mtcars"
> dbListFields(con. "mtcars")
 [1] "row names" "mpg" "cvl" "disp" "hp" "drat" "wt"
                                                            "asec"
               "am" "gear" "carb"
 [9] "vs"
> dbReadTable(con, "mtcars")
                   mpg cyl disp hp drat wt qsec vs am gear carb
                21.0 6 160.0 110 3.90 2.620 16.46 0 1 4
Mazda RX4
Mazda RX4 Wag 21.0 6 160.0 110 3.90 2.875 17.02 0 1
. . .
Maserati Bora 15.0 8 301.0 335 3.54 3.570 14.60 0 1
Volvo 142E
                 21.4 4 121.0 109 4.11 2.780 18.60 1 1
```

### **SQL** Databases

```
> res <- dbSendQuery(con, "select * from mtcars where cyl = 4")
> gry <- dbFetch(res)
> dbGetInfo(res)$fields
       name
              Sclass type len
  row names character TEXT NA
        mpg double REAL 8
3
4
        cyl double REAL 8
       disp double REAL 8
         hp double REAL 8
5
6
7
       drat double REAL 8
         wt double REAL 8
8
       qsec double REAL 8
         vs double REAL 8
         am double REAL 8
10
11
       gear double REAL 8
       carb double REAL 8
12
> dbGetRowCount(res)
[1] 11
> qry$row_names
 [1] "Datsun 710" "Merc 240D" "Merc 230"
                                                   "Fiat 128"
 [5] "Honda Civic" "Toyota Corolla" "Toyota Corona" "Fiat X1-9"
 [9] "Porsche 914-2" "Lotus Europa" "Volvo 142E"
> gry$mpg
 [1] 22.8 24.4 22.8 32.4 30.4 33.9 21.5 27.3 26.0 30.4 21.4
> dbClearResult(res)
[1] TRUE
```

### **SQL** Databases

```
> res <- dbSendQuery(con, "update mtcars set mpg = -22 where cyl = 4")
> dbClearResult(res)
[1] TRUE
> dbReadTable(con, "mtcars")
                mpg cyl disp hp drat wt qsec vs am gear carb
Mazda RX4
              21.0 6 160.0 110 3.90 2.620 16.46 0 1
Mazda RX4 Wag 21.0 6 160.0 110 3.90 2.875 17.02 0 1
Datsun 710 -22.0 4 108.0 93 3.85 2.320 18.61 1 1
. . .
Volvo 142E -22.0 4 121.0 109 4.11 2.780 18.60 1 1
> res <- dbSendQuery(con, "insert into mtcars
+ (row_names, mpg, cyl, disp, hp, drat, wt, qsec, vs, am, gear, carb)
+ values ('ABCD', 40.0, 4, 100.0, 200, 4.00, 1.5, 20.0, 1, 1, 5, 1)")
> dbClearResult(res)
[1] TRUE
> dbReadTable(con, "mtcars")
                mpg cyl disp hp drat wt qsec vs am gear carb
             21.0 6 160.0 110 3.90 2.620 16.46 0 1
Mazda RX4
Mazda RX4 Wag 21.0 6 160.0 110 3.90 2.875 17.02 0 1
. . .
Volvo 142E -22.0 4 121.0 109 4.11 2.780 18.60 1 1
ABCD
             40.0 4 100.0 200 4.00 1.500 20.00 1 1
> dbDisconnect(con)
[1] TRUE
```

### Web Services

- Web services are collections of functions that can be called through the web by user programs.
- User programs call functions via Application Programmer Interface (API).
- A simple API, useful for querying, is REST (Representational State Transfer). REST embeds queries in standard (HTTP) web requests.
- JavaScript Object Notation (JSON) is a popular format for returning data.
- The R package jsonlite can be used to query a REST service that returns JSON.

### Web Services

- Transport for Finland lets us query real-time positions of its trams.
- Users often have to register for an API key before using web service. No key is required for this one.
- For more information about the service, see http://digitransit.fi/en/developers/services-and-apis.
- If we access the URL directly,

```
$ curl http://api.digitransit.fi/realtime/vehicle-positions/v1/hfp/
    journey/tram/#
{"/hfp/journey/tram/RHKL00401/1007A/2/XXX/2247/undefined
    /60;24/29/17/50":{"VP":{"desi":"1007A","dir":"2","oper":"XXX","
    veh":"RHKL00401","tst":"2016-08-02T01:42:55.0002","tsi
    ":1470102175,"spd":0,"hdg":210,"lat":60.215367,"long
    ":24.970981,"dl":567,"oday":"XXX","jrn":"XXX","line":"1007A","
    start":"2247","stop_index":17}}}
```

#### Web Services

Reading it with jsonlite package,

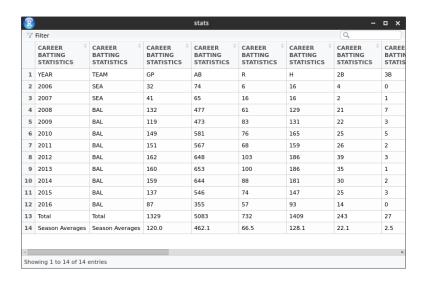
```
> library(jsonlite)
> url <- "http://api.digitransit.fi/realtime/vehicle-positions/v1/
    hfp/journey/tram/#"
> rea <- fromJSON(url)</pre>
> str(rea)
List of 1
$ /hfp/journey/tram/RHKL00401/1007A/2/XXX/2247/undefined
    /60;24/29/17/50:List of 1
  ..$ VP:List of 16
  .. .. $ desi : chr "1007A"
 .. ..$ dir : chr "2"
  .... $ veh : chr "RHKL00401"
  ....$ tst : chr "2016-08-02T01:39:24.000Z"
  .. ..$ tsi : int 1470101964
  .. .. $ hdg : int 210
. . .
  .. .. $ lat : num 60.2
 .. ..$ long : num 25
 .. ..$ dl : int 567
  ....$ line : chr "1007A"
  .. ..$ start : chr "2247"
  .. .. $ stop_index: int 17
```

- Data on the web is often prepared for viewing (rendered in HTML) rather than for analysis (e.g. a CSV or Excel file).
- "Web scraping" is the process of writing a script to extract the data from the HTMI.
- The rvest package supports web scraping in R.



The %>% operator is defined in the magrittr package.

- Feeds data into a function.
- Many of them can be strung together.
- Behaves like the "pipe" operator on the Linux command line.

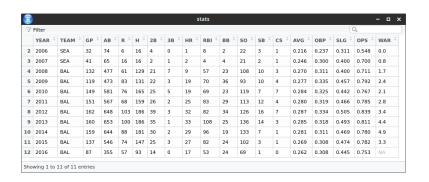


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```
# Fix the header
colnames(stats) <- stats[1,]

# Remove the extra first row, and the row of totals and averages
stats <- stats[-c(1,13,14),]

# Change columns 3, ..., k to numeric
k <- ncol(stats)
for (j in 3:k) {
    stats[,j] <- as.numeric(stats[,j])
}</pre>
```



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### **Big Datasets**

- Base R expects all objects (vectors, matrices, data frames) to be completely loaded into memory.
- Modern datasets may be too large to fit into memory.
- The bigmemory and ff packages store matrices and data frames on disk, but allow them to be accessed somewhat like regular R objects.
  - 1. The ff project: http://ff.r-forge.r-project.org
  - 2. The bigmemory project: http://www.bigmemory.org

# Data Manipulation with dplyr

### **Tidyverse**

 "an opinionated collection of R packages designed for data science. All packages share an underlying philosophy and common APIs."

**R**'s **biggest challenge** is that most **R** users are **not programmers**.



- Tidyverse includes:
  - a. ggplot2 grammar for plotting.
  - b. dplyr grammar for data manipulation. (\*\*\*)
  - c. readr, readxl, haven reading data from files.
  - d. magrittr provides the pipe operator (%>%).
- Many tidyverse packages are discussed in the book R for Data Science
   (?), which is available online.

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### Data Manipulation with dplyr

... Demonstration ... (See dplyr.Rmd)

### References I

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