

# R four ways (plus a few)

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2017-10-29

# Introduction

- ▶ The Social Security Administration provides **state-level babynames data** annually since 1910.
- ▶ Create a single file containing all state-level babynames data with the shell command

```
cat *.TXT > allstates.TXT
```

- ▶ The resulting file has 5.8 million rows and no header.

# File contents

- ▶ Using the head command (in Bash):

```
head -n 6 data/allstates.TXT
AK,F,1910,Mary,14
AK,F,1910,Annie,12
AK,F,1910,Anna,10
AK,F,1910,Margaret,8
AK,F,1910,Helen,7
AK,F,1910,Elsie,6
```

The fields (i.e., columns) are:

- ▶ state, a two-digit abbreviation
- ▶ sex, M or F
- ▶ year, yyyy
- ▶ name
- ▶ number of births

# The tasks

- ▶ Four basic data manipulation tasks:
  1. Count the number of distinct states in the data
  2. Count the number of distinct years in the data
  3. Count the number of distinct names in the data
  4. Create a new CSV file that contains the top 10 names, by sex, for each year.
- ▶ We will use Base R with and without loops, `dplyr`, and `data.table`
- ▶ The challenge is finding the right level of abstraction for a given problem

## R: Base R

- ▶ Natural instinct for this problem is to write a loop.
- ▶ Apart from speed, we will see that this is relatively clumsy.
- ▶ Don't be afraid of loops, and don't be in love with them

# Using only loops

- ▶ The following is *very* slow. Experienced R users will wince at the code.

```
x = read.csv('data/allstates.TXT', header=FALSE,
             stringsAsFactors=FALSE)
names(x) <- c('state', 'sex', 'year', 'name', 'n')
print(length(table(x$state)))
print(length(table(x$year)))
print(length(table(x$name)))
top10 <- list()
sexes <- unique(x$sex)
for (i in unique(x$year)) {
  for (j in sexes) {
    tmp <- x[x$year == i & x$sex == j, ]
    names <- unique(tmp$name)
    lnames <- length(names)
    nvec <- vector(length=lnames)
    for (k in 1:lnames) {
      nvec[k] <- sum(tmp$n[tmp$name == names[k]])
    }
    tmp <- data.frame(year=i, sex=j, name=names, n=nvec)
    tmp <- tmp[order(-tmp$n), ]
    top10 <- rbind(top10, head(tmp, n=10), make.row.names=FALSE)
  }
}
write.csv(top10, file='data/babynames10Rbase_loop2.csv',
          row.names=FALSE)
print(head(top10))
```

## Results: R with explicit loops

```
[1] 51
```

```
[1] 107
```

```
[1] 31014
```

	year	sex	name	n
1	1910	F	Mary	22848
2	1910	F	Helen	10479
3	1910	F	Margaret	8222
4	1910	F	Dorothy	7314
5	1910	F	Ruth	7209
6	1910	F	Anna	6433

	user	system	elapsed
	124.312	0.688	125.032

## R with some loops

```
x = read.csv('data/allstates.TXT', header=FALSE,
             stringsAsFactors=FALSE)
names(x) <- c('state', 'sex', 'year', 'name', 'n')
print(length(table(x$state)))
print(length(table(x$year)))
print(length(table(x$name)))
xa <- aggregate(n ~ year + sex + name, data=x, FUN=sum)
xa <- xa[order(xa$year, xa$sex, -xa$n), ]
top10 <- data.frame()
for (i in unique(xa$year)) {
  for (j in unique(xa$sex)) {
    tmp = head(subset(xa, xa$year == i & xa$sex == j), n=10)
    top10 <- rbind(top10, tmp, make.row.names=FALSE)
  }
}
write.csv(top10, file='data/babynames10Rbase_loop.csv',
          row.names=FALSE)
print(head(top10))
```



## Results: R with some loops

- Better, but still clunky

```
[1] 51
[1] 107
[1] 31014
```

	year	sex	name	n
1	1910	F	Mary	22848
2	1910	F	Helen	10479
3	1910	F	Margaret	8222
4	1910	F	Dorothy	7314
5	1910	F	Ruth	7209
6	1910	F	Anna	6433

```
user system elapsed
28.208 0.648 28.875
```

## Without explicit loops

- ▶ Avoiding loops leads to cleaner, more “R-ish” code.
- ▶ Some may find this less transparent and it is faster, but not by much.

```
x = read.csv('data/allstates.TXT', header=FALSE,
             stringsAsFactors=FALSE)
names(x) <- c('state', 'sex', 'year', 'name', 'n')
print(length(table(x$state))) ## note the similarity to python
print(length(table(x$year)))
print(length(table(x$name)))
xa <- aggregate(n ~ year + sex + name, data=x, FUN=sum)
xa <- xa[order(xa$year, xa$sex, -xa$n), ]
xatop10 <- by(xa, list(xa$year, xa$sex), head, n=10)
top10 <- do.call(rbind, xatop10)
write.csv(top10, file='data/babynames10Rbase_noloop.csv',
          row.names=FALSE)
print(head(top10))
```

## Results: R without explicit loops

```
[1] 51
```

```
[1] 107
```

```
[1] 31014
```

	year	sex	name	n
399169	1910	F	Mary	22848
236460	1910	F	Helen	10479
388683	1910	F	Margaret	8222
163023	1910	F	Dorothy	7314
498889	1910	F	Ruth	7209
37086	1910	F	Anna	6433

user	system	elapsed
23.984	0.284	24.273

## Aside: read.csv vs read\_csv

- ▶ How fast are the different functions for reading csv files?.
- ▶ Note that read\_csv without column types will throw an error because it tries to treat sex as logical (please no jokes. . .)

```
system.time(x <- read.csv('data/allstates.TXT',  
                          header=FALSE))  
  
   user  system elapsed  
 6.456   0.196   6.656  
system.time(  
  x <- read_csv('data/allstates.TXT',  
                progress=FALSE,  
                col_names=c('state', 'sex', 'year', 'name', 'n'),  
                col_types = cols(sex = col_character())  
  )  
)  
  
   user  system elapsed  
 2.228   0.036   2.264
```

# What about saving and reading in R format?

- ▶ Contrast save and load with `saveRDS(compress=FALSE)` and `readRDS`
- ▶ Saving first; compression slows things down a lot

```
system.time(save(x, file='/tmp/save.Rdata'))
  user  system elapsed
 6.900   0.012   6.921
system.time(save(x, file='/tmp/save2.Rdata', compress=FALSE))
  user  system elapsed
 1.988   0.192   2.251
system.time(saveRDS(x, file='/tmp/save.RDS', compress=FALSE))
  user  system elapsed
 2.080   0.196   2.365
cat(system('ls -al /tmp/save*', intern=TRUE), sep='\n')
-rw-rw-r-- 1 rmcd rmcd 238673928 Oct 27 12:27 /tmp/save2.Rdata
-rw-rw-r-- 1 rmcd rmcd 17278554 Oct 27 12:27 /tmp/save.Rdata
-rw-rw-r-- 1 rmcd rmcd 238673902 Oct 27 12:27 /tmp/save.RDS
```

## Reading the files back in

```
system.time(load('/tmp/save.Rdata'))
  user  system elapsed
4.080   0.032   4.115
system.time(load('/tmp/save2.Rdata'))
  user  system elapsed
2.760   0.060   2.819
system.time(y <- readRDS(file='/tmp/save.RDS'))
  user  system elapsed
2.752   0.052   2.805
```

- ▶ The actual relative times depend on both CPU speed and disk speed

## R: dplyr

- Manipulate data with echoes of SQL. The code focuses on the task

```
x <- read_csv('data/allstates.TXT',
              col_names=c('state', 'sex', 'year', 'name', 'n'),
              col_types = cols(sex = col_character())
            )

print(nrow(distinct(x, state)))
print(nrow(distinct(x, year)))
print(nrow(distinct(x, name)))
out = x %>%
  group_by(year, sex, name) %>%
  summarize(n = sum(n)) %>%
  arrange(year, sex, desc(n)) %>%
  filter(row_number(desc(n)) <= 10)
## do(head(., n=10)) ## works in place of filter
write_csv(out, path='data/babynames10Rdplyr.csv')
print(head(out))
```

## Results: dplyr

```
[1] 51
[1] 107
[1] 31014
# A tibble: 6 x 4
# Groups:   year, sex [1]
   year  sex  name    n
  <int> <chr> <chr> <int>
1  1910    F   Mary 22848
2  1910    F   Helen 10479
3  1910    F Margaret 8222
4  1910    F  Dorothy 7314
5  1910    F    Ruth 7209
6  1910    F    Anna 6433
  user  system elapsed
7.152   0.220   7.374
```



## R: data.table

- ▶ data.table is designed explicitly for manipulation of large data sets. The syntax is more abstract than in dplyr
- ▶ Like dplyr, it permits chaining commands.
- ▶ For a data table, DT, with row i, column j, grouped by by, the syntax is DT[i, j, by]

```
library(data.table)
y <- fread("data/allstates.TXT",
           col.names=c('state', 'sex', 'year', 'name', 'n'))
print(y[, uniqueN(state)])
print(y[, uniqueN(year)])
print(y[, uniqueN(name)])
y2 = y[, .(total = sum(n)), by=.(year, sex, name)][
  order(year, sex, -total)]
out = y2[, head(.SD, 10), by=.(year, sex)]
fwrite(out, file='data/babynames10RDT.csv')
print(head(out))
```

## Results: data.table

```
[1] 51
```

```
[1] 107
```

```
[1] 31014
```

	year	sex	name	total
1:	1910	F	Mary	22848
2:	1910	F	Helen	10479
3:	1910	F	Margaret	8222
4:	1910	F	Dorothy	7314
5:	1910	F	Ruth	7209
6:	1910	F	Anna	6433

user	system	elapsed
1.896	0.080	1.971

# Creating an SQL Connection

- ▶ It is also possible to use dplyr with an SQL connection
- ▶ SQL databases usually have their own passwords
  - ▶ Password security becomes an issue when creating scripts. Two solutions are the keyringr package, which reads your local keyring, and the getPass package, which will prompt you for the password when making a connection.)

```
conn = DBI::dbConnect(RPostgreSQL::PostgreSQL(),  
                      user=username,  
                      password=pw,  
                      dbname='babynames_by_state',  
                      host='localhost')
```

## R, using a connection to an SQL database

- ▶ A database connection can be used with either SQL or R.
- ▶ This shows that the same dplyr code as before works the remote database

```
names.tbl <- tbl(conn, 'names')
names.tbl %>% select(state) %>% distinct %>% count
names.tbl %>% select(year) %>% distinct %>% count
names.tbl %>% select(name) %>% distinct %>% count
tmp <- names.tbl %>%
  group_by(year, sex, name) %>%
  summarize(total=sum(n)) %>%
  arrange(year, sex, -total) %>%
  filter(row_number() <= 10)
print(head(tmp))
```

## Results: SQL via dplyr

- It's hard to assess the relative speed because the remote SQL engine and network play a role

```
# Source:      lazy query [?? x 4]
# Database:    postgres 9.5.9 [kbaby@localhost:5432/babynames_by_state]
# Groups:      year, sex
# Ordered by:  year, sex, -total
   year  sex    name total
  <int> <chr>   <chr> <dbl>
1  1910    F      Mary 22848
2  1910    F      Helen 10479
3  1910    F Margaret  8222
4  1910    F  Dorothy  7314
5  1910    F      Ruth  7209
6  1910    F      Anna  6433
   user  system elapsed
0.192   0.004   24.564
```

# The dplyr query

- Use `show_query()` to examine the query constructed by dplyr

```
show_query(tmp)
<SQL>
SELECT "year", "sex", "name", "total"
FROM (SELECT "year", "sex", "name", "total", row_number() OVER (PARTITION BY "year", "sex" ORDER BY "year"
FROM (SELECT *
FROM (SELECT "year", "sex", "name", SUM("n") AS "total"
FROM "names"
GROUP BY "year", "sex", "name") "fnihsuryas"
ORDER BY "year", "sex", -"total") "hbgphuijrr") "bxcwbpydeq"
WHERE ("zzz3" <= 10.0)
```

# Manipulation using SQL

- ▶ Access the SQL connection by setting `connection=conn` in the the chunk options.

```
select count(distinct state) from names;
```

count
51

```
select count(distinct year) from names;
```

count
107

```
select count(distinct name) from names;
```

count
31014

# Direct SQL

- ▶ The following chunk is pure SQL. The result of the statement will be assigned to the data frame `babynames10sql`, specified in the chunk options as `output.var='babynames10sql'`.

```
-- name the output with chunk option "output.var='babynames10sql'"
create temp table tmp as
select * from
(
  select name, year, sex, SUM(n),
  ROW_NUMBER () OVER (
  PARTITION BY year, sex
  order by year, sex, sum(n) desc
  )
from names
group by year, sex, name
order by year, sex, sum desc
) as foo
where row_number <= 10;
select year, sex, name, sum from tmp;
```



## Back to R to look at the results...

- Now we're using R again.

```
head(babynames10sql)
  year sex   name  sum
1 1910  F   Mary 22848
2 1910  F  Helen 10479
3 1910  F Margaret  8222
4 1910  F  Dorothy  7314
5 1910  F   Ruth  7209
6 1910  F   Anna  6433
write_csv(babynames10sql, path='data/babynames10sql.csv')
```

# Command line

- ▶ You can use the command line to do some of this.
- ▶ This works in Linux, OS X, and Windows with either git-bash or the [Linux Subsystem for Windows](#).

```
## Number of states
```

```
cut -d, -f1 data/allstates.TXT | uniq | wc -l  
51
```

```
## Number of years
```

```
cut -d, -f3 data/allstates.TXT | uniq | sort | uniq | wc -l  
107
```

```
## Number of names
```

```
cut -d, -f4 data/allstates.TXT | uniq | sort | uniq | wc -l  
31014
```

# Conclusions

- ▶ Use `dplyr` or `data.table` (especially for large data)
- ▶ For large files, save uncompressed
- ▶ Some loops are okay, but using loops for everything kills performance and takes too much time to code
- ▶ Learn to use the command line
  - ▶ If you are using Linux or OS X, you have what you need
  - ▶ If you are using Windows, you will need to install either `git-bash` or the `Linux Subsystem for Windows` (only for Windows 10)