# Lecture 7: Split/Apply/Combine

STAT UN2102 Statistical Computing & Introduction to Data Science

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March 20, 2018

### Last Time

• Writing functions in R

### **Topics for Today**

- The Split/Apply/Combine Model. A general strategy for working with big data.
- The plyr Package. Improves on the apply() family.

The Split/Apply/Combine Model

# Summary

### lterating in R without for()

- Subsetting by indexing with conditionals
- apply(): apply a function to rows or columns of a matrix or data frame
- lapply(), sapply(): apply a function to elements of a list or vector
- cbind(), rbind(): concatenate these objects in a known pattern.

# General Strategy

### Split/Apply/Combine

Today we will learn a general strategy that can be summarized in three conceptual steps:

- Split whatever data object we have into meaningful chunks
- Apply the function of interest to each element in this division
- Combine the results into a new object of the desired structure

# General Strategy

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These are conceptual steps; often the apply and combine steps can be performed for us by a single call to the appropriate function from the apply() family

# Split/Apply/Combine

### Simple but powerful

Does split-apply-combine sound simple? It is, but it's very powerful when combined with the right data structures.

- As usual, compared to explicit for() loops, often requires far less code.
- Makes you think: What do I want to do? vs How do I want to do it?
- Sets you in the right direction towards learning how to use MapReduce/Hadoop for really, really big data sets.

Data set on 18 countries over 35 years (compiled by Bruce Western, in the Sociology Department at Harvard University). The measured variables:

- country, year: country and year of data collection
- strike.volume: days on strike per 1000 workers
- unemployment: unemployment rate
- inflation: inflation rate
- left.parliament: leftwing share of the government
- centralization: centralization of unions
- density: density of unions

Since  $18 \times 35 = 630$ , some years missing from some countries

```
> strikes <- read.csv("strikes.csv", as.is = TRUE)
```

> dim(strikes)

```
[1] 625 8
```

> head(strikes, 3)

	country	year	strike.volume u	unemployment	inflation
1	Australia	1951	296	1.3	19.8
2	Australia	1952	397	2.2	17.2
3	Australia	1953	360	2.5	4.3
	left.parli	ament	centralization	n density	
1		43	0.3748588	B NA	
2		43	0.3751829	9 NA	
3		43	0.3745076	6 NA	

#### Our Research Question

Is there a relationship between a country's ruling party alignment (left versus right) and the volume of strikes?

How could we approach this?

- Worst way: by hand, write 18 separate code blocks
- Bad way: explicit for() loop, where we loop over countries
- Best way: split appropriately, then use sapply()

### Let's Study Just a Single Country

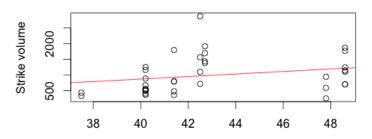
```
> italy.strikes <- subset(strikes, country == "Italy")
> # Equivalently,
> italy.strikes <- strikes[strikes$country == "Italy", ]
> dim(italy.strikes)
```

### Let's Study Just a Single Country

```
> head(italy.strikes, 5)
```

```
country year strike.volume unemployment inflation
311
    Italy 1951
                     437
                               8.8
                                      14.3
312 Italy 1952
                               9.5 1.9
                   337
313 Italy 1953
                         10.0 1.4
                  545
314 Italy 1954
                   493
                          8.7 2.4
315
                  511
                           7.5
                                    2.3
    Italy 1955
   left.parliament centralization density
311
           37.5
                   0.2513799
                               NΑ
312
           37.5
                   0.2489860
                               NΑ
313
           40.2
                   0.2482739
                               NΑ
314
           40.2
                               NΑ
                   0.2466577
315
           40.2
                   0.2540366
                               NΑ
```

### Italy Strike Volume Versus Left-Wing Alignment



#### One Down, Seventeen To Go

It's tedious and dangerous to do this repeatedly – typos! How can we do this an easier way?

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Now let's generalize our functions. We want the linear model coefficients:

```
(Intercept) left.parliament -738.74531 40.29109
```

### We could for() loop it...

```
> strike.coef <- NULL
> my.countries <- c("France", "Italy", "USA")
> for (this.country in my.countries) {
+ country.dat <- subset(strikes, country == this.country)
+ new.coefs <- my.strike.lm(country.dat)
+ strike.coef <- cbind(strike.coef, new.coefs)
+ }
> colnames(strike.coef) <- my.countries
> strike.coef
```

```
France Italy USA (Intercept) 202.4261408 -738.74531 111.440651 left.parliament -0.4255319 40.29109 5.918647
```

### The Best Way

#### Steps:

 Split our data into appropriate chunks, each of which can be handled by our function. Here, the function split() is often helpful. Recall, split(df, f = my.factor) splits a data frame df into several data frames, defined by constant levels of the factor my.factor.

### The Best Way

### Steps:

- Split our data into appropriate chunks, each of which can be handled by our function. Here, the function split() is often helpful. Recall, split(df, f = my.factor) splits a data frame df into several data frames, defined by constant levels of the factor my.factor.
- 2. Apply our function to each chunk of data. Here, the functions lapply() or sapply() are often helpful.
- 3. Combine the results.

#### One Down, Seventeen To Go

First we subset for every country using split().

```
> strikes.split <- split(strikes, strikes$country)
> names(strikes.split)
```

```
Г17
    "Australia"
                   "Austria"
                                   "Belgium"
                                                  "Canada"
 [5] "Denmark"
                    "Finland"
                                   "France"
                                                  "Germany"
 [9] "Ireland"
                   "Italy"
                                   "Japan"
                                                  "Netherlands"
[13] "New.Zealand" "Norway"
                                   "Sweden"
                                                  "Switzerland'
[17] "UK"
                    "USA"
```

### The Best Way

So we want to apply my.strikes.lm() to each data frame in strikes.split. Think about what the output will be from each function call: vector of length 2 (intercept and slope), so we can use sapply().

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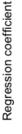
```
> strike.coef <- sapply(strikes.split[1:12], my.strike.lm)
> strike.coef
```

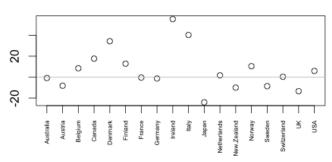
```
Australia Austria Belgium Canada
(Intercept) 414.7712254 423.077279 -56.926780 -227.8218
left.parliament -0.8638052 -8.210886 8.447463
                                              17,6766
                  Denmark Finland
                                     France
                                             Germany
(Intercept)
              -1399.35735 108.2245 202.4261408 95.657134
left.parliament
                 34.34477 12.8422 -0.4255319 -1.312305
                Ireland
                           Italy
                                    Japan Netherlands
(Intercept) -94.78661 -738.74531 964.73750 -32.627678
left.parliament 55.46721 40.29109 -24.07595 1.694387
```

### The Best Way

We don't care about the intercepts, only the slopes (2nd row). Some are positive, some are negative! Let's plot them:

#### Countrywise labor activity by leftwing score





#### **Tasks**

- Using split() and sapply(), compute the average unemployment rate, inflation rates, and strike volume for each year in the strikes data set. The output should be a matrix of dimension 3 x 35.
- Display the average unemployment rate by year and the average inflation rate by year, in the same plot. Label the axes and title the plot appropriately. Include an informative legend.

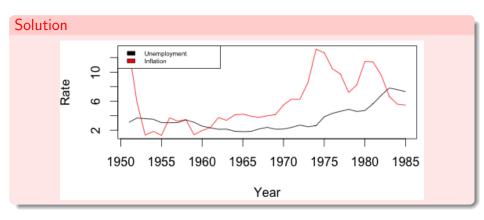
#### Solution

Γ17 3 35

#### Solution

```
> years.mat[, 1:8]
                 1951
                           1952
                                     1953
                                               1954
unemployment 3.088889 3.683333 3.594444 3.505556
inflation 13.088889 5.794444 1.333333 1.833333
strike.volume 359.222222 588.666667 211.944444 139.333333
                 1955
                           1956
                                     1957
                                               1958
          3.044444 3.033333 3.055556 3.422222
unemployment
inflation
            1.294444 3.705556 3.255556 3.472222
strike.volume 215.277778 561.944444 216.111111 145.611111
```

#### Solution



### Section II

Using plyr

# Reminder: iterating in R without for()

We've learned some tools in R for iteration without explicit for() loops:

- Indexing with conditionals + vectorization
- apply(): apply a function to rows or columns of a matrix or data frame
- lapply(): apply a function to elements of a list or vector
- sapply(): same as the above, but simplify the output (if possible)
- tapply(): apply a function to levels of a factor vector

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- tapply(): apply a function to levels of a factor vector

Clever indexing + vectorization is always useful, when possible.

The apply() family is often useful, but it has some issues: primarily, inconsistent output.

### The plyr package

Most popular R package of all time (most downloads): plyr

Provides us with an extremely useful family of apply-like functions. Advantage over the built-in apply() family is its consistency

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Provides us with an extremely useful family of apply-like functions. Advantage over the built-in apply() family is its consistency

All plyr functions are of the form \*\*ply(). Replace \*\* with characters denoting types:

- First character: input type, one of a, d, 1
- Second character: output type, one of a, d, 1, or \_ (drop)

# a\*ply(): The Input is an Array

The signature for all a\*ply() functions is:

```
a*ply(.data, .margins, .fun, ...)
```

- .data : an array
- .margins : index (or indices) to split the array by
- .fun : the function to be applied to each piece
- ... : additional arguments to be passed to the function

# a\*ply(): The Input is an Array

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- . . . : additional arguments to be passed to the function

#### Note that this looks like:

```
apply(X, MARGIN, FUN, ...)
```

```
> my.array
 , Bart
  C1 C2 C3
R1
R2 2 5 8
R3 3 6 9
  , Lisa
  C1 C2 C3
R1 10 13 16
R2 11 14 17
R3 12 15 18
```

```
> my.array[, , 3]

C1 C2 C3
R1 19 22 25
R2 20 23 26
R3 21 24 27
```

```
> library(plyr)
> aaply(my.array, 1, sum) # Get back an array
R1 R2 R3
117 126 135
> adply(my.array, 1, sum) # Get back a data frame
 X1 V1
1 R.1 117
2 R2 126
3 R3 135
```

```
> alply(my.array, 1, sum) # Get back a list
$`1`
[1] 117
$`2`
[1] 126
$`3`
[1] 135
attr(,"split_type")
[1] "array"
attr(, "split_labels")
  X 1
1 R1
```

```
X2
X1 Bart Lisa Maggie
```

```
> adply(my.array, 2:3, sum) # Get back a data frame
 X1 X2 V1
1 C1 Bart 6
2 C2 Bart 15
3 C3 Bart 24
4 C1 Lisa 33
5 C2 Lisa 42
6 C3 Lisa 51
7 C1 Maggie 60
8 C2 Maggie 69
9 C3 Maggie 78
```

```
> alply(my.array, 2:3, sum) # Get back a list
$`1`
[1] 6
$`2`
[1] 15
$`3`
[1] 24
$`4`
[1] 33
$`5`
[1] 42
```

# 1\*ply(): The Input is a List

The signature for all 1\*ply() functions is:

```
1*ply(.data, .fun, ...)
```

- .data: a list
- .fun: the function to be applied to each element
- ... : additional arguments to be passed to the function

## 1\*ply() : The Input is a List

```
The signature for all 1*ply() functions is:
```

```
l*ply(.data, .fun, ...)
```

- .data: a list
- .fun : the function to be applied to each element
- ... : additional arguments to be passed to the function

#### Note that this looks like:

```
lapply(X, FUN, ...)
```

```
> my.list <- list(nums = rnorm(1000), lets = letters,
                 pops = state.x77[ ,"Population"])
+
> head(my.list[[1]], 5)
[1] -0.5058503 1.0244058 1.0628137 0.3826200 1.5695791
> head(my.list[[2]], 5)
[1] "a" "b" "c" "d" "e"
> head(my.list[[3]], 5)
  Alabama
              Alaska
                        Arizona Arkansas California
     3615
                 365
                           2212
                                     2110 21198
```

```
> laply(my.list, range) # Get back an array
[1,] "-3.2207101450142" "3.14576985212618"
[2,] "a"
                         "2"
[3,] "365"
                         "21198"
> ldply(my.list, range) # Get back a data frame
   .id
                      V1
                                        V2
1 nums -3.2207101450142 3.14576985212618
2 lets
                       а
                                         7.
                     365
                                     21198
3 pops
```

```
> llply(my.list, range) # Get back a list
$nums
[1] -3.22071 3.14577
$lets
[1] "a" "z"
$pops
[1] 365 21198
```

- > # Doesn't work! Outputs have different types/lengths
  > # laply(my.list, summary)
  > # ldply(my.list, summary)
  > llply(my.list, summary) # Works just fine
- \$nums

Min. 1st Qu. Median Mean 3rd Qu. Max. -3.221000 -0.631600 -0.032320 -0.000448 0.616300 3.146000

\$lets

Length Class Mode 26 character character

\$pops

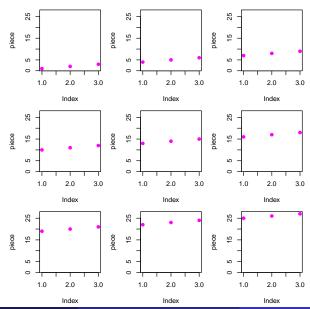
Min. 1st Qu. Median Mean 3rd Qu. Max. 365 1080 2838 4246 4968 21200

# The Fourth Option for \*

The fourth option for \* is \_: the function a\_ply() (or 1\_ply()) has no explicit return object, but still runs the given function over the given array (or list), possibly producing side effects

```
> par(mfrow = c(3, 3), mar = c(4, 4, 1, 1))
> a_ply(my.array, 2:3, plot, ylim = range(my.array),
+ pch = 19, col = 6)
```

# The Fourth Option for \*



## d\*ply() : The Input is a Data Frame

```
The signature for all d*ply() functions is:
```

```
d*ply(.data, .variables, .fun, ...)
```

- .data : a data frame
- .variables : variable (or variables) to split the data frame by
- .fun : the function to be applied to each piece
- . . . : additional arguments to be passed to the function

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The signature for all d*ply() functions is:
```

```
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```

- .data : a data frame
- .variables : variable (or variables) to split the data frame by
- .fun : the function to be applied to each piece
- . . . : additional arguments to be passed to the function

#### Note that this looks like:

```
tapply(X, INDEX, FUN, ...)
```

#### Recall, data set on political economy of strikes:

```
> # Function to compute coefficients from regressing number
> # of strikes (per 1000 workers) on leftwing share of the
> # government
>
> my.strike.lm <- function(country.df) {
+ return(coef(lm(strike.volume ~ left.parliament,
+ data=country.df)))
+ }</pre>
```

```
> # Getting regression coefficients separately
> # for each country, old way:
>
> strikes.list <- split(strikes, f = strikes$country)
> strikes.coefs <- sapply(strikes.list, my.strike.lm)
> strikes.coefs[, 1:12]
```

```
Australia Austria Belgium Canada (Intercept) 414.7712254 423.077279 -56.926780 -227.8218 left.parliament -0.8638052 -8.210886 8.447463 17.6766 Denmark Finland France Germany (Intercept) -1399.35735 108.2245 202.4261408 95.657134 left.parliament 34.34477 12.8422 -0.4255319 -1.312305 Ireland Italy Japan Netherlands (Intercept) -94.78661 -738.74531 964.73750 -32.627678 left.parliament 55.46721 40.29109 -24.07595 1.694387
```

```
> # Getting regression coefficient separately for each
> # country, new way, in three formats:
>
> strike.coef.a <- daply(strikes, .(country), my.strike.lm)
> # Get back an array, note the difference to sapply()
> head(strike.coef.a)
```

```
      country
      (Intercept)
      left.parliament

      Australia
      414.77123
      -0.8638052

      Austria
      423.07728
      -8.2108864

      Belgium
      -56.92678
      8.4474627

      Canada
      -227.82177
      17.6766029

      Denmark
      -1399.35735
      34.3447662

      Finland
      108.22451
      12.8422018
```

```
> strike.coef.d <- ddply(strikes, .(country), my.strike.lm)
> head(strike.coef.d) # Get back a data frame
   country (Intercept) left.parliament
 Australia 414.77123 -0.8638052
2
   Austria 423.07728
                        -8.2108864
   Belgium -56.92678 8.4474627
3
4
    Canada -227.82177 17.6766029
5
   Denmark -1399.35735
                          34.3447662
6
   Finland 108.22451 12.8422018
```

```
> strike.coef.l <- dlply(strikes, .(country), my.strike.lm)
> head(strike.coef.1, 3) # Get back a list
$Australia
    (Intercept) left.parliament
   414.7712254 -0.8638052
$Austria
    (Intercept) left.parliament
    423.077279 -8.210886
$Belgium
    (Intercept) left.parliament
    -56.926780 8.447463
```

The function d\*ply() makes it very easy to split on two (or more) variables: we just specify them, separated by a "," in the .variables argument

```
> # First create a variable that indicates whether the year
> # is pre 1975, and add it to the data frame
>
> strikes$yearPre1975 <- strikes$year <= 1975</pre>
```

```
> head(strike.coef.75)
```

```
country yearPre1975 (Intercept) left.parliament
 Australia
                FALSE.
                       973.34088
                                     -11.8094991
                 TRUE -169.59900
                                      12.0170866
 Australia
3
                FALSE 19.51823
                                     -0.3470889
   Austria
4
  Austria
                 TRUE 400.83004
                                    -7.7051918
5
  Belgium
              FALSE -4182.06650
                                     148,0049261
6
   Belgium
                 TRUE -103.67439
                                      9.5802824
```

```
> head(strike.coef.75)
```

```
country I(year <= 1975) (Intercept) left.parliament
 Australia
                    FALSE.
                            973.34088
                                         -11.8094991
                                          12.0170866
 Australia
                    TRUE -169.59900
3
                    FALSE.
                             19.51823
                                          -0.3470889
   Austria
4
  Austria
                     TRUE 400.83004
                                          -7.7051918
5
  Belgium
                    FALSE -4182.06650
                                         148,0049261
6
   Belgium
                     TRUE -103.67439
                                           9.5802824
```

#### **Parallelization**

- What happens if we have a really large data set and we want to use split-apply-combine?
- If the individual tasks are unrelated, then we should be speed up the computation by performing them **in parallel**.

#### **Parallelization**

- What happens if we have a really large data set and we want to use split-apply-combine?
- If the individual tasks are unrelated, then we should be speed up the computation by performing them **in parallel**.
- The plyr functions make this quite easy: let's take a look at the full signature for daply():

```
daply(.data, .variables, .fun = NULL, ...,
   .progress = "none", .inform = FALSE, .drop_i = TRUE,
   .drop_o = TRUE, .parallel = FALSE, .paropts = NULL)
```

- The second to last argument .parallel (default FALSE) is for parallelization. If set to TRUE, then it performs the individual tasks in parallel, using the foreach package
- The last argument .paropts is for more advanced parallelization, these are additional arguments to be passed to foreach

#### **Parallelization**

- For more, read the foreach package first. May take some time to set up the parallel backend (this is often system specific)
- But once set up, parallelization is simple and beautiful with \*\*ply()!
   The difference is just, e.g.,

#### Tasks

- Compute the average inflation rate for each country pre and post 1975, from strikes, using a single call to daply(), i.e., without using any auxiliary columns in strikes, like the ones created in yearPre1975, countryPre1975. (Hint: Recall the function I(). You'll also have to write a quick function to get the inflation mean.)
- Do the same thing with split() and sapply() to check your results.

#### Solutions

```
> inflation.mean <- function(country.df) {
+ return(mean(country.df$inflation))
+ }
> inflation75 <- ddply(strikes, .(country, I(year<=1975)),
+ inflation.mean)
> dim(inflation75)
```

[1] 36 3

#### Solutions

> head(inflation75)

```
country I(year <= 1975) V1
1 Australia
                     FALSE 9.460
 Australia
                      TRUE 5.448
3
  Austria
                     FALSE 5.080
4 Austria
                      TRUE 5.112
5
 Belgium
                     FALSE 6.400
6
   Belgium
                      TRUE 3.700
```

#### Solutions

```
> split.list <- list(strikes$country, I(strikes$year<=1975))
> data.split <- split(strikes, f = split.list)
> inflation75 <- sapply(data.split, inflation.mean)
> dim(inflation75)
```

#### NULL

```
> head(inflation75)
```

```
Australia.FALSE Austria.FALSE Belgium.FALSE
9.46 5.08 6.40
Canada.FALSE Denmark.FALSE Finland.FALSE
8.11 9.17 9.70
```