Lecture 14: Split/Apply/Combine

STAT GR5206 *Statistical Computing & Introduction to Data Science*

Gabriel Young
Columbia University

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Last Time

- Gradient Descent
- Newton's Method
- Logistic Regression
- Maximum Likelihood Estimation in Logistic Regression

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

Iterating in R without `for()` (a loop)

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

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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.

Example: Strikes dataset

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 goverment
- `centralization`: centralization of unions
- `density`: density of unions

Example: Strikes dataset

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 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.parliament centralization density
1              43      0.3748588      NA
2              43      0.3751829      NA
3              43      0.3745076      NA
```

Example: Strikes dataset

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()`

Example: Strikes dataset

Let's Study Just a Single Country

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

```
[1] 35  8
```

Example: Strikes dataset

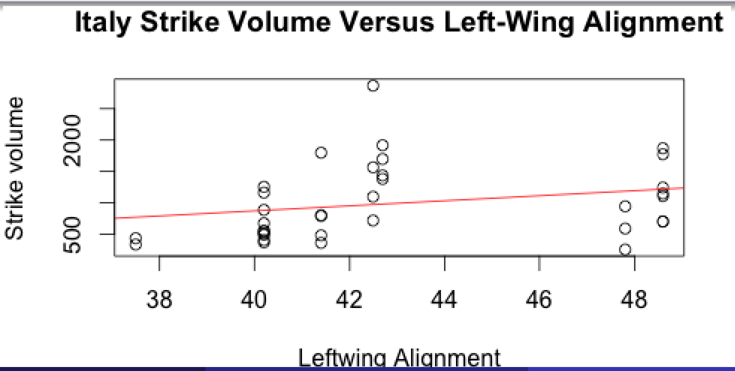
Let's Study Just a Single Country

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

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

Example: Strikes dataset

```
> italy.fit <- lm(strike.volume ~ left.parliament,
+                 data = italy.strikes)
> plot(strike.volume~left.parliament, data = italy.strikes,
+      main="Italy Strike Volume Versus Leftwing Alignment",
+      ylab = "Strike volume", xlab = "Leftwing Alignment")
> abline(italy.fit, col = 2)
```



Example: Strikes dataset

One Down, Seventeen To Go

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

Example: Strikes dataset

One Down, Seventeen To Go

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

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

```
> my.strike.lm <- function(country.df) {
+   return(lm(strike.volume ~ left.parliament,
+             data = country.df)$coeff)
+ }
> my.strike.lm(subset(strikes, country == "Italy"))
```

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

Example: Strikes dataset

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
```

Example: Strikes dataset

The Best Way

Steps:

1. 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`.

Example: Strikes dataset

The Best Way

Steps:

1. 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.

Example: Strikes dataset

One Down, Seventeen To Go

First we subset for every country using `split()`.

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

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

Example: Strikes dataset

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()`.

Example: Strikes dataset

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()`.

```
> 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
```

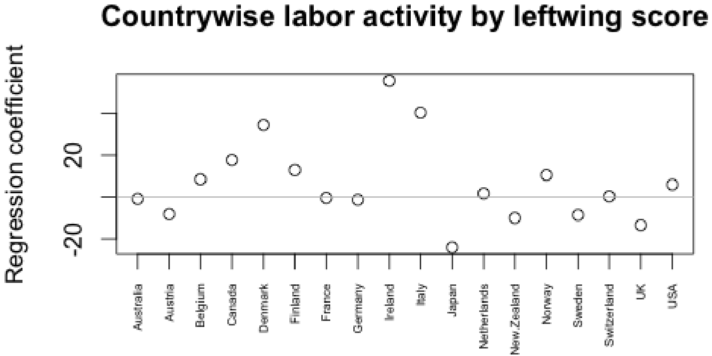
Example: Strikes dataset

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:

```
> plot(1:ncol(strike.coef), strike.coef[2, ], xaxt = "n",
+       xlab = "", ylab = "Regression coefficient",
+       main="Countrywise labor activity by leftwing score")
> axis(side = 1, at = 1:ncol(strike.coef),
+       labels = colnames(strike.coef), las = 2,
+       cex.axis = 0.5)
> abline(h = 0, col = "grey")
```

Example: Strikes dataset



Check Yourself

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.

Check Yourself

Solution

```
> three.mean <- function(df) {
+   return(apply(df[, c("unemployment", "inflation",
+                       "strike.volume")], 2, mean))
+ }
> years.split <- split(strikes, strikes$year)
> years.mat   <- sapply(years.split, three.mean)
> dim(years.mat)
```

```
[1]  3 35
```

Check Yourself

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
unemployment  3.044444   3.033333   3.055556   3.422222
inflation     1.294444   3.705556   3.255556   3.472222
strike.volume 215.277778 561.944444 216.111111 145.611111
```

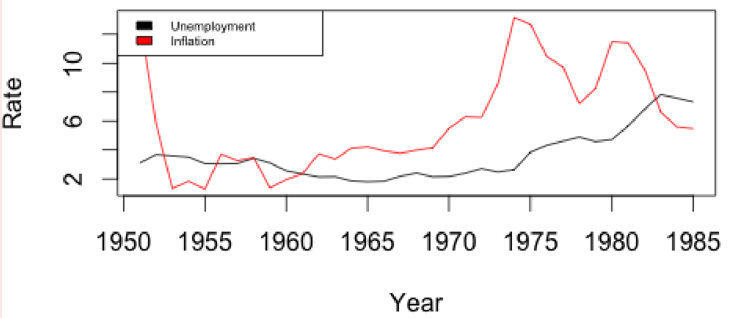
Check Yourself

Solution

```
> max.rate <- max(years.mat[1:2, ])
> min.rate <- min(years.mat[1:2, ])
> plot(colnames(years.mat), years.mat[1, ], xlab = "Year",
+      ylab="Rate", type="l", ylim = c(min.rate, max.rate))
> points(colnames(years.mat), years.mat[2, ], type = "l",
+         col = "red")
> legend("topleft", c("Unemployment", "Inflation"),
+         fill = c("black", "red"), cex = .5)
```

Check Yourself

Solution



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

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
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- `sapply()`: same as the above, but simplify the output (if possible)
- `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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Most popular R package of all time (most downloads): `plyr`

Provides us with an extremely useful family of apply-like functions.
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All `plyr` functions are of the form `**ply()`. Replace `**` with characters denoting types:

you change these.

input

- First character: input type, one of a, d, l

array dataframe list

- Second character: output type, one of a, d, l, or _ (drop) out

input array output list:

alply()

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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- `.fun` : the function to be applied to each piece
- `...` : additional arguments to be passed to the function

Note that this looks like:

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

Examples

```
> my.array              <- array(1:27, c(3,3,3))
> rownames(my.array) <- c("R1", "R2", "R3")
> colnames(my.array) <- c("C1", "C2", "C3")
> dimnames(my.array)[[3]] <- c("Bart", "Lisa", "Maggie")
```

Examples

```
> my.array
```

```
, , Bart

   C1 C2 C3
R1  1  4  7
R2  2  5  8
R3  3  6  9

, , Lisa

   C1 C2 C3
R1 10 13 16
R2 11 14 17
R3 12 15 18
```

Array is more than 2 dimensions

3 dimensions

Bart
Rows
Columns

Examples

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

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

Examples

```
> 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 R1 117
2 R2 126
3 R3 135
```

Examples

```
> 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")
  X1
1 R1
```

Examples

sum columns & 3rd dimension

```
> aaply(my.array, 2:3, sum) # Get back a 3 x 3 array
```

```
    X2
X1   Bart Lisa Maggie
  C1    6   33     60
  C2   15   42     69
  C3   24   51     78
```

Examples

```
> 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
```

Examples

```
> 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
```

`l*ply()` : The Input is a List

The signature for all `l*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

`l*ply()` : The Input is a List

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

Note that this looks like:

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

Examples

```
> my.list <- list(nums = rnorm(1000), lets = letters,
+                  pops = state.x77[ ,"Population"])
> head(my.list[[1]], 5)
```

```
[1] -0.1592102  1.2775853 -0.1612624 -1.0191692 -0.6084487
```

```
> 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
```

Examples

```
> laply(my.list, range) # Get back an array
```

```
     1                   2
[1,] "-3.41929284262538" "3.49197028620251"
[2,] "a"                 "z"
[3,] "365"               "21198"
```

```
> ldply(my.list, range) # Get back a data frame
```

```
   .id                V1               V2
1 nums -3.41929284262538 3.49197028620251
2 lets                 a                z
3 pops               365            21198
```

Examples

```
> llply(my.list, range) # Get back a list
```

```
$nums
[1] -3.419293  3.491970

$lets
[1] "a" "z"

$pops
[1]   365 21198
```

Examples

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

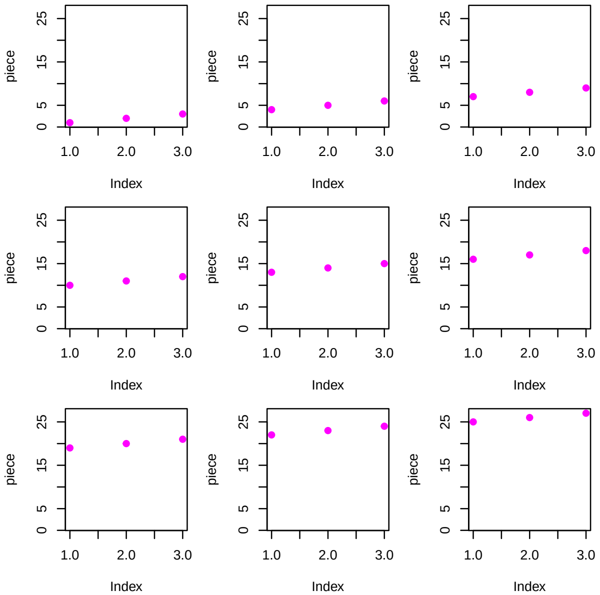
```
$nums
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-3.41900 -0.75450 -0.08982 -0.05617  0.60990  3.49200

$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 `l_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
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- .data : a data frame
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- .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, ...)
```

Strikes Data Set, Revisited

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)))
+ }
```

Strikes Data Set, Revisited

```
> # 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
```

Strikes Data Set, Revisited

```
> # 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
```

Strikes Data Set, Revisited

```
> strike.coef.d <- ddply(strikes, .(country), my.strike.lm)
> head(strike.coef.d) # Get back a data frame
```

```
    country (Intercept) left.parliament
1 Australia   414.77123      -0.8638052
2   Austria   423.07728      -8.2108864
3   Belgium   -56.92678       8.4474627
4    Canada  -227.82177      17.6766029
5   Denmark -1399.35735      34.3447662
6   Finland   108.22451      12.8422018
```

Strikes Data Set, Revisited

```
> strike.coef.l <- dlply(strikes, .(country), my.strike.lm)
> head(strike.coef.l, 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
```

Splitting on Two or More Variables

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
```

```
> # Then use (say) ddply() to compute regression
> # coefficients for each country pre & post 1975
>
> strike.coef.75 <- ddply(strikes, .(country, yearPre1975),
+                          my.strike.lm)
> dim(strike.coef.75) # Note there are 18 x 2 = 36 rows
```

```
[1] 36  4
```

Splitting on Two or More Variables

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

```
    country yearPre1975 (Intercept) left.parliament
1 Australia       FALSE   973.34088     -11.8094991
2 Australia        TRUE  -169.59900      12.0170866
3   Austria       FALSE    19.51823      -0.3470889
4   Austria        TRUE   400.83004      -7.7051918
5   Belgium       FALSE -4182.06650     148.0049261
6   Belgium        TRUE  -103.67439       9.5802824
```

Splitting on Two or More Variables

```
> # Can also create factor variables on-the-fly with I()
>
> strike.coef.75 <- ddply(strikes,
+                         .(country, I(year<=1975)),
+                         my.strike.lm)
> dim(strike.coef.75) # Again, 18 x 2 = 36 rows
```

```
[1] 36  4
```

Splitting on Two or More Variables

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

```
    country I(year <= 1975) (Intercept) left.parliament
1 Australia           FALSE   973.34088     -11.8094991
2 Australia            TRUE  -169.59900      12.0170866
3   Austria           FALSE    19.51823      -0.3470889
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.,

  ```
  daply(strikes.df, .(country), my.strike.lm)
  ```

  versus

  ```
  daply(strikes.df, .(country), my.strike.lm,
        .parallel = TRUE)
  ```

Check Yourself

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.

Check Yourself

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
```

Check Yourself

Solutions

```
> head(inflation75)
```

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

Check Yourself

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
```

Reshaping Dataframes

Reshaping

Common to have data where some variables identify units and others are measurements corresponding to the unit.

- **Wide** form: columns for ID variables plus 1 column per measurement.
- **Narrow** form: columns for ID variables, plus 1 column identifying measurement, plus 1 column giving value.

Reshaping

Common to have data where some variables identify units and others are measurements corresponding to the unit.

- **Wide** form: columns for ID variables plus 1 column per measurement.
- **Narrow** form: columns for ID variables, plus 1 column identifying measurement, plus 1 column giving value.

Often want to convert from wide to narrow, or change what's ID and what's measure.

Reshaping

- `reshape` package introduced data-reshaping tools.
- `reshape2` package simplifies lots of common uses.
- `melt()` turns a wide dataframe into a narrow one.
- `dcast()` turns a narrow dataframe into a wide one.
- `acast()` turns a narrow dataframe into a wide array.

Reshaping

Example [1]

`snoqualmie.csv` has precipitation every day in Snoqualmie, WA for 36 years (1948–1983). One row per year, one column per day, units of 1/100 inch.

```
> snoq <- read.csv("snoqualmie.csv", header = FALSE,
+                  as.is = TRUE)
> colnames(snoq) <- 1:366
> snoq$year      <- 1948:1983
```

[a] From P. Guttorp, Stochastic Modeling of Scientific Data

Reshaping

```
> dim(snoq)
```

```
[1]  36 367
```

```
> snoq[1:3, 1:10]
```

```
    1   2  3  4  5   6   7  8 9 10
1 136 100 16 80 10  66  88 38 1 87
2  17  14  0  0  1  11  90  6 0  0
3   1  35 13 13 18 122  22 25 8 48
```

```
> snoq[1:3, 360:367]
```

```
  360 361 362 363 364 365 366 year
1   0   0   0   0  49 114  17 1948
2  47 245 121  72  27  41  NA 1949
3   4  40  10   5  93  23  NA 1950
```

Reshaping

Example

```
> #install.packages("reshape2")
> require(reshape2)
> snoq.melt <- melt(snoq, id.vars = "year",
+                   variable.name = "day",
+                   value.name = "precip")
> head(snoq.melt)
```

```
  year day precip
1 1948   1    136
2 1949   1     17
3 1950   1      1
4 1951   1     34
5 1952   1      0
6 1953   1      2
```

Reshaping

Example

```
> tail(snoq.melt)
```

```
      year day precip
13171 1978 366     NA
13172 1979 366     NA
13173 1980 366     80
13174 1981 366     NA
13175 1982 366     NA
13176 1983 366     NA
```

```
> dim(snoq.melt) # 36*366
```

```
[1] 13176     3
```

Reshaping

Example

Being sorted by day of the year and then by year is a bit odd

```
>  snoq.melt.chron <- snoq.melt[order(snoq.melt$year,
+                                     snoq.melt$day), ]
>  head(snoq.melt.chron)
```

```
    year day precip
1   1948   1    136
37  1948   2    100
73  1948   3     16
109 1948   4     80
145 1948   5     10
181 1948   6     66
```

Reshaping

Example

Most years have 365 days so some missing values:

```
> leap.days <- snoq.melt.chron$day == 366
> sum(is.na(snoq.melt.chron$precip[leap.days]))
```

```
[1] 27
```

Reshaping

Example

Most years have 365 days so some missing values:

```
> leap.days <- snoq.melt.chron$day == 366
> sum(is.na(snoq.melt.chron$precip[leap.days]))
```

```
[1] 27
```

Tidy with `na.omit()`:

```
> snoq.melt.chron <- na.omit(snoq.melt.chron)
```

Reshaping

Example

`dcast()` turns back into wide form, with a formula of IDs $\sim$ measures.

```
> snoq.recast <- dcast(snoq.melt, year ~ ...)
> dim(snoq.recast)
```

```
[1]  36 367
```

```
> snoq.recast[1:4, 1:15]
```

```
  year   1   2  3  4  5   6  7  8 9 10 11 12 13 14
1 1948 136 100 16 80 10  66 88 38 1 87  8  4  0  0
2 1949  17  14  0  0  1  11 90  6 0  0  0  0  0  3
3 1950   1  35 13 13 18 122 22 25 8 48  3  2  8  0
4 1951  34 183 11 20 11   0  9  1 0  3 16 21 53  2
```

`acast()` casts into an array rather than a dataframe.

Reshaping

Example

- The formula could also specify multiple ID variables (including original measure variables), different measure variables (including original ID variables)...
- Also possible to apply functions to aggregates which all have the same IDs, select subsets of the data, etc.
- Strongly recommended reading:
    - Hadley Wickham, "Reshaping Data with the reshape Package", *Journal of Statistical* Software 21 (2007): 12, `http://www.jstatsoft.org/v21/i12`