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Computing by groups within data.frames with plyr

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This material was last used in 2014. Since then, we are turning more to dplyr, including for data aggregation. But plyr is still a very useful package and so we leave this material here.

Install and load plyr

If you have not already done so, you'll need to install plyr.

```
install.packages("plyr", dependencies = TRUE)
```

We also need to load it.

```
library (plyr)
```

Note: if you are using both plyr and dplyr in a script, you should always load plyr first, then dplyr.

plyr Big Ideas

The plyr functions will not make much sense viewed individually, e.g. simply reading the help for ddply() is not the fast track to competence. There is a very important over-arching logic for the package and it is well worth reading the article The split-apply-combine strategy for data analysis (http://www.jstatsoft.org /v40/i01/paper). Though it is no substitute for reading the above, here is the most critical information:

- **split-apply-combine**: A common analytical pattern is to split data into pieces, apply some function to each pieces, and combine the results back together again. Recognize when you're solving such a problem and exploit the right tools.
- The computations on these pieces must be truly independent, i.e. the problem must be embarrassingly or pleasingly parallel (http://en.wikipedia.org/wiki/Embarrassingly_parallel), in order to use plyr.
- The heart of plyr is a set a functions with names like this: xyply where x specifies what sort of input you're giving and y specifies the sort of output you want.
 - o a = array, where matrices and vectors are important special cases
 - o d = data.frame
 - 1 = list
 - \circ _ = no output; only valid for $\mbox{$_{\Upsilon}$}$, obviously; useful when you're operating on a list purely for the side effects, e.g., making a plot or sending output to screen/file
- The usage is very similar across these functions. Here are the main arguments:
 - .data is the first argument = the input
 - the next argument specifies how to split up the input into pieces; it does not exist when the input is a list, because the pieces must be the list components
 - then comes the function and further arguments needed to describe the computation to be applied to the pieces

Today we emphasize $\mathtt{ddply}()$ which accepts a data.frame, splits it into pieces based on one or more factors, computes on the pieces, then returns the results as a data.frame. For the record, the base R functions most relevant to $\mathtt{ddply}()$ are $\mathtt{tapply}()$ and friends.

Load the Gapminder data

As usual, load the Gapminder excerpt.

```
library(gapminder)
```

Introduction to ddply()

Let's say we want the maximum life expectancy for each continent. We're providing a data.frame as input and we want a data.frame as output. Therefore this is a job for $\mathtt{ddply}()$. We want to divide the data.frame into pieces based on $\mathtt{continent}$. Here's the call

Let's study the return value.

```
str(max_le_by_cont)
## 'data.frame': 5 obs. of 2 variables:
## $ continent: Factor w/ 5 levels "Africa", "Americas",..: 1 2 3 4
5
## $ max_le : num 76.4 80.7 82.6 81.8 81.2
levels(max_le_by_cont$continent)
## [1] "Africa" "Americas" "Asia" "Europe" "Oceania"
```

We got a data.frame back, with one observation per continent, and two variables: the maximum life expectancies and the continent, as a factor, with the same levels in the same order, as for the input data.frame <code>gapminder</code>. If you have sweated to do such things with base R, this minor miracle might make you cry tears of joy (or anguish over all the hours you have wasted.)

summarize() or its synonym summarise() is a function provided by plyr that creates a new data.frame from an old one. It is related to the built-in function transform() that transforms variables in a data.frame or adds new ones. Feel free to play with it a bit in some top-level commands; you will use it alot inside plyr calls.

The two variables in $\max_{l=by_cont}$ come from two sources. The continent factor is provided by ddply() and represents the labelling of the life expectancies with their associated continent. This is the book-keeping associated with dividing the input into little bits, computing on them, and gluing the results together again in an orderly, labelled fashion. We can take more credit for the other variable $\max_{l=0}$ which has a name we chose and arises from applying a function we specified ($\max_{l=0}$) to a variable of our choice ($\lim_{l=0}$).

You try: compute the minimum GDP per capita by continent. Here's what I get:

You might have chosen a different name for the minimum GDP/capita's, but your numerical results should match.

The function you want to apply to the continent-specific data.frames can be built-in, like $\max()$ above, or a custom function you've written. This custom function can be written in advance or specified 'on the fly'. Here's one way to count the number of countries in this dataset for each continent.

```
ddply(gapminder, ~ continent,
     summarize, n uniq countries = length(unique(country)))
##
    continent n uniq countries
## 1
      Africa
                            52
## 2 Americas
                            25
      Asia
## 3
                            33
## 4 Europe
                            30
                             2
## 5 Oceania
```

Here is another way to do the same thing that doesn't use summarize() at all:

In pseudo pseudo-code, here's what's happening above:

```
returnValue <- an empty receptacle with one "slot" per country
for each possible country i {
    x <- subset(gapminder, subset = country == i)
    returnValue[i] <- length(unique(x$country))
    name or label for returnValue[i] is set to country i
}
ddply packages returnValue and associated names/labels as a nice dat
a.frame</pre>
```

You don't have to compute just one thing for each sub-data.frame, nor are you limited to computing on just one variable. Check this out.

Recall the function we wrote to fit a linear model

We recently learned how to write our own R functions (Part 1 (block011_write-your-own-function-01.html), Part 2 (block011_write-your-own-function-02.html), Part 3 (block011_write-your-own-function-03.html)). We then wrote a function (block012_function-regress-lifeexp-on-year.html) to use on the Gapminder dataset. This function $le_lin_fiit()$ takes a data.frame and expects to find variables for life expectancy and year. It returns the estimated coefficients from a simple linear regression. We wrote it with the goal of applying it to the data from each country in Gapminder. That's what we do here.

Make the function available in the workspace

Define the function developed elsewhere (block012_function-regress-lifeexp-

on-year.html):

```
le_lin_fit <- function(dat, offset = 1952) {
  the_fit <- lm(lifeExp ~ I(year - offset), dat)
  setNames(coef(the_fit), c("intercept", "slope"))
}</pre>
```

Let's try it out on the data for one country, just to reacquaint ourselves with it.

```
le_lin_fit(subset(gapminder, country == "Canada"))
## intercept slope
## 68.8838462 0.2188692
```

Apply our function inside ddply

We are ready to scale up to **all countries** by placing this function inside a ddply() call.

```
j coefs <- ddply(gapminder, ~ country, le lin fit)</pre>
str(j_coefs)
## 'data.frame': 142 obs. of 3 variables:
## $ country : Factor w/ 142 levels "Afghanistan",..: 1 2 3 4 5 6
7 8 9 10 ...
## $ intercept: num 29.9 59.2 43.4 32.1 62.7 ...
## $ slope : num 0.275 0.335 0.569 0.209 0.232 ...
tail(j_coefs)
##
                country intercept
                                       slope
## 137 Venezuela 57.51332 0.32972168
## 138
                Vietnam 39.01008 0.67161538
## 139 West Bank and Gaza 43.79840 0.60110070
## 140 Yemen, Rep. 30.13028 0.60545944
## 141
                Zambia 47.65803 -0.06042517
               Zimbabwe 55.22124 -0.09302098
## 142
```

We did it! By the time we've packaged the computation in a function, the call itself is deceptively simple. To review, here's the script I would save from our work in this tutorial:

```
library(plyr)
library(gapminder)
le_lin_fit <- function(dat, offset = 1952) {
   the_fit <- lm(lifeExp ~ I(year - offset), dat)
   setNames(coef(the_fit), c("intercept", "slope"))
}
j_coefs <- ddply(gapminder, ~ country, le_lin_fit)</pre>
```

That's all. After we've developed the $le_lin_fit()$ function and gotten to know ddply(), this task requires about 5 lines of R code.

Reflect on how incredibly convenient this is. If you're coming from another analytical environment, how easy would this task have been? If you had been asked to do this with R a week ago, would you have written a for loop or given up? The take away message is this: if you are able to write custom functions, the plyr package can make you extremely effective at computing on pieces of a data structure and reassembling the results.

References

plyr paper: The split-apply-combine strategy for data analysis (http://www.jstatsoft.org/v40/i01/paper), Hadley Wickham, Journal of Statistical Software, vol. 40, no. 1, pp. 1–29, 2011. Go here (http://www.jstatsoft.org/v40/i01/) for supplements, such as example code from the paper.

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