A quick introduction to plyr

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September 11, 2013

`plyr` is an R package that makes it simple to split data apart, do stuff to it, and mash it back together. This is a common data-manipulation step. Importantly, `plyr` makes it easy to control the input and output data format from a syntactically consistent set of functions.

Or, from the documentation:

"`plyr` is a set of tools that solves a common set of problems: you need to break a big problem down into manageable pieces, operate on each piece and then put all the pieces back together. It's already possible to do this with split and the apply functions, but `plyr` just makes it all a bit easier..."

This is a very quick introduction to `plyr`. For more details see Hadley Wickham's introductory guide *The split-apply-combine strategy for data analysis* (2011, Journal of Statistical Software, Vol 40). There's quite a bit of discussion online in general, and especially on stackoverflow.com.

1 Why use `apply` functions instead of `for` loops?

1. The code is cleaner (once you're familiar with the concept). The code can be easier to code and read, and less error prone because:
   (a) you don't have to deal with subsetting
   (b) you don't have to deal with saving your results
2. Apply functions can be faster than for loops, sometimes dramatically.

2 Why use `plyr` over base `apply` functions?

1. `plyr` has a common syntax — easier to remember
2. `plyr` requires less code since it takes care of the input and output format
3. `plyr` can easily be run in parallel — faster

3 `plyr` basics

`plyr` builds on the built-in `apply` functions by giving you control over the input and output formats and keeping the syntax consistent across all variations. It also adds some niceties like error processing, parallel processing, and progress bars.

The basic format is 2 letters followed by `ply()`. The first letter refers to the format in and the second to the format out.

The 3 main letters are:

1. `d` = data frame
2. `a` = array (includes matrices)
3. `l` = list

So, `ddply` means: take a data frame, split it up, do something to it, and return a data frame. I find I use this the majority of the time since I often work with data frames. `ldply` means: take a list, split it up, do something to it, and return a data frame. This extends to all combinations. In the following table, the columns are the input formats and the rows are the output format:

	data frame	list	array
data frame	`ddply`	`ldply`	`adply`
list	`dlply`	`llply`	`alply`
array	`daply`	`laply`	`aaply`

I've ignored some less common format options:

1. `m` = multi-argument function input

2. `r` = replicate a function `n` times.

3. `_` = throw away the output

For plotting, you might find the underscore (`_`) option useful. It will do something with the data (say add line segments to a plot) and then throw away the output (e.g., `d_ply()`).

4 Base R `apply` functions and `plyr`

`plyr` provides a consistent and easy-to-work-with format for `apply` functions with control over the input and output formats. Some of the functionality can be duplicated with base R functions (but with less consistent syntax). Also, few R `apply` functions work directly with data frames as input and output and data frames are a common object class to work with.

Base R `apply` functions (from a presentation given by Hadley):

	array	data frame	list	nothing
array	`apply`	.	.	.
data frame	.	`aggregate`	`by`	.
list	`sapply`	.	`lapply`	.
n replicates	`replicate`	.	`replicate`	.
function arguments	`mapply`	.	`mapply`	.

5 A general example with `plyr`

Let's take a simple example. We'll take a data frame, split it up by `year`, calculate the coefficient of variation of the `count`, and return a data frame. This could easily be done on one line, but I'm expanding it here to show the format a more complex function could take.

```
> set.seed(1)
> d <- data.frame(year = rep(2000:2002, each = 3),
+ count = round(runif(9, 0, 20)))
> print(d)
```

```
  year count
1 2000     5
2 2000     7
3 2000    11
4 2001    18
5 2001     4
6 2001    18
7 2002    19
8 2002    13
9 2002    13
```

```
> library(plyr)
> ddply(d, "year", function(x) {
+   mean.count <- mean(x$count)
+   sd.count <- sd(x$count)
+   cv <- sd.count/mean.count
+   data.frame(cv.count = cv)
+ })
```

```
  year  cv.count
1 2000 0.3984848
2 2001 0.6062178
3 2002 0.2309401
```

6 `transform` and `summarise`

It is often convenient to use these functions within `plyr`. `transform` acts as it would normally as the base R function and modifies an existing data frame. `summarise` creates a new (usually) condensed data frame.

```
> ddply(d, "year", summarise, mean.count = mean(count))
```

```
  year mean.count
1 2000   7.666667
2 2001  13.333333
3 2002  15.000000
```

```
> ddply(d, "year", transform, total.count = sum(count))

  year count total.count
1 2000     5          23
2 2000     7          23
3 2000    11          23
4 2001    18          40
5 2001     4          40
6 2001    18          40
7 2002    19          45
8 2002    13          45
9 2002    13          45
```

Bonus function: `mutate`. `mutate` works like `transform` but lets you build on columns you build.

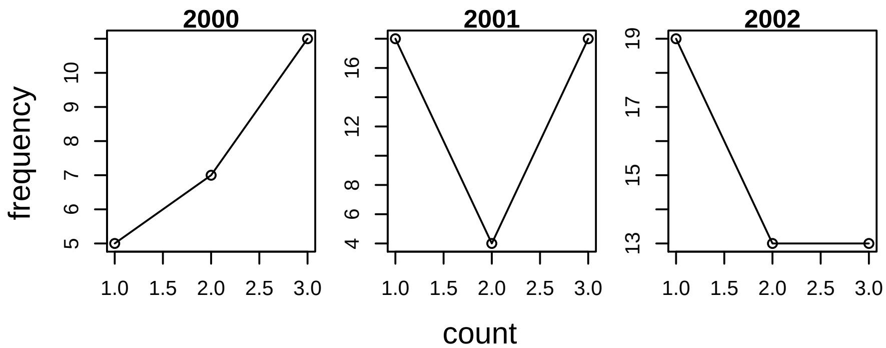
```
> ddply(d, "year", mutate, mu = mean(count), sigma = sd(count),
+   cv = sigma/mu)

  year count        mu    sigma        cv
1 2000     5  7.666667 3.055050 0.3984848
2 2000     7  7.666667 3.055050 0.3984848
3 2000    11  7.666667 3.055050 0.3984848
4 2001    18 13.333333 8.082904 0.6062178
5 2001     4 13.333333 8.082904 0.6062178
6 2001    18 13.333333 8.082904 0.6062178
7 2002    19 15.000000 3.464102 0.2309401
8 2002    13 15.000000 3.464102 0.2309401
9 2002    13 15.000000 3.464102 0.2309401
```

7 Plotting with `plyr`

You can use `plyr` to plot data by throwing away the output with an underscore (`_`). This is a bit cleaner than a for loop since you don't have to subset the data manually.

```
> par(mfrow = c(1, 3), mar = c(2, 2, 1, 1), oma = c(3, 3, 0, 0))
> d_ply(d, "year", transform, plot(count, main = unique(year), type = "o"))
> mtext("count", side = 1, outer = TRUE, line = 1)
> mtext("frequency", side = 2, outer = TRUE, line = 1)
```



8 Nested chunking of the data

The basic syntax can be easily extended to break apart the data based on multiple columns:

```
> baseball.dat <- subset(baseball, year > 2000) # data from the plyr package
> x <- ddply(baseball.dat, c("year", "team"), summarize,
+   homeruns = sum(hr))
> head(x)
```

```
  year team homeruns
1 2001  ANA        4
2 2001  ARI      155
3 2001  ATL       63
4 2001  BAL       58
5 2001  BOS       77
6 2001  CHA       63
```

9 Other useful options

9.1 Dealing with errors

You can use the `failwith` function to control how errors are dealt with.

```
> f <- function(x) if (x == 1) stop("Error!") else 1
> safe.f <- failwith(NA, f, quiet = TRUE)
> #llply(1:2, f)
> llply(1:2, safe.f)
```

```
[[1]]
[1] NA

[[2]]
[1] 1
```

9.2 Parallel processing

In conjunction with `doMC` (or `doSMP` on Windows) you can run your function separately on each core of your computer. On a dual core machine this could double your speed in some situations. Set `.parallel = TRUE`.

```
>   x <- c(1:10)
>   wait <- function(i) Sys.sleep(0.1)
>   system.time(llply(x, wait))
```

```
   user  system elapsed 
  0.001   0.000   1.009 
```

```
>   system.time(sapply(x, wait))
```

```
   user  system elapsed 
  0.001   0.000   1.010 
```

```
>   library(doMC)
>   registerDoMC(2)
>   system.time(llply(x, wait, .parallel = TRUE))
```

```
   user  system elapsed 
  0.020   0.006   0.535 
```

10 So, why would I *not* want to use plyr?

`plyr` can be slow — particularly if you are working with very large datasets that involve a lot of subsetting. Hadley is working on this and an in-development version of `plyr`, `dplyr`, can run much faster. However, it's important to remember that typically the speed that you can write code and understand it later is the rate-limiting step.

Three faster options:

(1) Use a base R apply function:

```
> system.time(ddply(baseball, "id", summarize, length(year)))
```

```
   user  system elapsed 
  0.601   0.013   0.614 
```

```
> system.time(tapply(baseball$year, baseball$id, function(x) length(x)))
```

```
   user  system elapsed 
  0.016   0.000   0.017 
```

(2) Use an immutable data frame. An immutable data frame (`idata.frame`) returns pointers to the original object when subset instead of creating a copy of itself each time. This is often the rate-limiting step in an apply function.

```
> system.time(ddply(idata.frame(baseball), "id", summarize, length(year)))
```

```
   user  system elapsed 
 11.058   2.166  13.227 
```

(3) Use the `data.table` package:

```
> library(data.table)
> dt <- data.table(baseball, key="id")
> system.time(dt[, length(year), by=list(id)])

   user  system elapsed 
  0.006   0.000   0.005 
```