Statistical Computing (36-350)

Lecture 22: Split/Apply/Combine, encore

36-350

Massive thanks to Vince Vu

10 November 2014

Agenda

- High-level overview of split/apply/combine
- Understanding how we split
- Tailoring the applied function to the split

Splitting and Aggregation in Data Analysis

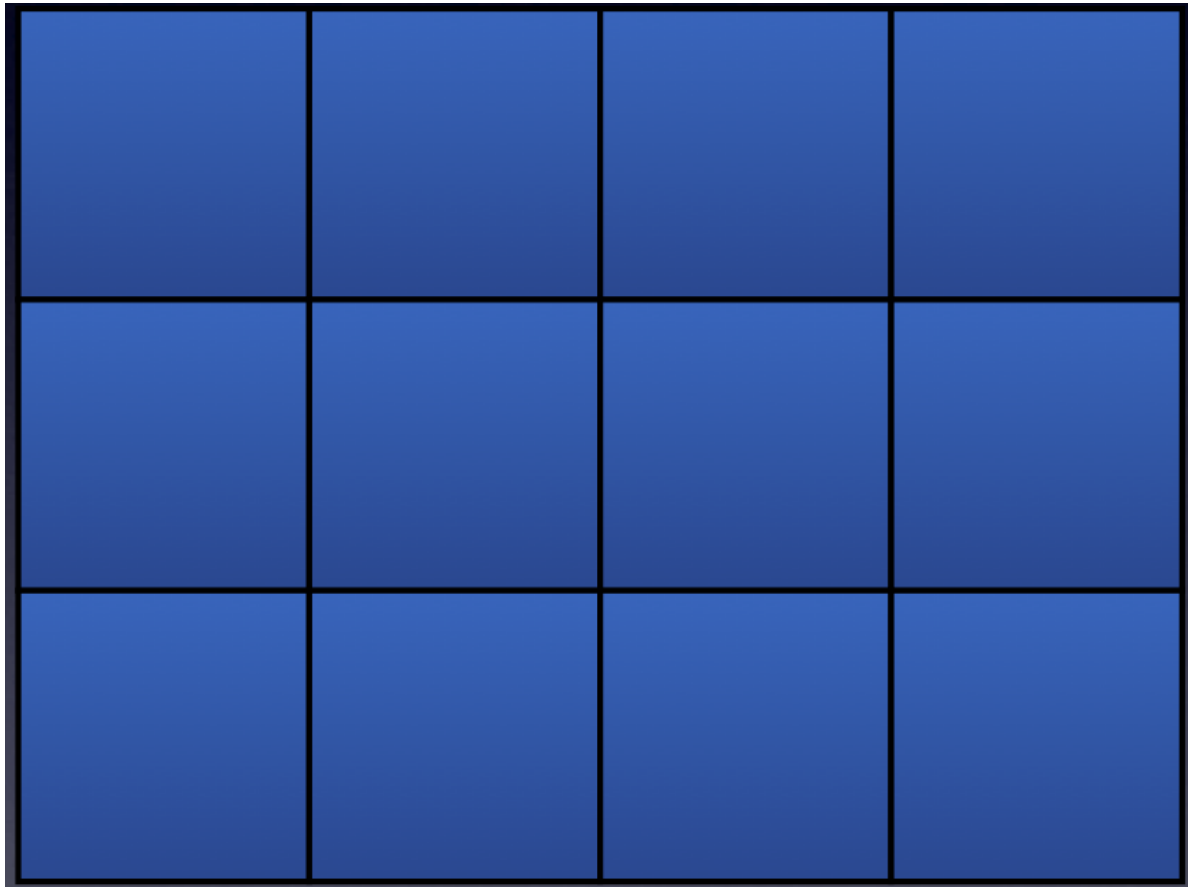
Large data sets are usually highly structured
Structure lets us group data in many different ways
Sometimes we focus on individual pieces of data
Often we aggregate information within groups, and compare across them

An Easy Warm-Up

Row (column) means of a matrix

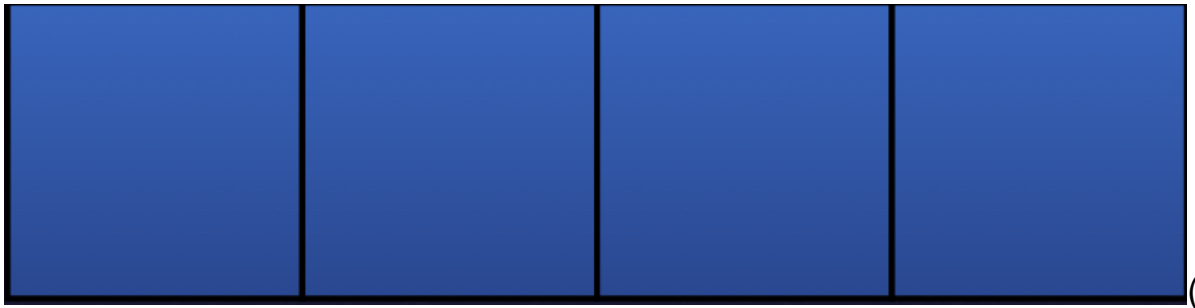
- Divide the matrix into rows (columns)
- Compute the mean of each row (column)
- Combine the results into a vector

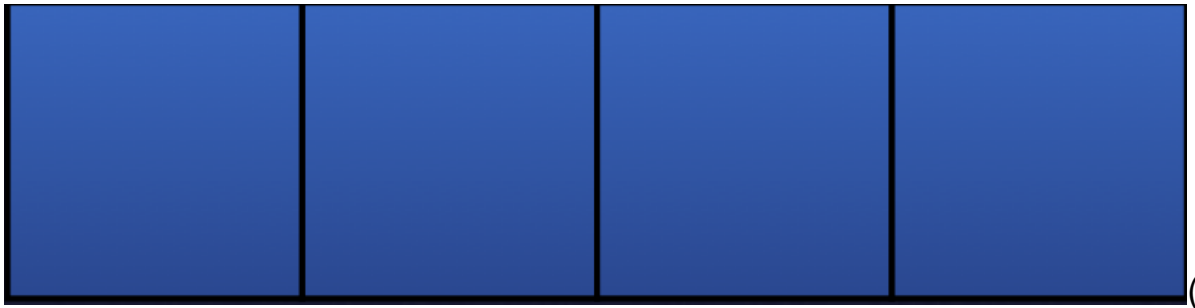
Row Means

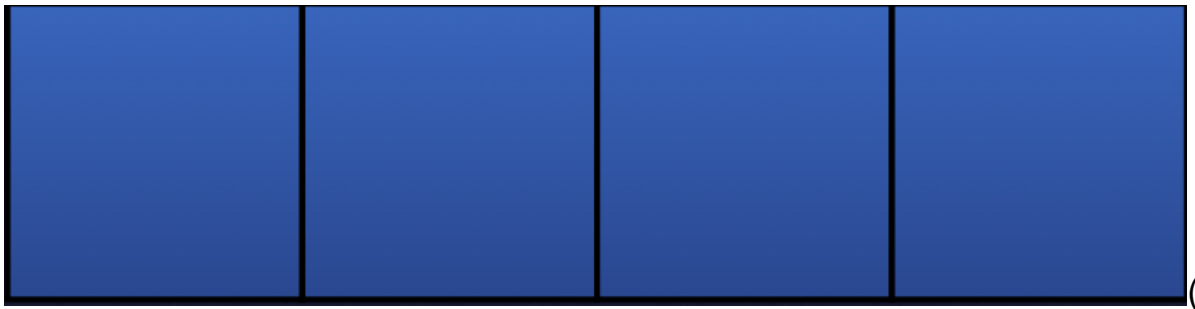


`matrix`
(array, 2 dimensional)

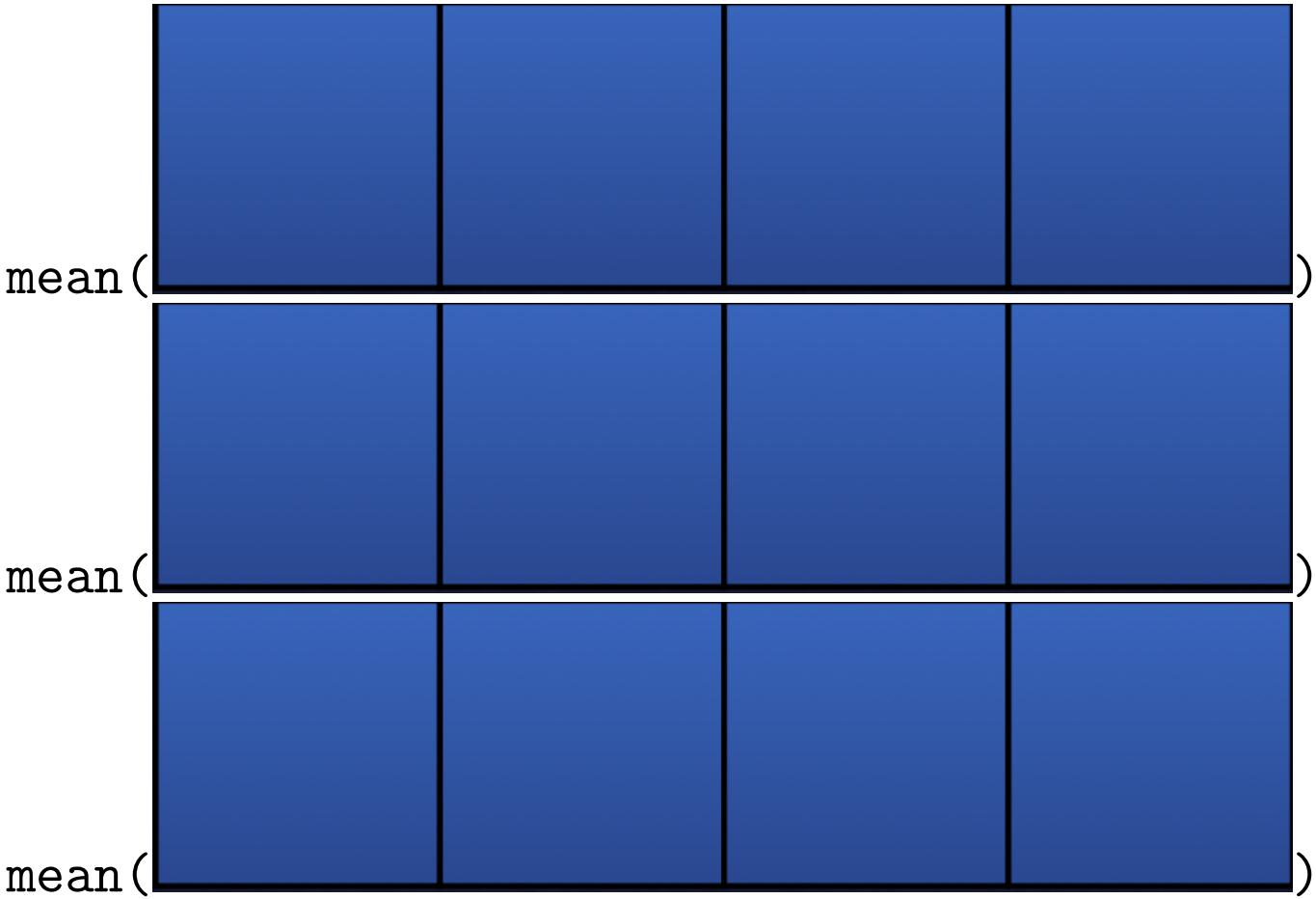
Row Means


(vector, 1 dimensional)


(vector, 1 dimensional)

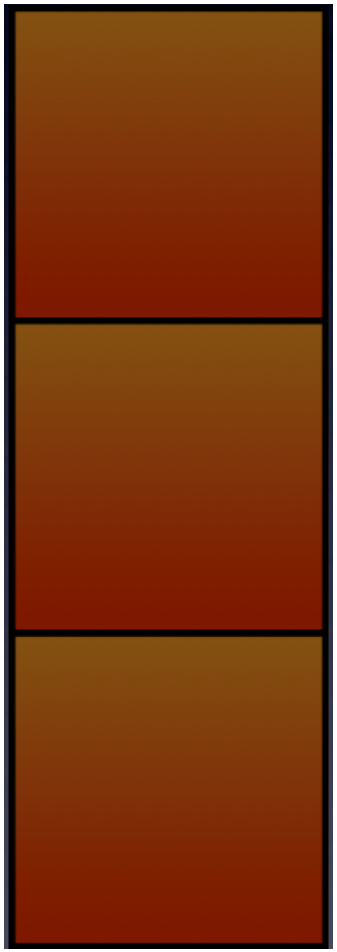

(vector, 1 dimensional)

Row Means



Row Means

Row Means

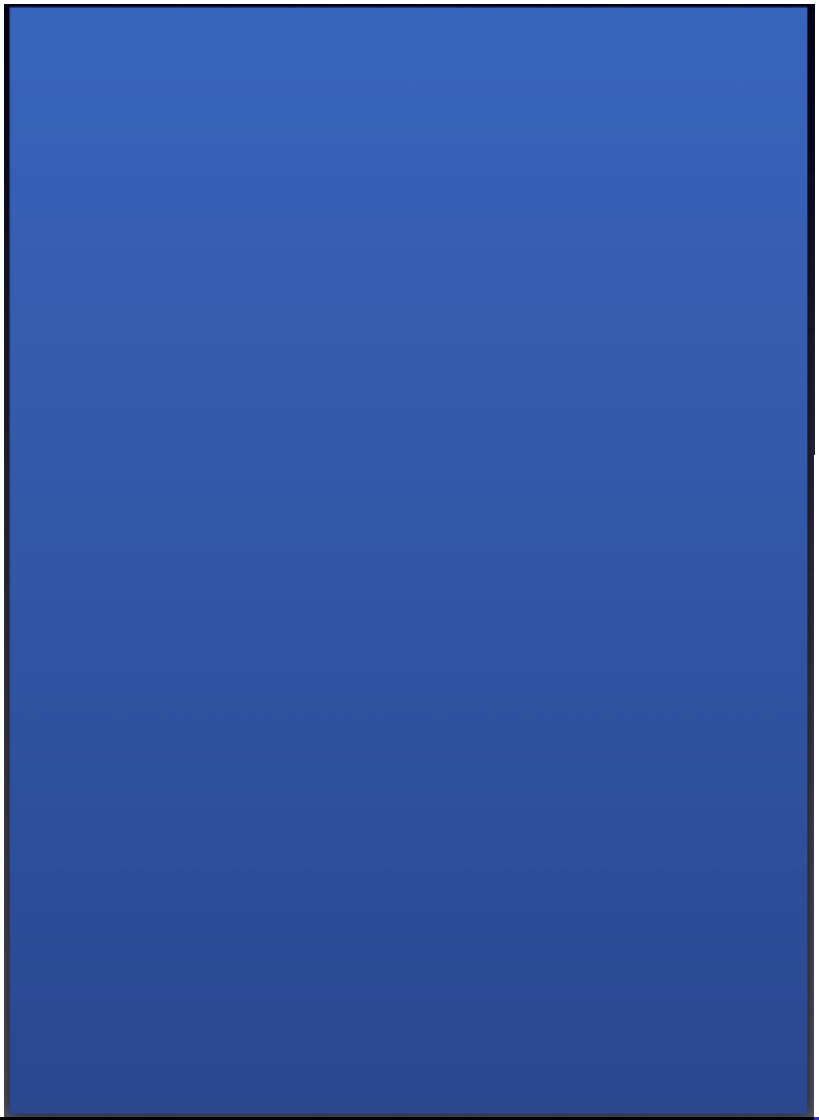


vector (1 dimensional)

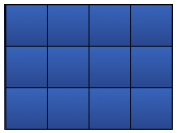
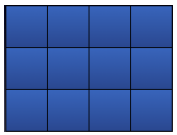
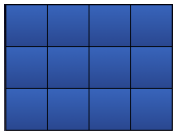
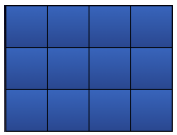
Another Example

Data organized into 48 continental states
Fit a different model for each of 4 different geographic regions

Splitting by Region



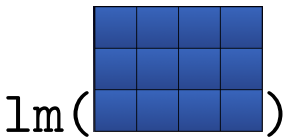
Splitting by Region

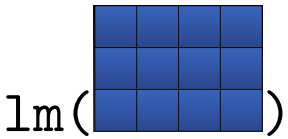





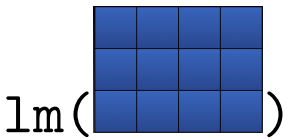


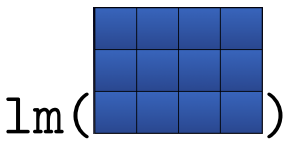

`data.frames`

Splitting by Region





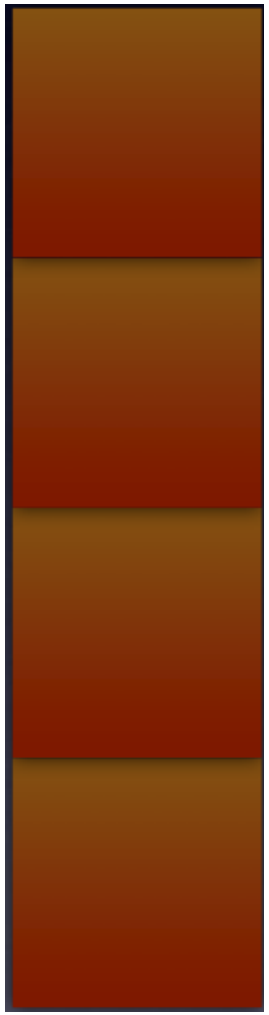




Splitting by Region

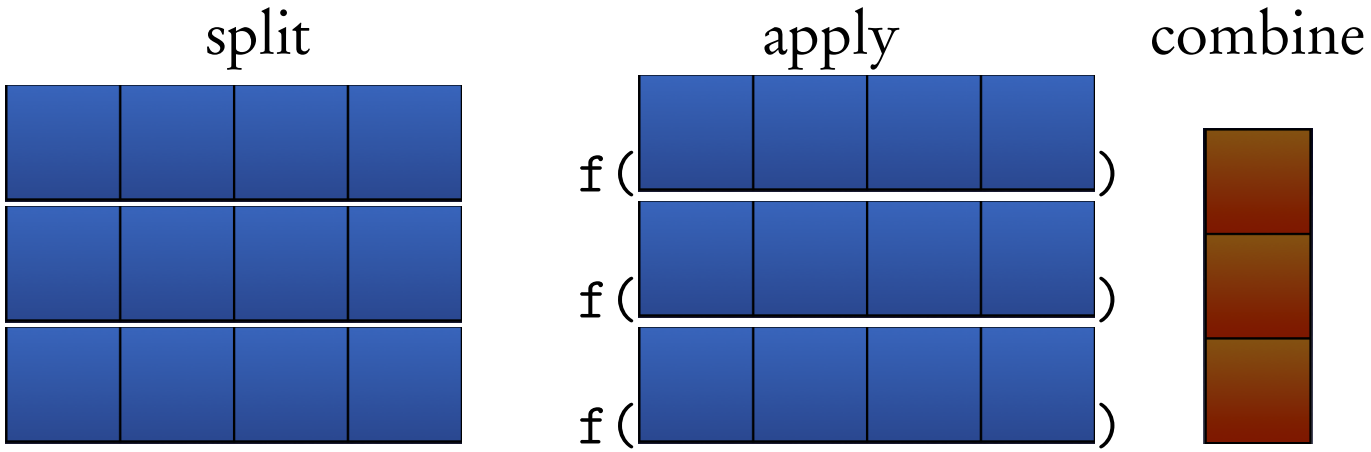
`lm` objects

Combine into a list



`list` of `lm` objects

The Basic Pattern



The Basic Pattern (cont'd.)

Split	divide the problem into smaller pieces
Apply	Work on each piece independently
Combine	Recombine the pieces

A common pattern for both programming and data analysis, many implementations

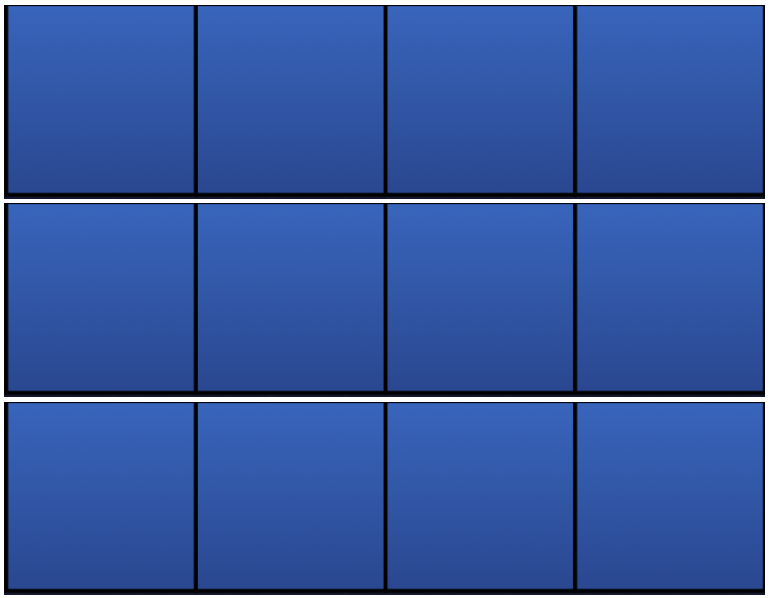
Python: map(), filter(), reduce()

Google `mapReduce`

R: `split`, `*apply`, `aggregate`,...

R: `plyr` package

Input Data Structure



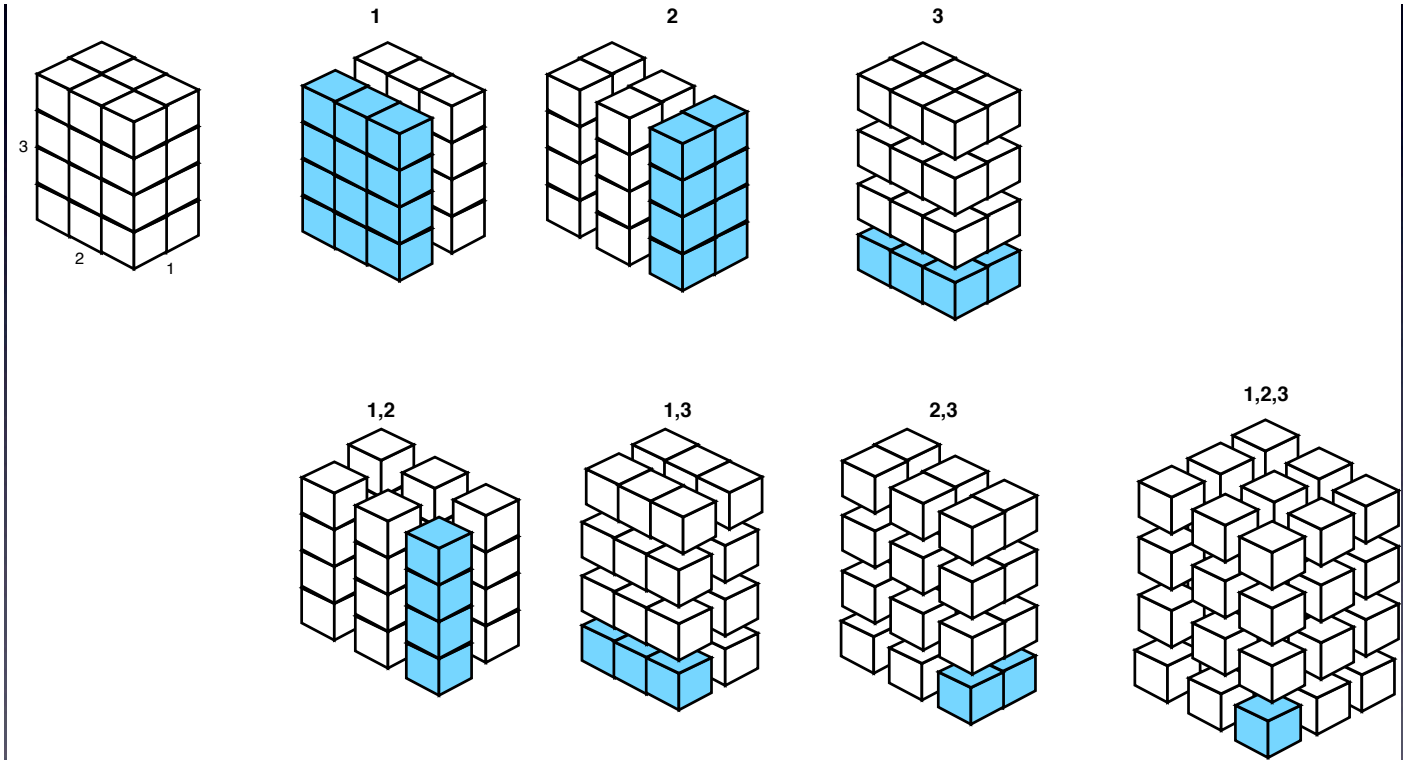
Each type (array, list, data frame) has its own ways of being split
Will mostly go over how `plyr` does it

Inputs: d-dimensional Arrays

d dimensions that can be subscripted independently
$\therefore$ can be split $2^d - 1$ different ways
2D arrays can be split 3 ways: rows, columns, cells

Splitting 3D Arrays

$2^3 - 1 = 7$ ways to split



from Wickham (2011)

a*ply()

```
y <- a*ply(.data, .margins, .fun, ...)
```

`.data` an array

`.margins` subscripts which the function gets applied over

`.fun` the function to be applied

`...` additional arguments to function

Returns a * (a = array, d = data frame, l = list, _ = nothing)

Why the Funny Argument Names?

Why `.data` or `.margins` instead of `data` or `margins`?
To avoid collisions with the extra arguments to the function `.fun`

`apply` vs. `aaply`

Base R: `apply(X,1,FUN,...)` (rows) or `apply(X,2,FUN,...)` (columns)
plyr: `aaply(.data,1,.fun,...)`, `aaply(.data,2,.fun,...)`
Pretty much equivalent, usually little point to plyr if that's all you're doing

Input: Lists — `l*ply()`

Lists can only be split one way

```
y <- l*ply(.data, .fun, ...)
```

Input: Data Frames

Can be split into groups according to the values of variables in the columns
Groups need not be of equal size
e.g., split census tracts by state
e.g., split census tracts by urban/suburban/rural
e.g., split census tracts by state *and* type

d*ply()

```
y <- d*ply(.data, .variables, .fun, ...)
```

`.data`	a data frame
`.variables`	variables used to define groups
`.fun`	the function to be applied
`...`	additional arguments to the function

Returns array, data frame, list, nothing

The Splitting Variables

`.variables` can be of two forms

`.(var1, var2)` or

`c('var1','var2')`

searches `.data` for those variables first, then the parent environment

Looking in the parent environment can lead to some odd type-conversion issues

Advice: make the variables you want to split on part of the data frame

The Splitting Variables

`.variables=.(var1)` splits off a new dataframe for each unique value of `var1`

`.variables=.(var1,var2)` splits on each unique combination of values of `var2`

What if e.g. you want to compare cases where `var1 >= var2` with those where `var1 < var2`?

The Splitting Variables

The splitting variables are *still* columns of the smaller dataframes that the function gets applied to
e.g., if you split on `Country` in the data from lab, each resulting dataframe still has a `Country` column

Data Frames Have Two Natures

Data frame is a list of vectors
∴ Can be split into separate columns
∴ Can be used with `l*ply()`
Data frame responds to array-like indexing
∴ Can be split like a 2D array
∴ Can be used with `a*ply()`

Processing Function

Function that is applied to each piece
Should:

- Take a piece as its first argument
- Return same type as eventual output (but there are exceptions)
- Sometimes cause side effects (plot, save, ...)

Things to Remember About the Processing Function

- Its input should be a *whole* piece of the original data
  - Row/column/slab of an array
  - A smaller dataframe from the original dataframe
- Not all of that piece may be relevant; do any selection inside the function
- You can write and debug that function by manually splitting off an example piece, and doing your processing on it first

Output Data Structure

Defines how results are combined and labeled

- Array (`a`)
- List (`l`)
- Data frame (`d`)
- Discarded (`_`) — for side effects, e.g., plotting

Output Arrays

Output organized in the expected way.
Processing function should return an object of same type each time it is called.
If processing function returns a list, then output will be a list-array (list with dimensions)

Avoid this

Output Data Frames

Output will contain results with additional label columns indicating which group the result corresponds to.

Applying the pattern to your problem

- check data type of
  - input data structure
  - output data structure
- Use a built-in function, or write a processing function and test it on one piece
- Call appropriate `**ply()`

Iteration Considered Unhelpful

Could always do the same thing with `for` loops, but those are

- verbose — lots of "how", obscures "what"
- painful/error-prone book-keeping (indices, placeholders, ...)
- clumsy — hard to parallelize

Examples

Regularly sampled spatial data

```
measures <- array(STUFF, dim = c(10, 10, 100))
```

10×10 grid of locations
100 measurements at each location
Problem: Standardize measurements at each location
Standardize one location:

```
z <- scale(measures[1, 1, ])
```

Iteration

Iteration

```
y <- array(dim = dim(measures))
for(i in 1:dim(measures)[1]) {
    for(j in 1:dim(measures)[2]) {
        y[i, j, ] <- scale(measures[i, j, ])
  }
}
```

Iteration

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for(i in 1:dim(measures)[1]) {
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Base R:

Iteration

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  }
}
```

Base R:

```
y <- apply(measures, 1:2, scale)
```

Iteration

```
y <- array(dim = dim(measures))
for(i in 1:dim(measures)[1]) {
    for(j in 1:dim(measures)[2]) {
        y[i, j, ] <- scale(measures[i, j, ])
  }
}
```

Base R:

```
y <- apply(measures, 1:2, scale)
```

plyr

```
y <- aaply(measures, 1:2, scale)
```

Ragged spatial data

```
measures <- data.frame(loc.x = FOO,
                       loc.y = BAR,
                       value = BAZ)
```

Irregularly sampled (x,y) locations
Different number of measurements at each location
Standardize measurements at each location

Handle one location:

```
df <- subset(measures, loc.x = 1 & loc.y = 1)
z <- scale(df$value)
```

Handle one location:

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Left as an exercise for the student
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Iteration

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```

Base R

```
Left as an exercise
```

plyr

```
y <- ddply(measures, .(loc.x, loc.y), function(df) { return(scale(df$value)) } )
```

Only want to scale one column of the split-off data frame

Used an anonymous function; could also define a function previously

Don't Force It

Don't use split/apply/combine as a fancy way of writing `for`

```
l_ply(1:708, function(i) {
  # several hundred lines of code follow
})
```

Use the pattern (and the tools) when:

- The problem naturally breaks the data into smaller pieces
- You can solve the problem on each piece in the same way, and independently of the other pieces
- You need to re-integrate the piecemeal solutions