Be Lazy - Intro to dplyr

Department of Biostatistics and Bioinformatics Emory University

Steve Pittard wsp@emory.edu

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Presentation

Code is available on Github

- https://github.com/steviep42/cdc_talk

Goals

1. R has many different ways to do the same thing
2. This is both a strength and weakness of R
3. Memorizing individual commands and associated arguments is tedious
4. Identify tools and packges that use a philosophy or approach (e.g. lattice, ggplot2, plyr, data.table, dplyr, caret)
5. Simplicity in workflow is everything !
6. After you have a solid workflow you can be lazy (at least as it relates to the various commands)

Data - First Steps

When first approaching data there are usually three major activities one pursues (not in any specific order):

1. **Data Aggregation:** The process of taking some data and putting it into a form that lends itself easily to summary, e.g. replace groups of observations with summary statistics
2. **Data Restructuring:** Change the structure of the data so that its new form is more convenient for a specific purpose (usually analysis). This can also involve merging existing data frames or bringing in new data (e.g. using SQL)
3. **Data Cleaning:** This could be considered as a sub activity to Data Restructuring. Here we address things like missing values, improbable or illegal values, and merging of disparate data sources

Aggregation

Command	Package	Purpose
table, xtabs	Native R	Summarize grouping variables with other grouping variables, Create Contingency Tables
tapply, split	Native R	Summarize a continuous variable by grouping variables
aggregate	Native R	Summarize continuous variable(s) by grouping variables
data table	data.table	Select rows and columns and aggregat and summarize
group_by, summarize	dplyr	Implement Split-Apply-Combine approach for aggregation and summary

Restructuring / Reshaping / Tidying

Command	Package	Purpose
melt, cast	reshape2	Convert data frames from wide to long format and do aggregation
ddply, ldply, l_ply	plyr	Implement Split-Apply-Combine approach for aggregation and summary
gather, spread	tidyr	Change a data frame from wide to long (or vice versa)
reshape	Native R	Change a data frame from wide to long (or vice versa)
stack, unstack	Native R	Change a data frame from wide to long (or vice versa)

Data - First Steps

mtcars is the most (in)famous data frame in R education

Motor Trend Car Road Tests

Description

The data was extracted from the 1974 *Motor Trend* US magazine, and comprises fuel consumption and 10 aspects of automobile design and performance for 32 automobiles (1973–74 models).

Usage

```
mtcars
```

Format

A data frame with 32 observations on 11 variables.

[, 1]	mpg	Miles/(US) gallon
[, 2]	cyl	Number of cylinders
[, 3]	disp	Displacement (cu.in.)
[, 4]	hp	Gross horsepower
[, 5]	drat	Rear axle ratio
[, 6]	wt	Weight (1000 lbs)
[, 7]	qsec	1/4 mile time
[, 8]	vs	V/S
[, 9]	am	Transmission (0 = automatic, 1 = manual)
[,10]	gear	Number of forward gears
[,11]	carb	Number of carburetors

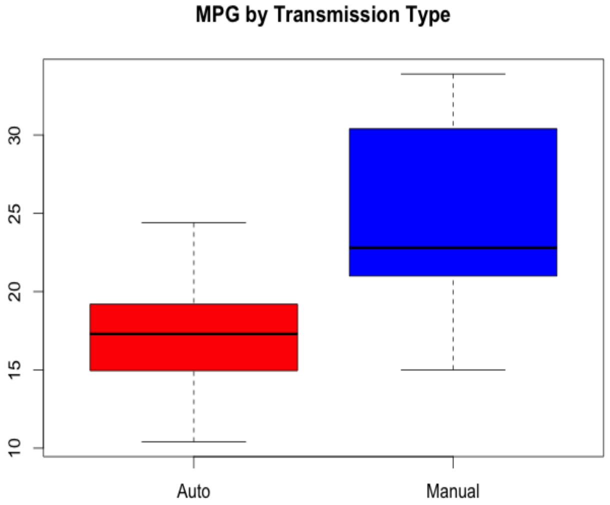
Data - First Steps

mtcars is the most infamous data frame in R education

```
str(mtcars)
'data.frame': 32 obs. of  11 variables:
 $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
 $ cyl : num  6 6 4 6 8 6 8 4 4 6 ...
 $ disp: num  160 160 108 258 360 ...
 $ hp  : num  110 110 93 110 175 105 245 62 95 123 ...
 $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
 $ wt  : num  2.62 2.88 2.32 3.21 3.44 ...
 $ qsec: num  16.5 17 18.6 19.4 17 ...
 $ vs  : num  0 0 1 1 0 1 0 1 1 1 ...
 $ am  : num  1 1 1 0 0 0 0 0 0 0 ...
 $ gear: num  4 4 4 3 3 3 3 4 4 4 ...
 $ carb: num  4 4 1 1 2 1 4 2 2 4 ...

# How many unique values does each column take ? This helps identify
# possible factors

sapply(mtcars, function(x) {length(unique(x))})
 mpg  cyl disp   hp drat   wt qsec   vs   am gear carb
  25    3   27   22   22   29   30    2    2    3    6
```

Data - Basic Plots

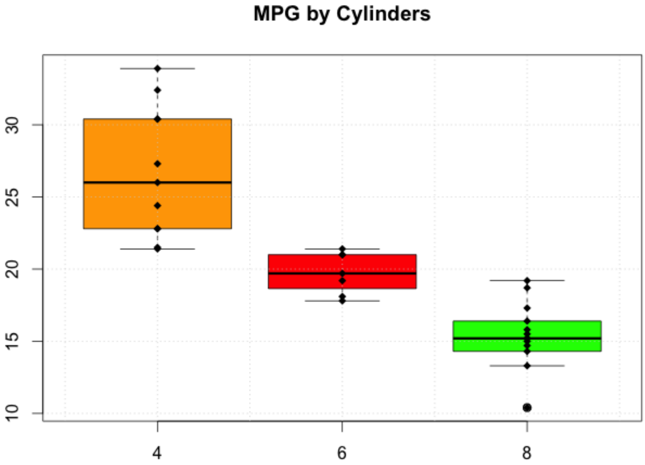
```
mtcars$am <- factor(mtcars$am,labels=c("Auto","Manual"))
boxplot(mpg~am,data=mtcars,col=c(2,4),main="MPG by Transmission Type")
```



Data - Basic Plots

```
mtcars$cyl <- factor(mtcars$cyl)
boxplot(mpg~cyl,data=mtcars,
        col=c("orange","red","green"),
        main="MPG by Cylinders")
grid()

# We will also plot the MPG points for each category. To do this
# we will "split" up the data frame on Cylinder which takes a
# value of 4,6, or 8

mydf <- split(mtcars,mtcars$cyl)
lapply(1:3,function(x) {
                        points(rep(x,length(mydf[[x]]$mpg)),
                                 mydf[[x]]$mpg,
                                 pch=18)
                        })
```

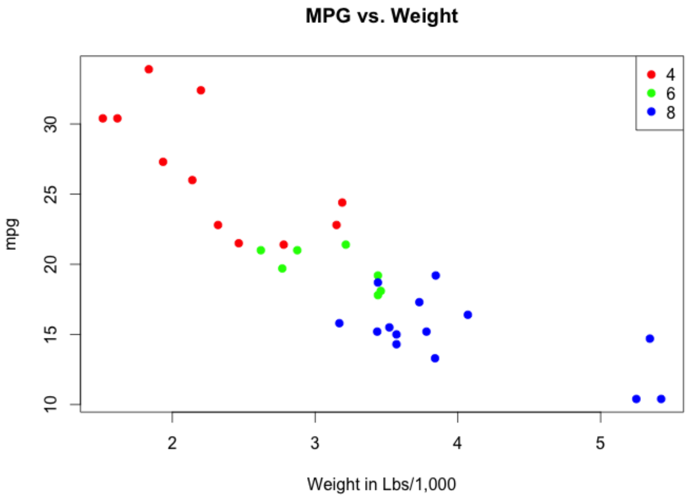
Data - Basic Plots



Data - Basic Plots

```
# Make a scatterplot of all MPG and provide each cylinder
# group with its own color

plot(mpg~wt,data=mtcars,type="n",main="MPG vs. Weight",
     xlab="Weight in Lbs/1,000")

# Split the data frame by cylinder value and create
# a color vector

mys <- split(mtcars,mtcars$cyl)
colors <- rainbow(3)

# Loop through the split data frame and put up points for each
# cylinder group

lapply(seq_along(mys),function(x) {
                         points(mys[[x]]$wt,
                                mys[[x]]$mpg,
                                col=colors[x],pch=19)
                       })

# Draw a legend
legend("topright",legend=sort(unique(mtcars$cyl)),pch=19,col=colors)
grid()
```

Data - Basic Plots



Aggregation - tables

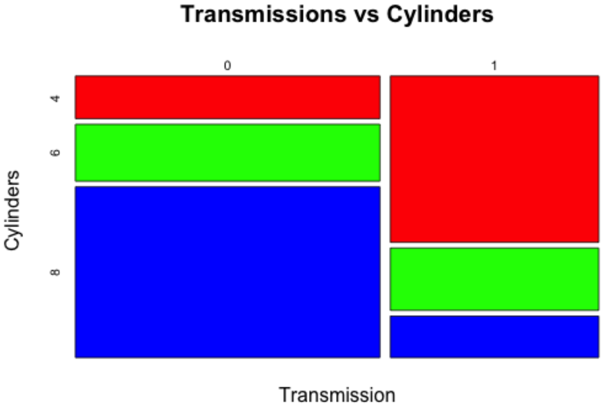
```
# How many 4,6, or 8 cylinder cars are there for each transmission type ?

table(Transmission=mtcars$am,Cylinders=mtcars$cyl)
            Cylinders
Transmission  4  6  8
           0  3  4 12
           1  8  3  2

# Create a proportion table

prop.table(table(Transmission=mtcars$am,Cylinders=mtcars$cyl))
            Cylinders
Transmission       4       6       8
           0 0.09375 0.12500 0.37500
           1 0.25000 0.09375 0.06250

# Add margins if you wish

addmargins(prop.table(table(Transmission=mtcars$am,Cylinders=mtcars$cyl)))
            Cylinders
Transmission       4       6       8     Sum
         0   0.09375 0.12500 0.37500 0.59375
         1   0.25000 0.09375 0.06250 0.40625
         Sum 0.34375 0.21875 0.43750 1.00000
```

Aggregation - tables

R knows how to plot tables without you having to supply too much information.

```
# How many 4,6, or 8 cylinder cars are there for each transmission type ?

myt <- table(Transmission=mtcars$am,Cylinders=mtcars$cyl)

plot(myt,color=rainbow(3),main="Transmissions vs Cylinders")
```

Aggregation - tables



Aggregation - xtabs

The **xtabs** function does much the same as **table** but it has the advantage of supporting a formula interface which R uses in many statistical modeling functions.

```
xtabs(~cyl,data=mtcars)
cyl
 4  6  8
11  7 14

xtabs(~am+cyl,data=mtcars)
   cyl
am   4  6  8
  0  3  4 12
  1  8  3  2

# We can subset out data

xtabs(~am+cyl,data=mtcars,subset=mpg < 25)
   cyl
am   4  6  8
  0  3  4 12
  1  2  3  2
```

Aggregation - tapply

Summarize a continuous quantity in terms of each category.

```
# Average MPG for each transmission type

tapply(mtcars$mpg,mtcars$am,mean)
       0        1
17.14737 24.39231

# For each cylinder group

tapply(mtcars$mpg,mtcars$cyl,mean)
       4        6        8
26.66364 19.74286 15.10000

# We can supply our own function

tapply(mtcars$mpg,mtcars$am,function(x) return(c(mean=mean(x),sd=sd(x))))
$`0`
     mean        sd
17.147368  3.833966

$`1`
     mean        sd
24.392308  6.166504
```

Aggregation - tapply

- With tapply we can summarize a single continuous quantity across multiple categories

```
tapply(mtcars$mpg, list(mtcars$am, mtcars$vs), mean)
              0        1
Automatic 15.05 20.74286
Manual    19.75 28.37143
```

- But we cannot conveniently summarize multiple continuous quantities across categories

```
tapply(list(mtcars$mpg,mtcars$hp), list(mtcars$am, mtcars$vs), mean)
Error in tapply(list(mtcars$mpg, mtcars$hp), list(mtcars$am, mtcars$vs),  :
  arguments must have same length
```

Aggregation - aggregate

This is where it gets confusing. We have to resort to another function. Why so many different approaches ?

```
# Here we summarize two continuous values in terms of two categories

aggregate(cbind(mpg,hp)~am+vs,data=mtcars,mean)
      am vs      mpg        hp
1   Auto  0 15.05000 194.16667
2 Manual  0 19.75000 180.83333
3   Auto  1 20.74286 102.14286
4 Manual  1 28.37143  80.57143

# We summarize mpg in terms of two categories

aggregate(mpg~cyl+am,data=mtcars,mean)
  cyl     am      mpg
1   4   Auto 22.90000
2   6   Auto 19.12500
3   8   Auto 15.05000
4   4 Manual 28.07500
5   6 Manual 20.56667
6   8 Manual 15.40000
```

Aggregation - aggregate

```
# We can even filter out data as we do the aggregate
# Get the mean MPG per Cylinder and Transmission groups
# but only in cases where MPG is > 20

aggregate(mpg~cyl+am,data=mtcars,mean,subset=mpg>20)
  cyl     am    mpg
1   4   Auto 22.900
2   6   Auto 21.400
3   4 Manual 28.075
4   6 Manual 21.000

# Similar but

aggregate(mpg~cyl,data=mtcars,range,subset=wt>mean(wt))
  cyl     am      mpg
1   4   Auto 22.90000
2   6   Auto 19.12500
3   8   Auto 15.05000
4   4 Manual 28.07500
5   6 Manual 20.56667
6   8 Manual 15.40000
```

Are you Confused ? / R you Confused ?

dplyr

Motivations

Hadley Wickham is also the author of these packages:

Command	**Package Purpose**
ggplot2	Data Visualization
tidyr	For tidying data
stringr	Working with Strings
lubridate	Working with dates and times
readr	Efficiently read .csv and fwf files
readxl	Reading .xls and .xlsx files
haven	For Reading SAS, SPSS, and Stata files
rvest	Scraping Web Sites
xml2	For Importing XML files
reshape2	Restructure and aggregate data
plyr	Tools for Splitting, Applying, and Combining Data

Motivations

dplyr is an add on package designed to efficiently transform and summarize tablular data such as data frames. The package has a number of functions ("verbs") that perform a number of data manipulation tasks:

- Filtering rows
- Select specific columns
- Re-ordering or arranging rows
- Summarizing and aggregating data

One of the unique strengths of **dplyr** is that it implements what is known as a Split-Apply-Combine technique that we will explore in this session.

The dyplr function can also be used with the **magrittr** package for setting up workflows or pipelines to process data.

Motivations

- **dplyr** is designed to work with data frames but it can also connect to relational databases that are locally or remotely available.
- Access to data frames or databases is accomplished uisng the same set of tools. You don't have to use different commands.
- Relative to databases you use the "verbs" provided with dplyr that in turn are translated into the appropriate SQL statements necessary to interact with the databases.
- Install **dplyr** as you would any other R package

Motivations

There are some common activites associated with a data frame:

- filter - find observations satisfying some condition(s)
- select - selecting specific columns by name
- mutate - adding new columns or changing existing ones
- arrange - reorder or sort the rows
- summarize - do some aggregation or summary by groups

Motivations

```
df <- data.frame(id = 1:5,
                 gender = c("MALE","MALE","FEMALE","MALE","FEMALE"),
                 age = c(70,76,60,64,68))
```

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

Filter

```
filter(df,gender == "FEMALE")
  id gender age
1  3 FEMALE  60
2  5 FEMALE  68
```

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

ID	GENDER	AGE
3	FEMALE	60
5	FEMALE	68

Filter

```
filter(df, id %in% c(1,3,5))
  id gender age
1  1   MALE  70
2  3 FEMALE  60
3  5 FEMALE  68
```

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

ID	GENDER	AGE
1	MALE	70
3	FEMALE	60
5	FEMALE	68

Mutate

Mutate is used to add or remove columns in a data frame

```
mutate(df,meanage = mean(age))
  id gender age meanage
1  1   MALE  70    67.6
2  2   MALE  76    67.6
3  3 FEMALE  60    67.6
4  4   MALE  64    67.6
5  5 FEMALE  68    67.6
```

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

ID	GENDER	AGE	MEANWT
1	MALE	70	67.6
2	MALE	76	67.6
3	FEMALE	60	67.6
4	MALE	64	67.6
5	FEMALE	68	67.6

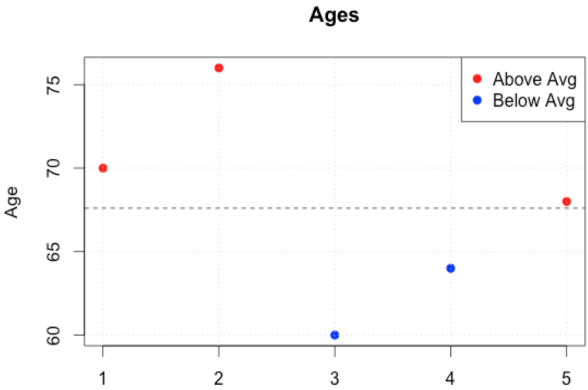
Mutate

- Here we create a new column designed to tell us if a given observation has an age that is greater than or equal to the average age.
- We create a variable called old_young and assing a value of “Y” if the are above the mean age and a value of “N” if they are not.

```
mutate(df,old_young=ifelse(df$age>=mean(df$age),"Y","N"))
  id gender age old_young
1  1   MALE  70         Y
2  2   MALE  76         Y
3  3 FEMALE  60         N
4  4   MALE  64         N
5  5 FEMALE  68         Y
```

Mutate

```
tmp <- mutate(df, color = ifelse(age > mean(age),"red","blue"))
plot(tmp$age,col=tmp$color,type="p",pch=19,main="Ages",ylab="Age")
grid()
abline(h=mean(tmp$age),lty=2)
legend("topright",c("Above Avg","Below Avg"),col=c("red","blue"),pch=19)
```



Arrange

Use arrange for sorting the data frame by a column(s)

```
# Sort df by age from highest to lowest

arrange(df, desc(age))
  id gender age
1  2   MALE  76
2  1   MALE  70
3  5 FEMALE  68
4  4   MALE  64
5  3 FEMALE  60

# Sort df by gender (alphabetically) and then by age
# from highest to lowest

arrange(df, gender,desc(age))
  id gender age
1  5 FEMALE  68
2  3 FEMALE  60
3  2   MALE  76
4  1   MALE  70
5  4   MALE  64
```

Select

Select allows us to select groups of columns from a data frame

```
select(df,gender,id,age)  # Reorder the columns
  gender id age
1   MALE  1  70
2   MALE  2  76
3 FEMALE  3  60
4   MALE  4  64
5 FEMALE  5  68

select(df,-age)   # Select all but the age column
  id gender
1  1   MALE
2  2   MALE
3  3 FEMALE
4  4   MALE
5  5 FEMALE

select(df,id:age)  # Can use : to select a range
  id gender age
1  1   MALE  70
2  2   MALE  76
3  3 FEMALE  60
4  4   MALE  64
5  5 FEMALE  68
```

group_by

group_by let's you organize a data frame by some factor or grouping variable

```
df
  id gender age
1  1   MALE  70
2  2   MALE  76
3  3 FEMALE  60
4  4   MALE  64
5  5 FEMALE  68

group_by(df,gender)   # Hmm. Did this really do anything ?

Source: local data frame [5 x 3]
Groups: gender

  id gender age
1  1   MALE  70
2  2   MALE  76
3  3 FEMALE  60
4  4   MALE  64
5  5 FEMALE  68
```

Summarize

```
summarize(group_by(df,gender),total=n())
Source: local data frame [2 x 2]

  gender total
1 FEMALE     2
2   MALE     3
```

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

GENDER	TOTAL
FEMALE	2
MALE	3

Summarize

```
summarize(group_by(df,gender),av_age=mean(age))
Source: local data frame [2 x 2]

  gender av_age
1 FEMALE     64
2   MALE     70
```

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

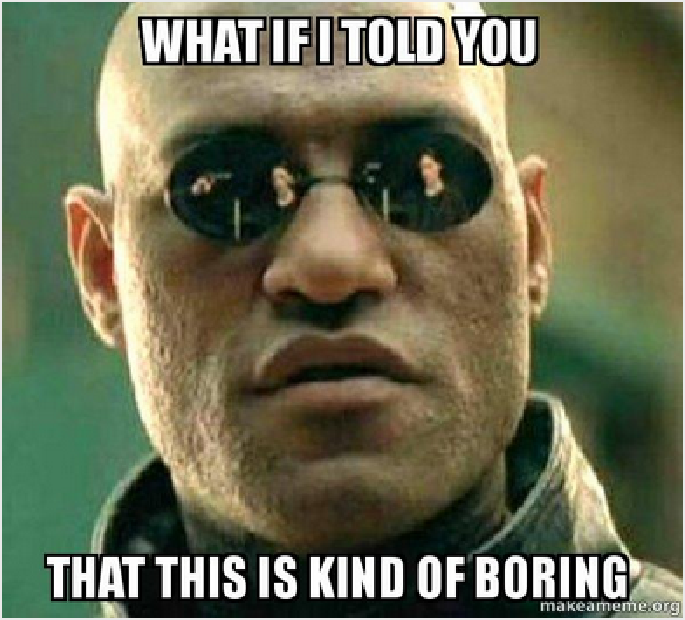
GENDER	AV_AGE
FEMALE	64
MALE	70

Summarize

```
summarize(group_by(df,gender),av_age=mean(age),total=n())
Source: local data frame [2 x 3]

  gender av_age total
1 FEMALE     64     2
2   MALE     70     3
```

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

GENDER	AV_AGE	TOTAL
FEMALE	64	2
MALE	70	3


WHAT IF I TOLD YOU
THAT THIS IS KIND OF BORING
makeameme.org

Split -> Apply -> Combine: Chaining

- Before moving forward let us consider the "pipe" operator that is included with the **magrittr** package. This is used to make it possible to "pipe" the results of one command into another command and so on.
- The inspiration for this comes from the UNIX/LINUX operating system where pipes are used all the time. So in effect using "pipes" is nothing new in the world of research computation.
- Warning: Once you get used to pipes it is hard to go back to not using them

Pipes

- A pipeline is a sequence of processes chained together by their standard streams, so that the output of each process (stdout) feeds directly as input (stdin) to the next one - Wikipedia
- The standard shell syntax for pipelines is to list multiple commands, separated by vertical bars (”pipes” in common unix verbiage) - Wikipedia

```
# For each line in the passwd file list only those userids
# that do not begin with a "_" character. Also ignore lines
# beginning with "#"

$ cat /etc/passwd | awk -F: '{print $1}' | grep -v _ | grep -v "#"
nobody
root
daemon
```

Split -> Apply -> Combine: Chaining

- When you load the dplyr package it in turn loads the necessary packages for supporting the piping capability.
- Let's use our "toy" data frame to illustrate the basics of the piping mechanism as used by dplyr.
- Here we will select the gender and age columns from df and view the top 3 rows

```
head(select(df, gender, age),3)
gender age
1   MALE  70
2   MALE  76
3 FEMALE  60
```

Split -> Apply -> Combine: Chaining

- Here we will select the gender and age columns from df and view the top 3 rows using dplyr and the piping operator
- Instead of nesting functions (reading from the inside to the outside), the idea of of piping is to read the functions from left to right.

```
df %>% select(gender, age) %>% head(3)
```

```
  gender age
1   MALE  70
2   MALE  76
3 FEMALE  60
```

Split -> Apply -> Combine: Chaining

What about this ? We can chain together the output of one command to the input of another !

```
df %>% group_by(gender) %>% summarize(avg=mean(age))
Source: local data frame [2 x 2]

  gender avg
1 FEMALE  64
2   MALE  70

df %>% group_by(gender) %>% summarize(avg=mean(age),total=n())
Source: local data frame [2 x 3]

  gender avg total
1 FEMALE  64     2
2   MALE  70     3

df %>% filter(gender == "MALE") %>% summarize(med_age=median(age))
  med_age
1      70
```

Split -> Apply -> Combine: Chaining

What about this ? We can chain together the output of one command to the input of another !

```
df %>% filter(gender == "MALE") %>% summarize(med_age=median(age))
  med_age
1      70
```

df

ID	GENDER	AGE
1	MALE	70
2	MALE	76
3	FEMALE	60
4	MALE	64
5	FEMALE	68

filter

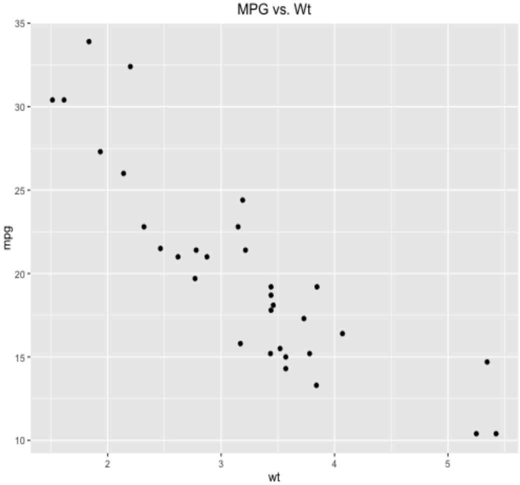
ID	GENDER	AGE
1	MALE	70
2	MALE	76
4	MALE	64

summarize

med_age
70

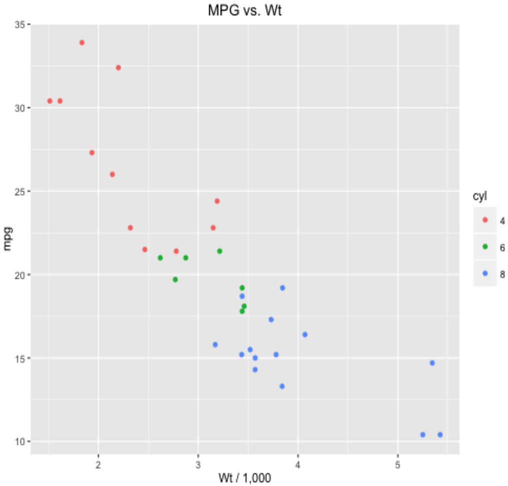
Split -> Apply -> Combine: Chaining

```
mtcars %>% ggplot(aes(x=wt,y=mpg)) + geom_point() + ggtitle("MPG vs. Wt")
```



Split -> Apply -> Combine: Chaining

```
mtcars %>% mutate(cyl=factor(cyl)) %>%
           ggplot(aes(x=wt,y=mpg)) + geom_point(aes(color=cyl)) +
           ggtitle("MPG vs. Wt") + xlab("Wt / 1,000")
```



Split -> Apply -> Combine: Chaining

Much easier and more logical than this:

```
# Make a scatterplot of all MPG and provide each cylinder
# group with its own color

plot(mpg~wt,data=mtcars,type="n",main="MPG vs. Weight",
     xlab="Weight in Lbs/1,000")

# Split the data frame by cylinder value and create
# a color vector

mys <- split(mtcars,mtcars$cyl)
colors <- rainbow(3)

# Loop through the split data frame and put up points for each
# cylinder group

lapply(seq_along(mys),function(x) {
                         points(mys[[x]]$wt,
                                mys[[x]]$mpg,
                                col=colors[x],pch=19)
                       })
# Draw a legend
legend("topright",legend=sort(unique(mtcars$cyl)),pch=19,col=colors)
grid()
```

Split -> Apply -> Combine: Chaining

- Using the built in mtcars dataframe filter out records where the wt is greater than 3.3 tons.
- Then create a column called ab_be (Y or N) that indicates whether that observation's mpg is greater (or not) than the average mpg for the filtered set.
- Then present the average mpg for each group

```
mtcars %>% filter(wt > 3.3)  %>%
        mutate(ab_be=ifelse(mpg > mean(mpg),"Y","N")  ) %>%
        group_by(ab_be) %>% summarize(mean_mpg=mean(mpg))

Source: local data frame [2 x 2]

  ab_be mean_mpg
1     N 13.77778
2     Y 18.10000
```

Split -> Apply -> Combine: Chaining

Using the built in mtcars dataframe filter out records where the wt is greater than 3.3 tons.

```
mtcars %>% filter(wt > 3.3)
```

```
    mpg cyl  disp  hp drat    wt  qsec vs am gear carb
1  18.7   8 360.0 175 3.15 3.440 17.02  0  0    3    2
2  18.1   6 225.0 105 2.76 3.460 20.22  1  0    3    1
3  14.3   8 360.0 245 3.21 3.570 15.84  0  0    3    4
4  19.2   6 167.6 123 3.92 3.440 18.30  1  0    4    4
5  17.8   6 167.6 123 3.92 3.440 18.90  1  0    4    4
6  16.4   8 275.8 180 3.07 4.070 17.40  0  0    3    3
7  17.3   8 275.8 180 3.07 3.730 17.60  0  0    3    3
8  15.2   8 275.8 180 3.07 3.780 18.00  0  0    3    3
9  10.4   8 472.0 205 2.93 5.250 17.98  0  0    3    4
10 10.4   8 460.0 215 3.00 5.424 17.82  0  0    3    4
11 14.7   8 440.0 230 3.23 5.345 17.42  0  0    3    4
12 15.5   8 318.0 150 2.76 3.520 16.87  0  0    3    2
13 15.2   8 304.0 150 3.15 3.435 17.30  0  0    3    2
14 13.3   8 350.0 245 3.73 3.840 15.41  0  0    3    4
15 19.2   8 400.0 175 3.08 3.845 17.05  0  0    3    2
16 15.0   8 301.0 335 3.54 3.570 14.60  0  1    5    8
```

Split -> Apply -> Combine: Chaining

Create a column called ab_be (Y or N) that indicates whether that observation's mpg is greater (or not) than the average mpg for the filtered set.

```
mtcars %>% filter(wt > 3.3) %>%
             mutate(ab_be=ifelse(mpg > mean(mpg),"Y","N")  )
    mpg cyl  disp  hp drat    wt  qsec vs am gear carb ab_be
1  18.7   8 360.0 175 3.15 3.440 17.02  0  0    3    2     Y
2  18.1   6 225.0 105 2.76 3.460 20.22  1  0    3    1     Y
3  14.3   8 360.0 245 3.21 3.570 15.84  0  0    3    4     N
4  19.2   6 167.6 123 3.92 3.440 18.30  1  0    4    4     Y
5  17.8   6 167.6 123 3.92 3.440 18.90  1  0    4    4     Y
6  16.4   8 275.8 180 3.07 4.070 17.40  0  0    3    3     Y
7  17.3   8 275.8 180 3.07 3.730 17.60  0  0    3    3     Y
8  15.2   8 275.8 180 3.07 3.780 18.00  0  0    3    3     N
9  10.4   8 472.0 205 2.93 5.250 17.98  0  0    3    4     N
10 10.4   8 460.0 215 3.00 5.424 17.82  0  0    3    4     N
11 14.7   8 440.0 230 3.23 5.345 17.42  0  0    3    4     N
12 15.5   8 318.0 150 2.76 3.520 16.87  0  0    3    2     N
13 15.2   8 304.0 150 3.15 3.435 17.30  0  0    3    2     N
14 13.3   8 350.0 245 3.73 3.840 15.41  0  0    3    4     N
15 19.2   8 400.0 175 3.08 3.845 17.05  0  0    3    2     Y
16 15.0   8 301.0 335 3.54 3.570 14.60  0  1    5    8     N
```

Split -> Apply -> Combine: Chaining

Then present the average mpg for each group as defined by ab_be

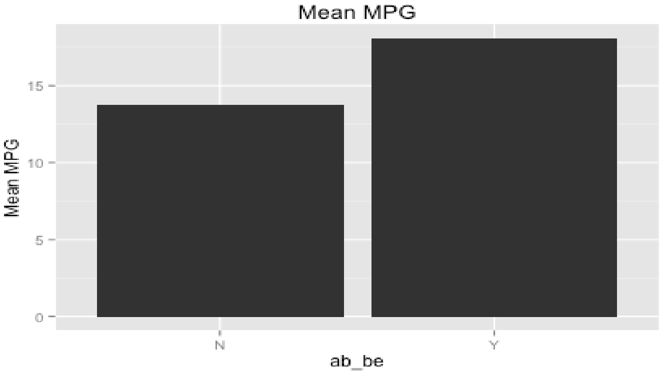
```
mtcars %>% filter(wt > 3.3)  %>%
         mutate(ab_be=ifelse(mpg > mean(mpg),"Y","N")  ) %>%
         group_by(ab_be) %>% summarize(mean_mpg=mean(mpg))
```

```
Source: local data frame [2 x 2]

  ab_be mean_mpg
1     N 13.77778
2     Y 18.10000
```

Split -> Apply -> Combine: Chaining

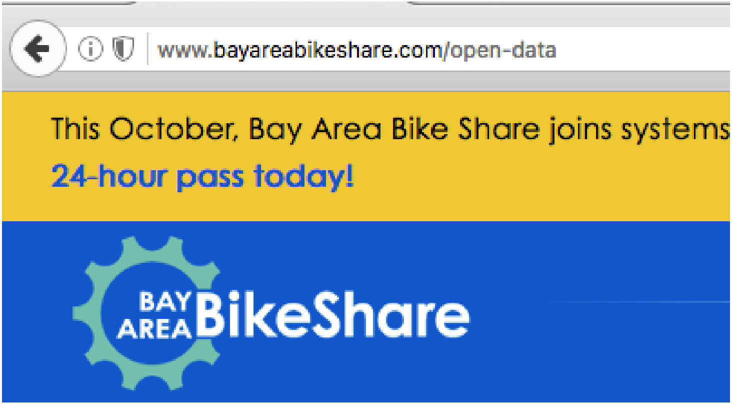
This could then be chained to the ggplot command

```
mtcars %>% filter(wt > 3.3)  %>%
        mutate(ab_be=ifelse(mpg > mean(mpg),"Y","N")  ) %>%
        group_by(ab_be) %>% summarize(mean_mpg=mean(mpg)) %>%
        ggplot(aes(x=ab_be,y=mean_mpg)) + geom_bar(stat="identity") +
        ggtitle("Mean MPG") + labs(x = "ab_be", y = "Mean MPG")
```



San Francisco Bike Data Project

The Bay Area Bike Share program allows Bay area residents to use bicycles for commuting in the area. Here is a description of the service from the website: I obtained usage data from 2013-2015.



San Francisco Bike Data Project

THE DATA

Each trip is anonymized and includes:

- Bike number
- Trip start day and time
- Trip end day and time
- Trip start station
- Trip end station
- Rider type – Annual or Casual (24-hour or 3-day member)
- If an annual member trip, it will also include the member's home zip code

The data set also includes:

- Weather information per day per service area
- Bike and dock availability per minute per station

Separately, participants may use our live JSON feed:

- Access our feed at bayareabikeshare.com/stations/json
- No API key needed, however apps should not fetch this feed more than once per minute

San Francisco Bike Data Project

The Bay Area Bike Share program allows Bay area residents to use bicycles for commuting in the area. Here is a description of the service from the website: I obtained usage data from 2013-2015.

```
library(readr)
url <- "http://steviep42.bitbucket.org/YOUTUBE.DIR/SF.ZIP"
download.file(url,"SF.ZIP")
system("unzip SF.ZIP")

stations <- read_csv("station.csv")

# Read in the trip date - you might get some messages
# about missing zipcodes but don't worry if you do

trips <- read_csv("trip.csv")

str(stations)
```

San Francisco Bike Data Project

```
str(stations)

Classes tbl_df, tbl and data.frame:   70 obs. of  7 variables:
 $ id              : int  2 3 4 5 6 7 8 9 10 11 ...
 $ name            : chr  "San Jose Diridon Caltrain Station" "San Jose Civic Center" "Santa Clara at Almaden"
 $ lat             : num  37.3 37.3 37.3 37.3 37.3 ...
 $ long            : num  -122 -122 -122 -122 -122 ...
 $ dock_count      : int  27 15 11 19 15 15 15 15 15 19 ...
 $ city            : chr  "San Jose" "San Jose" "San Jose" "San Jose" ...
 $ installation_date: chr  "8/6/2013" "8/5/2013" "8/6/2013" "8/5/2013" ...

str(trips)

Classes tbl_df, tbl and data.frame:   669959 obs. of  11 variables:
 $ id                : int  4576 4607 4130 4251 4299 4927 4500 4563 4760 4258 ...
 $ duration          : int  63 70 71 77 83 103 109 111 113 114 ...
 $ start_date        : chr  "8/29/2013 14:13" "8/29/2013 14:42" "8/29/2013 10:16" "8/29/2013 11:29" ...
 $ start_station_name: chr  "South Van Ness at Market" "San Jose City Hall" "Mountain View City Hall" "San Jose
 $ start_station_id  : int  66 10 27 10 66 59 4 8 66 10 ...
 $ end_date          : chr  "8/29/2013 14:14" "8/29/2013 14:43" "8/29/2013 10:17" "8/29/2013 11:30" ...
 $ end_station_name  : chr  "South Van Ness at Market" "San Jose City Hall" "Mountain View City Hall" "San Jose
 $ end_station_id    : int  66 10 27 10 67 59 5 8 66 11 ...
 $ bike_id           : int  520 661 48 26 319 527 679 687 553 107 ...
 $ subscription_type : chr  "Subscriber" "Subscriber" "Subscriber" "Subscriber" ...
 $ zip_code          : int  94127 95138 97214 95060 94103 94109 95112 95112 94103 95060 ...
```

San Francisco Bike Data Project

How Many Bikes Are There ?

```
trips %>% select(bike_id) %>% distinct()
Source: local data frame [700 x 1]

   bike_id
     (int)
1      520
2      661
3       48
4       26
5      319
6      527
7      679
8      687
9      553
10     107
..     ...

# But if we wanted a single result we could do this

trips %>% select(bike_id) %>% distinct() %>% nrow()
[1] 700
```

San Francisco Bike Data Project

How many times was each bike used ?

```
trips %>% group_by(bike_id) %>%
          summarize(times_used=n()) %>%
          arrange(desc(times_used))

Source: local data frame [700 x 2]

   bike_id times_used
     (int)      (int)
1      392       2061
2      489       1975
3      558       1955
4      267       1951
5      631       1948
6      518       1942
7      532       1933
8      592       1932
9      395       1927
10     368       1926
..     ...        ...
```

San Francisco Bike Data Project

How many times was each bike used ?

```
trips %>% count(bike_id,sort=TRUE)
Source: local data frame [700 x 2]

   bike_id     n
     (int) (int)
1      392  2061
2      489  1975
3      558  1955
4      267  1951
5      631  1948
6      518  1942
7      532  1933
8      592  1932
9      395  1927
10     368  1926
..     ...   ...
```

San Francisco Bike Data Project

How many cities use this service ? How many stations per city are there ?

```
stations %>% count(city)
Source: local data frame [5 x 2]

           city     n
          (chr) (int)
1 Mountain View     7
2     Palo Alto     5
3  Redwood City     7
4 San Francisco    35
5      San Jose    16

# We could also sort the result from highest count to lowest

stations %>% count(city,sort=TRUE)
Source: local data frame [5 x 2]

           city     n
          (chr) (int)
1 San Francisco    35
2      San Jose    16
3 Mountain View     7
4  Redwood City     7
5     Palo Alto     5
```

San Francisco Bike Data Project

Recall that in the **stations** data frame we have latitutde and logitude information.

```
str(stations)
```

```
Classes tbl_df, tbl and data.frame:   70 obs. of  7 variables:
 $ id              : int  2 3 4 5 6 7 8 9 10 11 ...
 $ name            : chr  "San Jose Diridon Caltrain Station" "San Jose Civic Cent
 $ lat             : num  37.3 37.3 37.3 37.3 37.3 ...
 $ long            : num  -122 -122 -122 -122 -122 ...
 $ dock_count      : int  27 15 11 19 15 15 15 15 15 19 ...
 $ city            : chr  "San Jose" "San Jose" "San Jose" "San Jose" ...
 $ installation_date: chr  "8/6/2013" "8/5/2013" "8/6/2013" "8/5/2013" ...
```

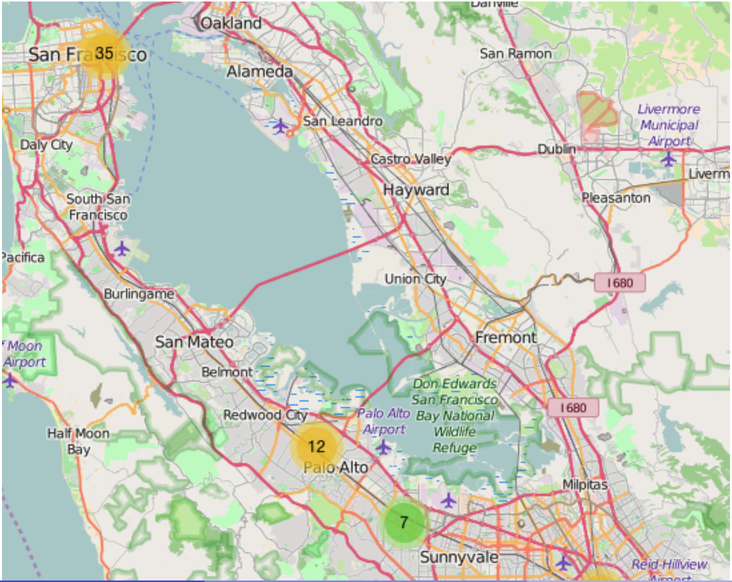
San Francisco Bike Data Project

Use the leaflet package to create an interactive map. This is a package that integrates with the Javascript library of the same name. The numbers on the graphic are interactive. Click on one of the cicles to drill down into the count data

```
library(leaflet)
m <- leaflet() %>% addTiles() %>%
     addMarkers(lng=stations$long,
                lat=stations$lat,
                popup=stations$name,
                clusterOptions = markerClusterOptions())


m
```

San Francisco Bike Data Project

Use the leaflet package to create an interactive map



San Francisco Bike Data Project

How many trips did not finish on the same day they began ?

```
trips %>% filter(substr(start_date,1,10)
                        != substr(end_date,1,10)) %>%
                        summarize(different_days=n())
 different_days
          (int)
1          2099
```

How many trips were there for each year ?

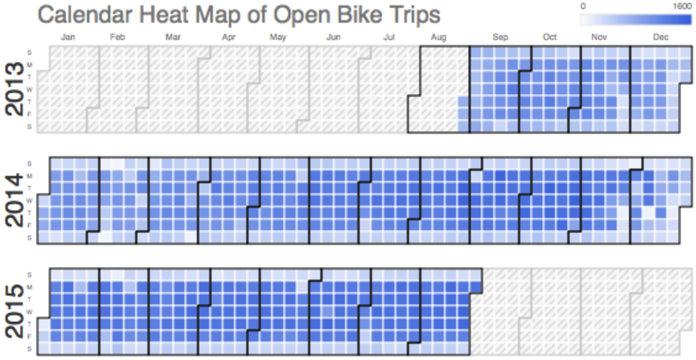
```
trips %>% count(substr(start_date,1,4))
Source: local data frame [3 x 2]

  substr(start_date, 1, 4)      n
                     (chr)  (int)
1                     2013 100563
2                     2014 326339
3                     2015 243057
```

San Francisco Bike Data Project

We will look at the number of trips for each day of each year and use the **googleVis** package to create a heatmap to visualize this

```
library(googleVis)

trips %>% mutate(start_date=as.Date(start_date),
                 end_date=as.Date(end_date)) %>%
                 filter(start_date == end_date) %>%
                 count(start_date) -> tripdates

# Create a Gvisplot and then plot it

plot(
  gvisCalendar(data=tripdates, datevar="start_date", numvar="n",
               options=list(
                 title="Calendar Heat Map of Open Bike Trips",
                 calendar="{cellSize:10,
                 yearLabel:{fontSize:20, color:'#444444'},
                 focusedCellColor:{stroke:'red'}}",
                 width=590, height=320),
               chartid="Calendar")
)
```

San Francisco Bike Data Project



Data: tripdates • Chart ID: Calendar • googleVis-0.5.10
R version 3.2.4 (2016-03-10) • Google Terms of Use • Documentation and Data Policy

Large Files

- How do the dplyr commands work on a really large data file ? Here we want to read in a 31 million row file that relates to some Wikipedia statistics
- I will be using a supporting package called **readr** which can efficiently read in large files.
- My computer has 8GB of RAM. If you have less then this example might be slow.

Large Files

Let's read in the file

```
library(readr)
url <- "http://steviep42.bitbucket.org/YOUTUBE.DIR/combined_wiki.zip"
download.file(url,"combined_wiki.zip")
system("unzip combined_wiki.zip")
dt <- read_delim("combined_wiki.zip",delim=" ")
nrow(dt)
[1] 31164567

head(dt,5)
   proj                                page acc bytes
1: aa.b                           Main_Page   1  5565
2: aa.b              MediaWiki:Image_sample   1  5179
3: aa.b        MediaWiki:Upload_source_file   1  5195
4: aa.b            Wikibooks:Privacy_policy   1  4925
5: aa.d MediaWiki:Group-abusefilter-member   1  4912
```

Large Files

Using dplyr commands, summarize the mean number of bytes (in megabytes) per unique project page and sort the resulting table in descencing order by the average in megabytes.

```
dt %>% mutate(MB=bytes/1000000) %>%
       group_by(proj)%>%
       summarize(avg=round(mean(MB),2)) %>%
       arrange(desc(avg))
Source: local data table [1,266 x 2]   # Note we have 1,266 rows

      V1      avg
1   en.mw 77518.22
2   ja.mw  9126.98
3   fr.mw  2020.45
4   ru.mw  1311.16
5   de.mw  1214.59
6   es.mw  1187.93
7   it.mw   472.27
8   zh.mw   374.91
9   ko.mw   234.63
10  pt.mw   207.78
```

Large Files

Using dplyr commands, summarize the mean number of bytes (in megabytes) per unique project page and sort the resulting table in descencing order by the average in megabytes.

```
system.time( dt %>% mutate(MB=bytes/1000000) %>%
        group_by(proj)%>%
        summarize(avg=round(mean(MB),2)) %>%
        arrange(desc(avg)) )

   user  system elapsed
   1.93    2.58    7.79
```

Large Files

Using dplyr commands, summarize the mean number of bytes (in megabytes) per unique project page and sort the resulting table in descencing order by the average in megabytes.

```
system.time( dt %>% mutate(MB=bytes/1000000) %>%
        group_by(proj)%>%
        summarize(avg=round(mean(MB),2)) %>%
        arrange(desc(avg)) )
```

```
   user  system elapsed
   1.93    2.58    7.79
```

Ackowledgements

This slide deck references:

- Becoming a data ninja with dplyr - `https://speakerdeck.com/dpastoor/becoming-a-data-ninja-with-dplyr`
- dplyr tutorial `http://genomicsclass.github.io/book/pages/dplyr_tutorial.html`

Additional Material

Also see my Blog and Youtube Channel

- `http://rollingyours.wordpress.com`
- `http://youtube.com/biorsph`
- My Consulting and R Training Company at `http://pconsdec.com`