

Data Manipulation Using R

Cleaning & Summarizing Datasets

ACM DataScience Camp

Packages Useful for this Presentation

dplyr

Ram Narasimhan

@ramnarasimhan

<http://goo.gl/DXe1zs>

What will we be covering today?

Basics of Data Manipulation

- **What do we mean by Data Manipulation?**
- 4 Reserved Words in R (NA, NaN, Inf & NULL)
- **Data Quality:** Cleaning up data
 - Missing Values | Duplicate Rows | Formatting Columns
- **Subsetting Data**
- “Factors” in R

Data Manipulation Made Intuitive

- **dplyr**
- The “pipe” operator `%>%` (‘and then’)

A note about Built-in datasets

Note

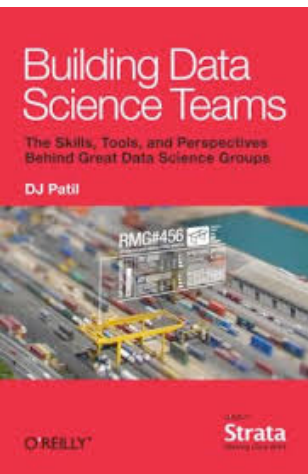
- Many datasets come bundled with R
- Many packages have their own data sets
- To find what you have, type **data()**

```
> data()  
#Examples: mtcars, iris, quakes, faithful, airquality,  
women  
#In ggplot2  
> movies; diamonds
```

Important: You won't permanently damage these, so feel free to experiment!

Why Data Carpentry?

Good data scientists understand, in a deep way, that the heavy lifting of cleanup and preparation isn't something that gets in the way of solving the problem – it is the problem.



DJ Patil, *Building Data Science Teams*

What are the ways to manipulate data?

Missing values

Data Summarization

Group By Factors

Aggregate

Subset / Exclude

Bucketing Values

Rearrange (Shape)

Merge Datasets

Data Quality



Data Quality

Datasets in real life are never perfect...

How to handle these real-life data quality issues?

- Missing Values
- Duplicate Rows
- Inconsistent Dates
- Impossible values (Negative Sales)
 - Check using if conditions
 - Outlier detection

NA, NULL, Inf & NaN

- **NA** # missing
- **NULL** # undefined
- **Inf** # infinite 3/0
- **NaN** # Not a number Inf/Inf

From R Documentation

- **NULL** represents the null object in R: it is a reserved word. NULL is often returned by expressions and functions whose values are undefined.
- **NA** is a logical constant of length 1 which contains a missing value indicator.

Dealing with NA's (Unavailable Values)

- To check if any value is NA: **is.na()**

Usage: **is.na(variable)**
is.na(vector)

```
> x <- c(3, NA, 4, NA, NA)
> is.na(x[2])
[1] TRUE
> is.na(x)
[1] FALSE TRUE FALSE TRUE TRUE
> !is.na(x)
[1] TRUE FALSE TRUE FALSE FALSE
```

Let's use the built-in dataset *airquality*

```
> is.na(airquality$Ozone)
#TRUE if the value is NA, FALSE otherwise
>!is.na(airquality$Ozone) #note the !(not)
Prints FALSE if any value is NA
```

How to Convert these NA's to 0's?

```
tf <- is.na(airquality$Solar.R) # TRUE FALSE
conditional vector
(TRUE if the values of the Solar.R variable is
NA, FALSE otherwise)
```

```
airquality$Solar.R[tf] <- 0
```

Cleaning the data



“iris” is a built-in dataset in R

- Duplicate Rows
 - Which rows are duplicated?

```
> duplicated(iris)
```

Formatting Columns

- `as.numeric()`
- `as.character()`

Subsetting Summarizing & Aggregation

- Categorical Variables in Statistics
 - Example: “Gender” = {Male, Female}
 - “Meal” = {Breakfast, Lunch, Dinner}
 - Hair Color = {blonde, brown, brunette, red}

Note: There is no intrinsic ordering to the categories

- In R, Categorical variables are called “Factors”
 - The limited set of values they can take on are called “Levels”

```
class(iris$Species)
iris$Species[1:5] #notice that all Levels are listed
str(mtcars)
#Let's make the "gear" column into a factor
mtcars$gear <- as.factor(mtcars$gear)
str(mtcars$gear)
```

The subset () function

Usage: **subset(dataframe, condition)**

- Very easy to use syntax
- One of the most useful commands

```
small_iris <- subset(iris, Sepal.Length > 7)
subset(movies, mpaa=='R')
```

Things to keep in mind

- Note that we don't need to say **df\$column_name**
- Note that equals condition is written as **==**
- Usually a good idea to verify the number of rows in the smaller data frame (using `nrow()`)

Aggregating using table()

Table counts the #Observations in each level of a factor

table(vector)

```
table(iris$Species)
table(mtcars$gear)
table(mtcars$cyl)
#put it together to create a summary table
table(mtcars$gear, mtcars$cyl)
```

These resulting tables are sometimes referred to as “frequency tables”

```
#Using "with": note that we don't need to use $
with(movies, table(year))
with(movies, table(length))
with(movies, table(length>200))
```




Data Manipulation - Key Takeaways

- 1.Data Quality: `is.na()`, `na.rm()`, `is.nan()`, `is.null()`**
- 2.`Table()` to get frequencies**
- 3.`Subset(df, var==value)`**



dplyr



Why Use dplyr?

- Very intuitive, once you understand the basics
- Very fast
 - Created with execution times in mind
- Easy for those migrating from the SQL world
- When written well, your code reads like a ‘recipe’
- “Code the way you think”



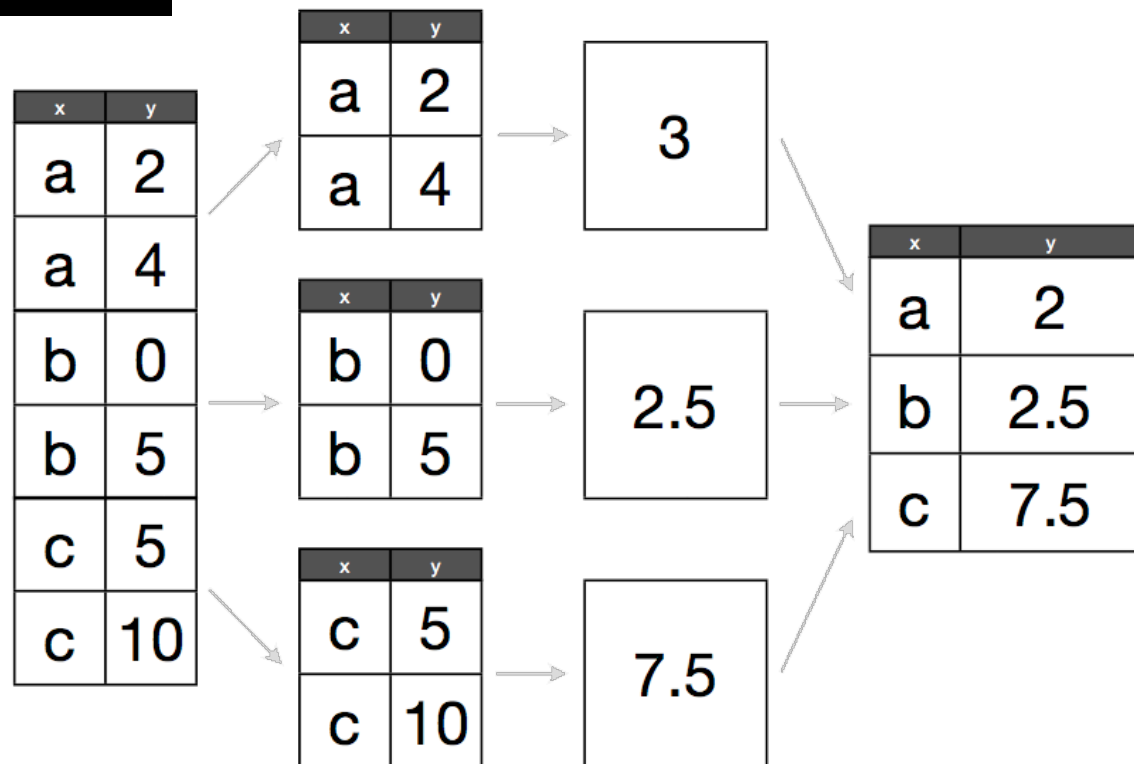
SAC – Split-Apply-Combine

- Let's understand the SAC idiom

Split up a big dataset

Apply a function to each piece

Combine all the pieces back together



tbl_df() and glimpse()

tbl_df is a 'wrapper' that prettifies a data frame

```
> library(ggplot2)
> glimpse(movies)
> pretty_movies <- tbl_df(movies)
> movies
> pretty_movies
```

```
> glimpse(movies)
Variables:
$ title      (chr) "$", "$1000 a Touchdown", "$21 a Day Once a Month", "$...
$ year       (int) 1971, 1939, 1941, 1996, 1975, 2000, 2002, 2002, 1987, ...
$ length     (int) 121, 71, 7, 70, 71, 91, 93, 25, 97, 61, 99, 96, 10, 10...
$ budget     (int) NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA...
$ rating     (dbl) 6.4, 6.0, 8.2, 8.2, 3.4, 4.3, 5.3, 6.7, 6.6, 6.0, 5.4,...
$ votes      (int) 348, 20, 5, 6, 17, 45, 200, 24, 18, 51, 23, 53, 44, 11...
$ r1         (dbl) 4.5, 0.0, 0.0, 14.5, 24.5, 4.5, 4.5, 4.5, 4.5, 4.5, 4....
$ r2         (dbl) 4.5, 14.5, 0.0, 0.0, 4.5, 4.5, 0.0, 4.5, 4.5, 0.0, 0.0...
$ r3         (dbl) 4.5, 4.5, 0.0, 0.0, 0.0, 4.5, 4.5, 4.5, 4.5, 4.5, 4.5,...
$ r4         (dbl) 4.5, 24.5, 0.0, 0.0, 14.5, 14.5, 4.5, 4.5, 0.0, 4.5, 1...
$ r5         (dbl) 14.5, 14.5, 0.0, 0.0, 14.5, 14.5, 24.5, 4.5, 0.0, 4.5,...
$ r6         (dbl) 24.5, 14.5, 24.5, 0.0, 4.5, 14.5, 24.5, 14.5, 0.0, 44....
$ r7         (dbl) 24.5, 14.5, 0.0, 0.0, 0.0, 4.5, 14.5, 14.5, 34.5, 14.5...
$ r8         (dbl) 14.5, 4.5, 44.5, 0.0, 0.0, 4.5, 4.5, 14.5, 14.5, 4.5, ...
$ r9         (dbl) 4.5, 4.5, 24.5, 34.5, 0.0, 14.5, 4.5, 4.5, 4.5, 4.5, 1...
$ r10        (dbl) 4.5, 14.5, 24.5, 45.5, 24.5, 14.5, 14.5, 14.5, 24.5, 4...
$ mpaa       (fctr) , , , , , , R, , , , , , , PG-13, PG-13, , , , , ...
$ Action     (int) 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, ...
$ Animation  (int) 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
$ Comedy     (int) 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, ...
$ Drama      (int) 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, ...
$ Documentary (int) 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, ...
$ Romance    (int) 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
$ Short      (int) 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, ...
```

```
> pretty_movies
Source: local data frame [58,788 x 24]
```

	title	year	length	budget	rating	votes	r1	r2	r3	r4
1	\$	1971	121	NA	6.4	348	4.5	4.5	4.5	4.5
2	\$1000 a Touchdown	1939	71	NA	6.0	20	0.0	14.5	4.5	24.5
3	\$21 a Day Once a Month	1941	7	NA	8.2	5	0.0	0.0	0.0	0.0
4	\$40,000	1996	70	NA	8.2	6	14.5	0.0	0.0	0.0
5	\$50,000 Climax Show, The	1975	71	NA	3.4	17	24.5	4.5	0.0	14.5
6	\$pent	2000	91	NA	4.3	45	4.5	4.5	4.5	14.5
7	\$windle	2002	93	NA	5.3	200	4.5	0.0	4.5	4.5
8	'15'	2002	25	NA	6.7	24	4.5	4.5	4.5	4.5
9	'38	1987	97	NA	6.6	18	4.5	4.5	4.5	0.0
10	'49-'17	1917	61	NA	6.0	51	4.5	0.0	4.5	4.5
..

Variables not shown: r5 (dbl), r6 (dbl), r7 (dbl), r8 (dbl), r9 (dbl), r10 (dbl), mpaa (fctr), Action (int), Animation (int), Comedy (int), Drama (int), Documentary (int), Romance (int), Short (int)

Understanding the Pipe Operator



- On January first of 2014, a new R package was launched on github

– maggritr

- A “magic” operator called the PIPE was introduced

`%>%`

(Read aloud as: THEN, “AND THEN”, “PIPE TO”)

```
round(sqrt(1000), 3)
```

```
library(magrittr)
```

```
1000 %>% sqrt %>% round()
```

```
1000 %>% sqrt %>% round(., 3)
```

Take 1000, and then its sqrt
And then round it

1000



Sqrt
function

31.62278



Round
function

32

dplyr takes advantage of Pipe



- Dplyr takes the `%>%` operator and uses it to great effect for manipulating data frames
- Works ONLY with Data Frames

A belief that 90% of data manipulation can be accomplished with 5 basic “verbs”



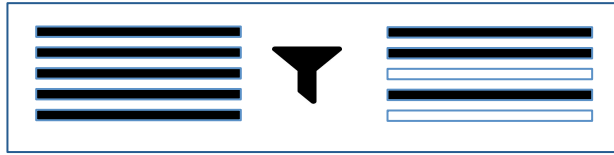
dplyr Package

- The five Basic “Verbs”

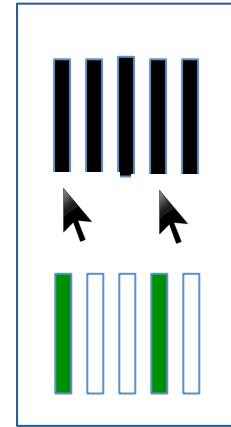
Verbs	What does it do?
filter()	Select a subset of ROWS by conditions
arrange()	Reorders ROWS in a data frame
select()	Select the COLUMNS of interest
mutate()	Create new columns based on existing columns (mutations!)
summarise()	Aggregate values for each group, reduces to single value

Remember these Verbs (Mnemonics)

- **FILTE^ROWS**



- **SELE^{CT} Column Types**



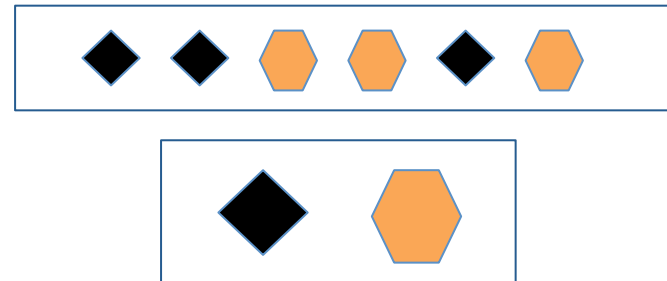
- **ArRange Rows (SORT)**



- **Mutate (into something new)**



- **Summarize by Groups**



filter()



- Usage: **filter(data, condition)**
 - Returns a subset of rows
 - Multiple conditions can be supplied.
 - They are combined with an AND

```
movies_with_budgets <- filter(movies_df, !is.na(budget))
filter(movies, Documentary==1)
filter(movies, Documentary==1) %>% nrow()
good_comedies <- filter(movies, rating > 9, Comedy==1)
dim(good_comedies) #171 movies
```

```
#' Let us say we only want highly rated comedies, which a lot
of people have watched, made after year 2000.
```

```
movies %>%
  filter(rating > 8, Comedy==1, votes > 100, year > 2000)
```

Select()

- Usage:

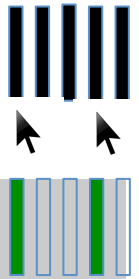
`select(data, columns)`

```
movies_df <- tbl_df(movies)
select(movies_df, title, year, rating) #Just the columns we want to see
select(movies_df, -c(r1:r10)) #we don't want certain columns

#You can also select a range of columns from start:end
select(movies_df, title:votes) # All the columns from title to votes
select(movies_df, -c(budget, r1:r10, Animation, Documentary, Short, Romance))

select(movies_df, contains("r")) # Any column that contains 'r' in its name
select(movies_df, ends_with("t")) # All vars ending with "t"

select(movies_df, starts_with("r")) # Gets all vars staring with "r"
#The above is not quite what we want. We don't want the Romance column
select(movies_df, matches("r[0-9]")) # Columns that match a regex.
```



arrange()



Usage:

arrange(data, column_to_sort_by)

- Returns a reordered set of rows
- Multiple inputs are arranged from left-to-right

```
movies_df <- tbl_df(movies)
arrange(movies_df, rating) #but this is not what we want
arrange(movies_df, desc(rating))
#Show the highest ratings first and the latest year...
#Sort by Decreasing Rating and Year
arrange(movies_df, desc(rating), desc(year))
```

What's the difference between these two?

```
arrange(movies_df, desc(rating), desc(year))
arrange(movies_df, desc(year), desc(rating))
```

mutate()



- Usage:

```
mutate(data, new_col = func(oldcolumns))
```

- Creates new columns, that are functions of existing variables

```
mutate(iris, aspect_ratio = Petal.Width/Petal.Length)

movies_with_budgets <- filter(movies_df, !is.na(budget))
mutate(movies_with_budgets, costPerMinute = budget/length) %>%
  select(title, costPerMinute)
```

group_by() & summarize()

```
group_by(data, column_to_group) %>%  
  summarize(function_of_variable)
```

- Group_by creates groups of data
- Summarize aggregates the data for each group

```
by_rating <- group_by(movies_df, rating)
```

```
by_rating %>% summarize(n())
```

```
avg_rating_by_year <-  
  group_by(movies_df, year) %>%  
  summarize(avg_rating = mean(rating))
```

Chaining the verbs together



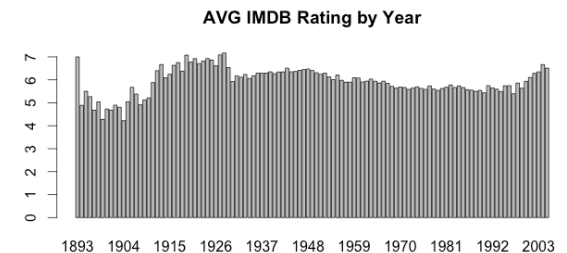
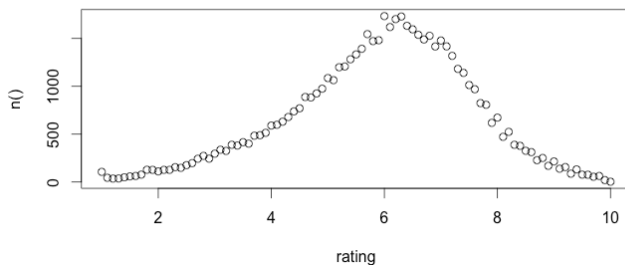
- Let's put it all together in a logical fashion
- Use a sequence of steps to find the most expensive movie per minute of eventual footage

```
producers_nightmare <-  
  filter(movies_df, !is.na(budget)) %>%  
  mutate(costPerMinute = budget/length) %>%  
  arrange(desc(costPerMinute)) %>%  
  select(title, costPerMinute)
```

Bonus: Pipe into Plot

- The output of a series of “pipes” can also be fed to a “plot” command

```
movies %>%  
  group_by(rating) %>%  
  summarize(n()) %>%  
  plot() # plots the histogram of movies by Each value of rating  
  
movies %>%  
  group_by(year) %>%  
  summarise(y=mean(rating)) %>%  
  with(barplot(y, names.arg=year, main="AVG IMDB Rating by Year"))
```



References

- Dplyr vignettes:
<http://cran.rstudio.com/web/packages/dplyr/vignettes/introduction.html>
- Kevin Markham's dplyr tutorial
 - <http://rpubs.com/justmarkham/dplyr-tutorial>
 - His YouTube video (38-minutes)
 - https://www.youtube.com/watch?feature=player_embedded&v=jWjqLW-u3hc
- <http://patilv.com/dplyr/>
 - Use arrows to move forward and back



Aggregating Data Using “Cut”

What does “cut” do?

- Bucketing
- Cuts a continuous variable into groups
- Extremely useful for grouping values



Take the **airquality** Temperature Data and group into buckets

```
range(airquality$Temp)
#First let's cut this vector into 5 groups:
cut(airquality$Temp, 5)
cut(airquality$Temp, 5, labels=FALSE)
#How many data points fall in each of the 5 intervals?
table(cut(airquality$Temp, 5))

Tempbreaks=seq(50,100, by=10)
TempBuckets <- cut(airquality$Temp, breaks=Tempbreaks)
summary(TempBuckets)
```



How many of each species do we have?

Usage: **aggregate(y ~ x, data, FUN)**

aggregate(numeric_variable ~ grouping variable, data)

How to read this?

“Split the **<numeric_variable>** by the **<grouping variable>**”

Split y into groups of x, and apply the function to each group

```
aggregate(Sepal.Length ~ Species, data=iris, FUN='mean')
```

Note the Crucial Difference between the two lines:

```
aggregate(Sepal.Length~Species, data=iris,  
FUN='length')
```

```
aggregate(Species ~ Sepal.Length, data=iris,  
FUN='length') # caution!
```



Note: If you are doing lots of summarizing, the “doBy” package is worth looking into