Thinking with Data Using R and RStudio: Powerful Idioms for Analysts

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- github repo for the talk at `https://github.com/Amherst-Statistics/JSM2016-thinkwithR`

Real acknowledgements

- R Core team
- R Foundation (`https://www.r-project.org/foundation`)
- Hadley Wickham and RStudio
- many others...

Intended audience

- Analysts who are new to R and RStudio
- Analysts who have used R somewhat, but it's been a while
- Statistical educators working to reinvigorate their curricula

Plan

- Motivational sermon: statistics and data science
- History and overview of R and RStudio
- Case study: airline delays
- Data wrangling
- Data

CATS, 1992

At its August 1992 meeting in Boston, the Committee on Applied and Theoretical Statistics (CATS) noted widespread sentiment in the statistical community that upper-level undergraduate and graduate curricula for statistics majors ... are currently structured in ways that do not provide sufficient exposure to modern statistical analysis, computational and graphical tools, communication skills, and the ever growing interdisciplinary uses of statistics.

CATS, 1992

Approaches and materials once considered standard are being rethought. The growth that statistics has undergone is often not reflected in the education that future statisticians receive. There is a need to incorporate more meaningfully into the curriculum the computational and graphical tools that are today so important to many professional statisticians. There is a need for improved training of statistics students in written and oral communication skills, which are crucial for effective interaction with scientists and policy makers. More realistic experience is needed in various application areas for which statistics is now a key to further progress.

ASA Undergrad Guidelines, 2014

- This is an exciting time to be a statistician.
- The contribution of the discipline of statistics to scientific knowledge is widely recognized with increasingly positive public perception.
- Many feel "daunted by the challenge of extracting understanding from floods of disconnected data that threaten to swamp every discipline" (Yamamoto, 2013).

`http://www.amstat.org/education/curriculumguidelines.cfm`

ASA Undergrad Guidelines, 2014

We are concerned that many of our graduates do not have sufficient skills to be effective in the modern workforce. Thomas Lumley (personal communication) has stated that our students know how to deal with $n \to \infty$, but cannot deal with a million observations. If statistics is the science of learning from data, then our students need to be able to "think with data" (as Diane Lambert of Google has so elegantly described).
- Horton and Hardin (TAS, 2015)

ASA Undergrad Guidelines, 2014

- Increased importance of data science
- Need for real applications
- Need for more diverse models and approaches
- Ability to communicate

ASA Undergrad Guidelines, 2014

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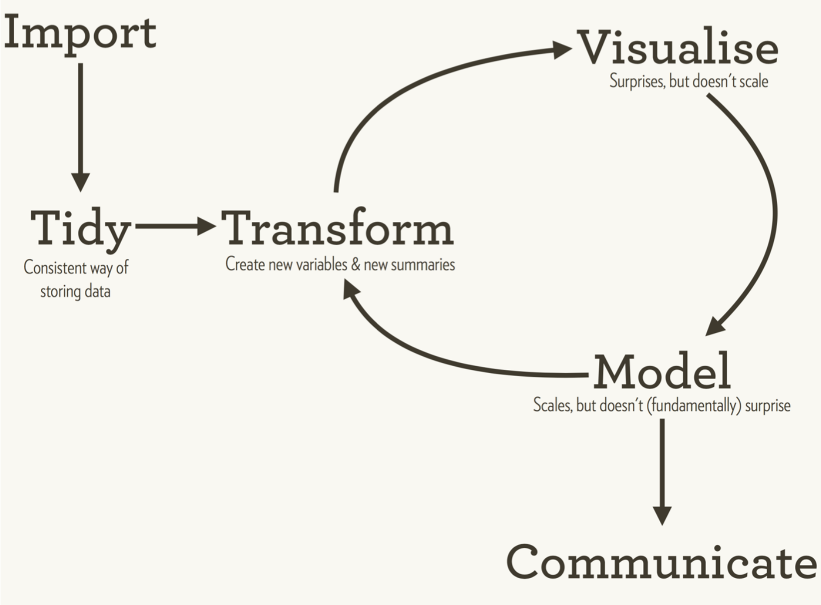
Good news: orders of magnitude decrease in degree of difficulty of data analysis

Statistical analysis cycle (Wickham)



Why R and RStudio?

- 40+ years of S: Becker, Chambers, many others
- key role of "Interfaces"

  No matter how complex and polished the individual operations are, it is often the quality of the glue that most directly determines the power of the system (Hal Abelson).

Why R and RStudio?

- 20+ years of R: Ihaka and Gentleman
- amazing efforts of the R Core and others
- open source with large community of developers and users
- more than 8,000 packages (up from 500 in 2005, 2000 in 2010)
- base R static (by design: too large an installed base to do more than tweak)

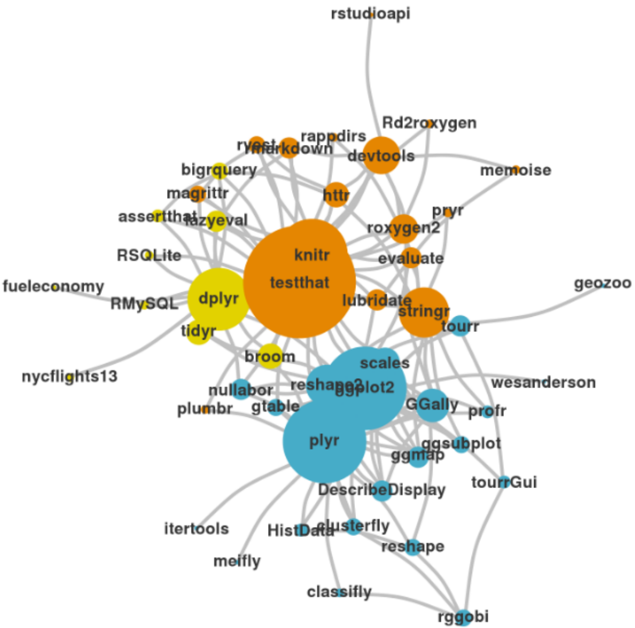
Why R and RStudio?

- 5+ years of RStudio
- designed for experts: great for novice users
- incremental improvement and punctuated equilibrium via new packages with professional polish
- development of "Hadleyverse" (83 co-authored packages)

Why R and RStudio?

- 5+ years of RStudio
- designed for experts: great for novice users
- incremental improvement and punctuated equilibrium via new packages with professional polish
- development of **tidyverse** (83 very useful packages)

More on the tidyverse (display by Adolfo Álvarez)



Design goals of tidyverse

- tools that work well together
- each one designed for a particular task
- if you don't succeed at first, try, try again
  1. `stats::reshape()`
  2. `reshape` package
  3. `reshape2` package
  4. `tidyr` package
- compose simple steps with the pipe (%>%) operator
- clarifies complex data wrangling workflow

Life without the pipe operator

```
foo_foo <- little_bunny()
bop_on(
  scoop_up(
    hop_through(foo_foo, forest),
    field_mouse
  ),
  head
)
```

Life with the pipe operator

```
foo_foo %>%
  hop_through(forest) %>%
  scoop_up(field_mouse) %>%
  bop_on(head)
```

Life with the pipe operator

dplyr::%>%

Passes object on left hand side as first argument (or . argument) of function on righthand side.

`x %>% f(y)` *is the same as* `f(x, y)`

`y %>% f(x, ., z)` *is the same as* `f(x, y, z )`

Airline delays: better traveling via data

- Collected by the Bureau of Transportation Statistics since 1987
- All commercial flights within the US (more than 180 million records)
- Easily motivated: have you ever been stuck in an airport because your flight was delayed or cancelled and wondered if you could have predicted it if you'd had more data? (Wickham, JCGS, 2011)
- Details at `http://stat-computing.org/dataexpo/2009`
- Anyone flying home at the end of the JSM?

Airline Delays Codebook (flights table: abridged)

year	$1987, 1998, \ldots, 2015$
month	1 through 12
day	1 through 31
dep_time	departure time
carrier	OH = Comair, DL = Delta, etc.
tailnum	plane identifier
arr_delay	arrival delay, in minutes
origin	BOS, MDW, ORD, SFO, etc.
dest	

Full details at
`http://www.transtats.bts.gov/Fields.asp?Table_ID=236`

A framework for tidy data

- 80% of data analysis spend on cleaning and preparation?
- we don't teach this effectively (or research how to teach!)
- some principles help make cleaning easier and more reliable
  1. Each variable forms a column
  2. Each observation forms a row
  3. Each type of observational unit forms a table

"Tidy Data" Wickham *JSS*, 2014, `https://www.jstatsoft.org/article/view/v059i10/v59i10.pdf`

Key idioms for dealing with big(ger) data

select: subset variables

filter: subset rows

mutate: add new columns

summarise: reduce to a single row

group-by: aggregate

Hadley Wickham, `bit.ly/bigrdata4` and "Building precursors to data science" (CHANCE, 2015, `https://www.amherst.edu/~nhorton/precursors`)

Key idioms for dealing with big(ger) data

select:	subset variables
filter:	subset rows
mutate:	add new columns
summarize:	reduce to a single row
group-by:	aggregate
join:	merge tables

Hadley Wickham, `bit.ly/bigrdata4` and "Building precursors to data science" (CHANCE, 2015, `https://www.amherst.edu/~nhorton/precursors`)

Statistical analysis cycle (Wickham)

Revolutions

Daily news about using open source R for big data analysis, predictive modeling, data visualization, since 2008

« Where are the R users? | Main | Because it's Friday: Boy and Bear in the snow »

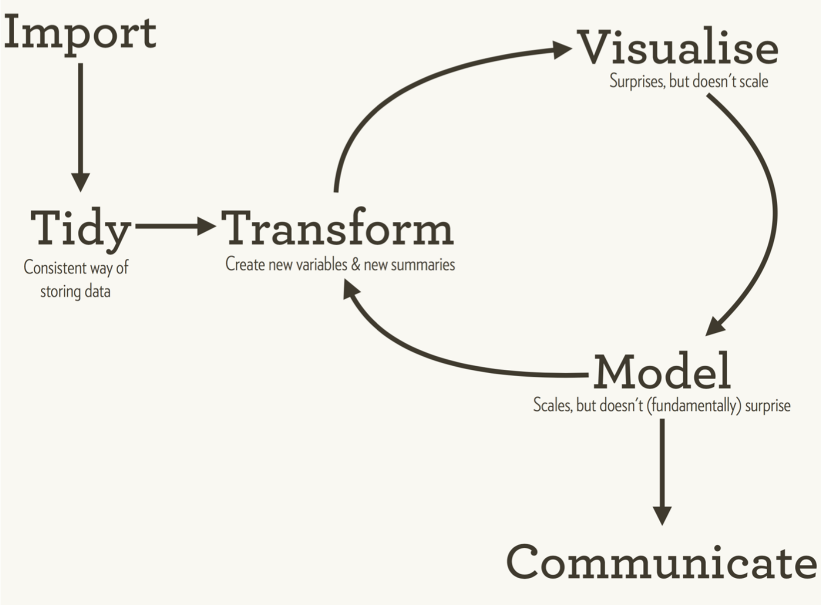
April 10, 2015

New packages for reading data into R — fast

Hadley Wickham and the RStudio team have created some new packages for R, which will be very useful for anyone who needs to read data into R (that is, everyone). The readr package provides functions for reading text data into R, and the readxl package provides functions for reading Excel spreadsheet data into R. Both are much faster than the functions you're probably using now.

The readr package provides several functions for reading tabular text data into R. This is a task normally accomplished with the `read.table` family of functions in R, and readr provides a number of replacement functions that provide additional functionality and are *much* faster.

Statistical analysis cycle (Wickham)



Importing the airline delays dataset (August, 2015)

- half a million domestic commericial flights last August
- ingest using `read.csv()` in around 30 seconds
- ingest using `readr::read_csv()` in about 8 seconds
- optimized for reading vast quantities of data *and no factors!*
- improved functionality in `haven` package (import from SPSS, Stata, and SAS)

Data wrangling idioms

- tidy data: each variable in its own column and observation in its row
- focus on Chicago area flights (`dplyr::filter()`)
- focus on desired variables (`dplyr::select()`)
- correct odd variable names (`dplyr::rename()`)
- efficiency lazy evaluation: only evaluated when and if used
- key resource: RStudio cheatsheets

Data wrangling cheatsheet

Subset Observations (Rows)

dplyr::filter(iris, Sepal.Length > 7)

Extract rows that meet logical criteria.

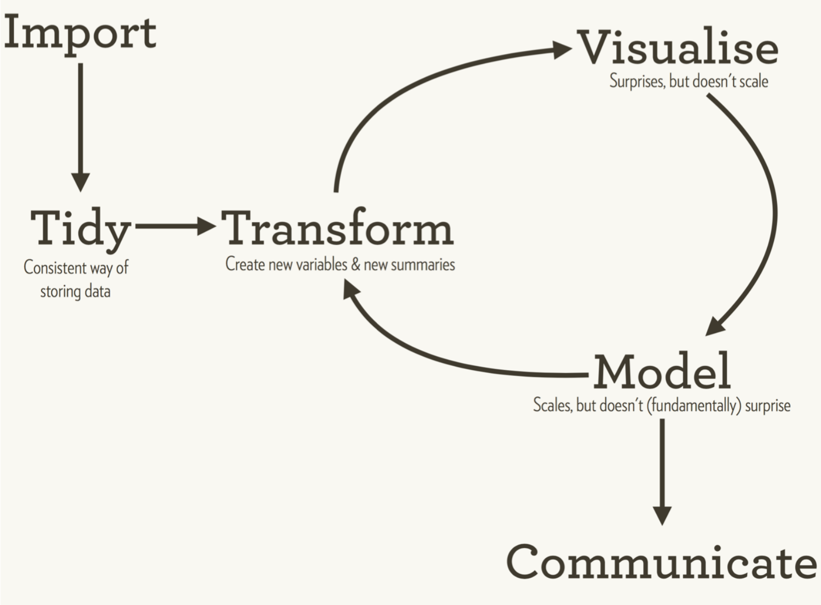
Data wrangling cheatsheet

Subset Variables (Columns)

dplyr::**select(iris, Sepal.Width, Petal.Length, Species)**

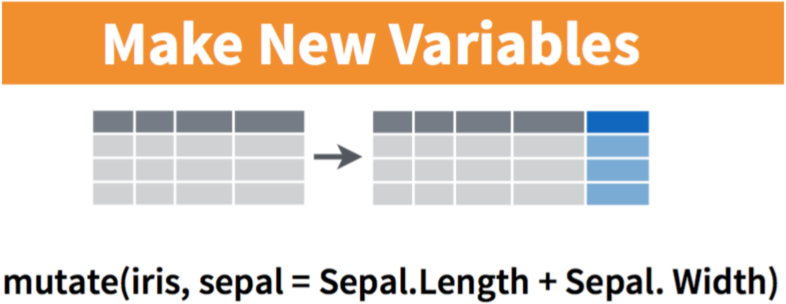
Select columns by name or helper function.

Statistical analysis cycle (Wickham)



Tidy and transform

```
> flights
    year month   day dep_time dep_delay arr_time arr_delay
   <int> <int> <int>    <int>     <int>    <int>     <int>
1   1987    10     1        3       318       41       321
2   1987    10     1        3        -2       38        -2
3   1987    10     1        3         4      728        16
4   1987    10     1        4        -5      607        -2
5   1987    10     1        5         0      119         5
6   1987    10     1        5         0       52        17
7   1987    10     1        5        -5       41        -9
8   1987    10     1        6        -2      534        17
9   1987    10     1        6        26       34        19
10  1987    10     1        7        -8       39        -8
# ... with more rows, and 8 more variables: tailnum <chr>,
#   flight <int>, origin <chr>, dest <chr>, air_time <int>,
#   distance <int>, cancelled <int>, diverted <int>
```


Make New Variables
mutate(iris, sepal = Sepal.Length + Sepal. Width)

```
library(mosaic) # add support for modeling
flights %>%
  mutate(incoming = ifelse(dest=="ORD" | dest=="MDW",
    TRUE, FALSE)) %>%
  filter(year==2015, month==8, incoming==TRUE) %>%
  favstats(arr_delay ~ dest, data=.)

##   dest min  Q1 median Q3  max mean   sd     n missing
## 1  MDW -43 -14     -7  5  604 2.15 34.2  7833      95
## 2  ORD -69 -16     -7  7 1134 5.00 46.3 27343     785
```

What's with the missing values?

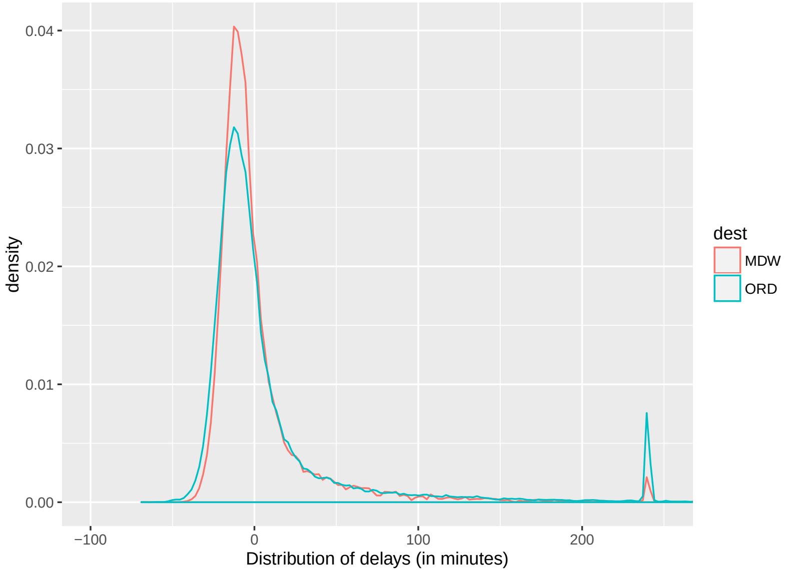
```
flights %>%
  filter(year==2015, month==8, is.na(arr_delay)) %>%
  select(dest, origin, carrier, cancelled) %>%
  head(3)

## # A tibble: 3 x 4
##    dest origin carrier cancelled
##   <chr>  <chr>   <chr>     <dbl>
## 1   ALB    ORD      UA         1
## 2   IAD    ORD      UA         1
## 3   ORD    BWI      UA         1
```

How to handle cancellations?

Tidy and transform

```
flights %>%
  mutate(
    incoming = ifelse(dest=="ORD" | dest=="MDW",
      TRUE, FALSE),
    true_delay = ifelse(cancelled, 240, arr_delay)) %>%
  filter(year==2015, month==8, incoming==TRUE) %>%
  favstats(true_delay ~ dest, data=.)

##   dest min  Q1 median Q3  max  mean   sd     n missing
## 1  MDW -43 -14     -7  5  604  3.72 39.1  7885      43
## 2  ORD -69 -16     -6  9 1134 10.42 57.8 27989     139
```

Visualize



0.04
0.03
0.02
0.01
0.00
density
−100
0
100
200
Distribution of delays (in minutes)
dest
MDW
ORD

Data wrangling cheatsheet

Summarise Data

```
summarise(iris, avg = mean(Sepal.Length))
```

Data wrangling cheatsheet

Group Data

dplyr::group_by(iris, Species)

Group data into rows with the same value of Species.

dplyr::ungroup(iris)

Remove grouping information from data frame.

iris %>% group_by(Species) %>% summarise(...)

Compute separate summary row for each group.

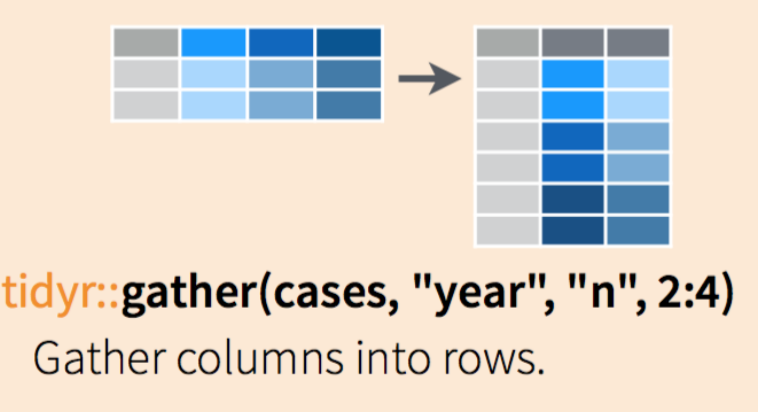
Summarize and aggregate

```
flights %>%
  filter(year==2015, origin=="ORD" | origin=="MDW"
    | dest=="ORD" | dest=="MDW") %>%
  group_by(incoming) %>%
  summarize(
    count = n(),
    meandelay = mean(true_delay, na.rm=TRUE))

## # A tibble: 2 x 3
##   incoming count meandelay
##      <lgl> <int>     <dbl>
## 1    FALSE 36077      9.63
## 2     TRUE 36056      8.95
```

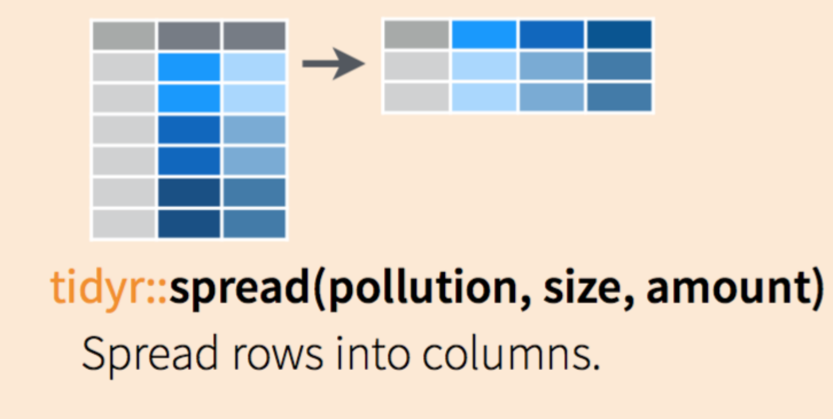
Summarize and aggregate

```r
aug2015 <- flights %>%
  filter(year==2015, origin=="ORD" | origin=="MDW"
    | dest=="ORD" | dest=="MDW") %>%
  group_by(airport, day) %>%
  summarize(
    count = n(), year = first(year),
    month = first(month),
    meandelay = mean(true_delay, na.rm=TRUE)) %>%
  arrange(day) %>% data.frame()
head(aug2015, 4)

##   airport day count year month meandelay
## 1     MDW   1   478 2015     8     13.64
## 2     ORD   1  1607 2015     8      3.22
## 3     MDW   2   533 2015     8     15.68
## 4     ORD   2  1852 2015     8     46.29
```

Data wrangling cheatsheet



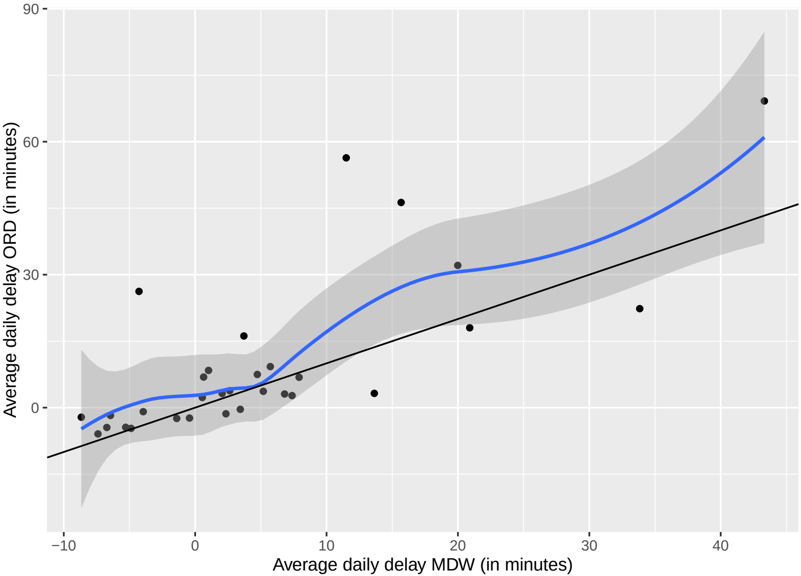
Data wrangling cheatsheet



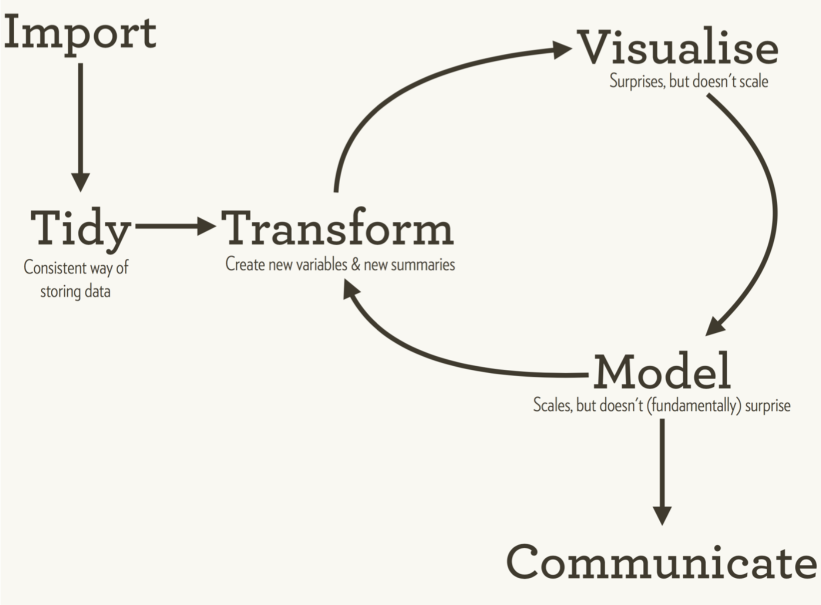
Reshape and transpose

```
oneline <- aug2015 %>%
  select(airport, year, month, day, meandelay) %>%
  spread(airport, meandelay)
head(oneline)

##   year month day   MDW   ORD
## 1 2015     8   1 13.64  3.22
## 2 2015     8   2 15.68 46.29
## 3 2015     8   3  5.72  9.27
## 4 2015     8   4  6.81  3.08
## 5 2015     8   5  2.05  3.20
## 6 2015     8   6  5.19  3.69
```

Visualize


90
60
30
0
−10
0
10
20
30
40
Average daily delay ORD (in minutes)
Average daily delay MDW (in minutes)

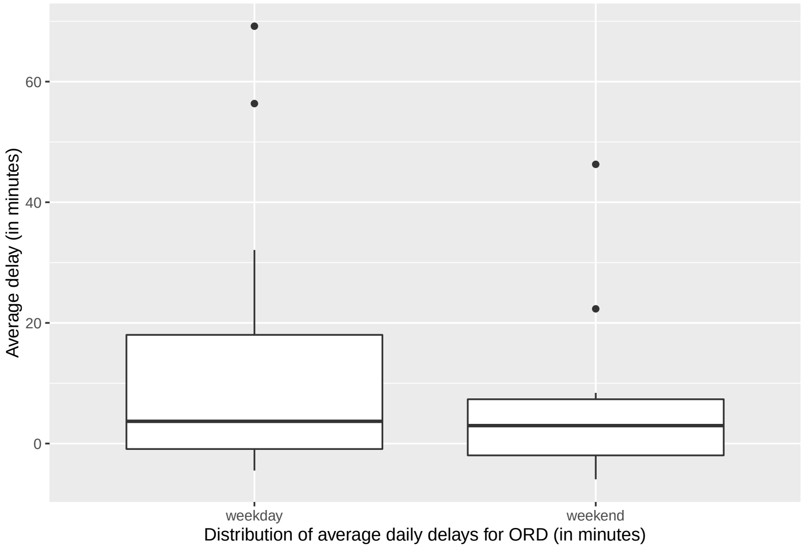
Statistical analysis cycle (Wickham)



Airline Delays

```
oneline <- oneline %>%
  mutate(dow = wday(ymd(paste(year, month, day))),
         daytype = ifelse(dow %in% 2:5,
           "weekday", "weekend"))
head(oneline, 4)

##   year month day   MDW   ORD dow daytype
## 1 2015     8   1 13.64  3.22   7 weekend
## 2 2015     8   2 15.68 46.29   1 weekend
## 3 2015     8   3  5.72  9.27   2 weekday
## 4 2015     8   4  6.81  3.08   3 weekday
```

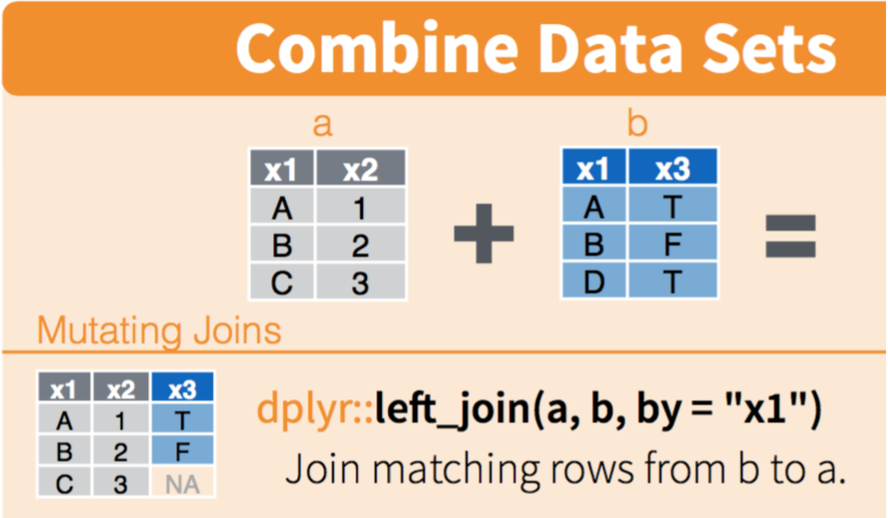
Airline Delays



Airline Delays

```
oneline %>%
  filter(ORD > 40)

##   year month day  MDW  ORD dow daytype
## 1 2015     8   2 15.7 46.3   1 weekend
## 2 2015     8  10 43.3 69.2   2 weekday
## 3 2015     8  17 11.5 56.4   2 weekday
```

Statistical analysis cycle (Wickham)



Join/merge

```
glimpse(airports)

## Observations: 1,458
## Variables: 9
## $ faa     <chr> "04G", "06A", "06C", "06N", "09J", "0A9"
## $ name    <chr> "Lansdowne Airport", "Moton Field Munic
## $ lat     <dbl> 41.1, 32.5, 42.0, 41.4, 31.1, 36.4, 41.5
## $ lon     <dbl> -80.6, -85.7, -88.1, -74.4, -81.4, -82.2
## $ alt     <int> 1044, 264, 801, 523, 11, 1593, 730, 492,
## $ tz      <dbl> -5, -6, -6, -5, -5, -5, -5, -5, -5, -8,
## $ dst     <chr> "A", "A", "A", "A", "A", "A", "A", "A",
## $ city    <chr> "Youngstown", "Tuskegee", "Schaumburg",
## $ country <chr> "United States", "United States", "Unite
```

Join/merge

```
outgoing <- flights %>%
  filter(incoming==FALSE) %>%
  rename(faa=dest)
merged <- left_join(outgoing, airports) %>%
  select(faa, tz, true_delay, year, month, day,
    carrier) %>%
  arrange(true_delay)

## Joining, by = "faa"
```

Join/merge

```
data.frame(merged) %>% head(2)

##   faa tz true_delay year month day carrier
## 1 PHX -7        -58 2015     8  30      AA
## 2 LAX -8        -55 2015     8  29      AA

favstats(true_delay ~ tz, data=merged)

##     tz min     Q1 median   Q3 max  mean   sd     n missin
## 1 -10 -17  -0.75    9.5 22.2 559 24.95 85.5    44
## 2  -9 -46 -12.00    5.0 28.0 152 10.85 33.4   109
## 3  -8 -55 -17.00   -5.0 13.0 600  6.75 43.2  4621       1
## 4  -7 -58 -15.00   -4.0 13.0 783  8.97 48.5  2480       1
## 5  -6 -51 -15.00   -6.0  9.0 609  8.81 49.3 11152       2
## 6  -5 -45 -13.00   -4.0 12.0 614 10.99 49.9 17473       4
```

```
merged %>%
  filter(tz==-10) %>%
  head(5)

## # A tibble: 5 x 7
##      faa    tz true_delay  year month   day carrier
##    <chr> <dbl>      <dbl> <int> <int> <int>   <chr>
## 1    HNL   -10        -17  2015     8    31      UA
## 2    HNL   -10        -16  2015     8    21      UA
## 3    HNL   -10        -13  2015     8    30      UA
## 4    HNL   -10        -12  2015     8    22      UA
## 5    OGG   -10         -8  2015     8    14      UA
```

Next steps

- what if we wanted to analyze all of the flight data?
- how to access 180 million records in R?
- answer: use a database that talks to `dplyr` (e.g., MySQL, SQLite, PostgreSQL)
- see the ETL package to facilitate setup (`http://github.com/beanumber/airlines`)

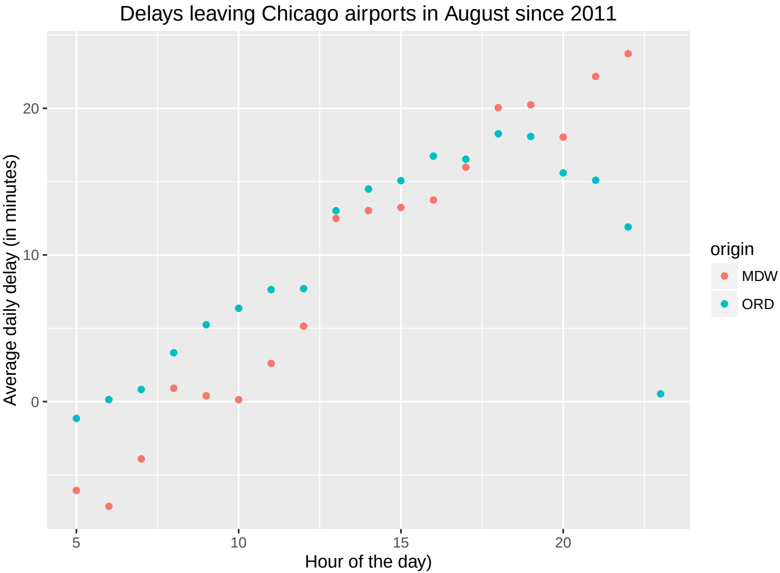
Airline delays: access via a database

```r
library(RMySQL)
db <- src_mysql(host="dbhost.mysite.com",
  user="r-user", password="XX",
  dbname = "airlines")
flights <- tbl(db, "flights")
airports <- tbl(db, "airports")
carriers <- tbl(db, "carriers")
planes <- tbl(db, "planes")
```

Airline Delays

```
sumhours <-
flights %>%
  filter(month==8, year > 2010,
    origin=="MDW" | origin=="ORD") %>%
  group_by(hour, origin) %>%
  summarize(count=n(), avgdelay=mean(arr_delay)) %>%
  collect()
```

Airline Delays



Next steps

- restrict to only recent Thursdays (use `lubridate` package)
- account for airline and destination in addition to time of day
- incorporate external information (weather?)
- incorporate external information (padded schedules)

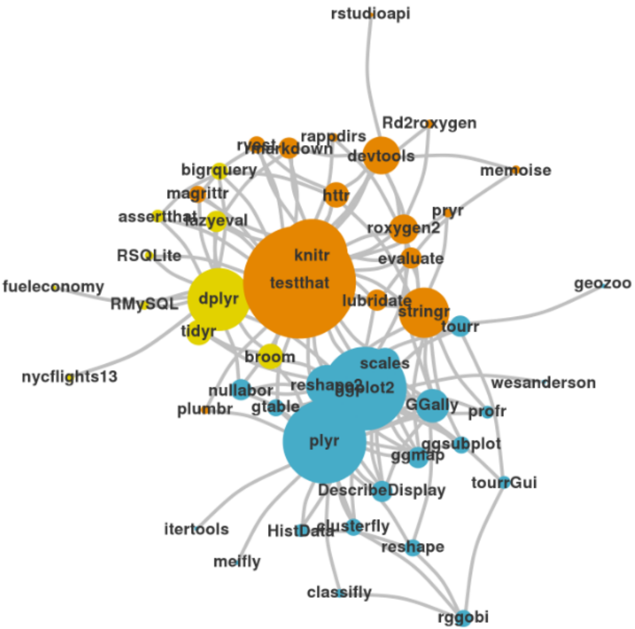
Modeling with broom (David Robinson et al)

- after fitting a regression model then tidy it
- `tidy(mod)`: construct data frame with model's statistical findings
- `augment(mod)`: add columns (predictions, residuals, cluster assignments)
- `glance(mod)`: construct one row summary of the model

Other interesting developments

- `rvest` package (easily harvest (scrape) web pages)
- `httr` package (work with URLs and HTTP)
- `stringr` simple wrappers for string operations
- `testthat` unit testing for fun and profit
- `ggplot2` implementation of the grammar of graphics

More on the tidyverse (display by Adolfo Álvarez)



Additional resources to help with wrangling in R

- Swirl (free)
  - see `https://github.com/swirldev/swirl_courses`
  - Getting and cleaning data (dplyr, tidyr, and lubridate)
- DataCamp (inexpensive)
  - Importing and cleaning data
  - Data manipulation
  - R Programming

Revision control systems

> *Version control is the only reasonable way to keep track of changes in code, manuscripts, presentations, and data analysis projects.*

Karl Broman,
`http://kbroman.org/github_tutorial/pages/why.html`

> *If you need to collaborate on data analysis or code development, then all involved should use Git.*

Jenny Bryan, `http://happygitwithr.com`

Segue to next talk

- R Markdown
- Shiny

Resources and copies of the slides

github repo for the talk at `https://github.com/Amherst-Statistics/JSM2016-thinkwithR`

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