# You can't do data science in a GUI

**March 2018** 

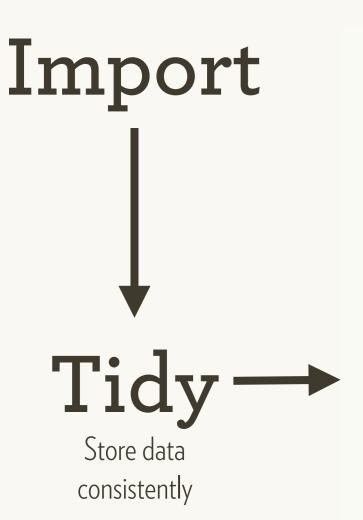
Hadley Wickham

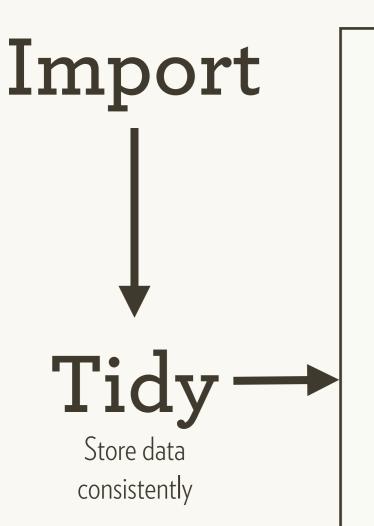
@hadleywickham
Chief Scientist, RStudio



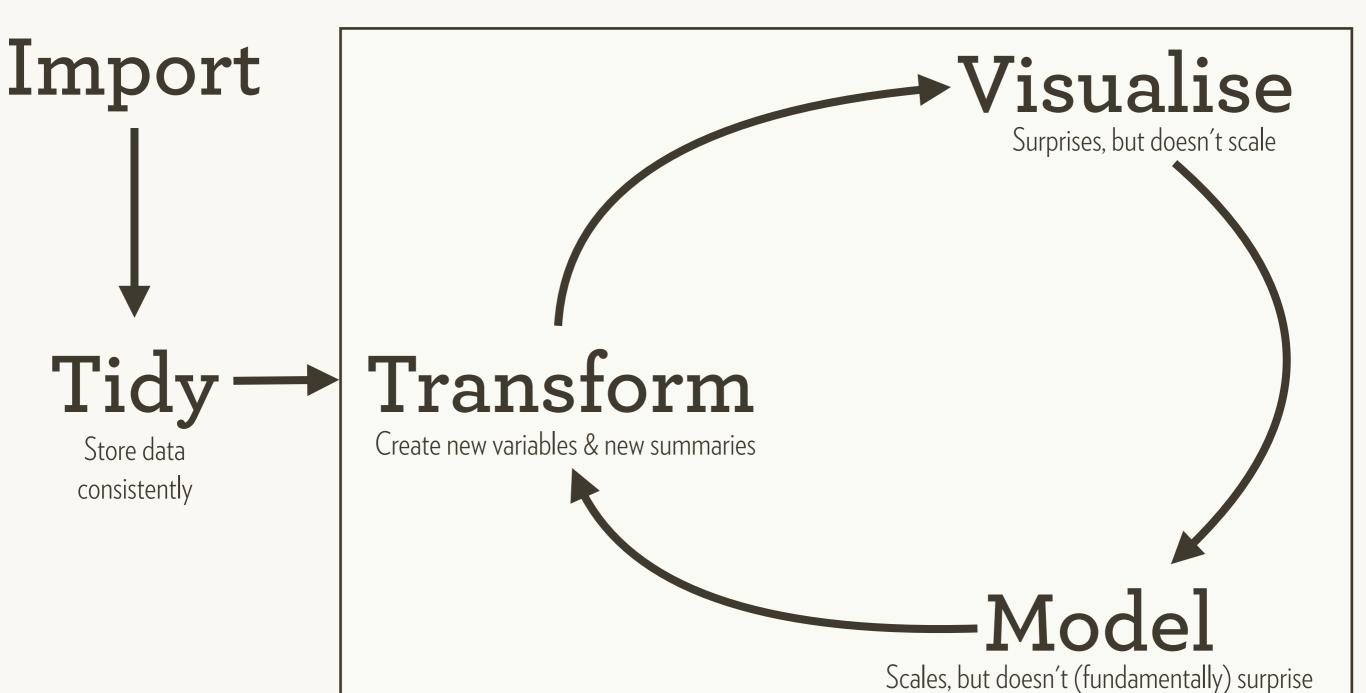
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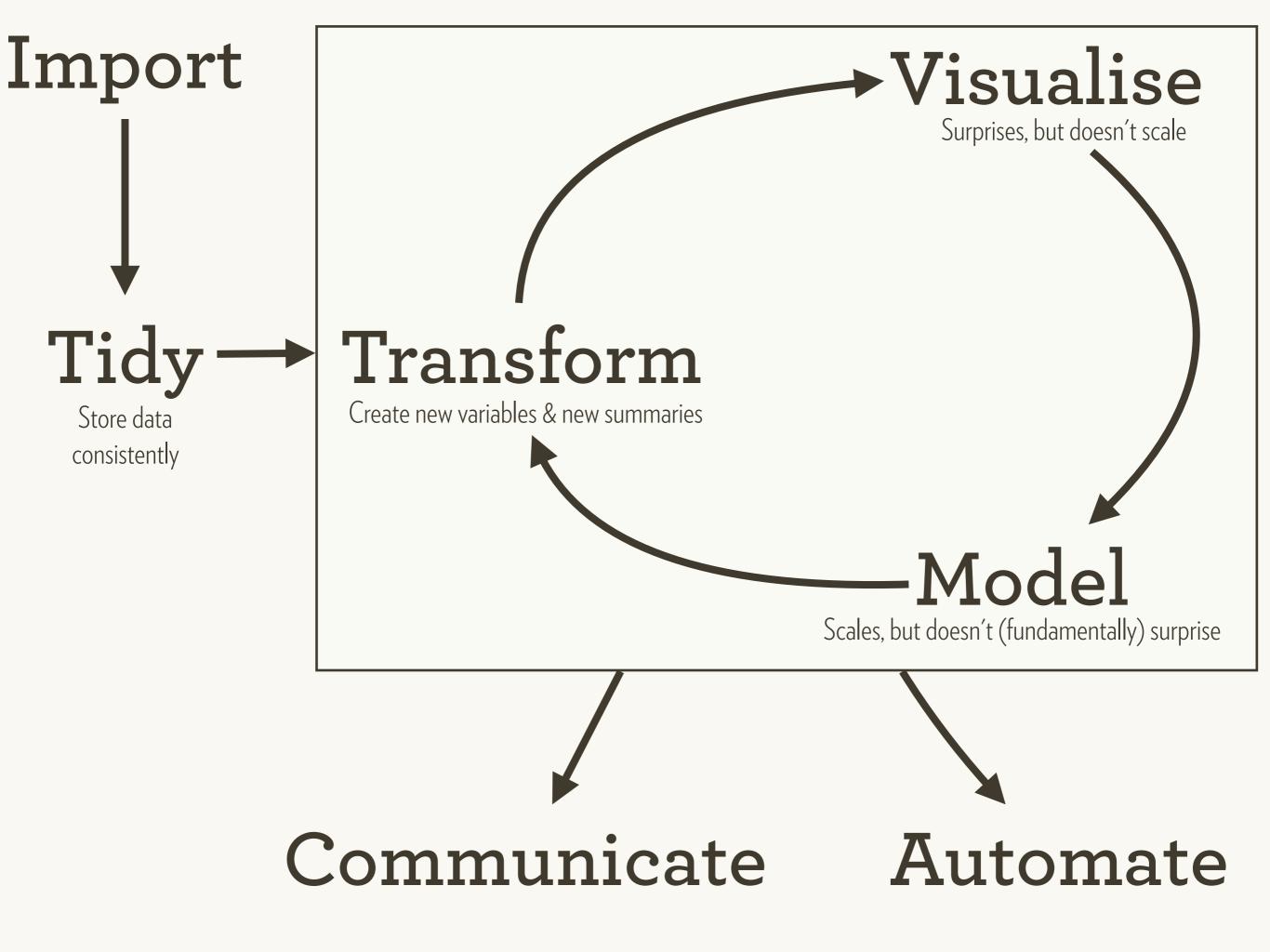
Data science is the process by which data becomes understanding, knowledge and insight

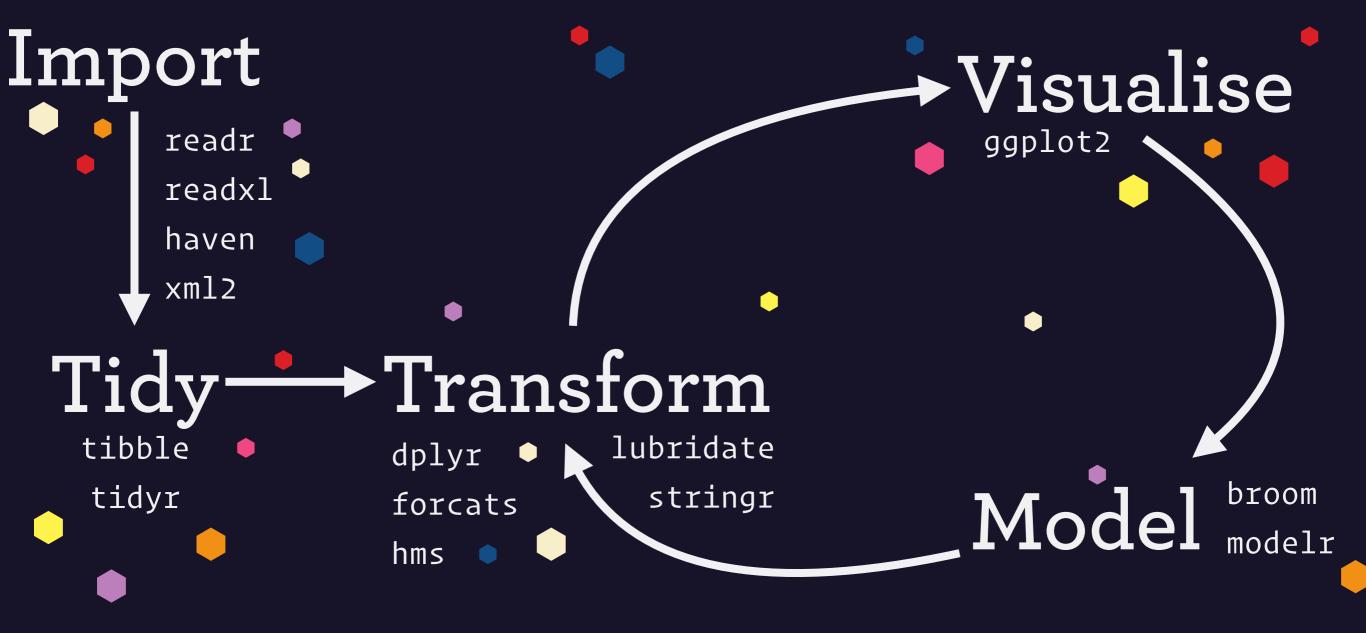




### Understand

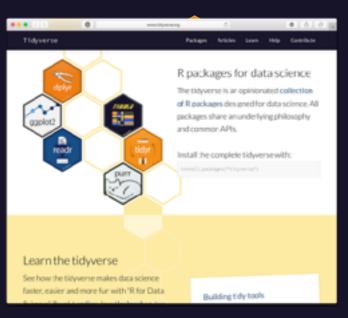




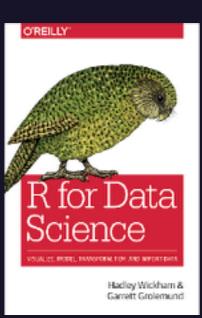






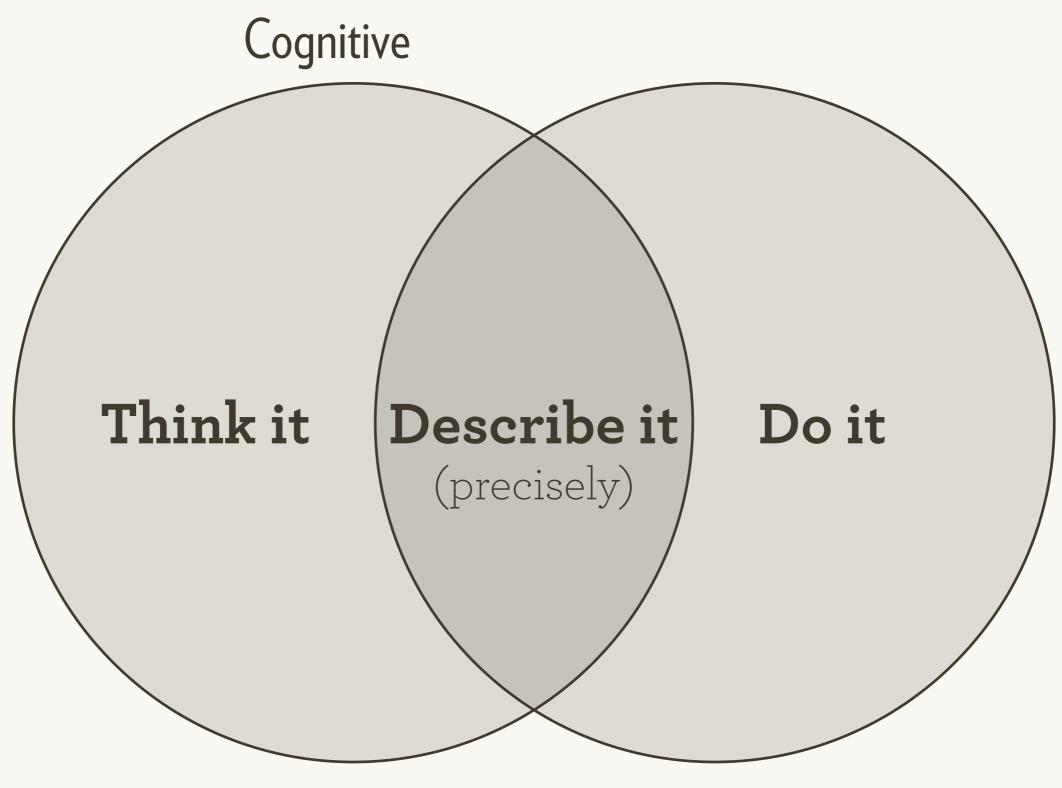


tidyverse.org

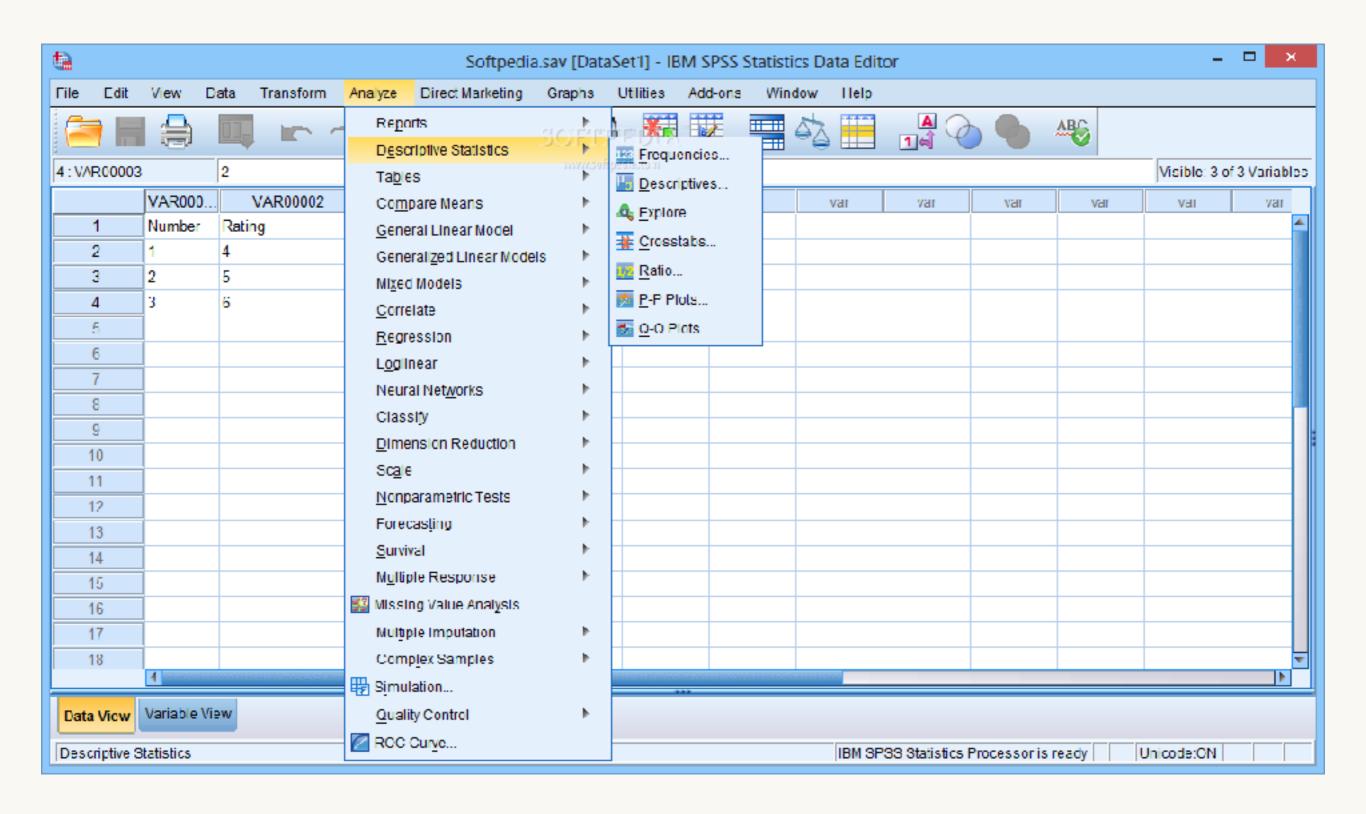


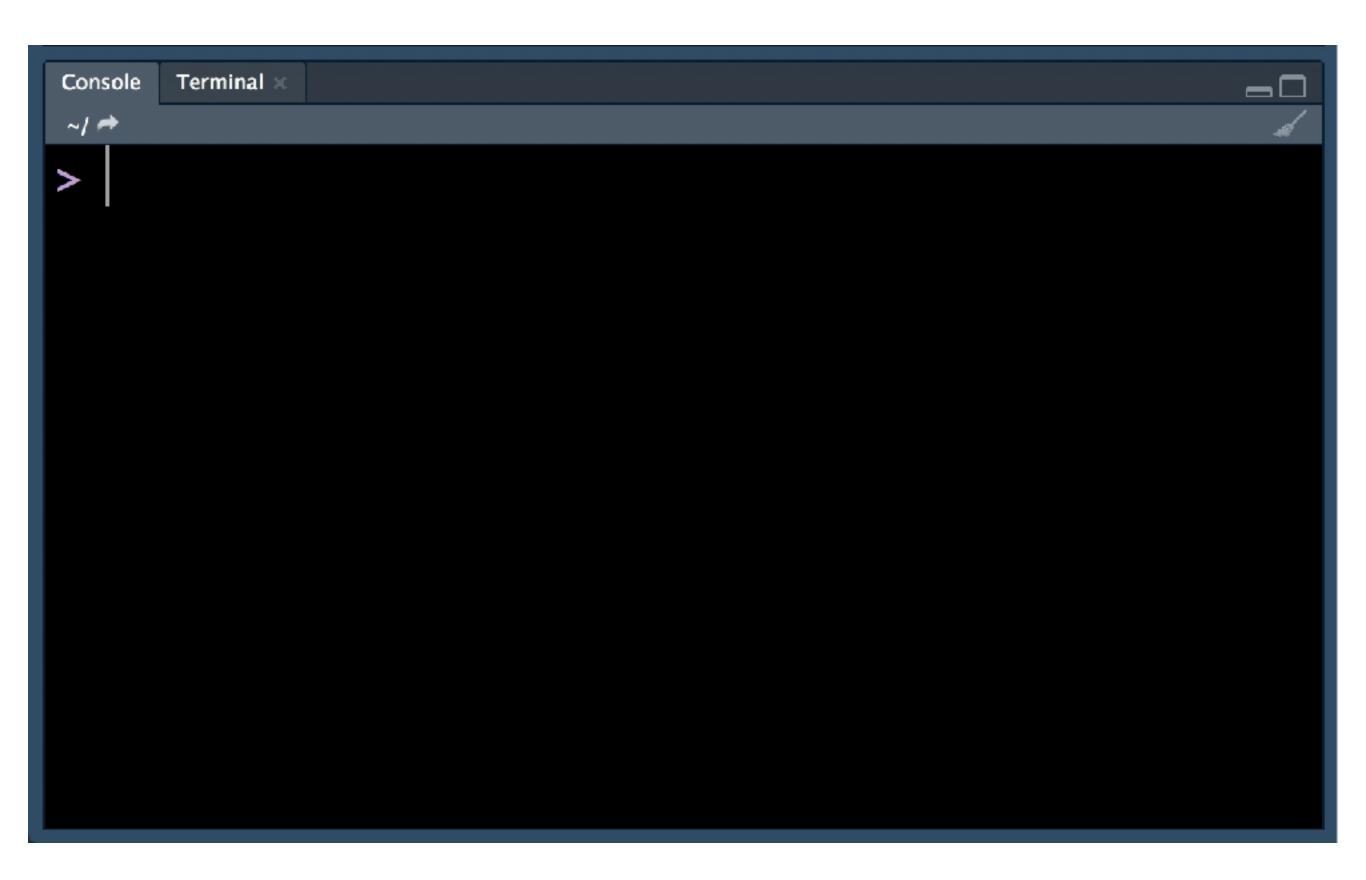
r4ds.had.co.nz

### Why program?



Computational





#### Programming languages are languages

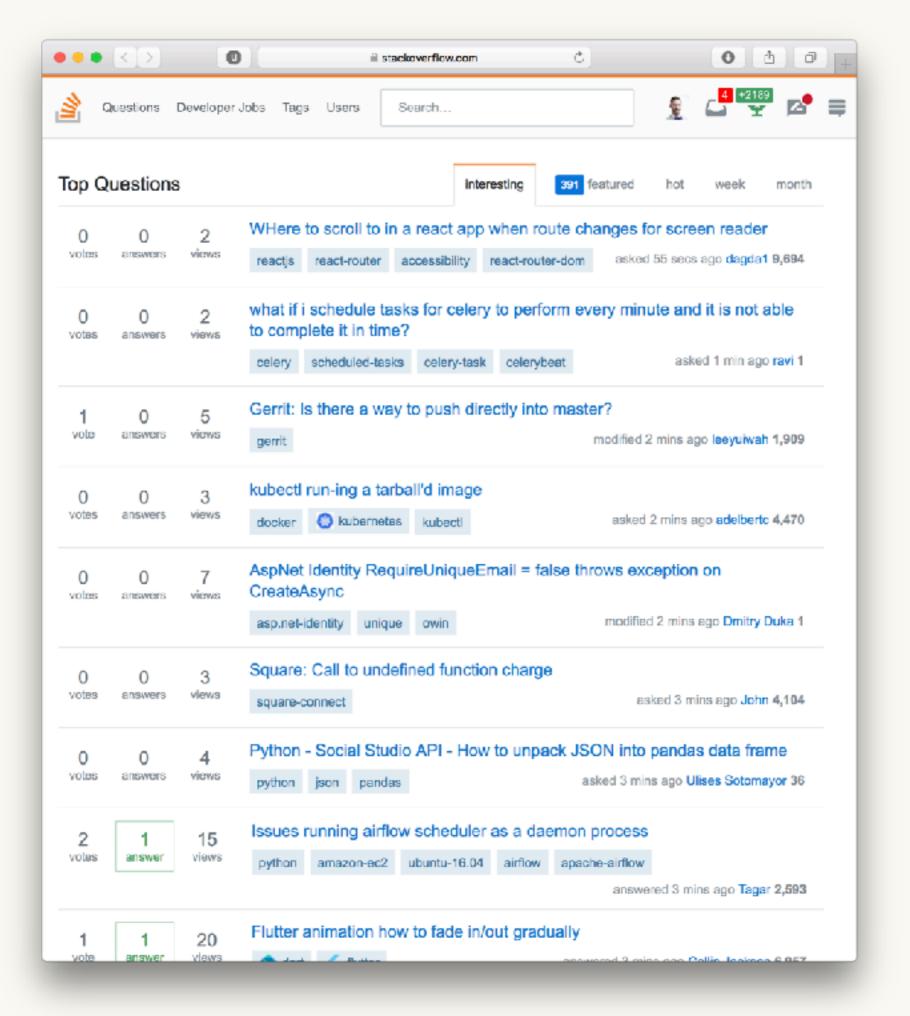
```
table %>%
  rename(player = X1, team = X2, position = X3) %>%
  filter(player != 'PLAYER') %>%
  mutate(
    college = ifelse(player == position, player, NA)
  ) %>%
  fill(college) %>%
  filter(player != college)
```

### It's just text!

And this gives you access to two extremely powerful techniques

## HOCO

B V

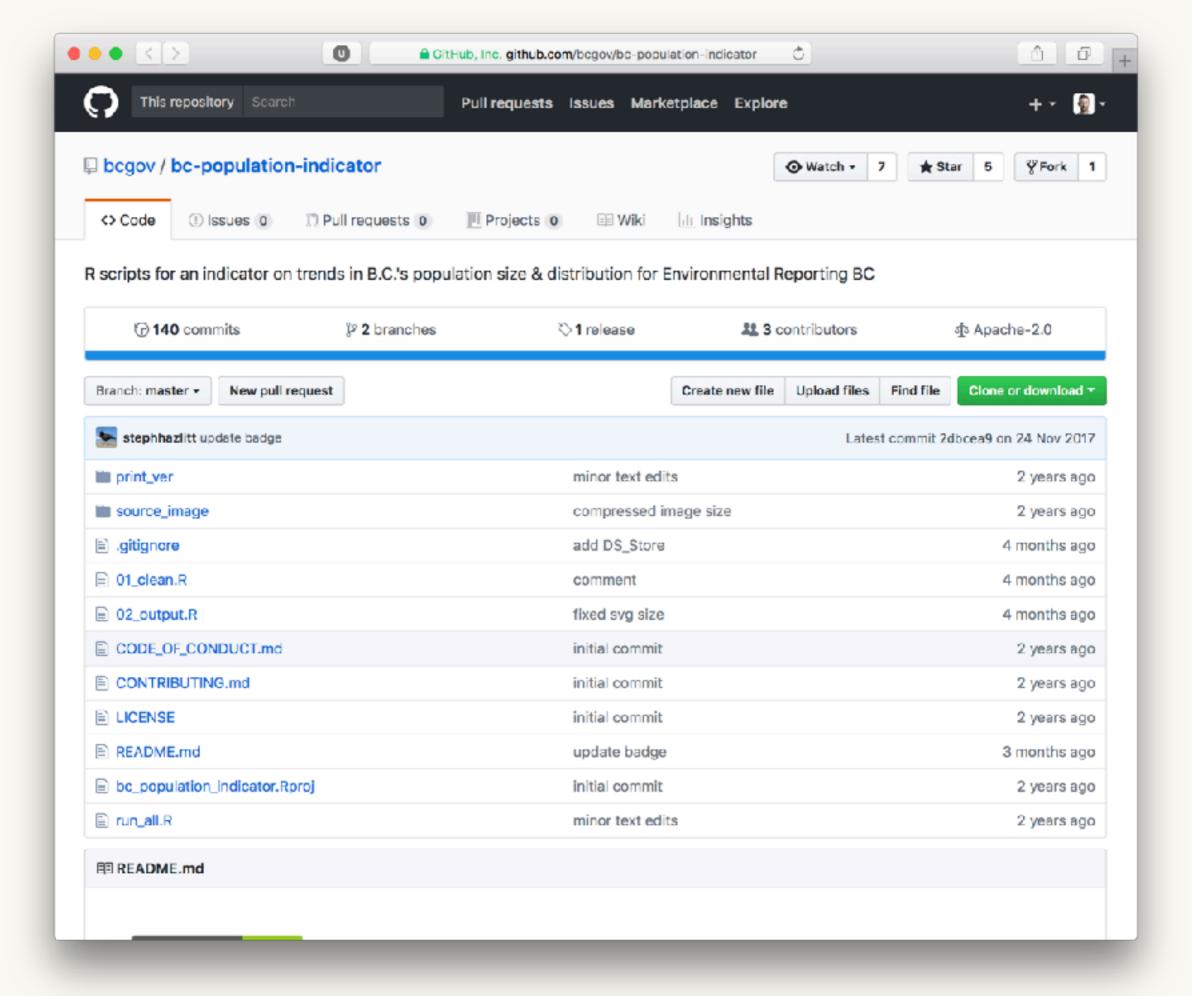


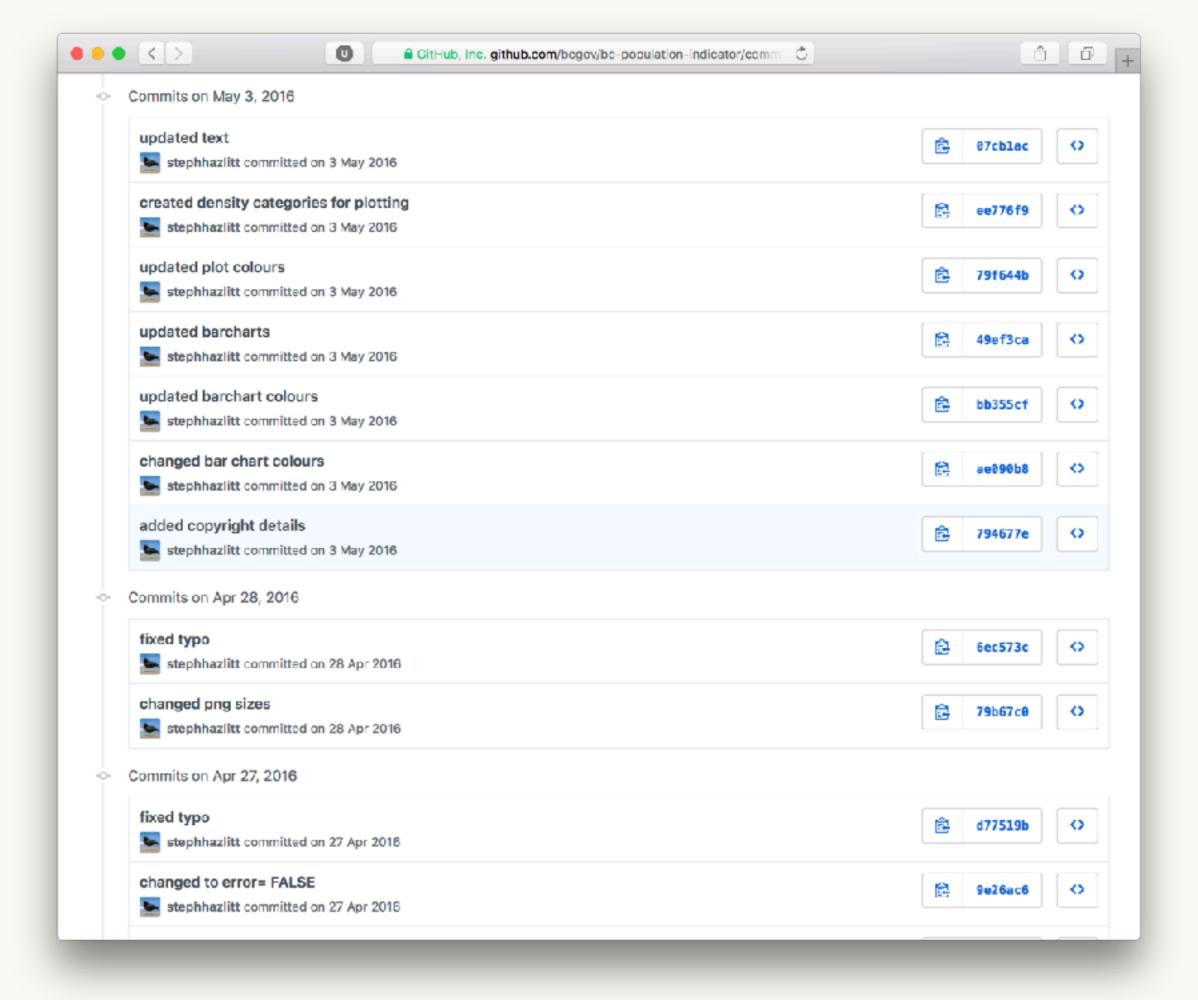
### Reproducible

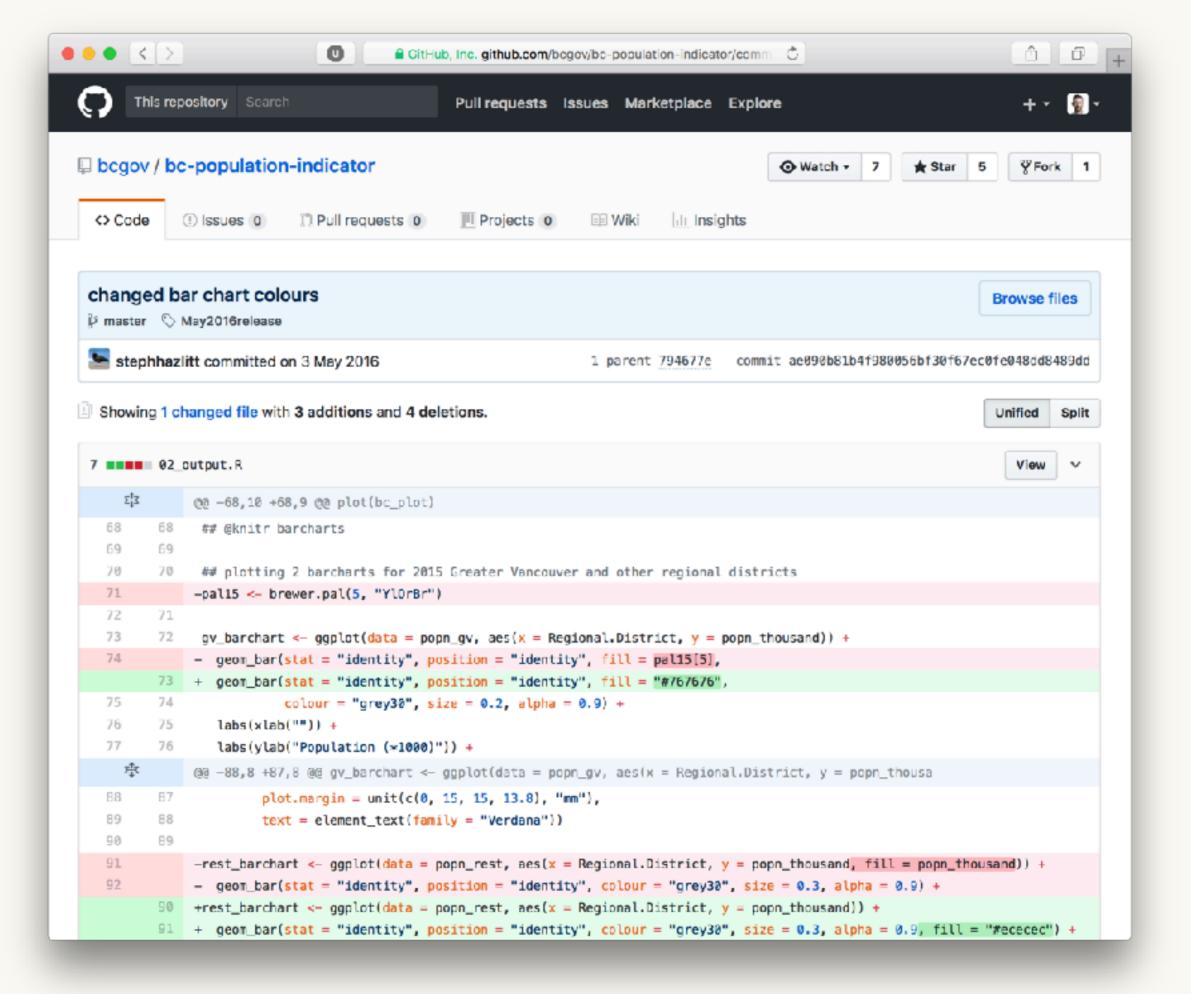
Diffable

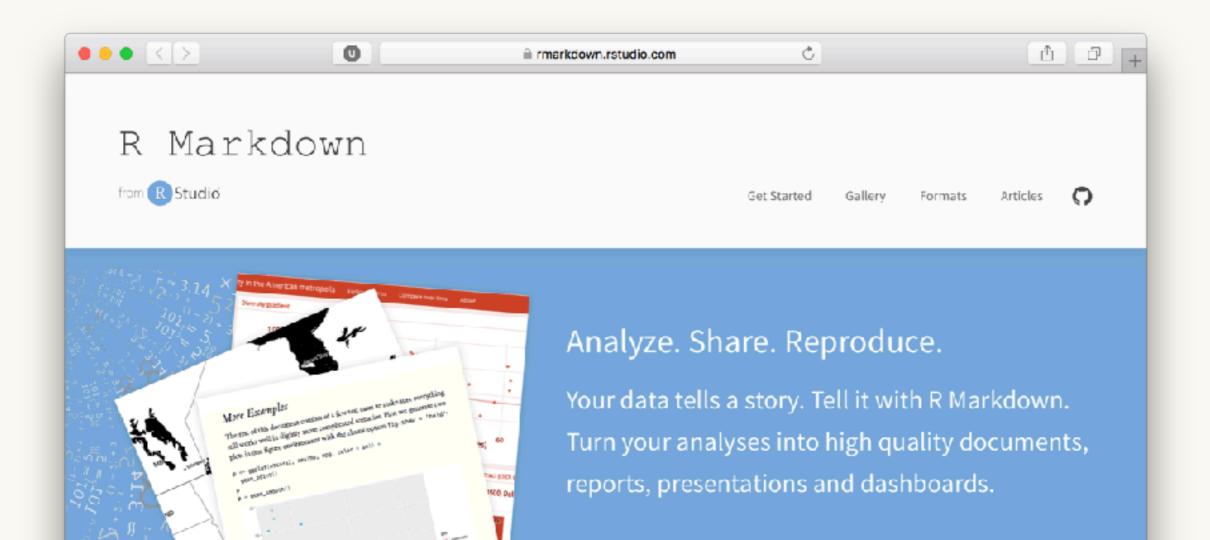
Readable

Open



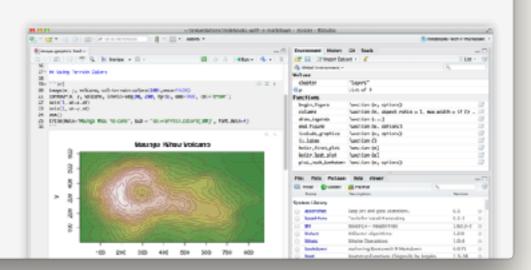


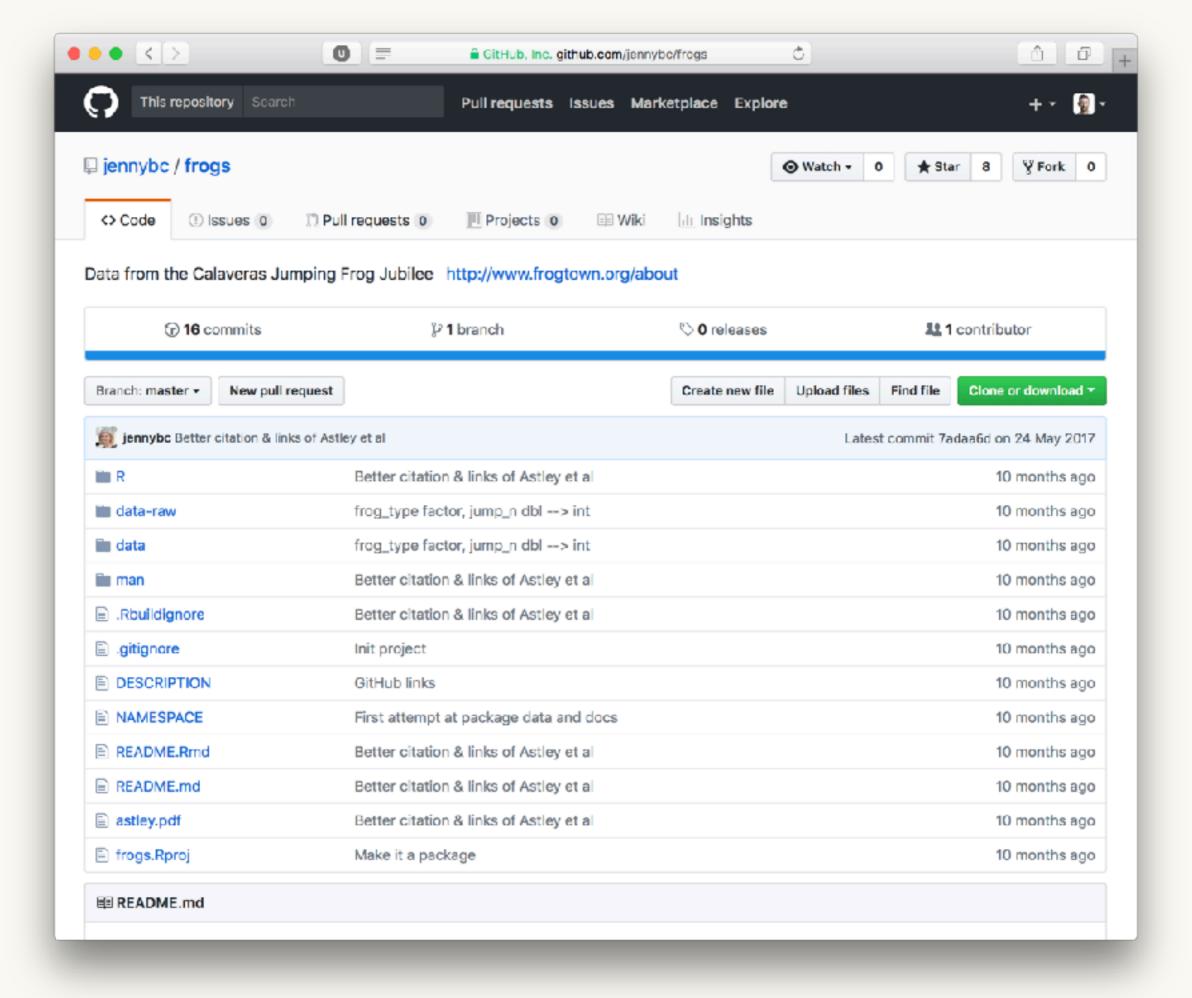




R Markdown documents are fully reproducible.

Use a productive notebook interface to weave together narrative text and code to produce





#### Getting to know the frogs

At this point, all we know is that each row is one frog-jump. Frog ids coming ...

```
library(frogs)
library(tidyverse)
#> + ggplot2 2.2.1
                           Date: 2017-05-24
#> + tibble 1.3.1
                            R: 3.3.2
#> + tidyr 0.6.2.9000
                           OS: OS X El Capitan 10.11.6
#> + readr 1.1.0
                            GUI: X11
#> + purrr 0.2.2.9000 Locale: en_CA.UTF-8
#> + dplyr 0.6.0
                           TZ: America/Vancouver
#> + stringr 1.2.0
\#> + forcats 0.2.0
#> Conflicts -----
#> * filter(), from dplyr, masks stats::filter()
#> * lag(), from dplyr, masks stats::lag()
frogs
#> # A tibble: 3,272 x 15
       row distance duration distance 3 jump_n frog_type distance 3 off
             <dbl>
                     <dbl>
                              <dbl> <int>
                                              <chr>
                                                           <dbl>
        1 165.950 0.58333
                                                              -1
                                               pro
        2 177.480 0.71667
                                                             -1
                                               pro
        3 0.000 0.00000
                                               pro
        4 27.158 0.43333
                                               pro
                                                             -1
      5 0.000 0.00000
                                               pro
                                                             -1
      6 0.000 0.00000
                                                             -1
                                               pro
      7 40.914 0.40000
                                                             -1
                                               pro
      8 0.000 0.00000
                                                             -1
                                               pro
                                  0 3
#> 9 0.000 0.00000
                                                             -1
                                               pro
-1
                                               pro
#> # ... with 3,262 more rows, and 8 more variables: distance_rel <dbl>,
#> # day <dbl>, angle_01 <dbl>, angle_10 <dbl>, angle_00 <dbl>,
#> # velocity_01 <dbl>, velocity_10 <dbl>, velocity_00 <dbl>
glimpse(frogs)
#> Observations: 3,272
#> Variables: 15
```

#### Getting to know the frogs

At this point, all we know is that each row is one frog-jump. Frog ids coming ...

```
library(frogs)
library(tidyverse)

frogs
glimpse(frogs)
```

An early figure. Do frogs need to warm up? Do they fatigue? Yes and yes.

```
frogs2 <- frogs %>%
  filter(jump_n < 7) %>%
  mutate(
    jump_n = as.factor(as.integer(jump_n))
)

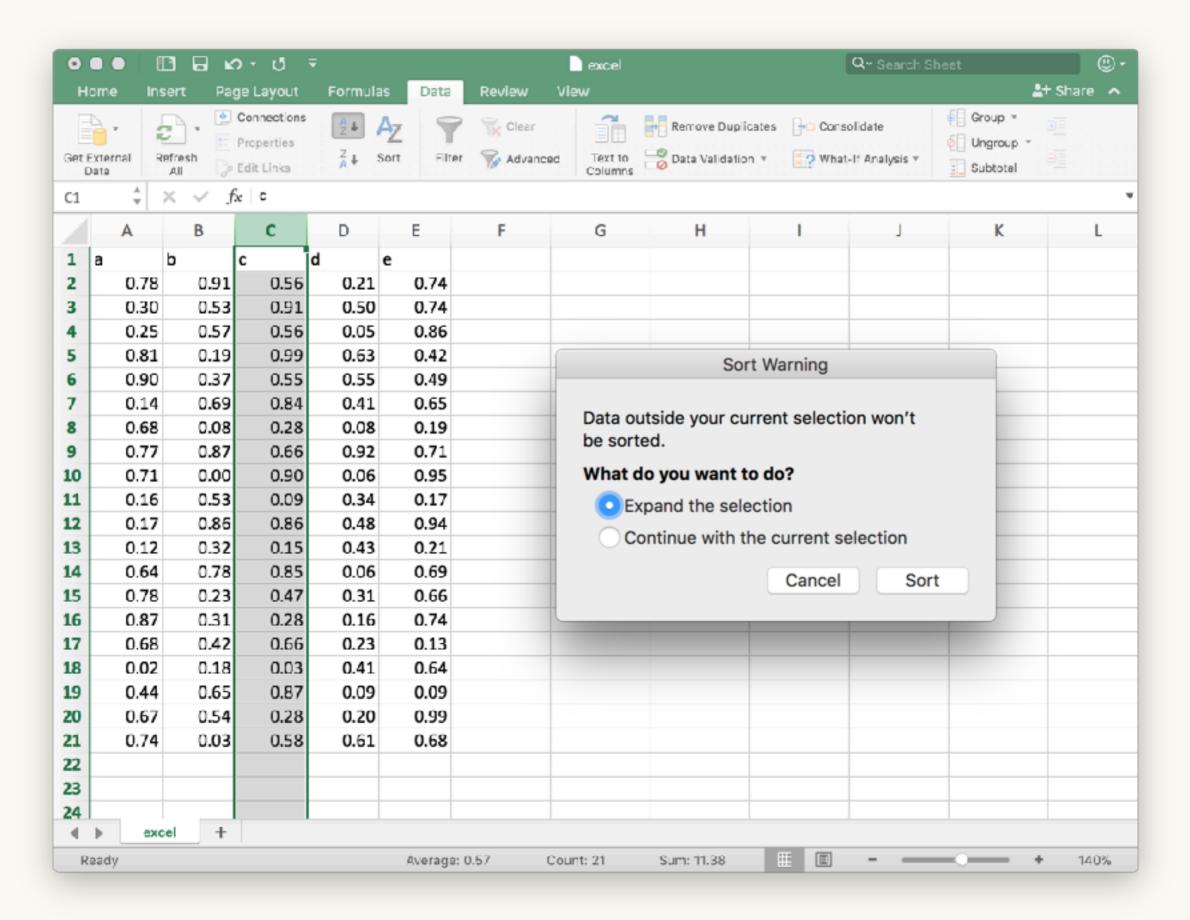
ggplot(frogs2, aes(x = distance, color = jump_n)) +
  geom_density()
```

Do professional frog jumping teams get better results? YES.

```
ggplot(frogs, aes(x = distance, color = frog_type)) +
  geom_density()
```

```
û D
                      i raw.githubusercontent.com/jennybc/frogs/master/R
# install.packages("devtools")
devtools::install_github("jennybc/frogs")
## Getting to know the frogs
At this point, all we know is that each row is one frog-jump. Frog ids coming ...
```{r}
library(frogs)
library(tidyverse)
frogs
glimpse(frogs)
An early figure. Do frogs need to warm up? Do they fatigue? Yes and yes.
```{r frog-fatigue, echo = FALSE}
frogs2 <- frogs %>%
  filter(jump n < 7) %>%
  mutate(
    jump n = as.factor(as.integer(jump n))
ggplot(frogs2, aes(x = distance, color = jump n)) +
  geom_density()
Do professional frog jumping teams get better results? YES.
```{r frog-type, echo = FALSE}
ggplot(frogs, aes(x = distance, color = frog type)) +
geom_density()
```

#### I live in fear of clicking the wrong thing



# Why program in R?

#### R is a vector language

```
x <- sample(100, 10)
x > 50
#> [1] TRUE FALSE FALSE TRUE TRUE
#> [6] TRUE TRUE FALSE FALSE TRUE
sum(x > 50)
#> [1] 6
# (There are no scalars! 🚱)
```

#### Missing values are baked in

```
y < - sample(c(1:5, NA))
#> [1] 1 NA 2 3 5 4
y > 2
#> [1] FALSE NA FALSE TRUE TRUE TRUE
y == NA
#> [1] NA NA NA NA NA NA
```

#### An example makes this clearer

```
john_age <- NA
mary_age <- NA

john_age == mary_age
#> [1] NA
```

#### Missing values are baked in

```
y \leftarrow sample(c(1:5, NA))
#> [1] 1 NA 2 3 5 4
y > 2
#> [1] FALSE NA FALSE TRUE TRUE TRUE
is.na(y)
#> [1] FALSE TRUE FALSE FALSE FALSE
```

#### So are relational tables (aka data frames/tibbles)

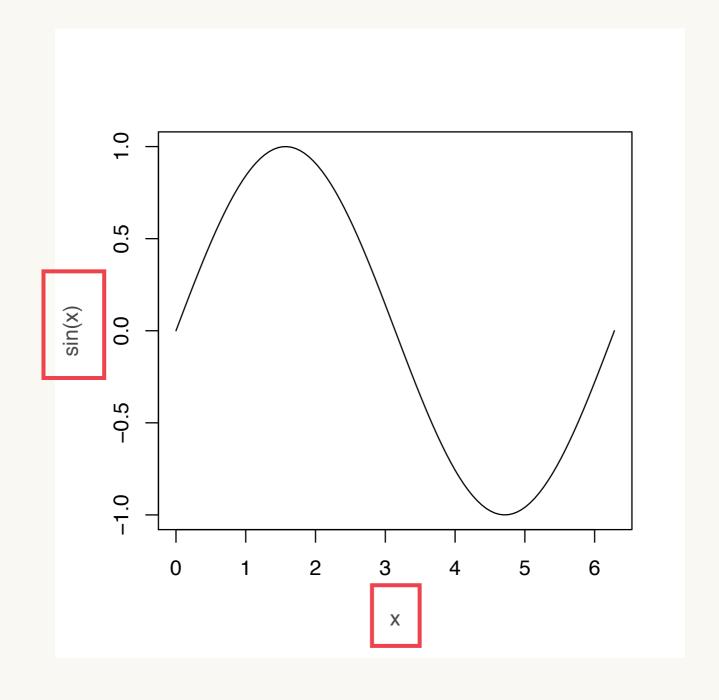
```
data.frame(
  x = 1:4,
  y = sample(letters[1:4]),
  z = runif(4)
#> x y
#> 1 1 c 0.1189635
#> 2 2 a 0.0518956
#> 3 3 b 0.4471441
#> 4 4 d 0.0818547
```

#### Functional programming

```
# It's well suited to data science but I
# can't (yet) articulate why
# Something about having a standard
# container for 80% of problems, and
# needing to do something to each element
# of that container
# Whole object thinking?
```

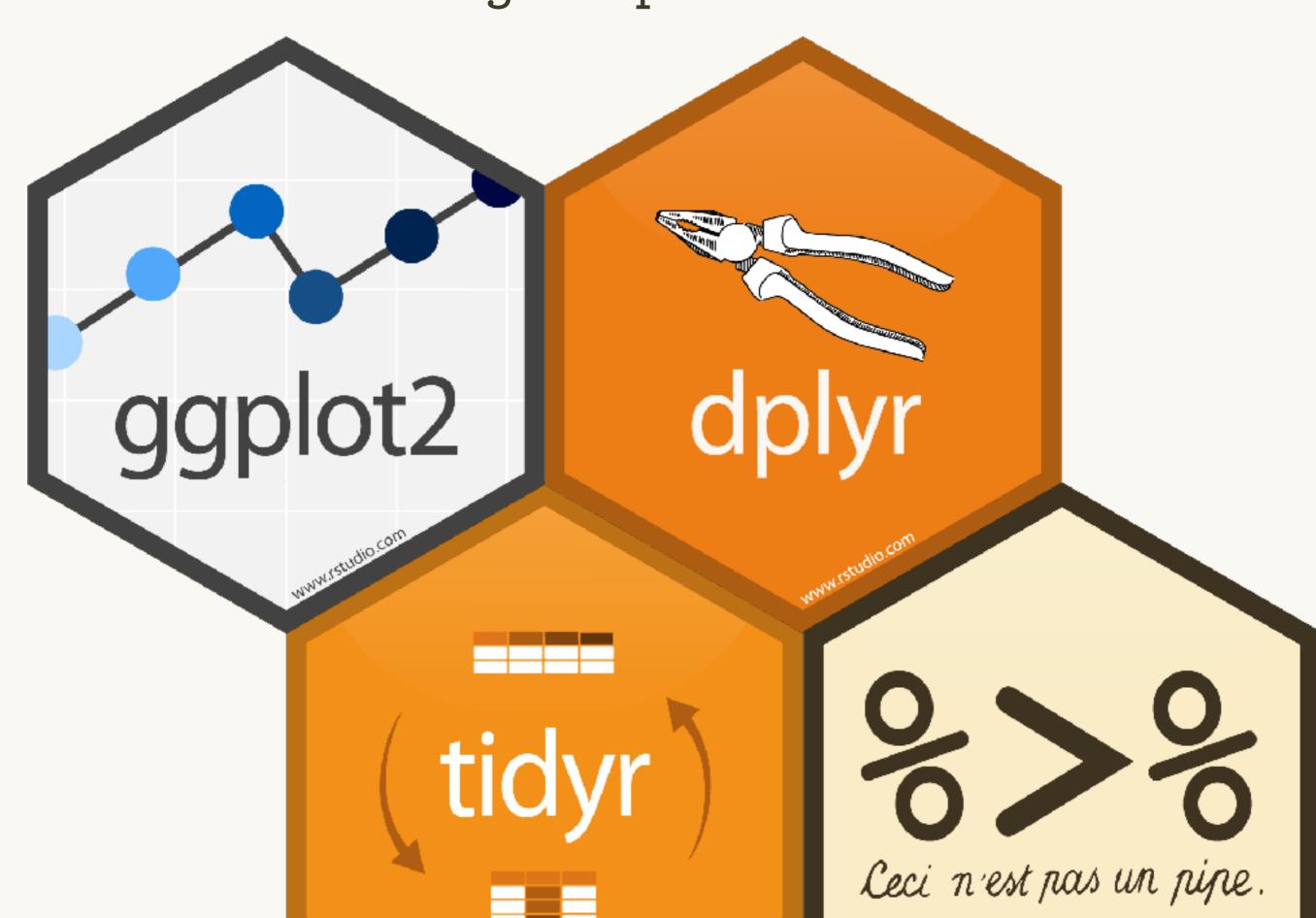
#### Metaprogramming

```
x <- seq(0, 2 * pi, length = 100)
plot(x, sin(x), type = "l")
```



```
> lobstr::ast(y <-1 + 1 + 2 * 3)
_^<-`
  | <del>|</del> 1
```

Which makes it a great place to write DSLs



# Why program in R with the tidyverse?



https://unsplash.com/photos/tjX\_sniNzgQ

# A small example

```
library(tidycensus)
geo <- get_acs(</pre>
  geography = "metropolitan statistical area...",
  variables = "DP03_0021PE",
  summary_var = "B01003_001",
  survey = "acs1",
  endyear = 2016
# Thanks to Kyle Walker (@kyle_e_walker)
# For package and example
```

# A tibble: 518 x 7

	GEOID	NAME	variable	estimate	moe	summary_est	summar
	(chr>	<chr></chr>	<chr></chr>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>
1	10140	"Aberdeen, WA Micro Area"	DP03_0021P	1.50	1.10	<b>716</b> 28	-5.56e <sup>8</sup>
2	10180	"Abilene, TX Metro Area"	DP03_0021P	1.20	0.600	<b>170</b> 860	2.84e³
3	10300	"Adrian, MI Micro Area"	DP03_0021P	0.100	0.100	98504	-5.56e <sup>8</sup>
4	10380	"Aguadilla-Isabela, PR Metro Area"	DP03_0021P	0.400	0.500	309764	1.96e³
5	10420	"Akron, OH Metro Area"	DP03_0021P	1.10	0.300	<b>702</b> 221	-5.56e <sup>8</sup>
6	10460	"Alamogordo, NM Micro Area"	DP03_0021P	0.700	1.00	65410	-5.56e <sup>8</sup>
7	10500	"Albany, GA Metro Area"	DP03_0021P	0.400	0.400	<b>152</b> 506	2.13e³
8	10540	"Albany, OR Metro Area"	DP03_0021P	0	0.100	122849	-5.56e <sup>8</sup>
9	10580	"Albany-Schenectady-Troy, NY Metro Area"	DP03_0021P	4.00	0.600	<b>881</b> 839	-5.56e <sup>8</sup>
10	10700	"Albertville, AL Micro Area"	DP03_0021P	0.800	0.800	<b>951</b> 57	-5.56e <sup>8</sup>
#	wit	h 508 more rows					

# Followed by data munging

```
big_metro <- geo %>%
  filter(summary_est > 2e6) %>%
  select(-variable) %>%
  mutate(
    NAME = gsub(" Metro Area", "", NAME)
  ) %>%
  separate(NAME, c("city", "state"), ", ") %>%
  mutate(
    city = str_extract(city, "^[A-Za-z ]+"),
    state = str_extract(state, "^[A-Za-z ]+"),
    name = paste0(city, ", ", state),
    summary_moe = na_if(summary_moe, -55555555)
```

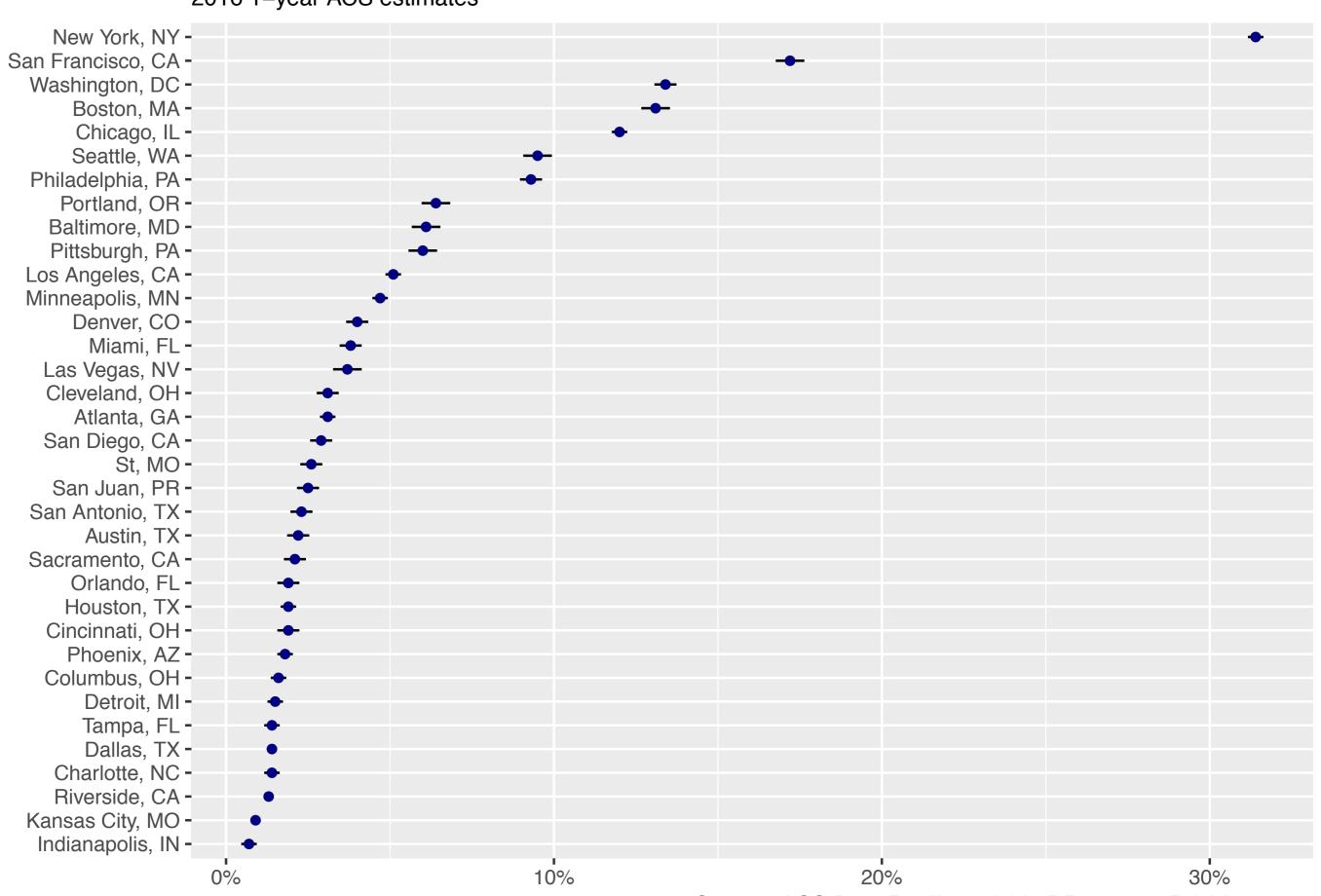
# A tibble: 35 x 8

	GEOID	city	state	estimate	moe	summary_est	summary_moe	name
	<chr></chr>	<chr></chr>	<chr></chr>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<chr></chr>
1	12060	Atlanta	GA	3.10	0.200	<b>579</b> 0210	2964	"Atlanta, GA"
2	12420	Austin	TX	2.20	0.300	2056405	NA	"Austin, TX"
3	12580	Baltimore	MD	6.10	0.400	<b>279</b> 8886	NA	"Baltimore, MD"
4	14460	Boston	MA	13.1	0.400	<b>479</b> 4447	NA	"Boston, MA"
5	16740	Charlotte	NC	1.40	0.200	<b>247</b> 4314	NA	"Charlotte, NC"
6	16980	Chicago	IL	12.0	0.200	<b>951</b> 2968	1542	"Chicago, IL"
7	17140	Cincinnati	ОН	1.90	0.300	<b>21</b> 61441	<b>445</b> 3	"Cincinnati, OH"
8	17460	Cleveland	ОН	3.10	0.300	<b>205</b> 5612	NA	"Cleveland, OH"
9	18140	Columbus	ОН	1.60	0.200	<b>204</b> 1520	NA	"Columbus, OH"
10	19100	Dallas	TX	1.40	0.100	<b>723</b> 2599	2088	"Dallas, TX"
# .	wit	th 25 more :	rows					

```
big_metro %>%
  ggplot(aes(
    x = estimate,
    y = reorder(name, estimate))
  ) +
  geom_errorbarh(
    aes(
      xmin = estimate - moe,
      xmax = estimate + moe
    width = 0.1
  ) +
  geom_point(color = "navy")
```

### Residents who take public transportation to work

2016 1-year ACS estimates



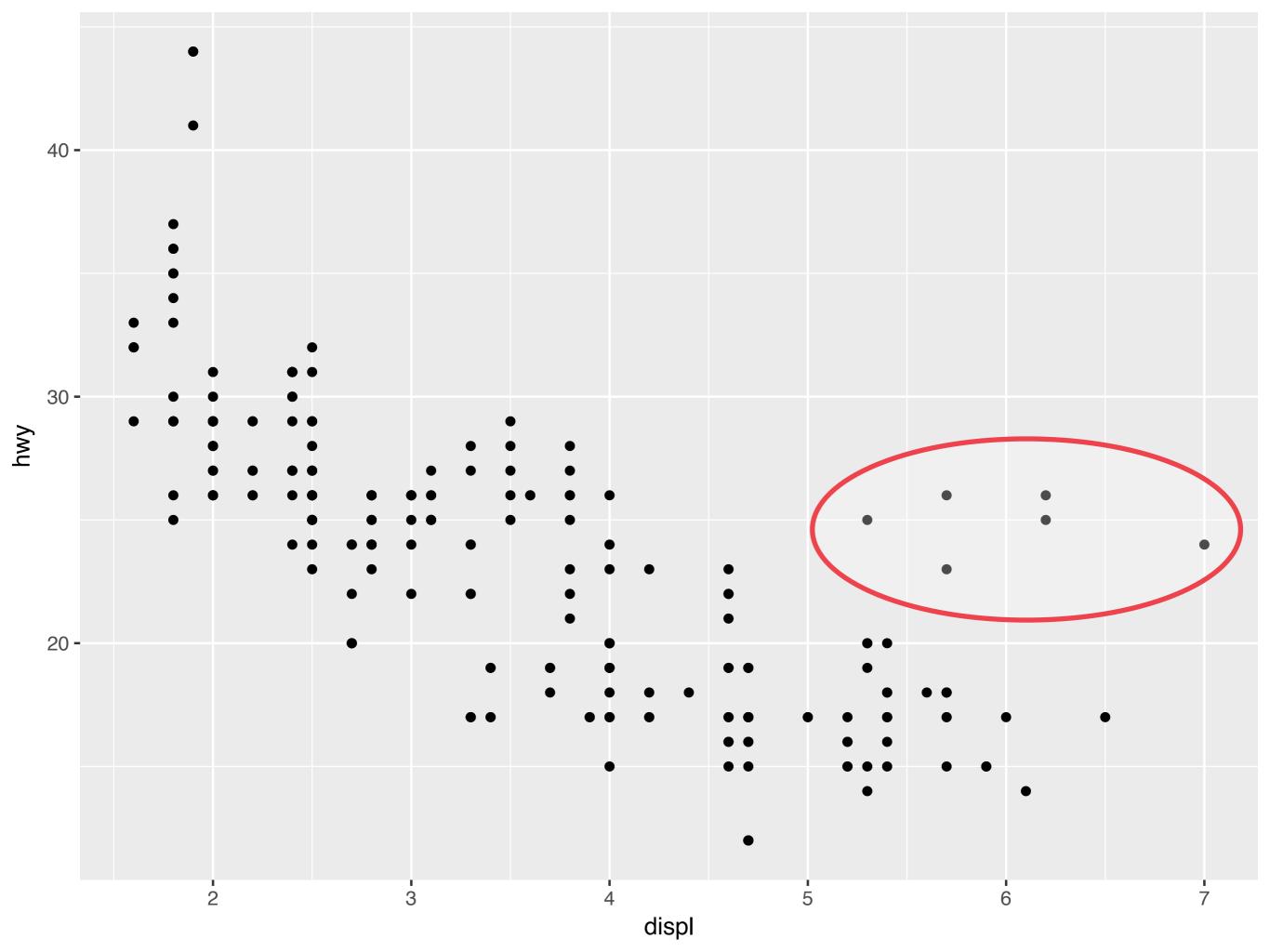
Source: ACS Data Profile variable DP03\_0021P / tidycensus

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

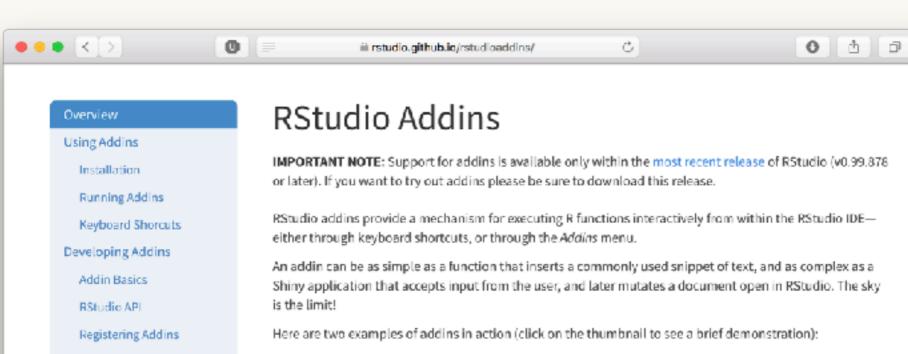


# But



# But this is painful!

```
df %>%
  select(
    date = `Date Created`,
    name = Name,
    plays = `Total Plays`,
    loads = `Total Loads`,
    apv = `Average Percent Viewed`
```



### Subset a dataset

Execution Modes

Shiny Gadgets

Gadget UI

Gadget Server

Gadget Viewer

Installation

More Examples

Putting It Together

# | The control of the

### Reformat R code



### Using Addins

This guide will walk you through the basics of installing addins, binding keyboard shorcuts to them, and finally developing your own addins.

### Installation

RStudio Addins are distributed as R packages. Once you've installed an R package that contains addins, they'll be immediately become available within RStudio.

Let's start by playing around with a couple of the example addins provided by the addinexamples package. Within RStudio, install this package (plus its requisite dependencies) with:

devtools::install\_github("rstudio/addinexamples", type = "source")

Punning Adding

# What next?

```
df %>%
  filter(n > 1e6) %>%
  mutate(x = f(y))) %>%
  ???

# How predictable is next step from
# previous steps?
```

# Can we do more with autocomplete?

```
abind
          acepack
          p addcol
          🔑 ash
          🔼 assertthat
            babynames
          backports
> library()
```

Where do dialogs and autocomplete intersect?

# Learning from examples

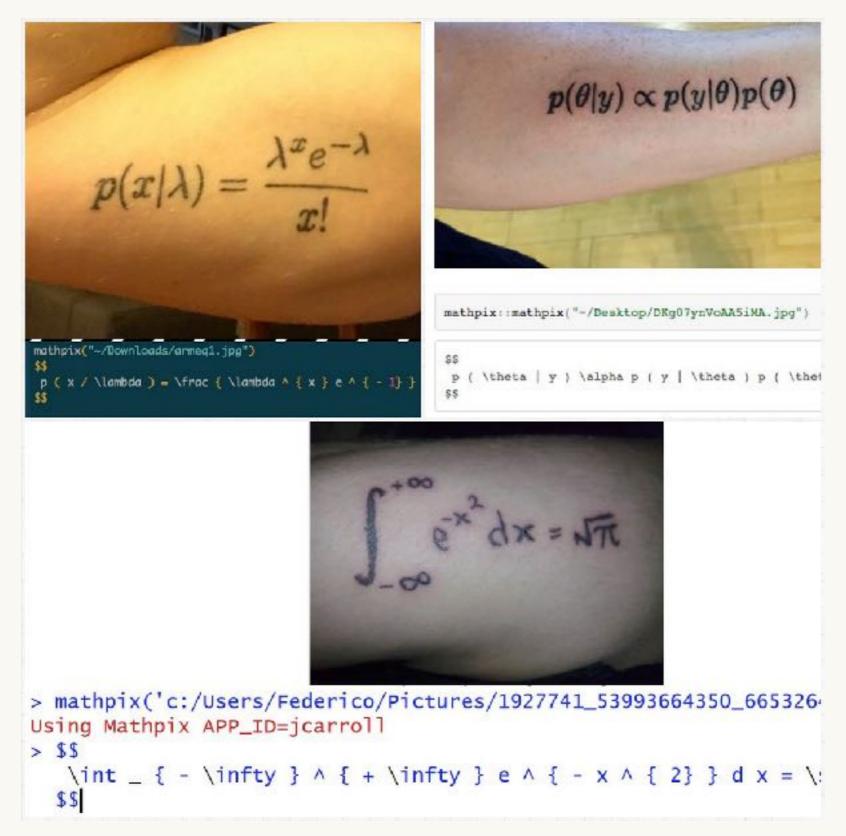
(a)

### Reported crime in Alabama

```
before:
                   {'in', ''}
                                    'Alabama' → {'Alabama', word}
(b) selection:
                   {'Alabama'}
                                    'in' \rightarrow {'in', word, lowercase}
                                    '' → {''}
     after:
                   {(''), ('in', ''), (word, ''), (lowercase, '')}
     before:
(c) selection:
                   {('Alabama'), (word)}
     after:
     {(),('Alabama'),()}
                                    \{(),(word),()\}
                                    {(word, ''),(),()}
     <del>{(','),(),()}</del>
                                    {(word, ''),('Alabama'),()}
     {(' '),('Alabama'),()}
(d) {(' '),(word),()}
                                    {(word, `'),(word),()}
     {('in', ''),(),()}
                                    {(lowercase, ' '),(),()}
     {('in', ''),('Alabama'),()} {(lowercase, ''),('Alabama'),()}
     {('in', ''),(word),()}
                                    {(lowercase, ' '),(word),()}
     \{(lowercase, '), ('Alabama'), ()\} \rightarrow /[a-z] + (Alabama)/
```

Figure 10. Regular Expression Inference. (a) The user selects text in a cell. (b) We tokenize selected and surrounding text. For clarity, the figure only includes two neighboring tokens. For each token, we generate a set of matching labels. (c) We enumerate all label sequences matching the text. (d) We then enumerate all candidate before, selection and after combinations. Patterns that do not uniquely match the selected text are filtered (indicated by strike-through). (e) Finally, we construct regular expressions for each candidate pattern.

# What about deep learning?



https://twitter.com/carroll\_jono/status/914254139873361920

# Conclusion

# I believe that:

- 1. Huge advantages to code
- 2. R provides great environment
- 3. DSLs help express your thoughts
- 4. Code should be primary artefact (but might be generated other than typing)