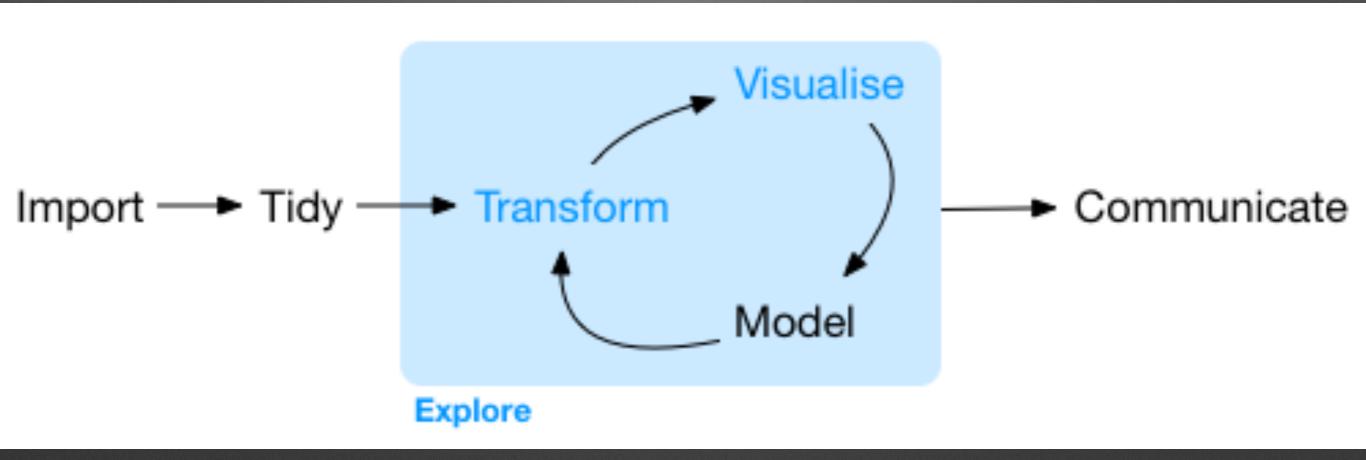
tidyverse[c("magrittr", "dplyr", "tidyr")]

Barret Schloerke Statistics PhD Candidate Purdue University

About myself

- Purdue University
 - 5th Year PhD Candidate in Statistics
 - Research in large data visualization using R deltarho.org
 - Dr. William Cleveland and Dr. Ryan Hafen
- Metamarkets.com 1.5 years
 - Front end engineer node.js
- Iowa State University
 - B.S. in Computer Engineering
 - Research in statistical data visualization with R
 - · Dr. Di Cook, Dr. Hadley Wickham, and Dr. Heike Hofmann

Exploratory Data Analysis



Magrittr

- "structuring sequences of data operations left-to-right (as opposed to from the inside and out),
- avoiding nested function calls,
- minimizing the need for local variables and function definitions, and
- making it easy to add steps anywhere in the sequence of operations."

Children's Story Example

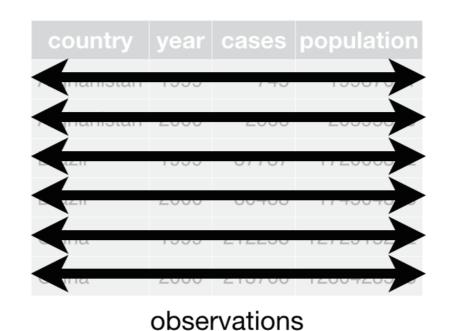
```
foo_foo <- little_bunny()</pre>
bop_on(
  scoop_up(
    hop_through(
      foo_foo,
      forest
    field_mouse
  head
```

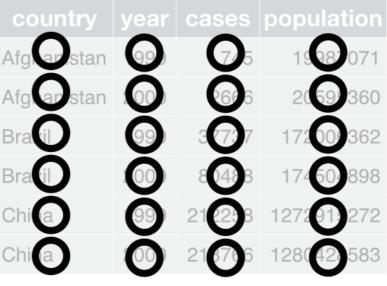
```
foo_foo %>%
  hop_through(forest) %>%
  scoop_up(field_mouse) %>%
  bop_on(head)
```

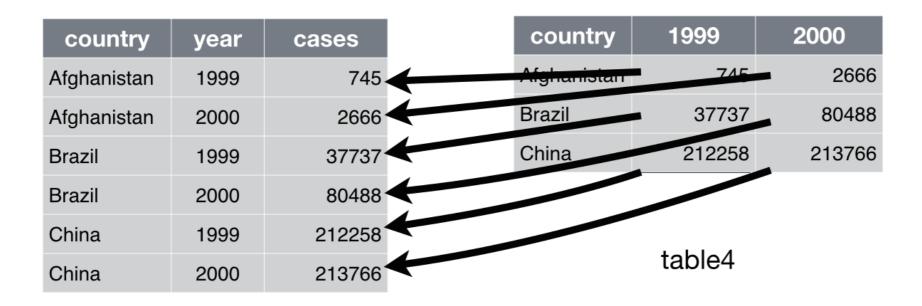
 "Happy families are all alike; every unhappy family is unhappy in its own way." — Leo Tolstoy

 "Tidy datasets are all alike, but every messy dataset is messy in its own way." — Hadley Wickham

country	year	cases	population
Afghanstan	100	45	18:57071
Afghanistan	2000	2666	20!95360
Brazil	1999	37737	172006362
Brazil	2000	80488	174904898
China	1999	212258	1272915272
Chin	200	21 66	1280 28583
variables			







http://r4ds.had.co.nz/tidy-data.html

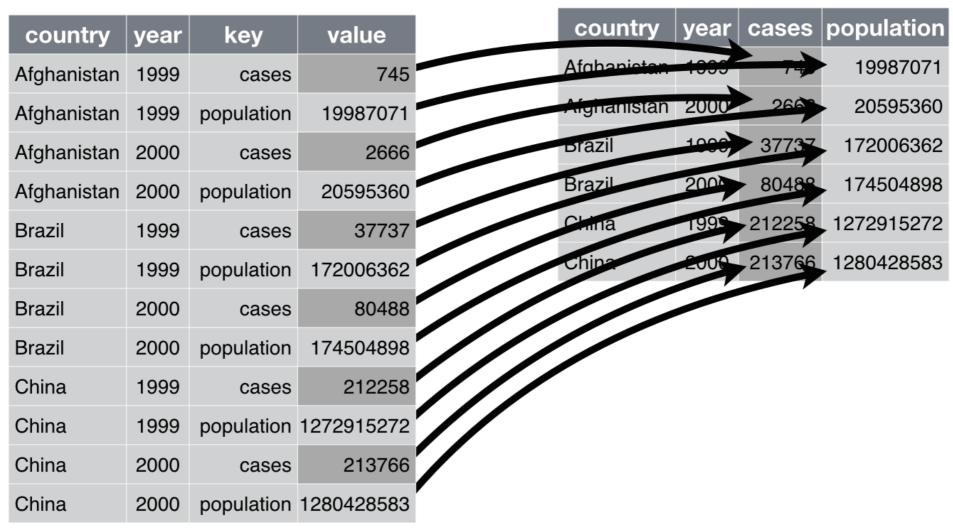


table2

- Disadvantages
 - More work after data is loaded
 - May require slightly more memory (~1 3x)
- Advantage
 - Consistent storage structure speeds up learning curve
 - Leverage the power of R's vector operations

When to NOT use tidy Data

 Alternative representations may have substantial performance or space advantages.

 Specialized fields have evolved their own conventions for storing data that may be quite different to the conventions of tidy data.

dplyr

- dplyr is the next iteration of plyr, focussed on tools for working with data frames (hence the d in the name). It has three main goals:
 - Identify the most important data manipulation tools needed for data analysis and make them easy to use from R.
 - Provide blazing fast performance for in-memory data by writing key pieces in C++.
 - Use the same interface to work with data no matter where it's stored, whether in a data frame, a data table or database.

dplyr verbs

- select(): focus on a subset of variables
- filter(): focus on a subset of rows
- mutate(): add new columns
- summarise(): reduce each group to a smaller number of summary statistics
- arrange(): re-order the rows
- group_by(): add subset rule for summarizations

dplyr example

```
library(nycflights13)
dim(flights)
#> [1] 336776 19
head(flights)
#> # A tibble: 6 x 19
#> year month day dep_time sched_dep_time dep_delay arr_time
#> <int> <int> <int> <int>
                                               <dbl> <int>
                                 <int>
#> 1 2013 1
                         517
                                        515
                                                         830
#> 2 2013 1
                          533
                                        529
                                                         850
#> 3 2013 1
                          542
                                        540
                                                         923
#> 4 2013
                          544
                                        545
                                                         1004
#> ... with 2 more rows, and 12 more variables: sched_arr_time <int>,
    arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#>
    origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour
#>
<db1>.
    minute <dbl>, time_hour <time>
#>
```

https://cran.rstudio.com/web/packages/dplyr/vignettes/introduction.html

dplyr::mutate

```
mutate(flights,
  gain = arr_delay - dep_delay,
  gain_per_hour = gain / (air_time / 60)
#> # A tibble: 336,776 x 21
     year month day dep_time sched_dep_time dep_delay arr_time
#>
#> <int> <int> <int> <int> <int> <int> 
#> 1 2013 1 1
                                       515
                         517
                                                        830
#> 2 2013 1 1 533
#> 3 2013 1 1 542
                                     529
                                                        850
                                     540
                                                        923
#> 4 2013 1 1
                         544
                                       545
                                                       1004
#> ... with 336,772 more rows, and 14 more variables: sched_arr_time <int>,
#> arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#>
    minute <dbl>, time_hour <time>, gain <dbl>, gain_per_hour <dbl>
#>
```

dplyr::transmute

dplyr::summarise

dplyr::sample_n dplyr::sample_frac

```
#> # A tibble: 10 x 19
     vear month
                  day dep_time sched_dep_time dep_delay arr_time
    <int> <int>
                        <int>
                                                 <dbl>
                                                         <int>
                                       <int>
#> 1 2013
                         2205
                                        2019
                                                   106
                                                          103
#> 2 2013
                        1602
                                        1545
                                                   17
                                                           NA
     2013 11 4
                         1459
                                        1459
                                                          1642
    2013
                         1354
                                        1350
                                                          1534
#> ... with 6 more rows, and 12 more variables: sched_arr_time <int>,
    arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
    origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
    minute <dbl>, time_hour <time>
sample_frac(flights, 0.01)
#> # A tibble: 3,368 x 19
     year month day dep_time sched_dep_time dep_delay arr_time
#>
    <int> <int> <int> <int>
                                       <int>
                                                 <dbl>
                                                         <int>
#> 1 2013 5 14
                                         850
                          850
                                                         1237
#> 2 2013 11 8
                          832
                                         840
                                                         1016
     2013
          12
                                                          1309
                         1155
                                        1155
#> 4 2013
                          929
                                         925
                                                          1220
#> ... with 3,364 more rows, and 12 more variables: sched_arr_time <int>,
    arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
    origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#>
    minute <dbl>, time_hour <time>
```

sample_n(flights, 10)

dplyr Example

Source: local data frame [49 x 5]

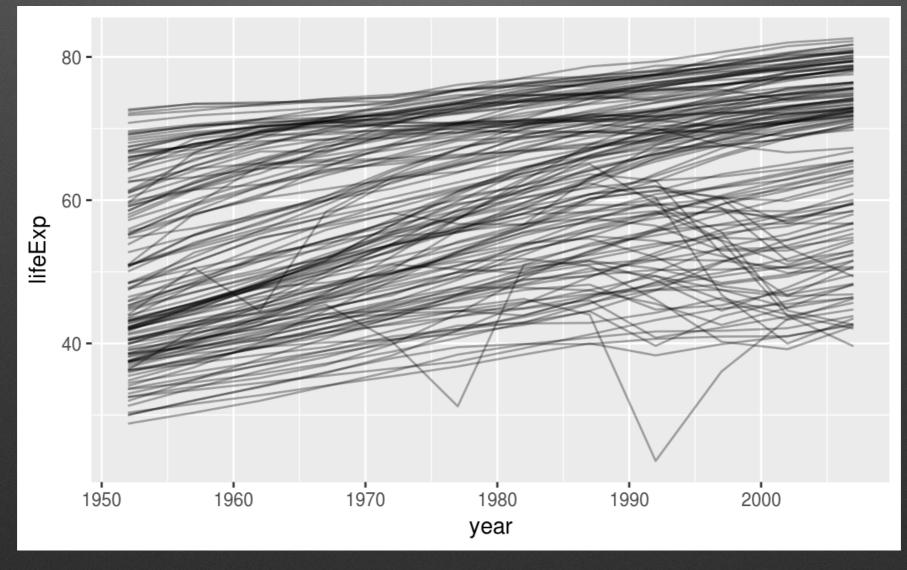
```
Groups: year, month [11]
flights %>%
                                                 year month
                                                            day arr
                                                                            dep
                                                <int> <int> <dbl>
                                                                          <db1>
  group_by(year, month, day) %>%
                                                 2013
                                                             16 34.24736 24.61287
  select(arr_delay, dep_delay) %>%
                                                 2013
                                                             31 32.60285 28.65836
                                                2013
2013
  summarise(
                                                                36.29009 39.07360
                                                             27 31.25249 37.76327
    arr = mean(arr_delay, na.rm = TRUE),
                                                 2013
                                                             8 85.86216 83.53692
    dep = mean(dep_delay, na.rm = TRUE)
                                                2013
                                                             18 41.29189 30.11796
  ) %>%
                                                2013
                                                             10 38.41231 33.02368
                                                 2013
                                                             12 36.04814 34.83843
  filter(arr > 30 | dep > 30)
                                                             18 36.02848 34.91536
                                                 2013
                                                2013
                                                             19 47.91170 46.12783
                                              # ... with 39 more rows
```

gapminder

```
library(gapminder)
gapminder
#> # A tibble: 1,704 x 6
#>
        country continent year lifeExp
                                         pop gdpPercap
                                                <dbl>
                 <fctr> <int>
                               <dbl>
#>
        <fctr>
                                       <int>
                   Asia 1952 28.8 8425333
#> 1 Afghanistan
                                                  779
#> 2 Afghanistan
                   Asia 1957 30.3 9240934
                                                  821
                   Asia 1962 32.0 10267083
#> 3 Afghanistan
                                                 853
#> 4 Afghanistan
                   Asia 1967 34.0 11537966
                                                 836
#> 5 Afghanistan Asia 1972 36.1 13079460
                                                 740
#> 6 Afghanistan
                   Asia 1977 38.4 14880372
                                                  786
#> # ... with 1,698 more rows
```

gapminder

```
gapminder %>%
   ggplot(aes(year, lifeExp, group = country)) +
   geom_line(alpha = 1/3)
```



http://r4ds.had.co.nz/many-models.html#nested-data

gapminder goals

- Want to compute a linear model for each country
- Want to see how well each country's life expectancy follows a linear model

data.frame() rules

- All data.frame()'s are lists
- All columns have the same length
- Each column (or list section) is of the same type

- Important!!
 - Lists may contain lists!

gapminder

```
group_by(country, continent) %>%
 nest()
by_country
# A tibble: 142 x 3
      country continent
                                     data
                                   st>
       <fctr>
                 <fctr>
  Afghanistan Asia <tibble [12 x 4]>
      Albania Europe <tibble [12 x 4]>
      Algeria Africa <tibble [12 x 4]>
       Angola
                 Africa <tibble [12 x 4]>
    Argentina
               Americas <tibble [12 x 4]>
               Oceania <tibble [12 x 4]>
    Australia
                 Europe <tibble [12 x 4]>
      Austria
                   Asia <tibble [12 \times 4]>
8
      Bahrain
                   Asia <tibble [12 x 4]>
   Bangladesh
                 Europe <tibble [12 x 4]>
      Belgium
  ... with 132 more rows
```

by_country <- gapminder %>%

gapminder: find model

```
country_model <- function(df) {
   lm(lifeExp ~ year, data = df)
}
models <- map(by_country$data, country_model)</pre>
```

gapminder: find model

```
by_country <- by_country %>%
 mutate(model = purrr::map(data, country_model))
by_country
#> # A tibble: 142 x 4
#> country continent
                          data model
#>
     <fctr> <fctr> <list> <list>
#> 2 Albania Europe <tibble [12 x 4]> <S3: lm>
#> 3 Algeria Africa <tibble [12 x 4]> <S3: lm>
#> 4 Angola Africa <tibble [12 x 4]> <S3: lm>
#> 5 Argentina Americas <tibble [12 x 4]> <S3: lm>
#> 6 Australia
              Oceania <tibble [12 x 4]> <S3: lm>
#> # ... with 136 more rows
```

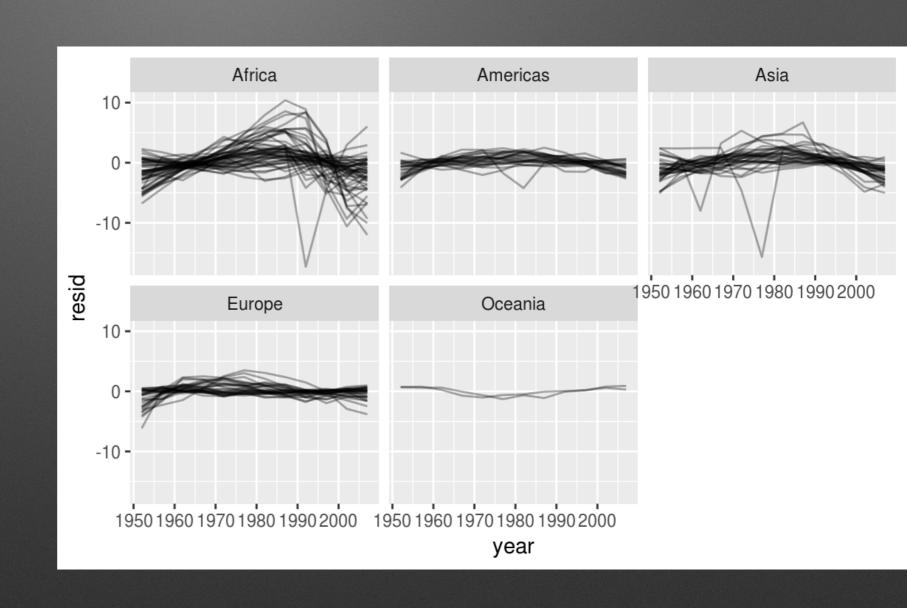
gapminder: residuals (use dplyr!)

```
by_country <- by_country %>%
 mutate(
   resids = purrr::map2(data, model, modelr::add_residuals)
by_country
#> # A tibble: 142 x 5
       country continent
                          data model
                                                   resids
#>
                        <fctr> <fctr>
                                                  t>
#>
#> 2 Albania Europe <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
\#>3 Algeria Africa <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
#> 4 Angola Africa <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
#> 5 Argentina Americas <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
#> 6 Australia Oceania <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
#> # ... with 136 more rows
```

gapminder: unnest

```
resids <- unnest(by_country, resids)</pre>
resids
#> # A tibble: 1,704 x 7
                                        pop gdpPercap
       country continent year lifeExp
#>
                                                     resid
        <fctr>
                 <fctr> <int>
                              <dbl> <int>
                                               <dbl>
                                                      <dbl>
#>
#> 1 Afghanistan
                   Asia 1952 28.8 8425333
                                                 779 -1.1063
  2 Afghanistan
                   Asia 1957 30.3 9240934
                                                 821 -0.9519
#> 3 Afghanistan Asia 1962 32.0 10267083
                                                 853 -0.6636
#> 4 Afghanistan Asia 1967 34.0 11537966
                                                 836 -0.0172
#> 5 Afghanistan Asia 1972 36.1 13079460
                                                 740 0.6741
#> 6 Afghanistan
              Asia 1977
                            38.4 14880372
                                                 786 1.6475
#> # ... with 1,698 more rows
```

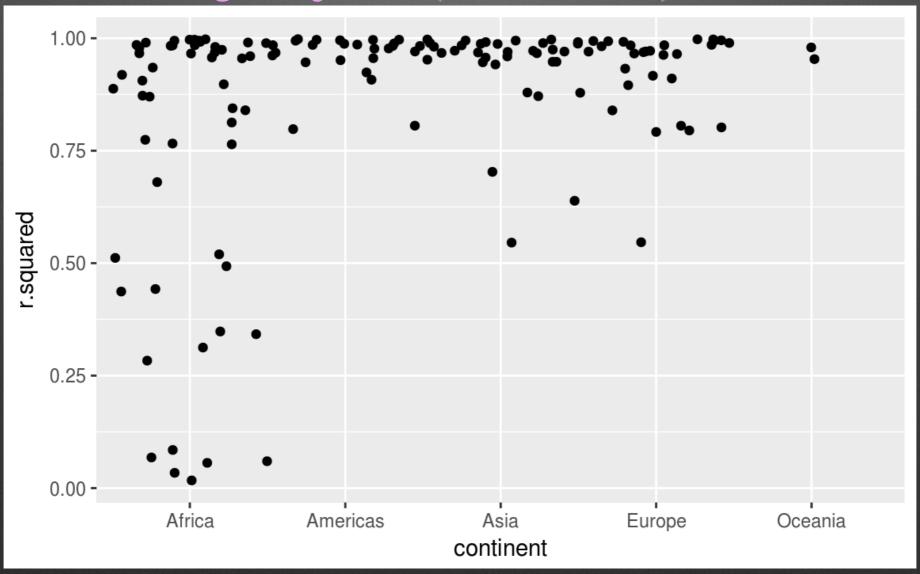
```
resids %>%
  ggplot(
    aes(
      x = year,
      y = resid,
      group = country
    geom_line(
      alpha = 1 / 3
    facet_wrap(
      ~continent
```



```
by_country %>%
 mutate(glance = purrr::map(model, broom::glance)) %>%
 unnest(glance)
#> # A tibble: 142 x 16
#> country continent
                               data model
                                                    resids
      <fctr> <fctr> <list> <list> <list>
#>
#> 1 Afghanistan Asia <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
#> 2 Albania Europe <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
#> 3 Algeria Africa <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
#> 4
      Angola Africa <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
#> 5 Argentina Americas <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
#> 6 Australia Oceania <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
    ... with 136 more rows, and 11 more variables: r.squared <dbl>,
#> #
      adj.r.squared <dbl>, sigma <dbl>, statistic <dbl>, p.value <dbl>,
#> #
      df <int>, logLik <dbl>, AIC <dbl>, BIC <dbl>, deviance <dbl>,
#> #
      df.residual <int>
#> #
```

```
glance <- by_country %>%
 mutate(glance = purrr::map(model, broom::glance)) %>%
 unnest(glance, .drop = TRUE)
glance
#> # A tibble: 142 x 13
  country continent r.squared adj.r.squared sigma statistic p.value
#>
                <fctr> <dbl> <dbl> <dbl>
      <fctr>
                                                   <db1>
                                                           <db1>
#>
#> 1 Afghanistan Asia 0.948
                                     0.942 1.223
                                                   181.2 9.84e-08
                                     0.902 1.983
#> 2 Albania Europe 0.911
                                                   101.8 1.46e-06
#> 3 Algeria Africa 0.985
                                     0.984 1.323
                                                   661.9 1.81e-10
#> 4 Angola Africa 0.888 0.877 1.407 79.1 4.59e-06
                                     0.995 0.292 2246.4 4.22e-13
#> 5 Argentina Americas 0.996
#> 6 Australia Oceania
                          0.980
                                     0.978 0.621 481.3 8.67e-10
#> # ... with 136 more rows, and 6 more variables: df <int>, logLik <dbl>,
#> # AIC <dbl>, BIC <dbl>, deviance <dbl>, df.residual <int>
```

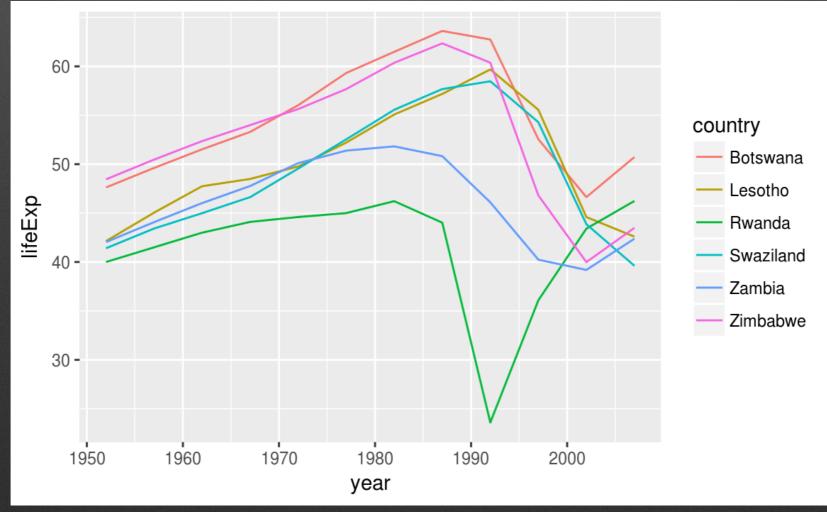
```
glance %>%
   ggplot(aes(continent, r.squared)) +
   geom_jitter(width = 0.5)
```



http://r4ds.had.co.nz/many-models.html#unnesting

bad_fit <- filter(glance, r.squared < 0.25)</pre>

```
gapminder %>%
  semi_join(bad_fit, by = "country") %>%
  ggplot(aes(year, lifeExp, colour = country)) +
    geom_line()
```



http://r4ds.had.co.nz/many-models.html#unnesting

Recap

- · magrittr
 - Keep code readable
- · dplyr
 - Works with data.frames
- · tidyr
 - Nest your data.frames

Questions?