# tidyverse

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## What is the tidyverse?

The tidyverse is a suite of R tools that follow a tidy philosophy:

### Tidy data

Put data in data frames

- Each dataset gets a data frame
- Each variable gets a column
- Each observation gets a row

Reuse existing data structures whenever possible!

### Tidy APIs

Functions should be consistent and easily (human) readable

- Take one step at a time
- Connect simple steps with the pipe

### Okay but really, what is it?

Suite of ~20 packages that provide consistent, user-friendly, smart-default tools to do most of what most people do in R.

- Core packages: ggplot2, dplyr, tidyr, readr, purrr, tibble
- Specialized data manipulation: hms, stringr, lubridate, forcats
- Data import: DBI, haven, httr, jsonlite, readxl, rvest, xml2
- Modeling: modelr, broom

`install.packages(tidyverse)` installs all of the above packages.

`library(tidyverse)` attaches only the core packages.

## Why tidyverse?

- Consistency
  - e.g. All `stringr` functions take string first
  - e.g. Many functions take data.frame first -> piping
    - Faster to write
    - Easier to read
  - Tidy data: Imposes good practices
  - Type specificity
- Implements simple solutions to common problems (e.g. `purrr::transpose`)
- Smarter defaults

  - e.g. `utils::write.csv(row.names = FALSE)` = `readr::write_csv()`
- Runs fast (thanks to `Rcpp`)
- Interfaces well with other tools (e.g. Spark with `dplyr` via `sparklyr`)

### tibble

A modern reimagining of data frames.

```
# note that this only attaches the core packages
library(tidyverse)
```

```
tdf <- tibble(x = 1:1e4, y = rnorm(1e4))    # == data_frame(x = 1:1e4, y = rnorm(1e4))
class(tdf)
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

Tibbles print politely.

```
tdf
```

```
## # A tibble: 10,000 × 2
##        x           y
##    <int>       <dbl>
## 1      1  0.32232309
## 2      2  1.49373062
## 3      3 -1.26928825
## 4      4  0.05351232
## 5      5 -0.81463451
## 6      6  0.58492395
## 7      7 -1.10531244
## 8      8  0.53060805
## 9      9 -0.97979281
## 10    10 -0.10480043
## # ... with 9,990 more rows
```

- Can customize print methods with `print(tdf, n = rows, width = cols)`
- Set default with `options(tibble.print_max = rows, tibble.width = cols)`

Tibbles have some convenient and consistent defaults that are different from base R data.frames.

#### strings as factors

```
dfs <- list(df = data.frame(abc = letters[1:3], xyz = letters[24:26]),
            tbl = data_frame(abc = letters[1:3], xyz = letters[24:26])
            )
sapply(dfs, function(d) class(d$abc))
```

```
##          df         tbl
##    "factor" "character"
```

#### partial matching of names

```
sapply(dfs, function(d) d$a)
```

```
## Warning: Unknown column 'a'
```

```
## $df
## [1] a b c
## Levels: a b c
##
## $tbl
## NULL
```

#### type consistency

```
sapply(dfs, function(d) class(d[, "abc"]))
```

```
## $df
## [1] "factor"
##
## $tbl
## [1] "tbl_df"     "tbl"        "data.frame"
```

Note that tidyverse import functions (e.g. `readr::read_csv`) default to tibbles and that *this can break existing code*.

#### List-columns!

```
tibble(ints = 1:5,
       powers = lapply(1:5, function(x) x^(1:x)))
```

```
## # A tibble: 5 × 2
##    ints    powers
##   <int>    <list>
## 1     1 <dbl [1]>
## 2     2 <dbl [2]>
## 3     3 <dbl [3]>
## 4     4 <dbl [4]>
## 5     5 <dbl [5]>
```

### The pipe %>%

Sends the output of the LHS function to the first argument of the RHS function.

```
sum(1:8) %>%
  sqrt()
```

```
## [1] 6
```

### dplyr

Common data(frame) manipulation tasks.

Four core "verbs": filter, select, arrange, group_by + summarize, plus many more convenience functions.

```
library(ggplot2movies)
str(movies)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    58788 obs. of  24 variables:
##  $ title      : chr  "$" "$1000 a Touchdown" "$21 a Day Once a Month" "$40,000" ...
##  $ year       : int  1971 1939 1941 1996 1975 2000 2002 2002 1987 1917 ...
```

```
##  $ length     : int  121 71 7 70 71 91 93 25 97 61 ...
##  $ budget     : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ rating     : num  6.4 6 8.2 8.2 3.4 4.3 5.3 6.7 6.6 6 ...
##  $ votes      : int  348 20 5 6 17 45 200 24 18 51 ...
##  $ r1         : num  4.5 0 0 14.5 24.5 4.5 4.5 4.5 4.5 4.5 ...
##  $ r2         : num  4.5 14.5 0 0 4.5 4.5 0 4.5 4.5 0 ...
##  $ r3         : num  4.5 4.5 0 0 0 4.5 4.5 4.5 4.5 4.5 ...
##  $ r4         : num  4.5 24.5 0 0 14.5 14.5 4.5 4.5 0 4.5 ...
##  $ r5         : num  14.5 14.5 0 0 14.5 14.5 24.5 4.5 0 4.5 ...
##  $ r6         : num  24.5 14.5 24.5 0 4.5 14.5 24.5 14.5 0 44.5 ...
##  $ r7         : num  24.5 14.5 0 0 0 4.5 14.5 14.5 34.5 14.5 ...
##  $ r8         : num  14.5 4.5 44.5 0 0 4.5 4.5 14.5 14.5 4.5 ...
##  $ r9         : num  4.5 4.5 24.5 34.5 0 14.5 4.5 4.5 4.5 4.5 ...
##  $ r10        : num  4.5 14.5 24.5 45.5 24.5 14.5 14.5 14.5 24.5 4.5 ...
##  $ mpaa       : chr  "" "" "" "" ...
##  $ Action     : int  0 0 0 0 0 0 1 0 0 0 ...
##  $ Animation  : int  0 0 1 0 0 0 0 0 0 0 ...
##  $ Comedy     : int  1 1 0 1 0 0 0 0 0 0 ...
##  $ Drama      : int  1 0 0 0 0 1 1 0 1 0 ...
##  $ Documentary: int  0 0 0 0 0 0 0 1 0 0 ...
##  $ Romance    : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Short      : int  0 0 1 0 0 0 0 1 0 0 ...
```

```
filter(movies, length > 360)
```

```
## # A tibble: 21 × 24
##                                             title  year length  budget
##                                             <chr> <int>  <int>   <int>
## 1                          Commune (Paris, 1871), La  2000    555      NA
## 2                             Cure for Insomnia, The  1987   5220      NA
## 3             Ebolusyon ng isang pamilyang pilipino  2004    647      NA
## 4                                          Empire  1964    485      NA
## 5                                Farmer's Wife, The  1998    390      NA
## 6                                     Foolish Wives  1922    384 1100000
## 7                                       Four Stars  1967   1100      NA
## 8                  Hitler - ein Film aus Deutschland  1978    407      NA
## 9                                Imitation of Christ  1967    480      NA
## 10 Longest Most Meaningless Movie in the World, The  1970   2880      NA
## # ... with 11 more rows, and 20 more variables: rating <dbl>, votes <int>,
## #   r1 <dbl>, r2 <dbl>, r3 <dbl>, r4 <dbl>, r5 <dbl>, r6 <dbl>, r7 <dbl>,
## #   r8 <dbl>, r9 <dbl>, r10 <dbl>, mpaa <chr>, Action <int>,
## #   Animation <int>, Comedy <int>, Drama <int>, Documentary <int>,
## #   Romance <int>, Short <int>
```

```
filter(movies, length > 360) %>%
  select(title, rating, votes)
```

```
## # A tibble: 21 × 3
##                                             title rating votes
##                                             <chr>  <dbl> <int>
## 1                          Commune (Paris, 1871), La    7.8    33
## 2                             Cure for Insomnia, The    3.8    59
## 3             Ebolusyon ng isang pamilyang pilipino    8.4     5
## 4                                          Empire    5.5    46
## 5                                Farmer's Wife, The    8.5    52
```

```
## 6                                    Foolish Wives    7.6   191
## 7                                       Four Stars    3.0    12
## 8                  Hitler - ein Film aus Deutschland    9.0    70
## 9                                Imitation of Christ    4.4     5
## 10 Longest Most Meaningless Movie in the World, The    6.4    15
## # ... with 11 more rows
```

```
filter(movies, Animation == 1, votes > 1000) %>%
  select(title, rating) %>%
  arrange(desc(rating))
```

```
## # A tibble: 135 × 2
##                                  title rating
##                                  <chr>  <dbl>
## 1         Sen to Chihiro no kamikakushi    8.6
## 2                             Duck Amuck    8.4
## 3  Wallace & Gromit: The Wrong Trousers    8.4
## 4                           Finding Nemo    8.3
## 5                         Hotaru no haka    8.3
## 6                       Incredibles, The    8.3
## 7                          Mononoke-hime    8.3
## 8                    What's Opera, Doc?    8.3
## 9                                Vincent    8.2
## 10      Wallace & Gromit: A Close Shave    8.2
## # ... with 125 more rows
```

`summarize` makes `aggregate` and `tapply` functionality easier, and the output is always a data frame.

```
filter(movies, mpaa != "") %>%
  group_by(year, mpaa) %>%
  summarize(avg_budget = mean(budget, na.rm = TRUE),
            avg_rating = mean(rating, na.rm = TRUE)) %>%
  arrange(desc(year), mpaa)
```

```
## Source: local data frame [128 x 4]
## Groups: year [54]
##
##     year  mpaa avg_budget avg_rating
##    <int> <chr>      <dbl>      <dbl>
## 1   2005 NC-17        NaN   6.700000
## 2   2005    PG   45857143   5.733333
## 3   2005 PG-13   42269333   5.326087
## 4   2005     R   24305882   4.595833
## 5   2004    PG   45126852   5.847619
## 6   2004 PG-13   46288254   6.080180
## 7   2004     R   19548519   5.848469
## 8   2003    PG   37057692   5.897674
## 9   2003 PG-13   46269491   5.949038
## 10  2003     R   21915505   5.702273
## # ... with 118 more rows
```

`count` for frequency tables. Note the consistent API and easy readability vs. `table`.

```
filter(movies, mpaa != "") %>%
  count(year, mpaa, Animation, sort = TRUE)
```

```
## Source: local data frame [156 x 4]
```

```
## Groups: year, mpaa [128]
##
##     year  mpaa Animation     n
##    <int> <chr>     <int> <int>
## 1   1999     R         0   366
## 2   2001     R         0   355
## 3   2002     R         0   343
## 4   2000     R         0   341
## 5   1998     R         0   335
## 6   1997     R         0   325
## 7   1996     R         0   310
## 8   1995     R         0   293
## 9   2003     R         0   264
## 10  2004     R         0   196
## # ... with 146 more rows
```

```
basetab <- with(movies[movies$mpaa != "", ], table(year, mpaa, Animation))
basetab[1:5, , ]
```

```
## , , Animation = 0
##
##       mpaa
## year   NC-17 PG PG-13 R
##   1934     0  1     0 0
##   1938     0  1     0 0
##   1945     0  0     1 0
##   1946     0  1     0 0
##   1951     0  2     0 0
##
## , , Animation = 1
##
##       mpaa
## year   NC-17 PG PG-13 R
##   1934     0  0     0 0
##   1938     0  0     0 0
##   1945     0  0     0 0
##   1946     0  0     0 0
##   1951     0  0     0 0
```

### joins

dplyr also does multi-table joins and can connect to various types of databases.

```
t1 <- data_frame(alpha = letters[1:6],
                 num = 1:6)
t2 <- data_frame(alpha = letters[4:10],
                 num = 4:10)
full_join(t1, t2, by = "alpha", suffix = c("_t1", "_t2"))
```

```
## # A tibble: 10 × 3
##    alpha num_t1 num_t2
##    <chr>  <int>  <int>
## 1      a      1     NA
## 2      b      2     NA
## 3      c      3     NA
```

```
## 4      d      4      4
## 5      e      5      5
## 6      f      6      6
## 7      g     NA      7
## 8      h     NA      8
## 9      i     NA      9
## 10     j     NA     10
```

### tidyr

Latest generation of `reshape`. `gather` to make wide table long, `spread` to make long tables wide.

```
who  # Tuberculosis data from the WHO
```

```
## # A tibble: 7,240 × 60
##        country  iso2  iso3  year new_sp_m014 new_sp_m1524 new_sp_m2534
##          <chr> <chr> <chr> <int>       <int>        <int>        <int>
## 1  Afghanistan    AF   AFG  1980          NA           NA           NA
## 2  Afghanistan    AF   AFG  1981          NA           NA           NA
## 3  Afghanistan    AF   AFG  1982          NA           NA           NA
## 4  Afghanistan    AF   AFG  1983          NA           NA           NA
## 5  Afghanistan    AF   AFG  1984          NA           NA           NA
## 6  Afghanistan    AF   AFG  1985          NA           NA           NA
## 7  Afghanistan    AF   AFG  1986          NA           NA           NA
## 8  Afghanistan    AF   AFG  1987          NA           NA           NA
## 9  Afghanistan    AF   AFG  1988          NA           NA           NA
## 10 Afghanistan    AF   AFG  1989          NA           NA           NA
## # ... with 7,230 more rows, and 53 more variables: new_sp_m3544 <int>,
## #   new_sp_m4554 <int>, new_sp_m5564 <int>, new_sp_m65 <int>,
## #   new_sp_f014 <int>, new_sp_f1524 <int>, new_sp_f2534 <int>,
## #   new_sp_f3544 <int>, new_sp_f4554 <int>, new_sp_f5564 <int>,
## #   new_sp_f65 <int>, new_sn_m014 <int>, new_sn_m1524 <int>,
## #   new_sn_m2534 <int>, new_sn_m3544 <int>, new_sn_m4554 <int>,
## #   new_sn_m5564 <int>, new_sn_m65 <int>, new_sn_f014 <int>,
## #   new_sn_f1524 <int>, new_sn_f2534 <int>, new_sn_f3544 <int>,
## #   new_sn_f4554 <int>, new_sn_f5564 <int>, new_sn_f65 <int>,
## #   new_ep_m014 <int>, new_ep_m1524 <int>, new_ep_m2534 <int>,
## #   new_ep_m3544 <int>, new_ep_m4554 <int>, new_ep_m5564 <int>,
## #   new_ep_m65 <int>, new_ep_f014 <int>, new_ep_f1524 <int>,
## #   new_ep_f2534 <int>, new_ep_f3544 <int>, new_ep_f4554 <int>,
## #   new_ep_f5564 <int>, new_ep_f65 <int>, newrel_m014 <int>,
## #   newrel_m1524 <int>, newrel_m2534 <int>, newrel_m3544 <int>,
## #   newrel_m4554 <int>, newrel_m5564 <int>, newrel_m65 <int>,
## #   newrel_f014 <int>, newrel_f1524 <int>, newrel_f2534 <int>,
## #   newrel_f3544 <int>, newrel_f4554 <int>, newrel_f5564 <int>,
## #   newrel_f65 <int>
```

```
who %>%
  gather(group, cases, -country, -iso2, -iso3, -year)
```

```
## # A tibble: 405,440 × 6
##        country  iso2  iso3  year       group cases
##          <chr> <chr> <chr> <int>       <chr> <int>
## 1  Afghanistan    AF   AFG  1980 new_sp_m014    NA
## 2  Afghanistan    AF   AFG  1981 new_sp_m014    NA
```

```
## 3  Afghanistan    AF   AFG  1982 new_sp_m014    NA
## 4  Afghanistan    AF   AFG  1983 new_sp_m014    NA
## 5  Afghanistan    AF   AFG  1984 new_sp_m014    NA
## 6  Afghanistan    AF   AFG  1985 new_sp_m014    NA
## 7  Afghanistan    AF   AFG  1986 new_sp_m014    NA
## 8  Afghanistan    AF   AFG  1987 new_sp_m014    NA
## 9  Afghanistan    AF   AFG  1988 new_sp_m014    NA
## 10 Afghanistan    AF   AFG  1989 new_sp_m014    NA
## # ... with 405,430 more rows
```

### readr

For reading flat files. Faster than base with smarter defaults.

```
bigdf <- data_frame(int = 1:1e6,
                    squares = int^2,
                    letters = sample(letters, 1e6, replace = TRUE))
```

```
system.time(
  write.csv(bigdf, "base-write.csv")
)
```

```
##    user  system elapsed
##   2.908   0.094   3.513
```

```
system.time(
  write_csv(bigdf, "readr-write.csv")
)
```

```
##    user  system elapsed
##   0.928   0.067   1.038
```

```
read.csv("base-write.csv", nrows = 3)
```

```
##   X int squares letters
## 1 1   1       1       q
## 2 2   2       4       d
## 3 3   3       9       e
```

```
read_csv("readr-write.csv", n_max = 3)
```

```
## Parsed with column specification:
## cols(
##   int = col_integer(),
##   squares = col_double(),
##   letters = col_character()
## )
```

```
## # A tibble: 3 × 3
##     int squares letters
##   <int>   <dbl>   <chr>
## 1     1       1       q
## 2     2       4       d
## 3     3       9       e
```

### purrr

purrr is kind of like dplyr for lists. It helps you repeatedly apply functions. Like the rest of the tidyverse, nothing you can't do in base R, but purrr makes the API consistent, encourages type specificity, and provides some nice shortcuts and speed ups.

```
df <- data_frame(fun = rep(c(lapply, map), 2),
                 n = rep(c(1e5, 1e7), each = 2),
                 comp_time = map2(fun, n, ~system.time(.x(1:.y, sqrt))))
df$comp_time
```

```
## [[1]]
##    user  system elapsed
##   0.040   0.002   0.042
##
## [[2]]
##    user  system elapsed
##   0.038   0.000   0.038
##
## [[3]]
##    user  system elapsed
##  13.755   0.284  14.111
##
## [[4]]
##    user  system elapsed
##   9.824   0.263  10.145
```

### map

Vanilla map is a slightly improved version of lapply. Do a function on each item in a list.

```
map(1:4, log)
```

```
## [[1]]
## [1] 0
##
## [[2]]
## [1] 0.6931472
##
## [[3]]
## [1] 1.098612
##
## [[4]]
## [1] 1.386294
```

Can supply additional arguments as with (x)apply

```
map(1:4, log, base = 2)
```

```
## [[1]]
## [1] 0
##
## [[2]]
## [1] 1
##
## [[3]]
```

```
## [1] 1.584963
##
## [[4]]
## [1] 2
```

Can compose anonymous functions like `(x)apply`, either the old way or with a new formula shorthand.

```
map(1:4, ~ log(4, base = .x))  # == map(1:4, function(x) log(4, base = x))
```

```
## [[1]]
## [1] Inf
##
## [[2]]
## [1] 2
##
## [[3]]
## [1] 1.26186
##
## [[4]]
## [1] 1
```

`map` always returns a list. `map_xxx` type-specifies the output type and simplifies the list to a vector.

```
map_dbl(1:4, log, base = 2)
```

```
## [1] 0.000000 1.000000 1.584963 2.000000
```

And throws an error if any output isn't of the expected type (which is a good thing!).

```
map_int(1:4, log, base = 2)
```

```
## Error: Can't coerce element 1 from a double to a integer
```

`map2` is like `mapply` – apply a function over two lists in parallel. `map_n` generalizes to any number of lists.

```
fwd <- 1:10
bck <- 10:1
map2_dbl(fwd, bck, `^`)
```

```
##  [1]     1   512  6561 16384 15625  7776  2401   512    81    10
```

`map_if` tests each element on a function and if true applies the second function, if false returns the original element.

```
data_frame(ints = 1:5,
           lets = letters[1:5],
           sqrts = ints^.5) %>%
  map_if(is.numeric, ~ .x^2)
```

```
## $ints
## [1]  1  4  9 16 25
##
## $lets
## [1] "a" "b" "c" "d" "e"
##
## $sqrts
## [1] 1 2 3 4 5
```

### Putting map to work

Split the movies data frame by mpaa rating, fit a linear model to each data frame, and organize the model results in a data frame.

```
movies %>%
  filter(mpaa != "") %>%
  split(.$mpaa) %>% # str()
  map(~ lm(rating ~ budget, data = .)) %>%
  map_df(tidy, .id = "mpaa-rating") %>%
  arrange(term)
```

```
## Error in as_function(.f, ...): object 'tidy' not found
```

List-columns make it easier to organize complex datasets. Can `map` over list-columns right in `data_frame/tibble` creation. And if you later want to calculate something else, everything is nicely organized in the data frame.

```
d <- data_frame(dist = c("normal", "poisson", "chi-square"),
                funs = list(rnorm, rpois, rchisq),
                samples = map(funs, ~.(100, 5)),
                mean = map_dbl(samples, mean),
                var = map_dbl(samples, var)
                )
d$median <- map_dbl(d$samples, median)
d
```

```
## # A tibble: 3 × 6
##         dist   funs     samples     mean        var   median
##        <chr> <list>      <list>    <dbl>      <dbl>    <dbl>
## 1     normal  <fun> <dbl [100]> 5.198593  0.9789476 5.138450
## 2    poisson  <fun> <int [100]> 5.500000  4.6767677 5.000000
## 3 chi-square  <fun> <dbl [100]> 4.990230 13.0899212 4.280592
```

Let's see if we can really make this purrr... Fit a linear model of diamond price by every combination of two predictors in the dataset and see which two predict best.

```
train <- sample(nrow(diamonds), floor(nrow(diamonds) * .67))
setdiff(names(diamonds), "price") %>%
  combn(2, paste, collapse = " + ") %>%
  structure(., names = .) %>%
  map(~ formula(paste("price ~ ", .x))) %>%
  map(lm, data = diamonds[train, ]) %>%
  map_df(augment, newdata = diamonds[-train, ], .id = "predictors") %>%
  group_by(predictors) %>%
  summarize(rmse = sqrt(mean((price - .fitted)^2))) %>%
  arrange(rmse)
```

```
## Error in as_function(.f, ...): object 'augment' not found
```

## stringr

All your string manipulation and regex functions with a consistent API.

```
library(stringr)  # not attached with tidyverse
fishes <- c("one fish", "two fish", "red fish", "blue fish")
str_detect(fishes, "two")
```

```
## [1] FALSE  TRUE FALSE FALSE
```

```
str_replace_all(fishes, "fish", "banana")
```

```
## [1] "one banana"  "two banana"  "red banana"  "blue banana"
```

```
str_extract(fishes, "[a-z]\\s")
```

```
## [1] "e " "o " "d " "e "
```

Let's put that string manipulation engine to work. Remember the annoying column names in the WHO data? They look like this new_sp_m014, new_sp_m1524, new_sp_m2534, where "new" or "new_" doesn't mean anything, the following 2-3 letters indicate the test used, the following letter indicates the gender, and the final 2-4 numbers indicates the age-class. A string-handling challenge if ever there was one. Let's separate it out and plot the cases by year, gender, age-class, and test-method.

```
who2 <- who %>%
        select(-iso2, -iso3) %>%
        gather(group, cases, -country, -year) %>%
        mutate(group = str_replace(group, "new_*", ""),
               method = str_extract(group, "[a-z]+"),
               gender = str_sub(str_extract(group, "_[a-z]"), 2, 2),
               age = str_extract(group, "[0-9]+"),
               age = ifelse(str_length(age) > 2,
                            str_c(str_sub(age, 1, -3), str_sub(age, -2, -1), sep = "-"),
                            str_c(age, "+"))) %>%
        group_by(year, gender, age, method) %>%
        summarize(total_cases = sum(cases, na.rm = TRUE))

who2
```

```
## Source: local data frame [1,904 x 5]
## Groups: year, gender, age [?]
##
##     year gender   age method total_cases
##    <int>  <chr> <chr>  <chr>       <int>
## 1   1980      f  0-14     ep           0
## 2   1980      f  0-14    rel           0
## 3   1980      f  0-14     sn           0
## 4   1980      f  0-14     sp          18
## 5   1980      f 15-24     ep           0
## 6   1980      f 15-24    rel           0
## 7   1980      f 15-24     sn           0
## 8   1980      f 15-24     sp          65
## 9   1980      f 25-34     ep           0
## 10  1980      f 25-34    rel           0
## # ... with 1,894 more rows
```

## ggplot2

Disclaimer: I am a recovering base R graphics expert. The learning curve for ggplot2 is quite steep. As I am still on the curve, some of what I'll share here might be done in a better way. Feel free to share any tricks you might have up your sleeve. There are also lots of excellent resources on the internet that will help you learn this.

Some good tutorials include:

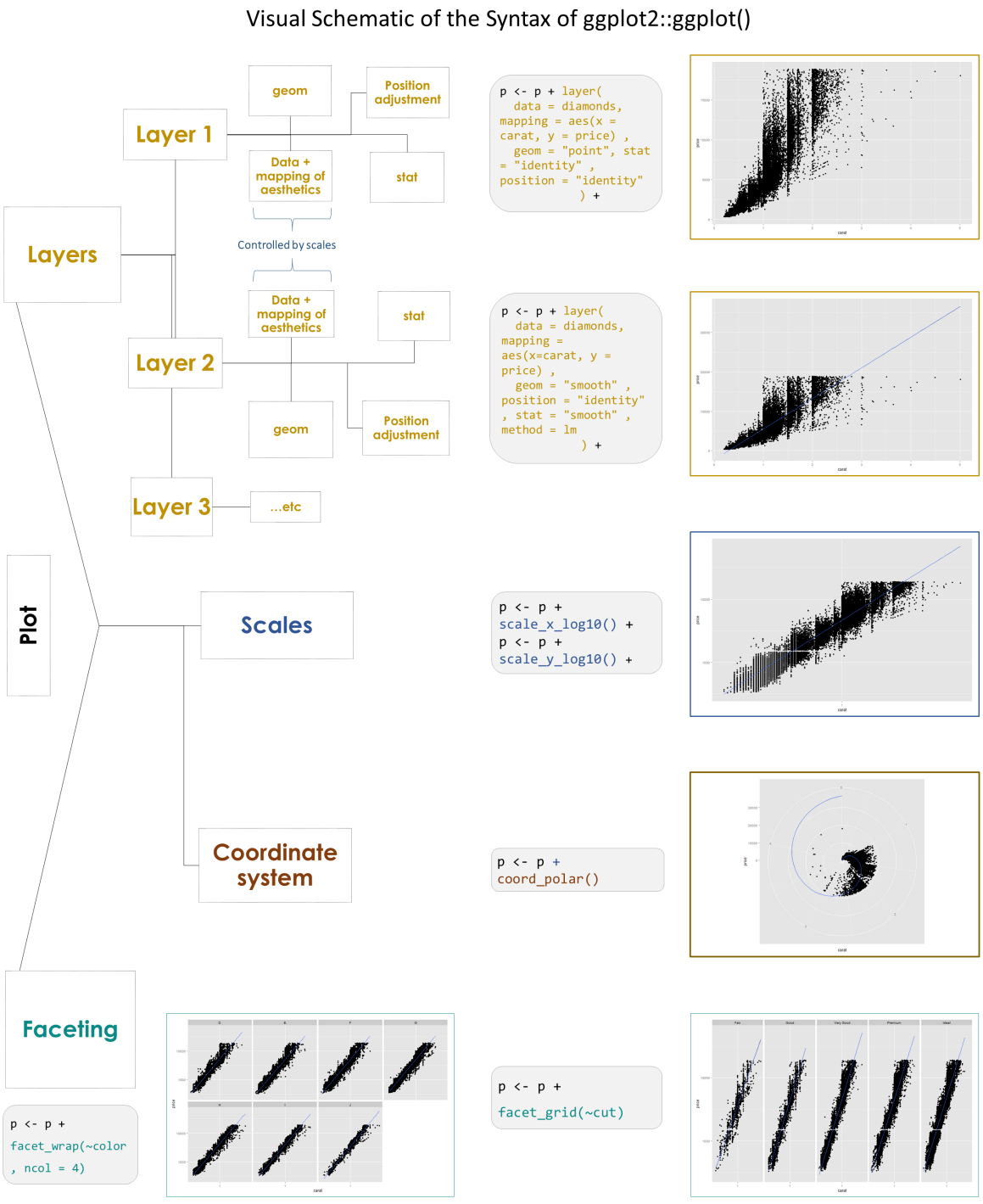
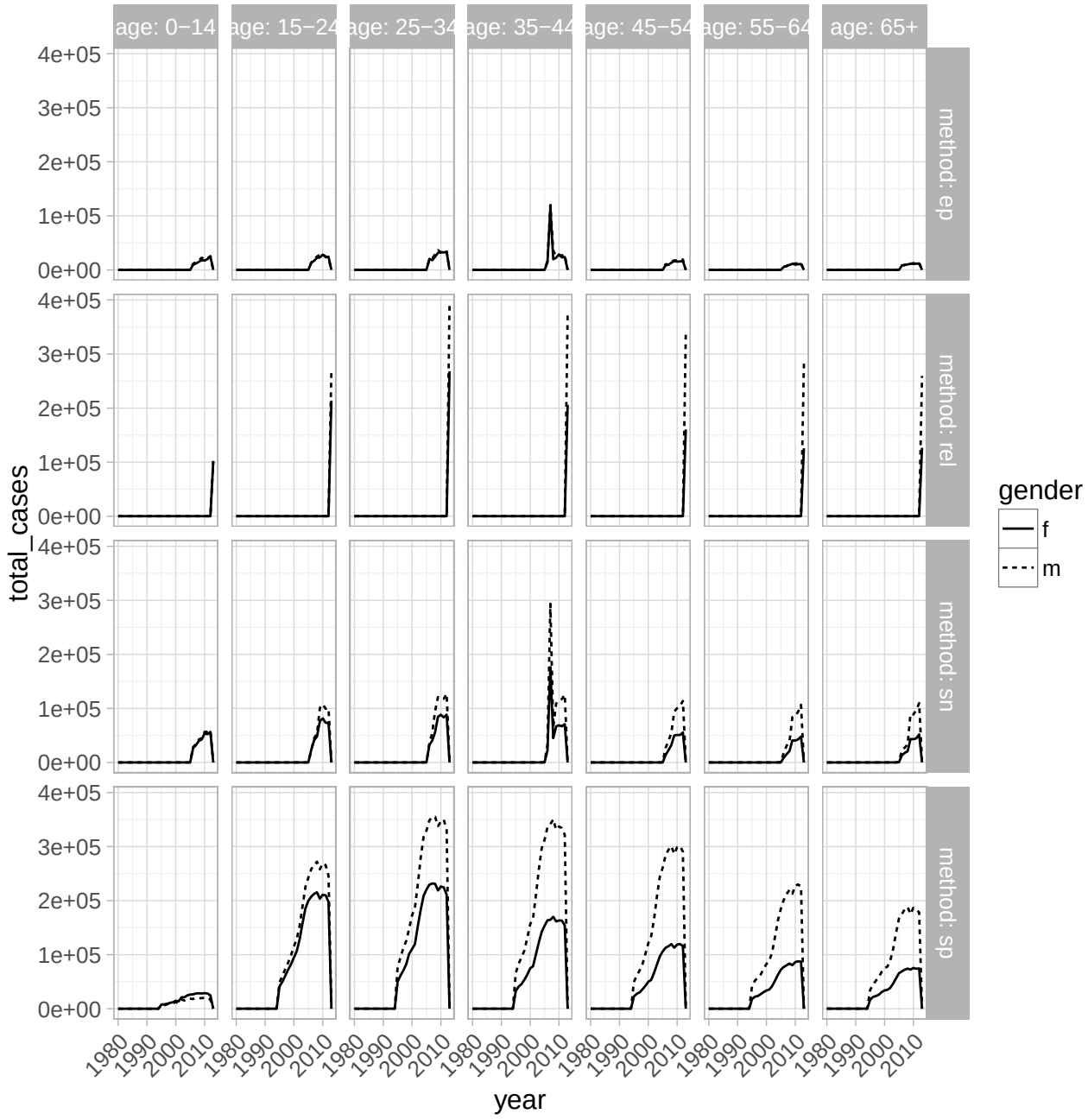



Figure 1: A visual schematic to help you think about ggplot2 correctly – credit: Myfanwy Johnston

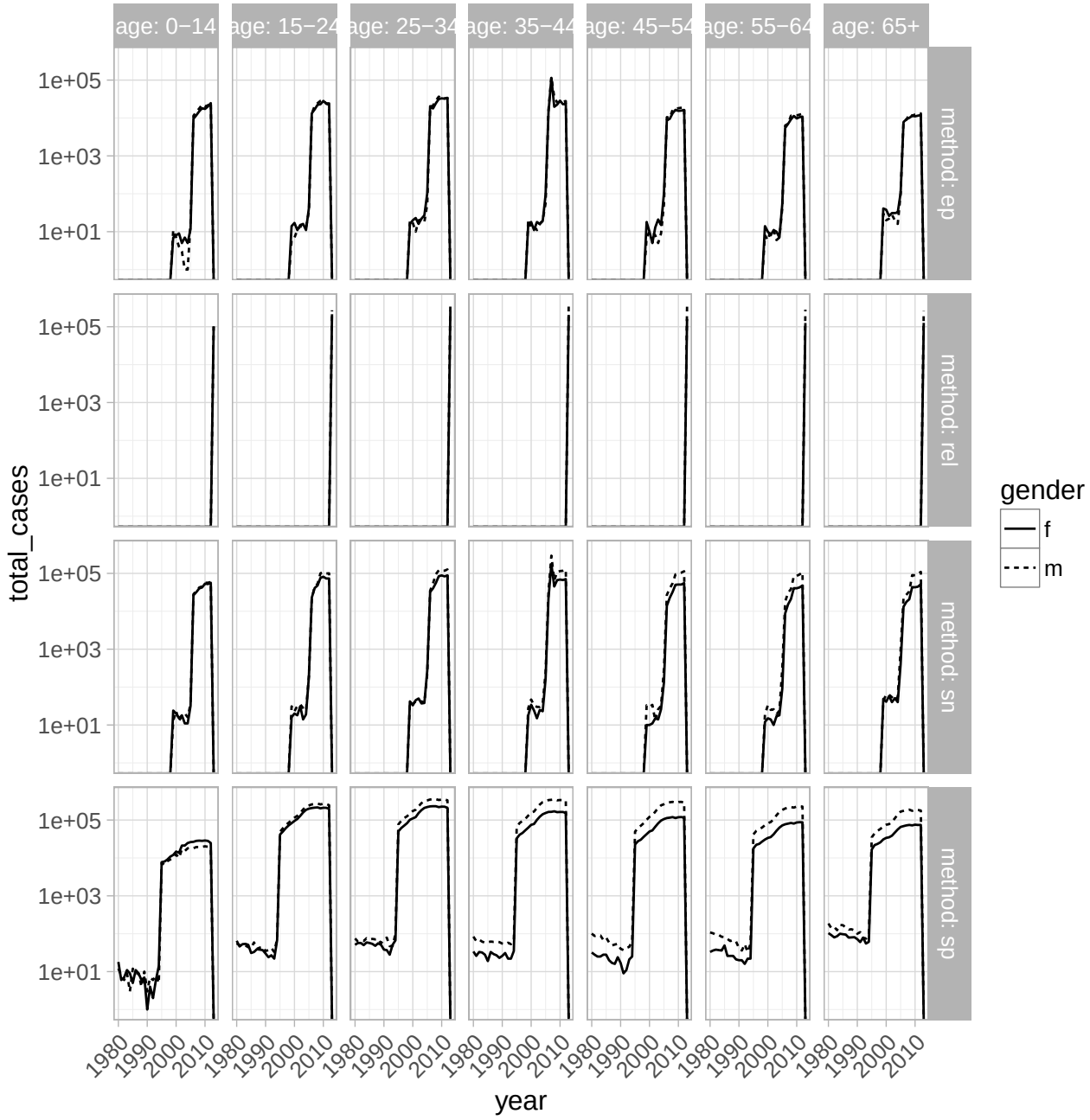
- Variance Explained

Note that the pipe and consistent API make it easy to combine functions from different packages, and the whole thing is quite readable.

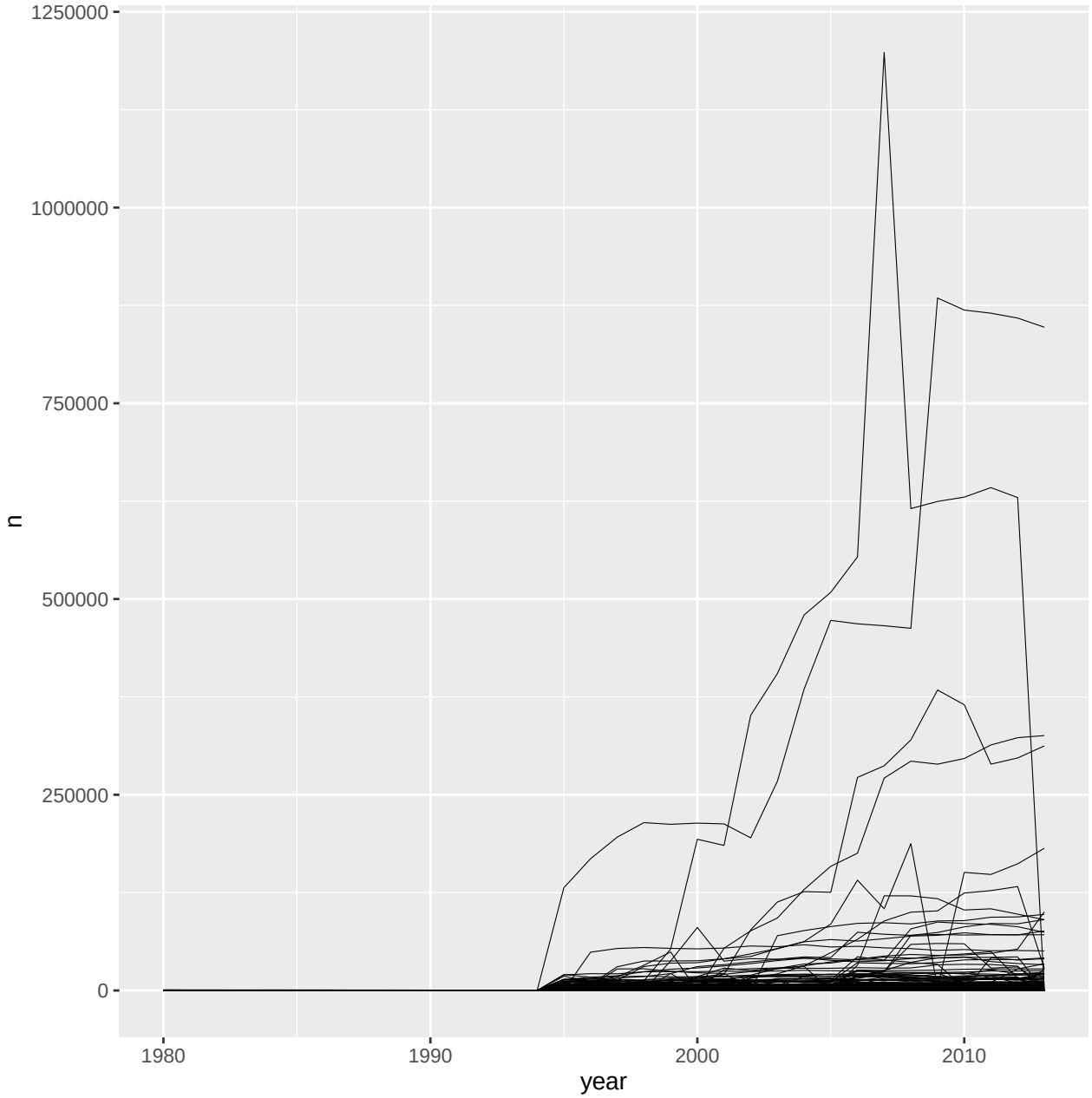
```
# first stab at ggplot
g <- ggplot(who2, aes(x = year, y = total_cases, linetype = gender)) +
  geom_line() +
  facet_grid(method ~ age,
             labeller = labeller(.rows = label_both, .cols = label_both)) +
  theme_light() +
  theme(axis.text.x = element_text(angle = 45, vjust = 1, hjust = 1))
g
```



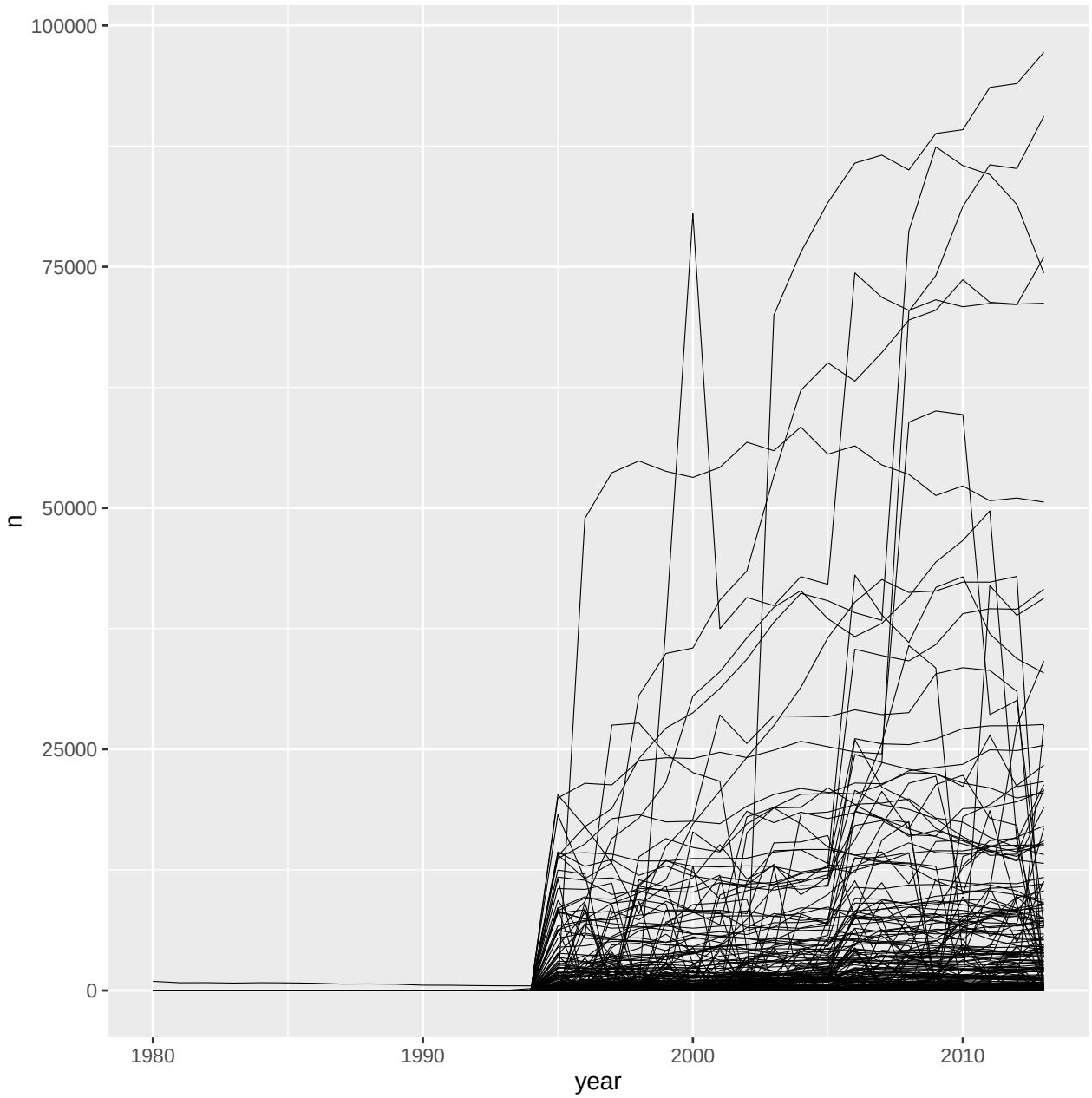
```
# lets try it with the y-axis on the log10 scale
g + scale_y_log10()
```




```
# combining what we learned above
who %>%
  select(-iso2, -iso3) %>%
  gather(group, cases, -country, -year) %>%
  count(country, year, wt = cases) %>%
# with ggplot
  ggplot(aes(x = year, y = n, group = country)) +
  geom_line(size = .2)
```




```
# lets drop the countries with incident cases over 250K
who %>%
  select(-iso2, -iso3) %>%
  gather(group, cases, -country, -year) %>%
  count(country, year, wt = cases) %>%
  group_by(country) %>%
  mutate(maxCases = max(n)) %>%
  filter(maxCases < 100000) %>%
# with ggplot
  ggplot(aes(x = year, y = n, group = country)) +
  geom_line(size = .2)
```


100000
75000
50000
25000
0
n
1980
1990
2000
2010
year