Data Visualization - 6. Work With Models

Kieran Healy

Code Horizons

October 2024

Work with Models

Load our packages

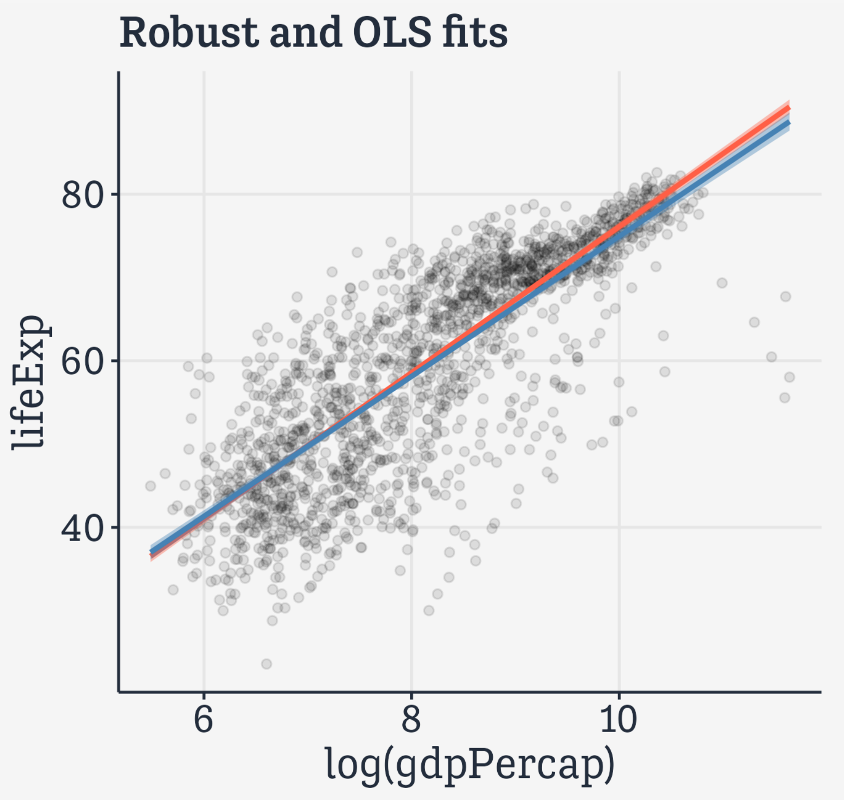
```r
library(here)      # manage file paths
library(socviz)    # data and some useful functions
library(tidyverse) # your friend and mine
library(gapminder) # Everyone's favorite dataset
library(broom)     # Tidy model output
library(marginaleffects) # Tidy marginal effects
library(modelsummary) # Tidy summary tables and graphs
library(scales)    # Format our axes and guides
```

```
Attaching package: 'scales'

The following object is masked from 'package:purrr':

    discard

The following object is masked from 'package:readr':

    col_factor
```

ggplot can work with models

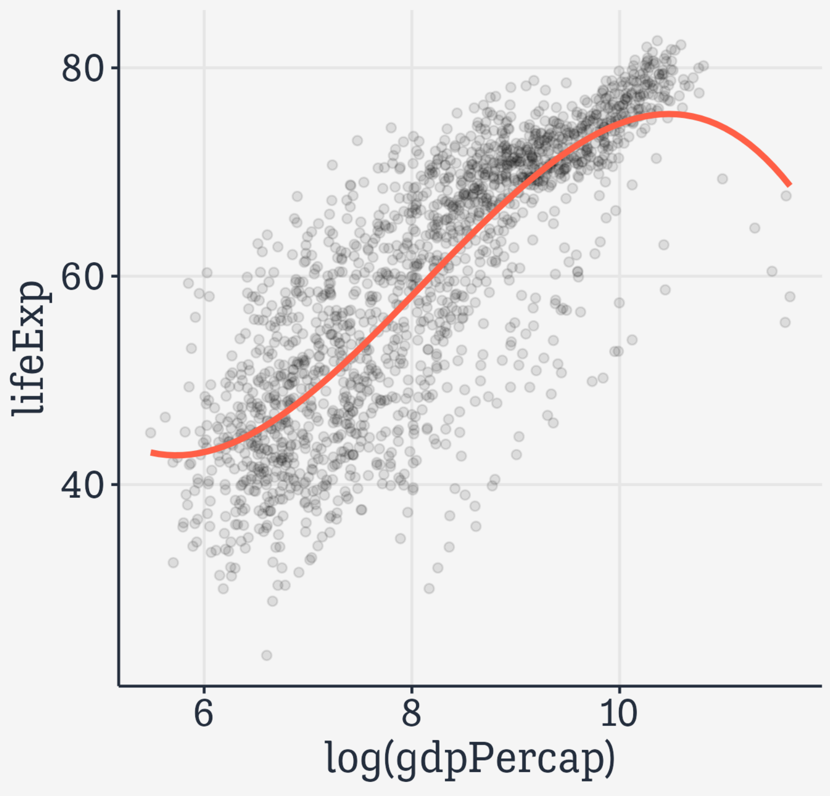
We know because geoms often do calculations in the background, via their stat functions.

```
p <- gapminder |>
  ggplot(mapping = aes(x = log(gdpPercap),
                       y = lifeExp))

p + geom_point(alpha=0.1) +
  geom_smooth(color = "tomato",
              fill="tomato",
              method = MASS::rlm) +
  geom_smooth(color = "steelblue",
              fill="steelblue",
              method = "lm") +
  labs(title = "Robust and OLS fits")
```



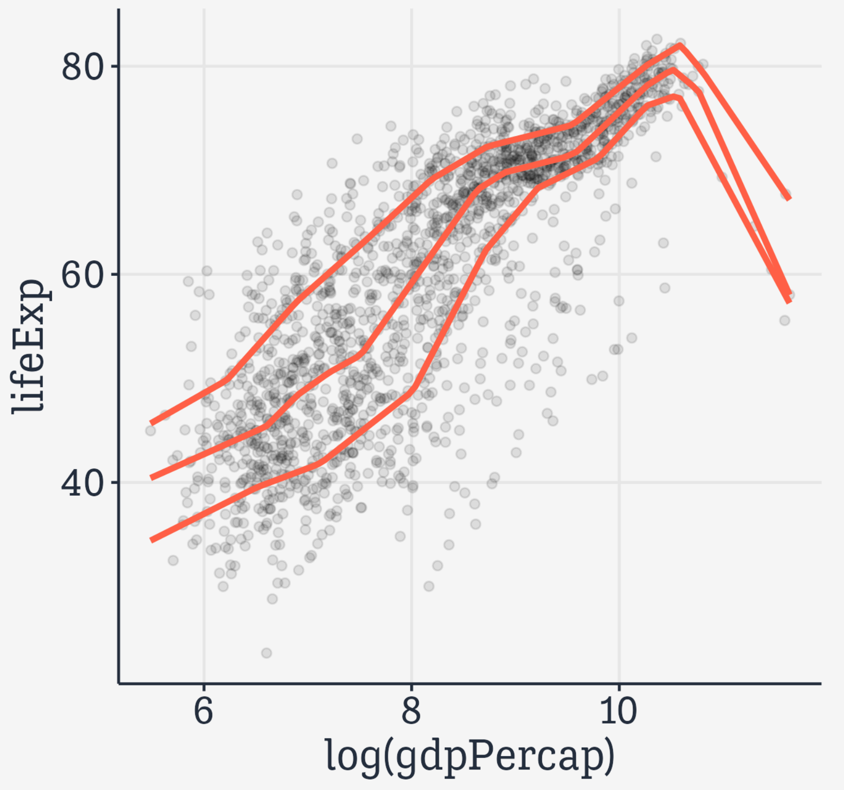
These can be complex ...

```r
p + geom_point(alpha=0.1) +
    geom_smooth(color = "tomato",
        method = "lm",
        size = 1.2,
        formula = y ~ splines::bs(x, 3),
        se = FALSE)
```



… but we usually won't do this in `ggplot`

```r
p + geom_point(alpha=0.1) +
    geom_quantile(color = "tomato",
        size = 1.2,
        method = "rqss",
        lambda = 1,
        quantiles = c(0.20, 0.5, 0.85))
```



Transform and summarize first. Then send your clean tables to ggplot.

Look inside the box

Objects are To-Do List Bento Boxes

```
gapminder
```

```
# A tibble: 1,704 × 6
   country     continent  year lifeExp      pop gdpPercap
   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
 1 Afghanistan Asia       1952    28.8  8425333      779.
 2 Afghanistan Asia       1957    30.3  9240934      821.
 3 Afghanistan Asia       1962    32.0 10267083      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.
 7 Afghanistan Asia       1982    39.9 12881816      978.
 8 Afghanistan Asia       1987    40.8 13867957      852.
 9 Afghanistan Asia       1992    41.7 16317921      649.
10 Afghanistan Asia       1997    41.8 22227415      635.
# ℹ 1,694 more rows
```

Fit a model

```r
out <- lm(formula = lifeExp ~ gdpPercap + log(pop) + continent,
          data = gapminder)

summary(out)
```

```

Call:
lm(formula = lifeExp ~ gdpPercap + log(pop) + continent, data = gapminder)

Residuals:
    Min      1Q  Median      3Q     Max 
-47.490  -4.614   0.250   5.293  26.094 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)       3.816e+01  2.050e+00  18.618  < 2e-16 ***
gdpPercap         4.557e-04  2.345e-05  19.435  < 2e-16 ***
log(pop)          6.394e-01  1.329e-01   4.810 1.64e-06 ***
continentAmericas 1.308e+01  6.063e-01  21.579  < 2e-16 ***
continentAsia     7.784e+00  5.810e-01  13.398  < 2e-16 ***
continentEurope   1.695e+01  6.350e-01  26.691  < 2e-16 ***
continentOceania  1.764e+01  1.779e+00   9.916  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Poke around inside

```
out
├── coefficients
├── residuals
├── effects
├── rank
├── qr
│   ├── qr
│   ├── pivot
│   ├── qraux
│   ├── tol
│   └── rank
├── df.residual
├── contrasts
├── xlevels
├── call
├── terms
└── model.frame
```

Use the Object Inspector to take a look

Predict from models:
DIY method

Behind the curtain

`predict()` and its methods do a lot of work behind the scenes

We won't usually need to do this stuff manually. But the idea is that the generic `predict()` function has *methods* for specific sorts of models. Give it a model and some new data and it will produce predicted values for the new data. Here's an example.

The labor-intensive way

```r
min_gdp <- min(gapminder$gdpPercap)
max_gdp <- max(gapminder$gdpPercap)
med_pop <- median(gapminder$pop)

# Make a grid of predictor values
pred_df <- expand_grid(gdpPercap = (seq(from = min_gdp,
                                        to = max_gdp,
                                        length.out = 100)),
                       pop = med_pop,
                       continent = c("Africa", "Americas",
                                     "Asia", "Europe", "Oceania"))

pred_df
```

```
# A tibble: 500 × 3
   gdpPercap      pop continent
       <dbl>    <dbl> <chr>
 1      241. 7023596. Africa
 2      241. 7023596. Americas
 3      241. 7023596. Asia
 4      241. 7023596. Europe
 5      241. 7023596. Oceania
 6     1385. 7023596. Africa
 7     1385. 7023596. Americas
 8     1385. 7023596. Asia
 9     1385. 7023596. Europe
10     1385. 7023596. Oceania
# ℹ 490 more rows
```

The labor-intensive way

```r
# Get the predicted values
pred_out <- predict(object = out,
                    newdata = pred_df,
                    interval = "confidence")
head(pred_out)
```

```
       fit      lwr      upr
1 48.35388 47.67735 49.03041
2 61.43646 60.43917 62.43375
3 56.13821 55.22045 57.05597
4 65.30361 64.21794 66.38927
5 65.99517 62.55277 69.43757
6 48.87530 48.20261 49.54799
```

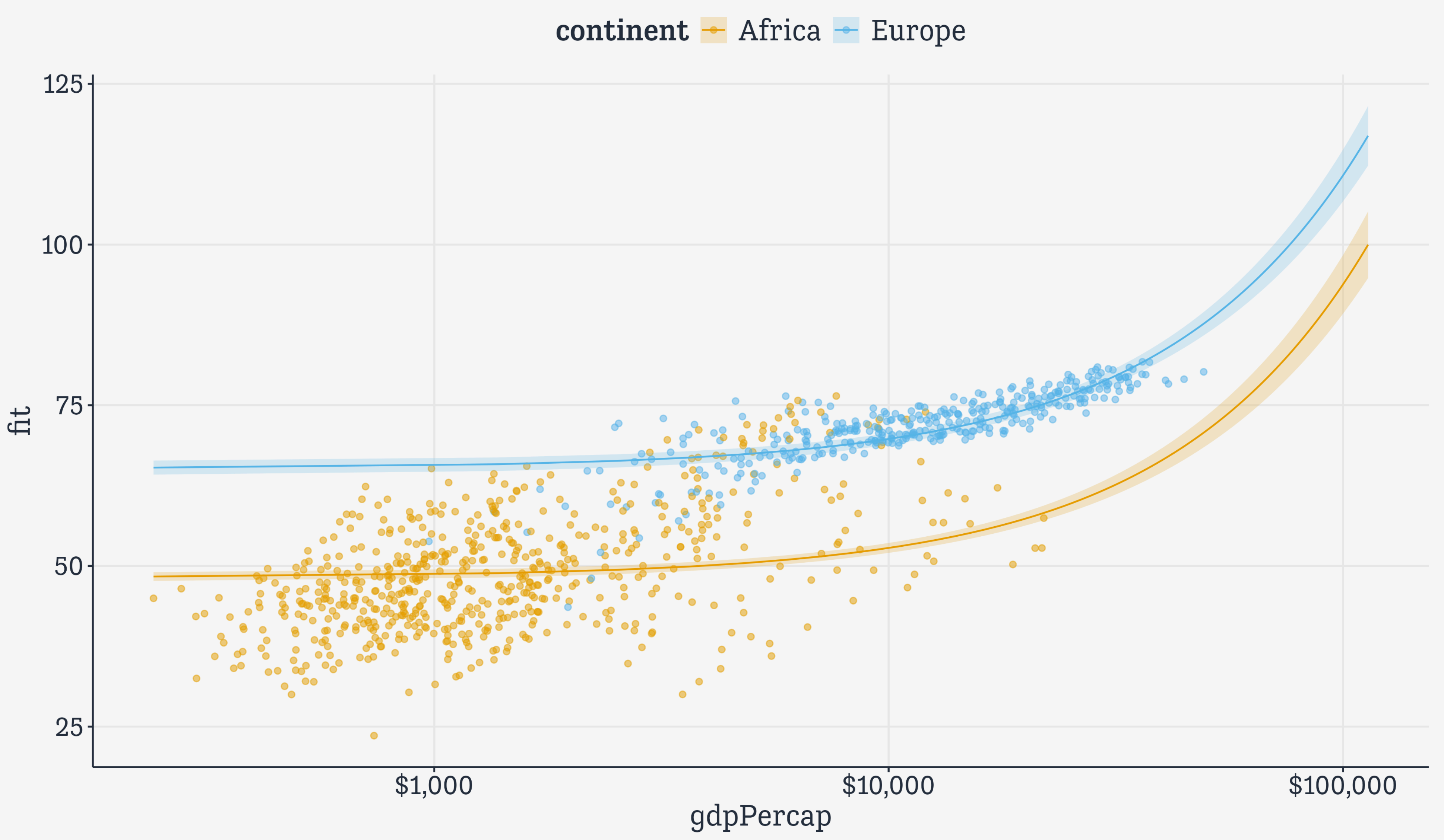
The labor-intensive way

```r
# Bind them into one data frame. We can do this safely
# here because we know the row order by construction.
# But this is not a safe approach in general.

pred_df <- cbind(pred_df, pred_out)
head(pred_df)
```

```
  gdpPercap     pop continent      fit      lwr      upr
1  241.1659 7023596    Africa 48.35388 47.67735 49.03041
2  241.1659 7023596  Americas 61.43646 60.43917 62.43375
3  241.1659 7023596      Asia 56.13821 55.22045 57.05597
4  241.1659 7023596    Europe 65.30361 64.21794 66.38927
5  241.1659 7023596   Oceania 65.99517 62.55277 69.43757
6 1385.4282 7023596    Africa 48.87530 48.20261 49.54799
```

The labor-intensive way

```r
p <- ggplot(data = subset(pred_df, continent %in% c("Europe", "Africa")),
            aes(x = gdpPercap,
                y = fit,
                ymin = lwr,
                ymax = upr,
                color = continent,
                fill = continent,
                group = continent))

# Use the original data as the point layer
p_out <- p + geom_point(data = subset(gapminder,
                              continent %in% c("Europe", "Africa")),
               mapping = aes(x = gdpPercap, y = lifeExp,
                   color = continent),
               alpha = 0.5,
               inherit.aes = FALSE) +
# And the predicted values to draw the lines
    geom_line() +
    geom_ribbon(alpha = 0.2, color = FALSE) +
    scale_x_log10(labels = scales::label_dollar())
```


continent
Africa
Europe
125
100
75
50
25
fit
$1,000
$10,000
$100,000
gdpPercap

Use `broom` to tidy models

We can't do anything with this

```r
out <- lm(formula = lifeExp ~ gdpPercap + log(pop) + continent,
          data = gapminder)

summary(out)
```

```

Call:
lm(formula = lifeExp ~ gdpPercap + log(pop) + continent, data = gapminder)

Residuals:
    Min      1Q  Median      3Q     Max 
-47.490  -4.614   0.250   5.293  26.094 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)       3.816e+01  2.050e+00  18.618  < 2e-16 ***
gdpPercap         4.557e-04  2.345e-05  19.435  < 2e-16 ***
log(pop)          6.394e-01  1.329e-01   4.810 1.64e-06 ***
continentAmericas 1.308e+01  6.063e-01  21.579  < 2e-16 ***
continentAsia     7.784e+00  5.810e-01  13.398  < 2e-16 ***
continentEurope   1.695e+01  6.350e-01  26.691  < 2e-16 ***
continentOceania  1.764e+01  1.779e+00   9.916  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Tidy regression output with **broom**

```r
library(broom)
```

```r
tidy(out)
```

```
# A tibble: 7 × 5
  term              estimate std.error statistic   p.value
  <chr>                <dbl>     <dbl>     <dbl>     <dbl>
1 (Intercept)      38.2      2.05          18.6  1.50e- 70
2 gdpPercap         0.000456 0.0000234     19.4  3.98e- 76
3 log(pop)          0.639    0.133          4.81 1.64e-  6
4 continentAmericas 13.1      0.606         21.6  1.85e- 91
5 continentAsia     7.78     0.581         13.4  5.52e- 39
6 continentEurope  16.9      0.635         26.7  2.43e-131
7 continentOceania 17.6      1.78           9.92 1.43e- 22
```

That's a *lot* nicer. Now it's just a tibble. We know those.

Tidy regression output with broom

```r
out_conf <- tidy(out, conf.int = TRUE)
out_conf
```

```
# A tibble: 7 × 7
  term                estimate std.error statistic   p.value  conf.low conf.high
  <chr>                  <dbl>     <dbl>     <dbl>     <dbl>     <dbl>     <dbl>
1 (Intercept)        38.2      2.05           18.6  1.50e- 70 34.1      42.2
2 gdpPercap           0.000456 0.0000234      19.4  3.98e- 76  0.000410  0.000502
3 log(pop)            0.639    0.133           4.81 1.64e-  6  0.379     0.900
4 continentAmericas 13.1      0.606          21.6  1.85e- 91 11.9      14.3
5 continentAsia       7.78     0.581          13.4  5.52e- 39  6.64      8.92
6 continentEurope    16.9      0.635          26.7  2.43e-131 15.7      18.2
7 continentOceania   17.6      1.78            9.92 1.43e- 22 14.2      21.1
```

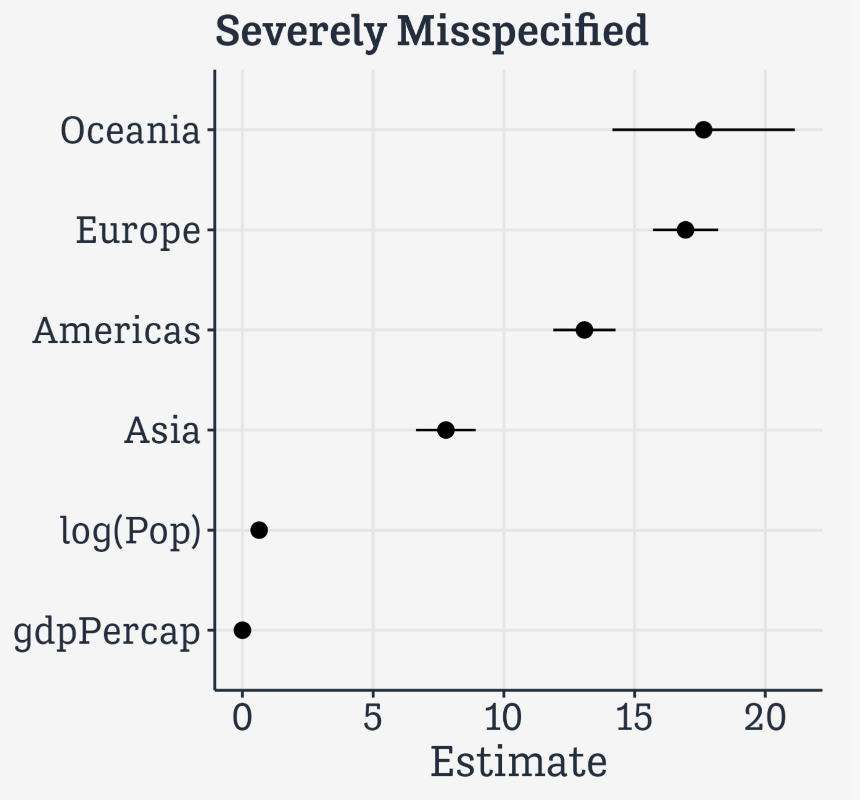
Tidy regression output with broom

```
out_conf ▷
    filter(term %nin% "(Intercept)") ▷
    mutate(nicelabs = prefix_strip(term, "continent")) ▷
    relocate(nicelabs)
```

```
# A tibble: 6 × 8
  nicelabs  term       estimate std.error statistic   p.value conf.low conf.high
  <chr>     <chr>         <dbl>     <dbl>     <dbl>     <dbl>    <dbl>     <dbl>
1 gdpPercap gdpPercap   4.56e-4 0.0000234     19.4  3.98e- 76  4.10e-4  0.000502
2 log(Pop)  log(pop)    6.39e-1 0.133          4.81 1.64e-  6  3.79e-1  0.900
3 Americas  continent…  1.31e+1 0.606         21.6  1.85e- 91  1.19e+1 14.3
4 Asia      continent…  7.78e+0 0.581         13.4  5.52e- 39  6.64e+0  8.92
5 Europe    continent…  1.69e+1 0.635         26.7  2.43e-131  1.57e+1 18.2
6 Oceania   continent…  1.76e+1 1.78           9.92 1.43e- 22  1.42e+1 21.1
```

Tidy regression output with broom

```r
out_conf |>
    filter(term %nin% "(Intercept)") |>
    mutate(nicelabs = prefix_strip(term, "conti
  ggplot(mapping = aes(x = estimate,
                       xmin = conf.low,
                       xmax = conf.high,
                       y = reorder(nicelabs,
                                   estimate)))
  geom_pointrange() +
  labs(x = "Estimate",
       y = NULL,
       title = "Severely Misspecified")
```



Three ways to tidy

Component level: `tidy()`

Three ways to tidy

Component level: `tidy()`

Observation level: `augment()`

Three ways to tidy

Component level: `tidy()`

Observation level: `augment()`

Model level: `glance()`

Component level

```
> summary(out)

Call:
lm(formula = lifeExp ~ gdpPercap + log(pop) + continent, data = gapminder)

Residuals:
    Min      1Q  Median      3Q     Max 
-47.490  -4.614   0.250   5.293  26.094 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)       3.816e+01  2.050e+00  18.618  < 2e-16 ***
gdpPercap         4.557e-04  2.345e-05  19.435  < 2e-16 ***
log(pop)          6.394e-01  1.329e-01   4.810 1.64e-06 ***
continentAmericas 1.308e+01  6.063e-01  21.579  < 2e-16 ***
continentAsia     7.784e+00  5.810e-01  13.398  < 2e-16 ***
continentEurope   1.695e+01  6.350e-01  26.691  < 2e-16 ***
continentOceania  1.764e+01  1.779e+00   9.916  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8.336 on 1697 degrees of freedom
Multiple R-squared:  0.585, Adjusted R-squared:  0.5835 
F-statistic: 398.7 on 6 and 1697 DF,  p-value: < 2.2e-16
```

Observation level

```
> summary(out)

Call:
lm(formula = lifeExp ~ gdpPercap + log(pop) + continent, data = gapminder)
```

```
Residuals:
    Min      1Q  Median      3Q     Max
-47.490  -4.614   0.250   5.293  26.094
```

```
:::
```

```
Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       3.816e+01  2.050e+00  18.618  < 2e-16 ***
gdpPercap         4.557e-04  2.345e-05  19.435  < 2e-16 ***
log(pop)          6.394e-01  1.329e-01   4.810 1.64e-06 ***
continentAmericas 1.308e+01  6.063e-01  21.579  < 2e-16 ***
continentAsia     7.784e+00  5.810e-01  13.398  < 2e-16 ***
continentEurope   1.695e+01  6.350e-01  26.691  < 2e-16 ***
continentOceania  1.764e+01  1.779e+00   9.916  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8.336 on 1697 degrees of freedom
Multiple R-squared:  0.585, Adjusted R-squared:  0.5835
F-statistic: 398.7 on 6 and 1697 DF,  p-value: < 2.2e-16
```

Observation level

```r
augment(out)
```

```
# A tibble: 1,704 × 10
   lifeExp gdpPercap `log(pop)` continent .fitted .resid     .hat .sigma .cooksd
     <dbl>     <dbl>      <dbl> <fct>       <dbl>  <dbl>    <dbl>  <dbl>   <dbl>
 1    28.8      779.       15.9 Asia         56.5  -27.7 0.00302    8.31 0.00479
 2    30.3      821.       16.0 Asia         56.6  -26.2 0.00299    8.31 0.00426
 3    32.0      853.       16.1 Asia         56.7  -24.7 0.00296    8.32 0.00372
 4    34.0      836.       16.3 Asia         56.7  -22.7 0.00294    8.32 0.00313
 5    36.1      740.       16.4 Asia         56.8  -20.7 0.00294    8.32 0.00259
 6    38.4      786.       16.5 Asia         56.9  -18.4 0.00292    8.33 0.00205
 7    39.9      978.       16.4 Asia         56.9  -17.0 0.00291    8.33 0.00174
 8    40.8      852.       16.4 Asia         56.9  -16.0 0.00292    8.33 0.00155
 9    41.7      649.       16.6 Asia         56.9  -15.2 0.00294    8.33 0.00140
10    41.8      635.       16.9 Asia         57.1  -15.3 0.00297    8.33 0.00144
# ℹ 1,694 more rows
# ℹ 1 more variable: .std.resid <dbl>
```

Observation level

For OLS models:

.fitted — The fitted values of the model.

.se.fit — The standard errors of the fitted values.

.resid — The residuals.

.hat — The diagonal of the hat matrix.

.sigma — An estimate of the residual standard deviation when the corresponding observation is dropped from the model.

.cooksd — Cook's distance, a common regression diagnostic.

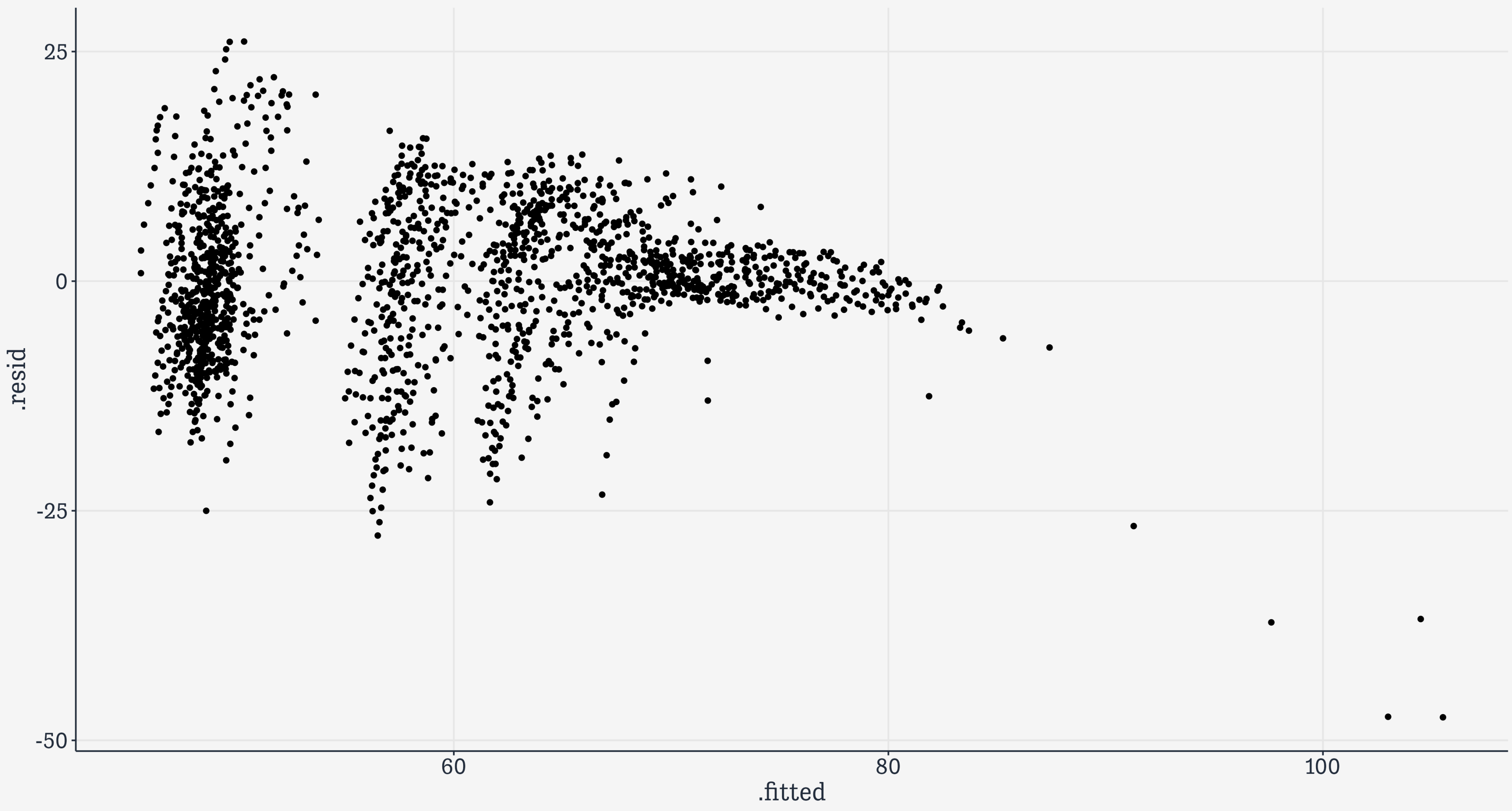
.std.resid — The standardized residuals.

Observation level

```r
# Adding the data argument puts back any additional columns from the original
# tibble
out_aug <- augment(out, data = gapminder)
head(out_aug)
```

```
# A tibble: 6 × 12
  country continent  year lifeExp    pop gdpPercap .fitted .resid    .hat .sigma
  <fct>   <fct>     <int>   <dbl>  <int>     <dbl>   <dbl>  <dbl>   <dbl>  <dbl>
1 Afghan… Asia       1952    28.8 8.43e6      779.    56.5  -27.7 0.00302   8.31
2 Afghan… Asia       1957    30.3 9.24e6      821.    56.6  -26.2 0.00299   8.31
3 Afghan… Asia       1962    32.0 1.03e7      853.    56.7  -24.7 0.00296   8.32
4 Afghan… Asia       1967    34.0 1.15e7      836.    56.7  -22.7 0.00294   8.32
5 Afghan… Asia       1972    36.1 1.31e7      740.    56.8  -20.7 0.00294   8.32
6 Afghan… Asia       1977    38.4 1.49e7      786.    56.9  -18.4 0.00292   8.33
# ℹ 2 more variables: .cooksd <dbl>, .std.resid <dbl>
```

```r
## Residuals vs Fitted Values
p <- ggplot(data = out_aug,
            mapping = aes(x = .fitted, y = .resid))
p_out <- p + geom_point()
```



(I told you it was misspecified)

Model level

```
> summary(out)

Call:
lm(formula = lifeExp ~ gdpPercap + log(pop) + continent, data = gapminder)

Residuals:
    Min      1Q  Median      3Q     Max 
-47.490  -4.614   0.250   5.293  26.094 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)       3.816e+01  2.050e+00  18.618  < 2e-16 ***
gdpPercap         4.557e-04  2.345e-05  19.435  < 2e-16 ***
log(pop)          6.394e-01  1.329e-01   4.810 1.64e-06 ***
continentAmericas 1.308e+01  6.063e-01  21.579  < 2e-16 ***
continentAsia     7.784e+00  5.810e-01  13.398  < 2e-16 ***
continentEurope   1.695e+01  6.350e-01  26.691  < 2e-16 ***
continentOceania  1.764e+01  1.779e+00   9.916  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 8.336 on 1697 degrees of freedom
Multiple R-squared:  0.585, Adjusted R-squared:  0.5835 
F-statistic: 398.7 on 6 and 1697 DF,  p-value: < 2.2e-16
```

Model level

```r
glance(out)
```

```
# A tibble: 1 × 12
  r.squared adj.r.squared sigma statistic   p.value    df logLik    AIC    BIC
      <dbl>         <dbl> <dbl>     <dbl>     <dbl> <dbl>  <dbl>  <dbl>  <dbl>
1     0.585         0.584  8.34      399. 1.01e-319     6 -6028. 12072. 12115.
# ℹ 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

The usefulness of `glance()` becomes clearer when dealing with ensembles of models.

Example

A Kaplan-Meier Curve

```r
library(survival)


head(lung)
```

```
  inst time status age sex ph.ecog ph.karno pat.karno meal.cal wt.loss
1    3  306      2  74   1       1       90       100     1175      NA
2    3  455      2  68   1       0       90        90     1225      15
3    3 1010      1  56   1       0       90        90       NA      15
4    5  210      2  57   1       1       90        60     1150      11
5    1  883      2  60   1       0      100        90       NA       0
6   12 1022      1  74   1       1       50        80      513       0
```

```r
tail(lung)
```

```
    inst time status age sex ph.ecog ph.karno pat.karno meal.cal wt.loss
223    1  116      2  76   1       1       80        80       NA       0
224    1  188      1  77   1       1       80        60       NA       3
225   13  191      1  39   1       0       90        90     2350      -5
226   32  105      1  75   2       2       60        70     1025       5
227    6  174      1  66   1       1       90       100     1075       1
228   22  177      1  58   2       1       80        90     1060       0
```

A Kaplan-Meier Curve

First we fit the model:

```r
## Hazard model
out_cph <- coxph(Surv(time, status) ~ age + sex, data = lung)

summary(out_cph)
```

```
Call:
coxph(formula = Surv(time, status) ~ age + sex, data = lung)

  n= 228, number of events= 165 

         coef exp(coef)  se(coef)      z Pr(>|z|)   
age  0.017045  1.017191  0.009223  1.848  0.06459 . 
sex -0.513219  0.598566  0.167458 -3.065  0.00218 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    exp(coef) exp(-coef) lower .95 upper .95
age    1.0172     0.9831    0.9990    1.0357
sex    0.5986     1.6707    0.4311    0.8311

Concordance= 0.603  (se = 0.025 )
Likelihood ratio test= 14.12  on 2 df,   p=9e-04
Wald test            = 13.47  on 2 df,   p=0.001
Score (logrank) test = 13.72  on 2 df,   p=0.001
```

A Kaplan-Meier Curve

Then we create the survival curve, which is *nearly* tidy out of the box:

```
## Hazard model
out_surv <- survfit(out_cph)

## See how this is just a print method,
## not a tibble, or even a data frame.
## So it just runs off the end of the slide.
summary(out_surv)
```

```
Call: survfit(formula = out_cph)

 time n.risk n.event survival std.err lower 95% CI upper 95% CI
    5    228       1   0.9958 0.00417       0.9877        1.000
   11    227       3   0.9833 0.00831       0.9671        1.000
   12    224       1   0.9791 0.00928       0.9611        0.997
   13    223       2   0.9706 0.01096       0.9494        0.992
   15    221       1   0.9664 0.01170       0.9438        0.990
   26    220       1   0.9622 0.01240       0.9382        0.987
   30    219       1   0.9579 0.01305       0.9327        0.984
   31    218       1   0.9537 0.01368       0.9273        0.981
   53    217       2   0.9452 0.01484       0.9165        0.975
   54    215       1   0.9409 0.01538       0.9112        0.972
   59    214       1   0.9366 0.01590       0.9060        0.968
   60    213       2   0.9280 0.01689       0.8955        0.962
   61    211       1   0.9237 0.01735       0.8903        0.958
   62    210       1   0.9194 0.01780       0.8852        0.955
 [ reached getOption("max.print") -- omitted 125 rows ]
```

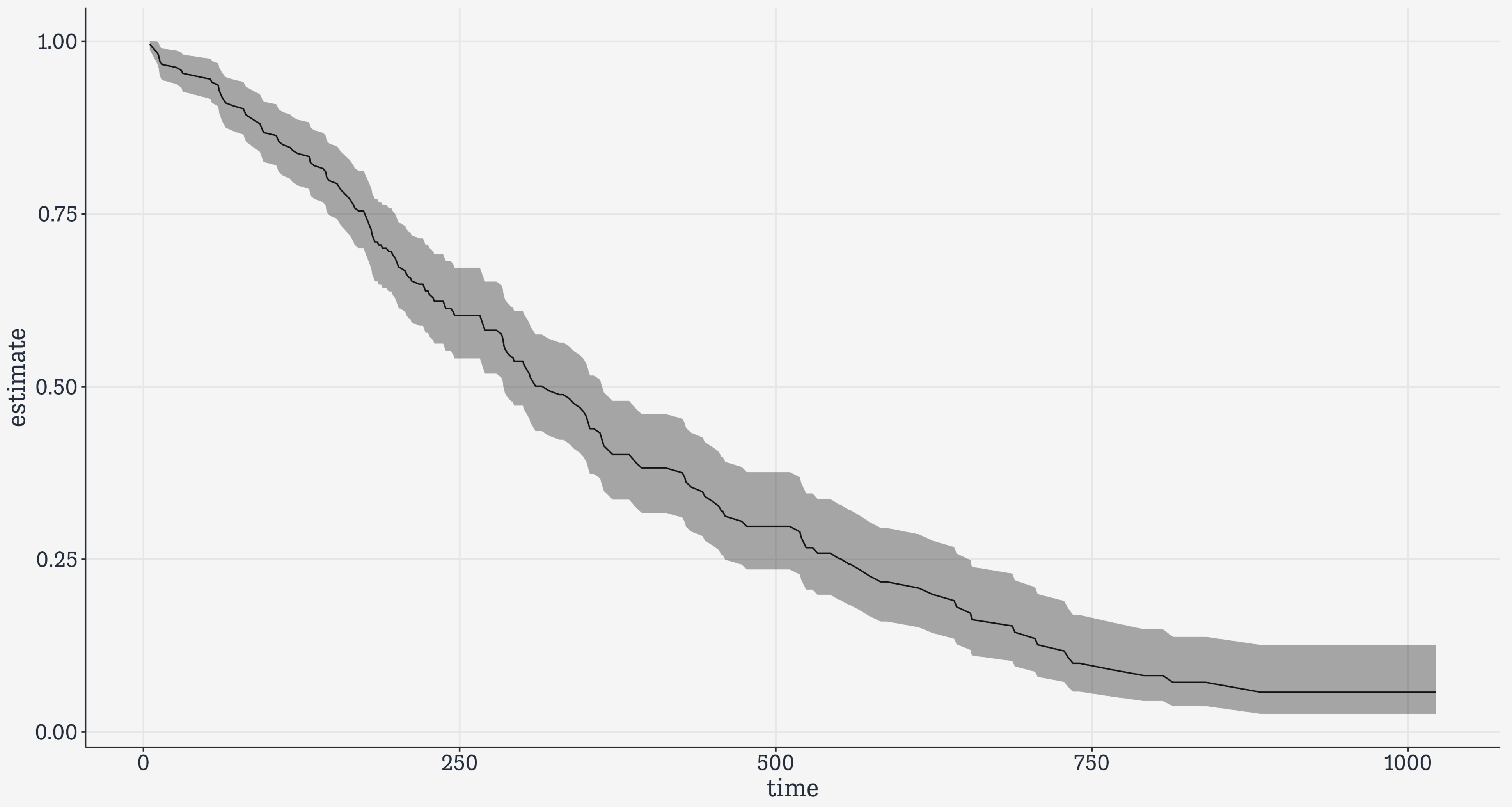
A Kaplan-Meier Curve

Then we tidy it and draw the plot.

```
## Much nicer. (See how the column headers have been regularized, too.)
out_tidy <- tidy(out_surv)
out_tidy
```

```
# A tibble: 186 × 8
    time n.risk n.event n.censor estimate std.error conf.high conf.low
   <dbl>  <dbl>   <dbl>    <dbl>    <dbl>     <dbl>     <dbl>    <dbl>
 1     5    228       1        0    0.996   0.00419     1        0.988
 2    11    227       3        0    0.983   0.00845     1.00     0.967
 3    12    224       1        0    0.979   0.00947     0.997    0.961
 4    13    223       2        0    0.971   0.0113      0.992    0.949
 5    15    221       1        0    0.966   0.0121      0.990    0.944
 6    26    220       1        0    0.962   0.0129      0.987    0.938
 7    30    219       1        0    0.958   0.0136      0.984    0.933
 8    31    218       1        0    0.954   0.0143      0.981    0.927
 9    53    217       2        0    0.945   0.0157      0.975    0.917
10    54    215       1        0    0.941   0.0163      0.972    0.911
# ℹ 176 more rows
```

```
p_out <- out_tidy |>
  ggplot(mapping = aes(x = time, y = estimate)) +
  geom_line() +
  geom_ribbon(mapping = aes(ymin = conf.low, ymax = conf.high),
              alpha = 0.4)
```



Kaplan-Meier Plot

Grouped Analysis with `broom`

Pipelines show their real power when used iteratively

Iteration without tears (or explicit loops)

You might be familiar with code that looks like this:

```r
x ← 10

for (i in 1:5) {
  print(x + i)
}
```

```
[1] 11
[1] 12
[1] 13
[1] 14
[1] 15
```

This is one way to do something repeatedly.

Iteration without tears (or explicit loops)

We can also write, e.g.,

```r
x <- c(10, 20, 30, 40)

for (i in 1:length(x)) {
  # Add 5 to the ith element of x
  print(x[i] + 5)
}
```

```
[1] 15
[1] 25
[1] 35
[1] 45
```

This way we can refer to each element of x in turn, and do the same thing do it.

Iteration without tears (or explicit loops)

The more complicated the thing we want to do, the more likely we are to use functions to help us out.

```r
x <- 10

for (i in 1:5) {
  print(sqrt(x + i))
}
```

```
[1] 3.316625
[1] 3.464102
[1] 3.605551
[1] 3.741657
[1] 3.872983
```

Isn't this like … Vectorized arithmetic?

The simplest cases are not that different from the vectorized arithmetic we saw before.

```r
a <- c(1:10)

b <- 1

# You know what R will do here
a + b
```

```
 [1]  2  3  4  5  6  7  8  9 10 11
```

Isn't this like … Vectorized arithmetic?

The simplest cases are not that different from the vectorized arithmetic we saw before.

```r
a <- c(1:10)

b <- 1

# You know what R will do here
a + b
```

```
 [1]  2  3  4  5  6  7  8  9 10 11
```

R's vectorized rules add b to every element of a. In a sense, the + operation can be thought of as a function that takes each element of a and does something with it. In this case "add b".

Repeatedly applying a function

We can make this explicit by writing a function:

```
a <- c(1:10)


add_b <- function(x) {
  b <- 1
  x + b # for any x
}
```

Now:

```
add_b(x = a)
```

```
 [1]  2  3  4  5  6  7  8  9 10 11
```

In effect we take the vector `a` and feed it to the `add_b()` function one element at a time.

Repeatedly applying a function

Again, R's vectorized approach means it automatically applies `add_b()` to every element of the x we give it.

```r
add_b(x = 10)
```

```
[1] 11
```

```r
add_b(x = c(1, 99, 1000))
```

```
[1]    2  100 1001
```

Iterating in a pipeline

Some operations can't directly be vectorized in this way, most often because the function we want to apply only knows what to do if it is handed, say, a vector. It doesn't understand what to do if it's handed a list of vectors or a tibble of them, etc. This is when we might find ourselves manually iterating—writing out every single step explicitly.

```
library(gapminder)
gapminder |>
  summarize(country_n = n_distinct(country),
            continent_n = n_distinct(continent),
            year_n = n_distinct(year),
            lifeExp_n = n_distinct(lifeExp),
            population_n = n_distinct(population))
```

```
# A tibble: 1 × 5
  country_n continent_n year_n lifeExp_n population_n
      <int>       <int>  <int>     <int>        <int>
1       142           5     12      1626         4060
```

That's tedious to write! Computers are supposed to allow us to avoid that sort of thing.

Iterating in a pipeline

So how would we iterate this? What we want is to apply the `n_distinct()` function to each column of `gapminder`. But we can't easily write a loop inside a pipeline. We want a way to iterate that lets us repeatedly apply a function without explicitly writing a loop.

```r
library(gapminder)
gapminder |>
  summarize(n_distinct(country),
            n_distinct(continent),
            n_distinct(year),
            n_distinct(lifeExp),
            n_distinct(population))
```

```
# A tibble: 1 × 5
  `n_distinct(country)` `n_distinct(continent)` `n_distinct(year)`
                  <int>                   <int>              <int>
1                   142                       5                 12
# ℹ 2 more variables: `n_distinct(lifeExp)` <int>,
#   `n_distinct(population)` <int>
```

Using `n_distinct()` in this context is an idea I got from Rebecca Barter's discussion of `purrr`.

Iterating in a pipeline

In real life, you'd use **across()**, like this:

```r
gapminder |>
  summarize(across(everything(), n_distinct))
```

```
# A tibble: 1 × 6
  country continent  year lifeExp   pop gdpPercap
    <int>     <int> <int>   <int> <int>     <int>
1     142         5    12    1626  1704      1704
```

Iterating in a pipeline

But you could also say "Feed each column of `gapminder` in turn to the `n_distinct()` function". This is what `map()` is for.

```r
map(gapminder, n_distinct)
```

```
$country
[1] 142

$continent
[1] 5

$year
[1] 12

$lifeExp
[1] 1626

$pop
[1] 1704

$gdpPercap
[1] 1704
```

Read it as "Feed each column of `gapminder` to the **`n_distinct()`** function.

Iterating in a pipeline

Or, in pipeline form:

```
gapminder |>
  map(n_distinct)
```

```
$country
[1] 142

$continent
[1] 5

$year
[1] 12

$lifeExp
[1] 1626

$pop
[1] 1704

$gdpPercap
[1] 1704
```

You can see we are getting a *list* back.

Iterating in a pipeline

Or, in pipeline form:

```r
result <- gapminder |>
  map(n_distinct)

class(result)
```

```
[1] "list"
```

```r
result$continent
```

```
[1] 5
```

```r
result[[2]]
```

```
[1] 5
```

Iterating in a pipeline

But we know `n_distinct()` should always return an integer. So we use `map_int()` instead of the generic `map()`.

```
gapminder |>
  map_int(n_distinct)
```

```
  country continent      year   lifeExp       pop gdpPercap
      142         5        12      1626      1704      1704
```

The thing about the `map()` family is that it can deal with all kinds of input types and output types.

So what's the use of all that stuff?

Grouped analysis and list columns

Let's say I want to fit a model to data for all countries in Europe in 1977.

```r
eu77 <- gapminder |>
  filter(continent == "Europe", year == 1977)

fit <- lm(lifeExp ~ log(gdpPercap), data = eu77)
```

```r
summary(fit)
```

```

Call:
lm(formula = lifeExp ~ log(gdpPercap), data = eu77)

Residuals:
    Min      1Q  Median      3Q     Max 
-7.4956 -1.0306  0.0935  1.1755  3.7125 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)      29.489      7.161   4.118 0.000306 ***
log(gdpPercap)    4.488      0.756   5.936 2.17e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.114 on 28 degrees of freedom
Multiple R-squared:  0.5572,	Adjusted R-squared:  0.5414 
F-statistic: 35.24 on 1 and 28 DF,  p-value: 2.173e-06
```

Grouped analysis and list columns

What if I want to do that for all Continent-Year combinations?

```r
out_le <- gapminder |> group_by(continent, year) |>
    nest()

out_le
```

```
# A tibble: 60 × 3
# Groups:   continent, year [60]
   continent  year data
   <fct>     <int> <list>
 1 Asia       1952 <tibble [33 × 4]>
 2 Asia       1957 <tibble [33 × 4]>
 3 Asia       1962 <tibble [33 × 4]>
 4 Asia       1967 <tibble [33 × 4]>
 5 Asia       1972 <tibble [33 × 4]>
 6 Asia       1977 <tibble [33 × 4]>
 7 Asia       1982 <tibble [33 × 4]>
 8 Asia       1987 <tibble [33 × 4]>
 9 Asia       1992 <tibble [33 × 4]>
10 Asia       1997 <tibble [33 × 4]>
# ℹ 50 more rows
```

Think of nesting as a kind of "super-grouping". Look in the object inspector.

Grouped analysis and list columns

Europe '77 is still in there.

```
out_le |>
  filter(continent == "Europe" & year == 1977) |>
  unnest(cols = c(data))
```

```
# A tibble: 30 × 6
# Groups:   continent, year [1]
   continent  year country                lifeExp      pop gdpPercap
   <fct>     <int> <fct>                    <dbl>    <int>     <dbl>
 1 Europe     1977 Albania                   68.9  2509048     3533.
 2 Europe     1977 Austria                   72.2  7568430    19749.
 3 Europe     1977 Belgium                   72.8  9821800    19118.
 4 Europe     1977 Bosnia and Herzegovina    69.9  4086000     3528.
 5 Europe     1977 Bulgaria                  70.8  8797022     7612.
 6 Europe     1977 Croatia                   70.6  4318673    11305.
 7 Europe     1977 Czech Republic            70.7 10161915    14800.
 8 Europe     1977 Denmark                   74.7  5088419    20423.
 9 Europe     1977 Finland                   72.5  4738902    15605.
10 Europe     1977 France                    73.8 53165019    18293.
# ℹ 20 more rows
```

Grouped analysis and list columns

Here we write a tiny, very specific function and `map()` it to every row in the `data` column.

```
fit_ols <- function(df) {
    lm(lifeExp ~ log(gdpPercap), data = df)
}

out_le <- gapminder |>
    group_by(continent, year) |>
    nest() |>
    mutate(model = map(data, fit_ols))
```

Grouped analysis and list columns

Now we have a new column. Each row of the `model` column contains a full regression for that continent-year.

```r
out_le
```

```
# A tibble: 60 × 4
# Groups:   continent, year [60]
   continent  year data              model
   <fct>     <int> <list>            <list>
 1 Asia       1952 <tibble [33 × 4]> <lm>
 2 Asia       1957 <tibble [33 × 4]> <lm>
 3 Asia       1962 <tibble [33 × 4]> <lm>
 4 Asia       1967 <tibble [33 × 4]> <lm>
 5 Asia       1972 <tibble [33 × 4]> <lm>
 6 Asia       1977 <tibble [33 × 4]> <lm>
 7 Asia       1982 <tibble [33 × 4]> <lm>
 8 Asia       1987 <tibble [33 × 4]> <lm>
 9 Asia       1992 <tibble [33 × 4]> <lm>
10 Asia       1997 <tibble [33 × 4]> <lm>
# ℹ 50 more rows
```

Grouped analysis and list columns

We can tidy the nested models, too.

```r
fit_ols <- function(df) {
    lm(lifeExp ~ log(gdpPercap), data = df)
}

out_tidy <- gapminder |>
    group_by(continent, year) |>
    nest() |>
    mutate(model = map(data, fit_ols),
           tidied = map(model, tidy))

out_tidy
```

```
# A tibble: 60 × 5
# Groups:   continent, year [60]
   continent  year data              model  tidied
   <fct>     <int> <list>            <list> <list>
 1 Asia       1952 <tibble [33 × 4]> <lm>   <tibble [2 × 5]>
 2 Asia       1957 <tibble [33 × 4]> <lm>   <tibble [2 × 5]>
 3 Asia       1962 <tibble [33 × 4]> <lm>   <tibble [2 × 5]>
 4 Asia       1967 <tibble [33 × 4]> <lm>   <tibble [2 × 5]>
 5 Asia       1972 <tibble [33 × 4]> <lm>   <tibble [2 × 5]>
 6 Asia       1977 <tibble [33 × 4]> <lm>   <tibble [2 × 5]>
 7 Asia       1982 <tibble [33 × 4]> <lm>   <tibble [2 × 5]>
 8 Asia       1987 <tibble [33 × 4]> <lm>   <tibble [2 × 5]>
 9 Asia       1992 <tibble [33 × 4]> <lm>   <tibble [2 × 5]>
10 Asia       1997 <tibble [33 × 4]> <lm>   <tibble [2 × 5]>
# ℹ 50 more rows
```

Grouped analysis and list columns

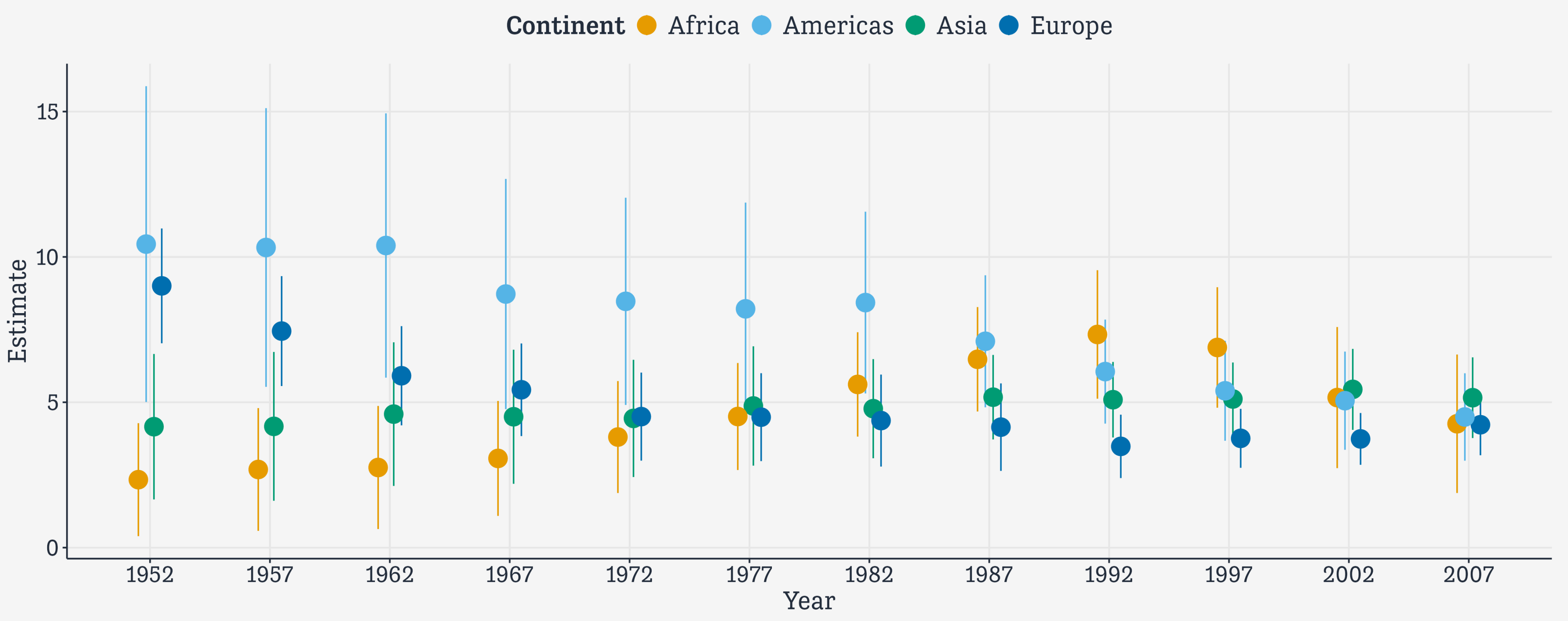
We can get the tidied results out into the main table if we like.

```r
out_tidy <- out_tidy |>
    unnest(cols = c(tidied)) |>
    filter(term %nin% "(Intercept)" &
           continent %nin% "Oceania")

out_tidy
```

```
# A tibble: 48 × 9
# Groups:   continent, year [48]
   continent  year data     model  term     estimate std.error statistic p.value
   <fct>     <int> <list>   <list> <chr>       <dbl>     <dbl>     <dbl>   <dbl>
 1 Asia       1952 <tibble> <lm>   log(gdp…     4.16     1.25       3.33 2.28e-3
 2 Asia       1957 <tibble> <lm>   log(gdp…     4.17     1.28       3.26 2.71e-3
 3 Asia       1962 <tibble> <lm>   log(gdp…     4.59     1.24       3.72 7.94e-4
 4 Asia       1967 <tibble> <lm>   log(gdp…     4.50     1.15       3.90 4.77e-4
 5 Asia       1972 <tibble> <lm>   log(gdp…     4.44     1.01       4.41 1.16e-4
 6 Asia       1977 <tibble> <lm>   log(gdp…     4.87     1.03       4.75 4.42e-5
 7 Asia       1982 <tibble> <lm>   log(gdp…     4.78     0.852      5.61 3.77e-6
 8 Asia       1987 <tibble> <lm>   log(gdp…     5.17     0.727      7.12 5.31e-8
 9 Asia       1992 <tibble> <lm>   log(gdp…     5.09     0.649      7.84 7.60e-9
10 Asia       1997 <tibble> <lm>   log(gdp…     5.11     0.628      8.15 3.35e-9
# ℹ 38 more rows
```

Plot what we have

```
p <- ggplot(data = out_tidy,
            mapping = aes(x = year, y = estimate,
                          ymin = estimate - 2*std.error,
                          ymax = estimate + 2*std.error,
                          group = continent,
                          color = continent))

p_out <- p +
  geom_pointrange(size = rel(1.25),
                  position = position_dodge(width = rel(1.3))) +
  scale_x_continuous(breaks = unique(gapminder$year)) +
  labs(x = "Year",
       y = "Estimate",
       color = "Continent")
```



Repeated Estimates of log GDP on Life Expectancy by Continent

And there's more …

Let's go back to this stage:

```r
# New model
fit_ols2 <- function(df) {
    lm(lifeExp ~ log(gdpPercap) + log(pop), data = df)
}

out_tidy <- gapminder |>
    group_by(continent, year) |>
    nest() |>
    mutate(model = map(data, fit_ols2),
           tidied = map(model, tidy))

out_tidy
```

```
# A tibble: 60 × 5
# Groups:   continent, year [60]
   continent  year data              model  tidied
   <fct>     <int> <list>            <list> <list>
 1 Asia       1952 <tibble [33 × 4]> <lm>   <tibble [3 × 5]>
 2 Asia       1957 <tibble [33 × 4]> <lm>   <tibble [3 × 5]>
 3 Asia       1962 <tibble [33 × 4]> <lm>   <tibble [3 × 5]>
 4 Asia       1967 <tibble [33 × 4]> <lm>   <tibble [3 × 5]>
 5 Asia       1972 <tibble [33 × 4]> <lm>   <tibble [3 × 5]>
 6 Asia       1977 <tibble [33 × 4]> <lm>   <tibble [3 × 5]>
 7 Asia       1982 <tibble [33 × 4]> <lm>   <tibble [3 × 5]>
 8 Asia       1987 <tibble [33 × 4]> <lm>   <tibble [3 × 5]>
 9 Asia       1992 <tibble [33 × 4]> <lm>   <tibble [3 × 5]>
10 Asia       1997 <tibble [33 × 4]> <lm>   <tibble [3 × 5]>
```

A function to draw a coef plot

```r
# Plot the output from our model
mod_plot <- function(data,
                     title){
  data |>
    filter(term %nin% "(Intercept)") |>
    ggplot(mapping = aes(x = estimate,
                         xmin = estimate - std.error,
                         xmax = estimate + std.error,
                         y = reorder(term, estimate))) +
    geom_pointrange() +
    labs(title = title,
         y = NULL)
}
```

Add it using `map2()` or `pmap()`

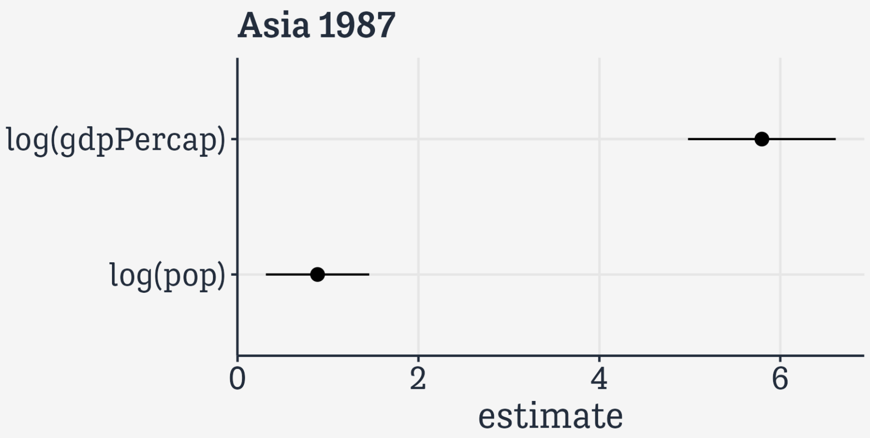
When we have two arguments to feed a function we can use `map2()`. The general case is `pmap()`, for passing any number of arguments in a list.

```r
out_tidy <- gapminder |> group_by(continent, year) |> nest() |>
    mutate(title = paste(continent, year),
           model = map(data, fit_ols2),
           tidied = map(model, tidy),
           ggout = pmap(list(tidied, title),
                        mod_plot))

out_tidy
```

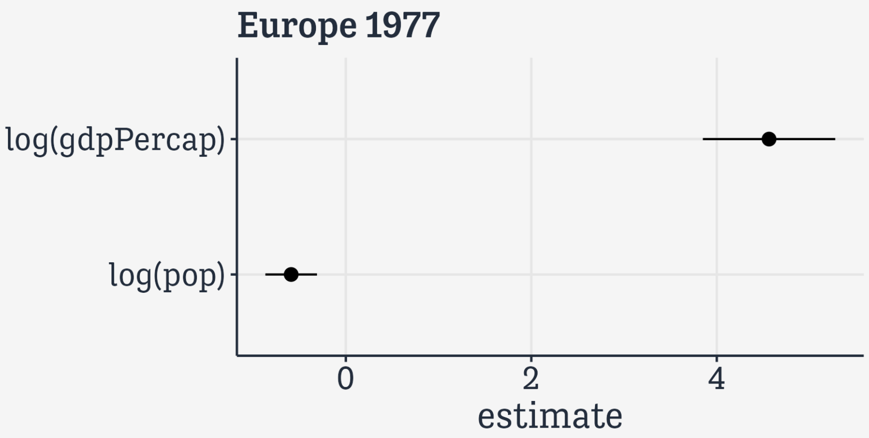
```
# A tibble: 60 × 7
# Groups:   continent, year [60]
   continent  year data              title     model  tidied           ggout
   <fct>     <int> <list>            <chr>     <list> <list>           <list>
 1 Asia       1952 <tibble [33 × 4]> Asia 1952 <lm>   <tibble [3 × 5]> <gg>
 2 Asia       1957 <tibble [33 × 4]> Asia 1957 <lm>   <tibble [3 × 5]> <gg>
 3 Asia       1962 <tibble [33 × 4]> Asia 1962 <lm>   <tibble [3 × 5]> <gg>
 4 Asia       1967 <tibble [33 × 4]> Asia 1967 <lm>   <tibble [3 × 5]> <gg>
 5 Asia       1972 <tibble [33 × 4]> Asia 1972 <lm>   <tibble [3 × 5]> <gg>
 6 Asia       1977 <tibble [33 × 4]> Asia 1977 <lm>   <tibble [3 × 5]> <gg>
 7 Asia       1982 <tibble [33 × 4]> Asia 1982 <lm>   <tibble [3 × 5]> <gg>
 8 Asia       1987 <tibble [33 × 4]> Asia 1987 <lm>   <tibble [3 × 5]> <gg>
 9 Asia       1992 <tibble [33 × 4]> Asia 1992 <lm>   <tibble [3 × 5]> <gg>
```

A plot!

```r
out_tidy$ggout[[8]]
```




```r
out_tidy$ggout[[18]]
```



We don't just put them in there for fun

We can e.g. `walk` the plots out to disk

`walk()` is `map()` for when you just want a "side-effect" such as printed output. There is also `walk2()` and `pwalk()`

```
pwalk(
  list(
    filename = paste0(out_tidy$title, ".png"),
    plot = out_tidy$ggout,
    path = here("figures"),
    height = 3, width = 4,
    dpi = 300
  ),
  ggsave
)
```

Peek in the `figures/` folder

```
fs::dir_ls(here("figures")) |>
  basename()
```

```
 [1] "Africa 1952.png"   "Africa 1957.png"   "Africa 1962.png"
 [4] "Africa 1967.png"   "Africa 1972.png"   "Africa 1977.png"
 [7] "Africa 1982.png"   "Africa 1987.png"   "Africa 1992.png"
[10] "Africa 1997.png"   "Africa 2002.png"   "Africa 2007.png"
[13] "Americas 1952.png" "Americas 1957.png" "Americas 1962.png"
[16] "Americas 1967.png" "Americas 1972.png" "Americas 1977.png"
[19] "Americas 1982.png" "Americas 1987.png" "Americas 1992.png"
[22] "Americas 1997.png" "Americas 2002.png" "Americas 2007.png"
[25] "Asia 1952.png"     "Asia 1957.png"     "Asia 1962.png"
[28] "Asia 1967.png"     "Asia 1972.png"     "Asia 1977.png"
[31] "Asia 1982.png"     "Asia 1987.png"     "Asia 1992.png"
[34] "Asia 1997.png"     "Asia 2002.png"     "Asia 2007.png"
[37] "Europe 1952.png"   "Europe 1957.png"   "Europe 1962.png"
[40] "Europe 1967.png"   "Europe 1972.png"   "Europe 1977.png"
[43] "Europe 1982.png"   "Europe 1987.png"   "Europe 1992.png"
[46] "Europe 1997.png"   "Europe 2002.png"   "Europe 2007.png"
[49] "Oceania 1952.png"  "Oceania 1957.png"  "Oceania 1962.png"
[52] "Oceania 1967.png"  "Oceania 1972.png"  "Oceania 1977.png"
[55] "Oceania 1982.png"  "Oceania 1987.png"  "Oceania 1992.png"
```

Get model-based graphics right

Present findings in substantive terms

Show degrees of confidence or uncertainty

Show the data when you can

But all this applies to data in *any* format. **Graphs are not special here!**

Plot Marginal Effects with the `marginaleffects` package

An example from the GSS

```r
gss_sm
```

```
# A tibble: 2,867 × 32
    year    id ballot       age childs sibs   degree race  sex   region income16
   <dbl> <dbl> <labelled> <dbl>  <dbl> <labe> <fct>  <fct> <fct> <fct>  <fct>   
 1  2016     1 1             47      3 2      Bache… White Male  New E… $170000…
 2  2016     2 2             61      0 3      High … White Male  New E… $50000 …
 3  2016     3 3             72      2 3      Bache… White Male  New E… $75000 …
 4  2016     4 1             43      4 3      High … White Fema… New E… $170000…
 5  2016     5 3             55      2 2      Gradu… White Fema… New E… $170000…
 6  2016     6 2             53      2 2      Junio… White Fema… New E… $60000 …
 7  2016     7 1             50      2 2      High … White Male  New E… $170000…
 8  2016     8 3             23      3 6      High … Other Fema… Middl… $30000 …
 9  2016     9 1             45      3 5      High … Black Male  Middl… $60000 …
10  2016    10 3             71      4 1      Junio… White Male  Middl… $60000 …
# ℹ 2,857 more rows
# ℹ 21 more variables: relig <fct>, marital <fct>, padeg <fct>, madeg <fct>,
#   partyid <fct>, polviews <fct>, happy <fct>, partners <fct>, grass <fct>,
#   zodiac <fct>, pres12 <labelled>, wtssall <dbl>, income_rc <fct>,
#   agegrp <fct>, ageq <fct>, siblings <fct>, kids <fct>, religion <fct>,
#   bigregion <fct>, partners_rc <fct>, obama <dbl>
```

Set up our model

```r
gss_sm$polviews_m <- relevel(gss_sm$polviews,
                             ref = "Moderate")

out_bo <- glm(obama ~ polviews_m + sex*race,
              family = "binomial",
              data = gss_sm)

tidy(out_bo)
```

```
# A tibble: 12 × 5
   term                               estimate std.error statistic  p.value
   <chr>                                 <dbl>     <dbl>     <dbl>    <dbl>
 1 (Intercept)                         0.296       0.134    2.21    2.70e- 2
 2 polviews_mExtremely Liberal         2.37        0.525    4.52    6.20e- 6
 3 polviews_mLiberal                   2.60        0.357    7.29    3.10e-13
 4 polviews_mSlightly Liberal          1.29        0.248    5.21    1.94e- 7
 5 polviews_mSlightly Conservative    -1.36        0.181   -7.48    7.68e-14
 6 polviews_mConservative             -2.35        0.200  -11.7     1.07e-31
 7 polviews_mExtremely Conservative   -2.73        0.387   -7.04    1.87e-12
 8 sexFemale                           0.255       0.145    1.75    7.96e- 2
 9 raceBlack                           3.85        0.501    7.68    1.61e-14
10 raceOther                          -0.00214     0.436   -0.00492 9.96e- 1
11 sexFemale:raceBlack                -0.198       0.660   -0.299   7.65e- 1
12 sexFemale:raceOther                 1.57        0.588    2.68    7.37e- 3
```

Calculate the Average Marginal Effects

```r
library(marginaleffects)

bo_mfx <- avg_slopes(out_bo)

## This gives us the marginal effects at the unit level
as_tibble(bo_mfx)
```

```
# A tibble: 9 × 12
  term       contrast    estimate std.error statistic   p.value s.value conf.low
  <chr>      <chr>          <dbl>     <dbl>     <dbl>     <dbl>   <dbl>    <dbl>
1 polviews_m mean(Conse…  -0.412     0.0283    -14.5  6.82e- 48  157.   -0.467
2 polviews_m mean(Extre…  -0.454     0.0420    -10.8  3.55e- 27   87.9  -0.536
3 polviews_m mean(Extre…   0.268     0.0295      9.10 9.07e- 20   63.3   0.210
4 polviews_m mean(Liber…   0.277     0.0229     12.1  1.46e- 33  109.    0.232
5 polviews_m mean(Sligh…  -0.266     0.0330     -8.06 7.65e- 16   50.2  -0.330
6 polviews_m mean(Sligh…   0.193     0.0303      6.39 1.66e- 10   32.5   0.134
7 race       mean(Black…   0.403     0.0173     23.4  1.18e-120  398.    0.369
8 race       mean(Other…   0.125     0.0386      3.23 1.24e-  3    9.66  0.0490
9 sex        mean(Femal…   0.0443    0.0177      2.51 1.22e-  2    6.36  0.00967
# ℹ 4 more variables: conf.high <dbl>, predicted_lo <dbl>, predicted_hi <dbl>,
#   predicted <dbl>
```

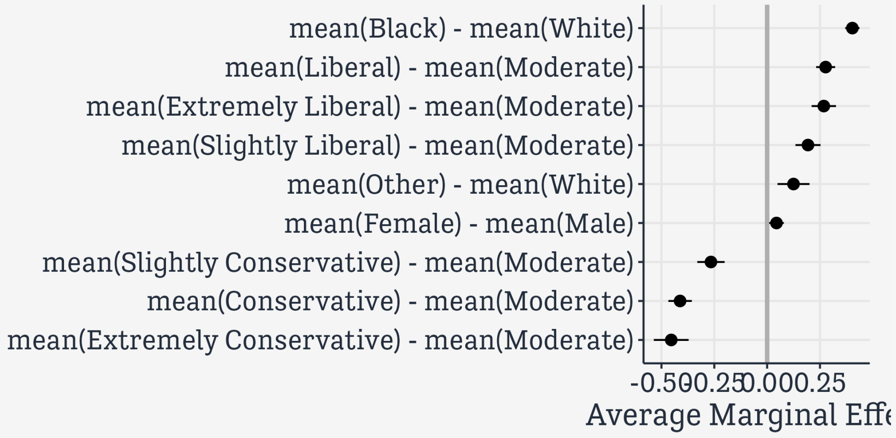
Alternatively, do it with `broom`

```r
tidy(bo_mfx)
```

```
# A tibble: 9 × 12
  term       contrast    estimate std.error statistic   p.value s.value conf.low
  <chr>      <chr>          <dbl>     <dbl>     <dbl>     <dbl>   <dbl>    <dbl>
1 polviews_m mean(Conse…  -0.412     0.0283    -14.5  6.82e- 48  157.   -0.467
2 polviews_m mean(Extre…  -0.454     0.0420    -10.8  3.55e- 27   87.9  -0.536
3 polviews_m mean(Extre…   0.268     0.0295      9.10 9.07e- 20   63.3   0.210
4 polviews_m mean(Liber…   0.277     0.0229     12.1  1.46e- 33  109.    0.232
5 polviews_m mean(Sligh…  -0.266     0.0330     -8.06 7.65e- 16   50.2  -0.330
6 polviews_m mean(Sligh…   0.193     0.0303      6.39 1.66e- 10   32.5   0.134
7 race       mean(Black…   0.403     0.0173     23.4  1.18e-120  398.    0.369
8 race       mean(Other…   0.125     0.0386      3.23 1.24e-  3    9.66  0.0490
9 sex        mean(Femal…   0.0443    0.0177      2.51 1.22e-  2    6.36  0.00967
# ℹ 4 more variables: conf.high <dbl>, predicted_lo <dbl>, predicted_hi <dbl>,
#   predicted <dbl>
```

Which gets us back to familiar territory

```r
tidy(bo_mfx) |>
  ggplot(mapping = aes(x = estimate,
                       xmin = conf.low,
                       xmax = conf.high,
                       y = reorder(contrast,
                                   estimate))) +
  geom_vline(xintercept = 0, color = "gray70",
             size = rel(1.2)) +
  geom_pointrange() +
  labs(x = "Average Marginal Effect",
       y = NULL)
```



`marginaleffects` can do a lot more

marginaleffects 0.4.1.9000 | Adjusted predictions | Marginal effects | Contrasts | Marginal means | Functions | Changelog

The `marginaleffects` package for `R`

`marginaleffects` is an R package to compute and plot adjusted predictions, marginal effects, contrasts, and marginal means for a *wide* variety of models.

Table of contents

Links

View on CRAN

Browse source code

Report a bug

License

Full license

GPL (>= 3)

Citation

Citing marginaleffects

Developers

Vincent Arel-Bundock

Author, maintainer, copyright holder

Dev status

codecov 90%

R-CMD-check passing

CRAN 0.4.1

dependencies 3/4

`marginaleffects` can do a lot more

It includes a range of plotting methods, to produce graphics directly.

These are built on `ggplot`. Similarly integration with `broom` means that you can use the package-specific plotting functions take the tidy output and adapt it to your own needs.

Also check out `modelsummary`, by the same author, for quick and flexible summaries of models and datasets. Again, this sort of package is very convenient to use directly. But with just a little facility with R and tidyverse-style idioms and patterns, you'll get even more out of it. You'll better understand how to adapt it and why its functions work as they do.

Complex Surveys with the `survey` and `srvyr` packages

Working with complex surveys

As always, our question is “What’s the smoothest way for me to get a tidy table of results I need to hand off to `ggplot`?”

For complex surveys, we use `survey`, the standard package for survey analysis in R, and `srvyr`, a helper package designed to integrate what `survey` can do with the Tiydverse framework.

```
## Load the packages
library(survey)
library(srvyr)
```

Example: The GSS again

This time, a small piece of the full GSS from the early 1970s to 2018.

```r
gss_lon
```

```
# A tibble: 62,466 × 25
    year    id ballot age   degree race  sex   siblings kids  bigregion income16
   <dbl> <dbl> <labe> <lab> <fct>  <fct> <fct> <fct>    <fct> <fct>     <fct>
 1  1972     1 NA     23    Bache… White Fema… 3        0     Midwest   <NA>
 2  1972     2 NA     70    Lt Hi… White Male  4        4+    Midwest   <NA>
 3  1972     3 NA     48    High … White Fema… 5        4+    Midwest   <NA>
 4  1972     4 NA     27    Bache… White Fema… 5        0     Midwest   <NA>
 5  1972     5 NA     61    High … White Fema… 2        2     Midwest   <NA>
 6  1972     6 NA     26    High … White Male  1        0     Midwest   <NA>
 7  1972     7 NA     28    High … White Male  6+       2     Midwest   <NA>
 8  1972     8 NA     27    Bache… White Male  1        0     Midwest   <NA>
 9  1972     9 NA     21    High … Black Fema… 2        2     South     <NA>
10  1972    10 NA     30    High … Black Fema… 6+       4+    South     <NA>
# ℹ 62,456 more rows
# ℹ 14 more variables: religion <fct>, marital <fct>, padeg <fct>, madeg <fct>,
#   partyid <fct>, polviews <fct>, happy <fct>, partners_rc <fct>, grass <fct>,
#   zodiac <fct>, pres12 <labelled>, wtssall <dbl>, vpsu <dbl>, vstrat <dbl>
```

Add the weighting information

```r
# These details are dependent on the kind of survey you're working with
options(survey.lonely.psu = "adjust")
options(na.action="na.pass")

gss_svy <- gss_lon |>
  filter(year > 1974) |>
  mutate(stratvar = interaction(year, vstrat)) |>
  as_survey_design(ids = vpsu,
                   strata = stratvar,
                   weights = wtssall,
                   nest = TRUE)

gss_svy # Now it's no longer simply a tibble
```

```
Stratified 1 - level Cluster Sampling design (with replacement)
With (4399) clusters.
Called via srvyr
Sampling variables:
  - ids: vpsu
  - strata: stratvar
  - weights: wtssall
Data variables:
  - year (dbl), id (dbl), ballot (labelled), age (labelled), degree (fct), race
    (fct), sex (fct), siblings (fct), kids (fct), bigregion (fct), income16
    (fct), religion (fct), marital (fct), padeg (fct), madeg (fct), partyid
    (fct), polviews (fct), happy (fct), partners_rc (fct), grass (fct), zodiac
    (fct), pres12 (labelled), wtssall (dbl), vpsu (dbl), vstrat (dbl), stratvar
    (fct)
```

Trends in the happy measure

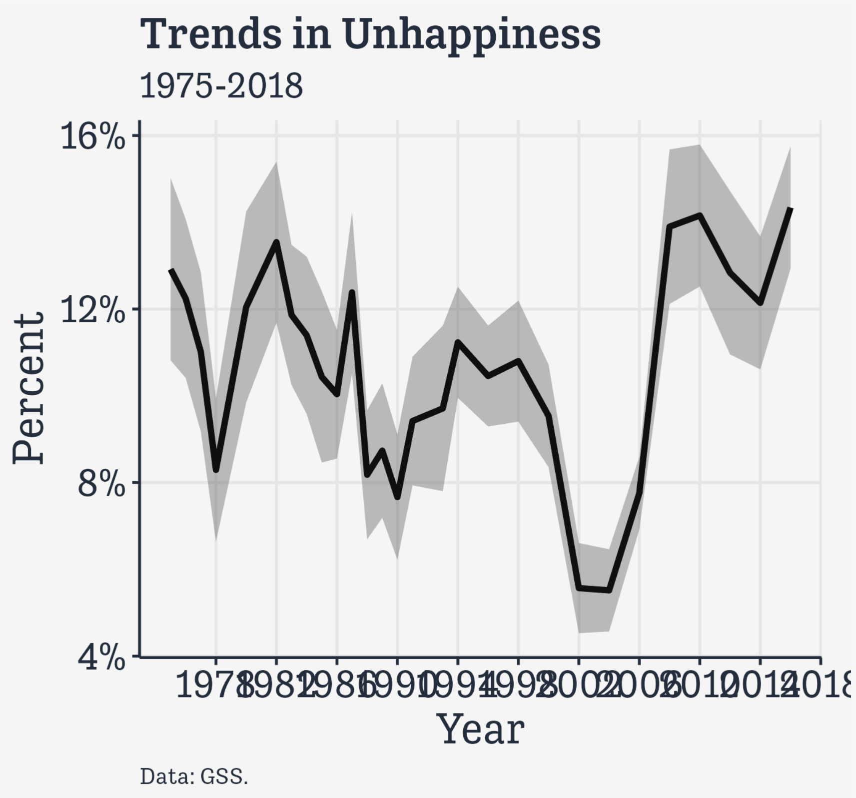
```r
out_hap <- gss_svy |>
    group_by(year, happy) |>
    summarize(prop = survey_mean(na.rm = TRUE, vartype = "ci"))

out_hap
```

```
# A tibble: 111 × 5
# Groups:   year [28]
    year happy            prop prop_low prop_upp
   <dbl> <fct>           <dbl>    <dbl>    <dbl>
 1  1975 Very Happy    0.333   0.304    0.361
 2  1975 Pretty Happy  0.534   0.504    0.565
 3  1975 Not Too Happy 0.129   0.108    0.150
 4  1975 <NA>          0.00375 0.000362 0.00714
 5  1976 Very Happy    0.348   0.321    0.376
 6  1976 Pretty Happy  0.529   0.504    0.555
 7  1976 Not Too Happy 0.122   0.104    0.141
 8  1977 Very Happy    0.357   0.330    0.384
 9  1977 Pretty Happy  0.532   0.504    0.560
10  1977 Not Too Happy 0.110   0.0918   0.128
# ℹ 101 more rows
```

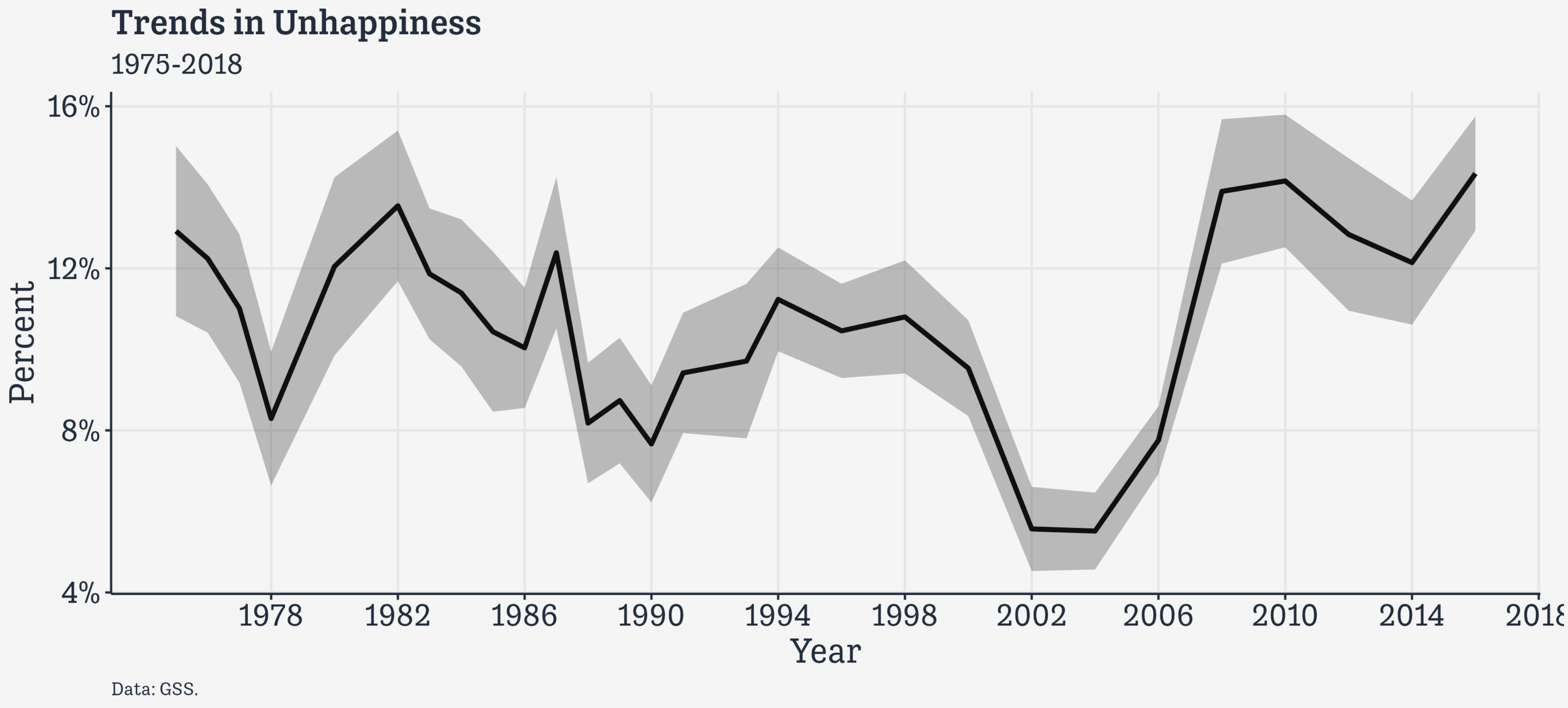
Once again, it’s now a tidy tibble, and we know what to do with those.

Trends in the happy measure

```r
out_hap |>
  filter(happy == "Not Too Happy") |>
  ggplot(mapping = aes(x = year,
                     y = prop,
                     ymin = prop_low,
                     ymax = prop_upp)) +
  geom_line(linewidth = 1.2) +
  geom_ribbon(alpha = 0.3) +
  scale_x_continuous(breaks =
                     seq(1978, 2018, 4)) +
  scale_y_continuous(labels =
                     label_percent(accuracy =
  labs(x = "Year",
    y = "Percent",
    title = "Trends in Unhappiness",
    subtitle = "1975-2018",
    caption = "Data: GSS.")
```



With a better aspect ratio



A more complex example

```r
gss_svy |>
  filter(year %in% seq(1976, 2016, by = 4)) |>
  group_by(year, race, degree) |>
  summarize(prop = survey_mean(na.rm = TRUE))
```

```
# A tibble: 162 × 5
# Groups:   year, race [30]
    year race  degree            prop prop_se
   <dbl> <fct> <fct>            <dbl>   <dbl>
 1  1976 White Lt High School 0.327   0.0160
 2  1976 White High School    0.517   0.0161
 3  1976 White Junior College 0.0128  0.00298
 4  1976 White Bachelor       0.101   0.00955
 5  1976 White Graduate       0.0392  0.00642
 6  1976 White <NA>           0.00285 0.00151
 7  1976 Black Lt High School 0.558   0.0603
 8  1976 Black High School    0.335   0.0476
 9  1976 Black Junior College 0.0423  0.0192
10  1976 Black Bachelor       0.0577  0.0238
# ℹ 152 more rows
```

Let’s put that in an object

```r
out_yrd <- gss_svy |>
  filter(year %in% seq(1976, 2016, by = 4)) |>
  group_by(year, race, degree) |>
  summarize(prop = survey_mean(na.rm = TRUE))
```

Check the sums

```
out_yrd ▷
  group_by(year, race) ▷
  summarize(tot = sum(prop))
```

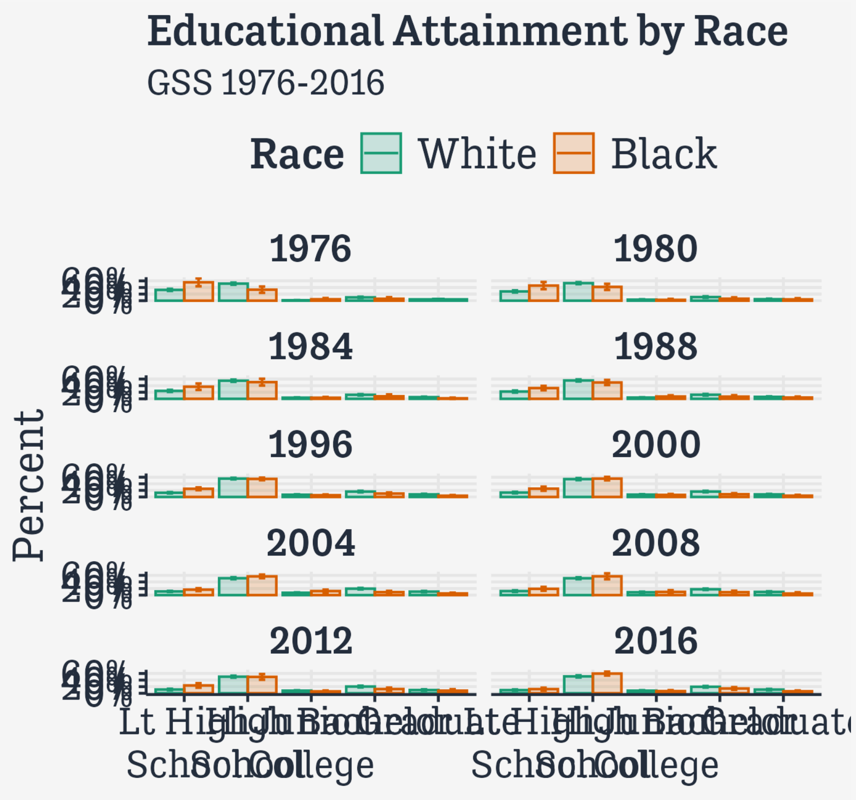
```
# A tibble: 30 × 3
# Groups:   year [10]
    year race    tot
   <dbl> <fct> <dbl>
 1  1976 White  1.00
 2  1976 Black  1.00
 3  1976 Other  1
 4  1980 White  1.00
 5  1980 Black  1
 6  1980 Other  1
 7  1984 White  1.00
 8  1984 Black  1.00
 9  1984 Other  1
10  1988 White  1.00
# ℹ 20 more rows
```

Set up the plot

```
p <- out_yrd |>
  drop_na() |>
  filter(race %nin% "Other") |>
  ggplot(mapping = aes(x = degree,
                       y = prop,
                       ymin = prop - 2*prop_se,
                       ymax = prop + 2*prop_se,
                       fill = race,
                       color = race,
                       group = race))

dodge_w <- position_dodge(width = 0.9)
```

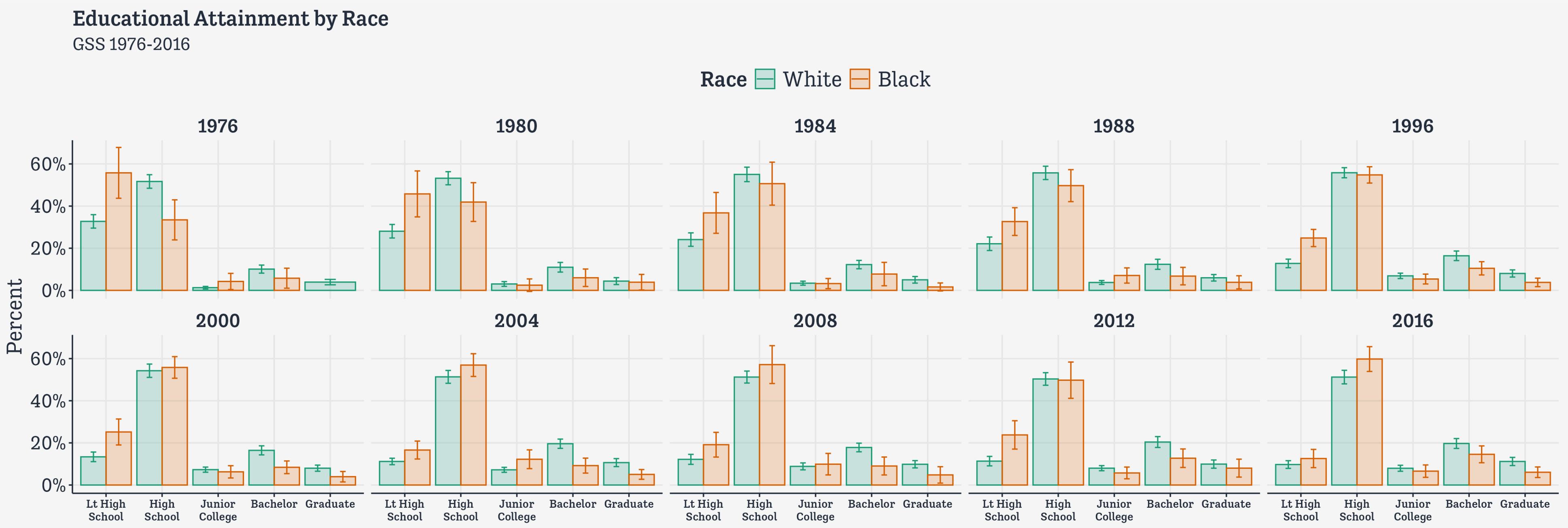
Draw the plot

```r
p + geom_col(position = dodge_w, alpha = 0.2) +
    geom_errorbar(position = dodge_w, width = 0
    scale_x_discrete(labels = wrap_format(10))
    scale_y_continuous(labels = label_percent()
    scale_color_brewer(type = "qual",
                       palette = "Dark2") +
    scale_fill_brewer(type = "qual",
                      palette = "Dark2") +
    labs(title = "Educational Attainment by Rac
         subtitle = "GSS 1976-2016",
         fill = "Race",
         color = "Race",
         x = NULL, y = "Percent") +
    facet_wrap(~ year, ncol = 2)
```



In full (but switch to rows)

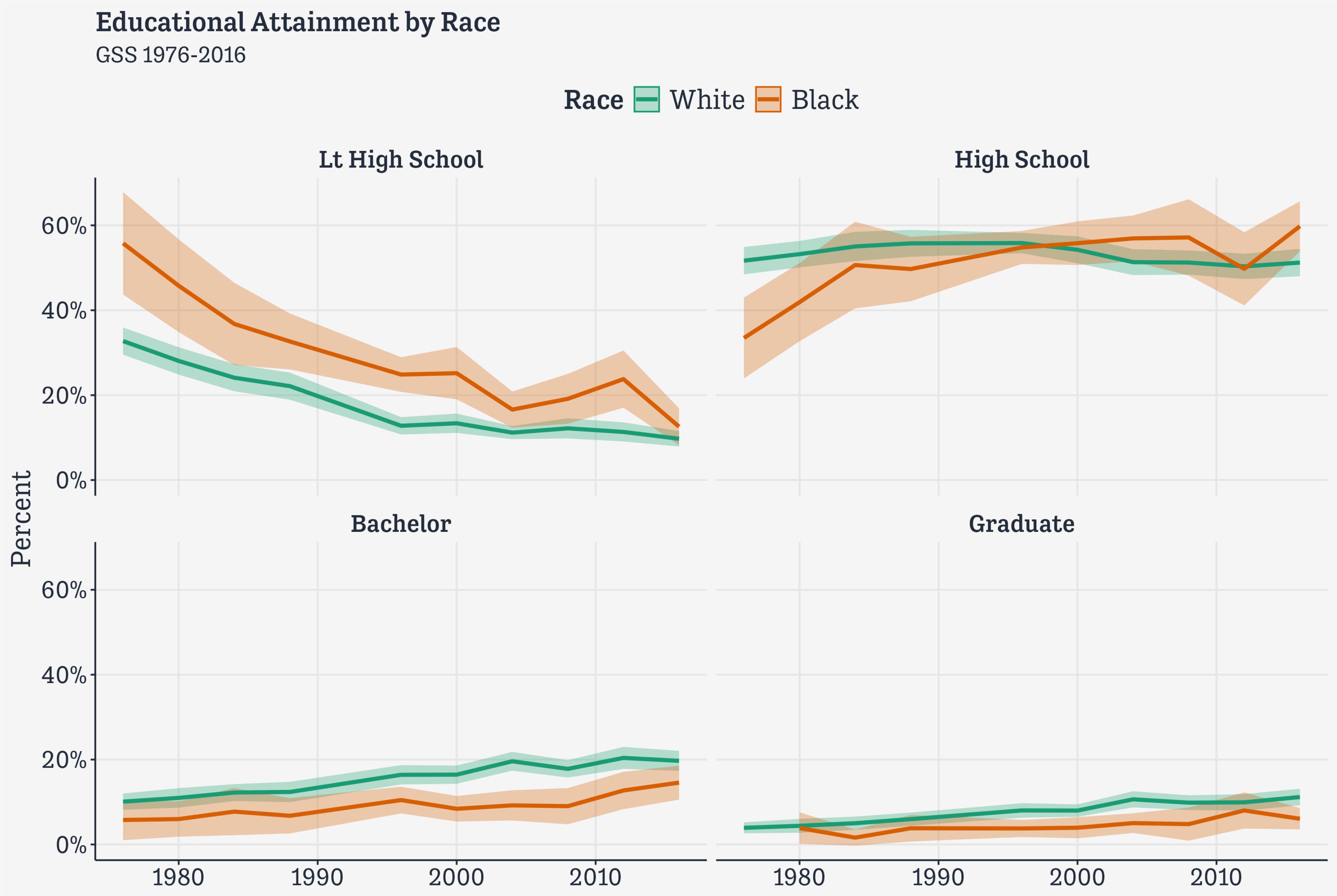
```r
p_out <- p +
  geom_col(position = dodge_w, alpha = 0.2) +
  geom_errorbar(position = dodge_w, width = 0.2) +
  scale_x_discrete(labels = wrap_format(10)) +
  scale_y_continuous(labels = label_percent()) +
  scale_color_brewer(type = "qual",
                     palette = "Dark2") +
  scale_fill_brewer(type = "qual",
                    palette = "Dark2") +
  labs(title = "Educational Attainment by Race",
       subtitle = "GSS 1976-2016",
       fill = "Race",
       color = "Race",
       x = NULL, y = "Percent") +
  facet_wrap(~ year, nrow = 2) +
  theme(axis.text.x =
          element_text(size = rel(0.6),
                       face = "bold"))
```


Educational Attainment by Race
GSS 1976-2016
Race White Black
1976
1980
1984
1988
1996
2000
2004
2008
2012
2016
Percent
60%
40%
20%
0%
Lt High School
High School
Junior College
Bachelor
Graduate

Is this figure effective? Not really!

Let's try a different view

```r
p <- out_yrd |>
  drop_na() |>
  filter(race %nin% "Other",
         degree %nin% "Junior College") |>
  ggplot(mapping = aes(x = year, y = prop,
                          ymin = prop - 2*prop_se,
                          ymax = prop + 2*prop_se,
                          fill = race, color = race,
                          group = race))

p_out <- p +
  geom_ribbon(mapping = aes(color = NULL),
              alpha = 0.3) +
  geom_line(linewidth = rel(1.25)) +
  scale_y_continuous(labels = label_percent()) +
  scale_color_brewer(type = "qual", palette = "Dark2") +
  scale_fill_brewer(type = "qual", palette = "Dark2") +
  facet_wrap(~ degree, ncol = 2) +
  labs(title = "Educational Attainment by Race",
       subtitle = "GSS 1976-2016", fill = "Race",
       color = "Race", x = NULL, y = "Percent")
```


Educational Attainment by Race
GSS 1976-2016
Race
White
Black
Lt High School
High School
Bachelor
Graduate
Percent
0%
20%
40%
60%
1980
1990
2000
2010