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Lecture 8: Modeling II

Data Science for Business Analytics

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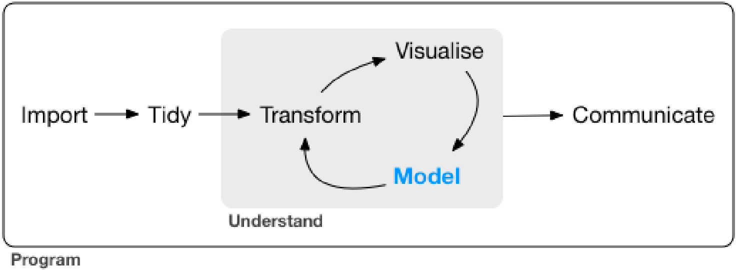
Today



- This morning:
  - how models work mechanistically (focus on linear models),
  - how to use models to find patterns in real data.
- This afternoon:
  - how to use **many** simple models,
  - how to combine modeling and programming tools.

As usual, most of the material is borrowed from R for data science.

Many models

To work with large numbers of models, use

1. many simple models to better understand complex datasets.
2. list-columns to store arbitrary data structures in a data frame.
3. the **broom** package to turn models into tidy data.

Note that this part:

- is harder than the others,
- and requires a deeper internalization of ideas (e.g., about modelling, data structures, and iteration).

Outline

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Reducing code duplication

Three main benefits:

1. Easier to see the intent of your code.
2. Easier to respond to changes in requirements.
3. Likely to have fewer bugs.

Main tools for reducing duplication:

- **Functions** identify repeated patterns of code and extract them out into independent pieces.
- **Iteration** helps you when you need to do the same thing to multiple inputs.

For loops

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```r
df <- tibble(a = rnorm(10), b = rnorm(10), c = rnorm(10), d = rnorm(10))

c(median(df$a), median(df$b), median(df$c), median(df$d))
```

```
## [1]  0.20443713 -0.35536298  0.09003127 -0.25752642
```

```r
output <- vector("double", ncol(df))  # 1. output
for (i in seq_along(df)) {            # 2. sequence
  output[[i]] <- median(df[[i]])      # 3. body
}
output
```

```
## [1]  0.20443713 -0.35536298  0.09003127 -0.25752642
```

A side note:

```r
y <- vector("double", 0)
seq_along(y)
```

```
## integer(0)
```

```r
1:length(y)
```

```
## [1] 1 0
```

Modifying an existing object

```r
df <- tibble(a = rnorm(10),
             b = rnorm(10),
             c = rnorm(10),
             d = rnorm(10))

rescale01 <- function(x) {
    rng <- range(x, na.rm = TRUE)
    (x - rng[1]) / (rng[2] - rng[1])
}

df$a <- rescale01(df$a)
df$b <- rescale01(df$b)
df$c <- rescale01(df$c)
df$d <- rescale01(df$d)

for (i in seq_along(df)) {
    df[[i]] <- rescale01(df[[i]])
}
```

For loops vs. functionals

To compute the mean of every column:

```
output <- vector("double", length(df))
for (i in seq_along(df)) {
  output[[i]] <- mean(df[[i]])
}
```

As a function:

```
col_mean <- function(df) {
  output <- vector("double", length(df))
  for (i in seq_along(df)) {
    output[i] <- mean(df[[i]])
  }
  output
}
```

How about other quantities?

```r
col_median <- function(df) {
  output <- vector("double", length(df))
  for (i in seq_along(df)) {
    output[i] <- median(df[[i]])
  }
  output
}
col_sd <- function(df) {
  output <- vector("double", length(df))
  for (i in seq_along(df)) {
    output[i] <- sd(df[[i]])
  }
  output
}
```

What's “wrong” here?

What's "wrong" here?


```r
f1 <- function(x) abs(x - mean(x)) ^ 1
f2 <- function(x) abs(x - mean(x)) ^ 2
f3 <- function(x) abs(x - mean(x)) ^ 3
```

What's "wrong" here?

```r
f1 <- function(x) abs(x - mean(x)) ^ 1
f2 <- function(x) abs(x - mean(x)) ^ 2
f3 <- function(x) abs(x - mean(x)) ^ 3
```

Without duplication:

```r
f <- function(x, i) abs(x - mean(x)) ^ i
```

Back to column summaries

```r
col_summary <- function(df, fun) {
  out <- vector("double", length(df))
  for (i in seq_along(df)) {
    out[i] <- fun(df[[i]])
  }
  out
}
col_summary(df, median)
```

```
## [1] 0.3684051 0.4523108 0.8108251 0.5468810
```

```r
col_summary(df, mean)
```

```
## [1] 0.4406485 0.4485883 0.6825104 0.5249303
```

Functional programming

- Use **functions that return functions** as output.
- Pass functions as arguments to others function.

The **purrr** package:

- Functions eliminating the need for many common for loops.
- Similar to the apply family in base R (`apply()`, `lapply()`, `tapply()`, etc), but more consistent and easier to learn.

The goal is to break code into independent pieces:

1. Solve a problem for a single element of the list.
   - Once this is done, purrr generalizes to every element in the list.
2. Break a complex problem down into bite-sized pieces.
   - With purrr, small pieces are composed together with the pipe.

The map functions

- `map()` makes a list.
- `map_lgl()` makes a logical vector.
- `map_int()` makes an integer vector.
- `map_dbl()` makes a double vector.
- `map_chr()` makes a character vector.

Each function:

1. Takes a vector as input.
2. Applies a function to each piece.
3. Returns a new vector that's the same length (and has the same names) as the input.

The return type is determined by the suffix.

Using map functions

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```r
map_dbl(df, mean)
map_dbl(df, median)
map_dbl(df, sd)
```

```
##         a         b         c         d
## 0.4406485 0.4485883 0.6825104 0.5249303
##         a         b         c         d
## 0.3684051 0.4523108 0.8108251 0.5468810
##         a         b         c         d
## 0.3362143 0.2640144 0.3516401 0.2929669
```

Using the pipe:

```r
df %>% map_dbl(mean)
df %>% map_dbl(median)
df %>% map_dbl(sd)
```

```
##         a         b         c         d
## 0.4406485 0.4485883 0.6825104 0.5249303
##         a         b         c         d
## 0.3684051 0.4523108 0.8108251 0.5468810
##         a         b         c         d
## 0.3362143 0.2640144 0.3516401 0.2929669
```

map_*() vs col_summary()

- All purrr functions are implemented in C (i.e., slightly faster).
- The second argument, .f, the function to apply, can be a formula, a character vector, or an integer vector.
- map_*() uses ... ([dot dot dot]) to pass along additional arguments to .f each time it's called:

```
map_dbl(df, mean, trim = 0.5)
```

```
##         a         b         c         d
## 0.3684051 0.4523108 0.8108251 0.5468810
```

- The map functions preserve names:

```
z <- list(x = 1:3, y = 4:5)
map_int(z, length)
```

```
## x y
## 3 2
```

Shortcut 1

Splits the `mtcars` dataset into three pieces and fits the same linear model to each piece:

```
models <- mtcars %>%
  split(.$cyl) %>%
  map(function(df) lm(mpg ~ wt, data = df))
```

Using a one-sided formula:

```
models <- mtcars %>%
  split(.$cyl) %>%
  map(~lm(mpg ~ wt, data = .))
```

Shortcut 2

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Extract a summary statistic like the R^2:

```
models %>%
  map(summary) %>%
  map_dbl(~.$r.squared)
```

```
##         4         6         8
## 0.5086326 0.4645102 0.4229655
```

Use a string:

```
models %>%
  map(summary) %>%
  map_dbl("r.squared")
```

```
##         4         6         8
## 0.5086326 0.4645102 0.4229655
```

Shortcut 3

Use an integer:

```
x <- list(list(1, 2, 3), list(4, 5, 6), list(7, 8, 9))
x %>% map_dbl(2)
```

```
## [1] 2 5 8
```

Dealing with failure using `safely()`

- `safely()` is an adverb: it takes a function (a verb) and returns a modified version.
- The modified function always returns a list with two elements:
    1. `result` is the original result.
    2. `error` is an error object.

```
safe_log <- safely(log)
str(safe_log(10))
```

```
## List of 2
##  $ result: num 2.3
##  $ error : NULL
```

```
str(safe_log("a"))
```

```
## List of 2
##  $ result: NULL
##  $ error :List of 2
##   ..$ message: chr "non-numeric argument to mathematical function"
##   ..$ call   : language log(x = x, base = base)
##   ..- attr(*, "class")= chr [1:3] "simpleError" "error" "condition"
```

safely() and map()

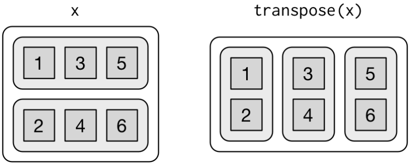
```r
x <- list(1, 10, "a")
y <- x %>% map(safely(log))
str(y)
```

```
## List of 3
##  $ :List of 2
##   ..$ result: num 0
##   ..$ error : NULL
##  $ :List of 2
##   ..$ result: num 2.3
##   ..$ error : NULL
##  $ :List of 2
##   ..$ result: NULL
##   ..$ error :List of 2
##   .. ..$ message: chr "non-numeric argument to mathematical function"
##   .. ..$ call   : language log(x = x, base = base)
##   .. ..- attr(*, "class")= chr [1:3] "simpleError" "error" "condition"
```

transpose()


```r
y <- y %>% transpose()
str(y)
```

```
## List of 2
##  $ result:List of 3
##   ..$ : num 0
##   ..$ : num 2.3
##   ..$ : NULL
##  $ error :List of 3
##   ..$ : NULL
##   ..$ : NULL
##   ..$ :List of 2
##   .. ..$ message: chr "non-numeric argument to mathematical function"
##   .. ..$ call   : language log(x = x, base = base)
##   .. ..- attr(*, "class")= chr [1:3] "simpleError" "error" "condition"
```



Typical use


```r
is_ok <- y$error %>% map_lgl(is_null)
x[!is_ok]
```

```
## [[1]]
## [1] "a"
```

```r
y$result[is_ok] %>% flatten_dbl()
```

```
## [1] 0.000000 2.302585
```

Two other useful adverbs

- `possibly()`: "simpler" than `safely()`, because you give it a default value to return when there is an error.

```
list(1, 10, "a") %>% map_dbl(possibly(log, NA_real_))
```

```
## [1] 0.000000 2.302585       NA
```

- `quietly()`: instead of capturing errors, it captures printed output, messages, and warnings.

```
list(1, -1) %>% map(quietly(log)) %>% str()
```

```
## List of 2
##  $ :List of 4
##   ..$ result  : num 0
##   ..$ output  : chr ""
##   ..$ warnings: chr(0)
##   ..$ messages: chr(0)
##  $ :List of 4
##   ..$ result  : num NaN
##   ..$ output  : chr ""
##   ..$ warnings: chr "NaNs produced"
##   ..$ messages: chr(0)
```

Mapping over multiple arguments


```r
mu <- list(5, 10, -3)
mu %>% map(rnorm, n = 5) %>% str()
```

```
## List of 3
##  $ : num [1:5] 4.2 6.25 5.77 4.78 4.58
##  $ : num [1:5] 9.58 11 9.72 11.26 10.65
##  $ : num [1:5] -1.7 -3.87 -2.99 -3.88 -2.4
```

What if you also want to vary the standard deviation?

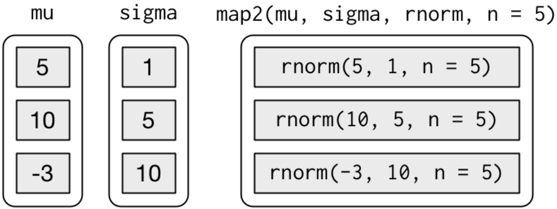
```r
sigma <- list(1, 5, 10)
seq_along(mu) %>% map(~rnorm(5, mu[[.]], sigma[[.]])) %>% str()
```

```
## List of 3
##  $ : num [1:5] 5.12 4.72 6.46 5.23 6
##  $ : num [1:5] 13.91 6.12 6.92 10.23 4.35
##  $ : num [1:5] 2.77 -15.81 13.25 -8.01 13.78
```

map2()


```r
map2(mu, sigma, rnorm, n = 5) %>%
    str()
```

```
## List of 3
##  $ : num [1:5] 4.59 4.03 5.03 5.03 3.32
##  $ : num [1:5] 15.3 4.4 11.7 12.5 10.7
##  $ : num [1:5] -4.19 -1.02 -13.69 -11.03 -14.14
```



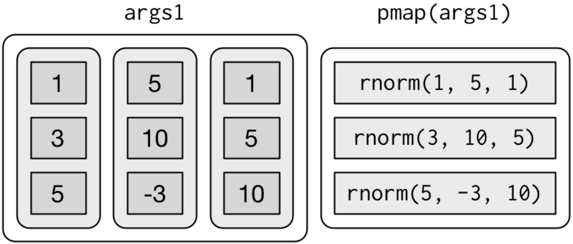
Note that the arguments that

- vary for each call come *before* the function,
- are the same for every call come *after* (using ...).

pmap()

```r
n <- list(1, 3, 5)
args1 <- list(n, mu, sigma)
args1 %>%
    pmap(rnorm) %>%
    str()
```

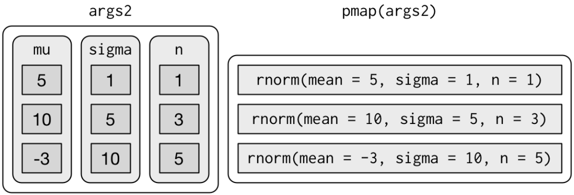
```
## List of 3
##  $ : num 6.58
##  $ : num [1:3] 17.49 11.31 3.84
##  $ : num [1:5] -3.04 12.12 -7.76 4.98 -12.74
```



pmap() cont'd

```r
args2 <- list(mean = mu, sd = sigma, n = n)
args2 %>%
    pmap(rnorm) %>%
    str()
```

```
## List of 3
##  $ : num 5.69
##  $ : num [1:3] 5.22 3.84 5.22
##  $ : num [1:5] -11.7 -12.11 4.41 -2.31 -6.24
```



Or better

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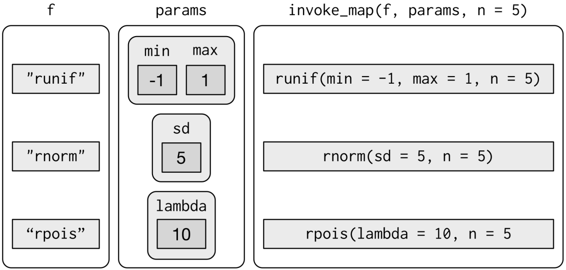
```r
params <- tribble(
  ~mean, ~sd, ~n,
    5,     1,  1,
   10,     5,  3,
   -3,    10,  5)
params %>%
  pmap(rnorm)
```

```
## [[1]]
## [1] 3.913497
##
## [[2]]
## [1] 4.920355 6.161049 4.401400
##
## [[3]]
## [1]  -7.481742   1.717364 -14.804907  11.702570 -16.114206
```

Invoking different functions


```r
f <- c("runif", "rnorm", "rpois")
param <- list(list(min = -1, max = 1), list(sd = 5), list(lambda = 10))
invoke_map(f, param, n = 5) %>% str()
```

```
## List of 3
##  $ : num [1:5] -0.0769 -0.2496 0.9822 -0.6473 0.6269
##  $ : num [1:5] -7.44 -5.38 5 -3.11 -6.92
##  $ : int [1:5] 15 11 9 13 12
```



Invoking different cont'd

```r
sim <- tribble(~f,      ~params,
               "runif", list(min = -1, max = 1),
               "rnorm", list(sd = 5),
               "rpois", list(lambda = 10))
sim %>%
    mutate(sim = invoke_map(f, params, n = 10)) %>%
    str()
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    3 obs. of  3 variables:
##  $ f     : chr  "runif" "rnorm" "rpois"
##  $ params:List of 3
##   ..$ :List of 2
##   .. ..$ min: num -1
##   .. ..$ max: num 1
##   ..$ :List of 1
##   .. ..$ sd: num 5
##   ..$ :List of 1
##   .. ..$ lambda: num 10
##  $ sim   :List of 3
##   ..$ : num  -0.464 0.524 0.973 -0.413 -0.201 ...
##   ..$ : num  1.038 11.54 0.529 2.285 -0.386 ...
##   ..$ : int  13 6 8 13 11 9 10 7 8 7
```

Outline

gapminder

- Summarizes the progression of countries over time using variables like life expectancy and GDP.
- Popularized by Hans Rosling, a Swedish doctor and statistician, in a short video filmed in conjunction with the BBC

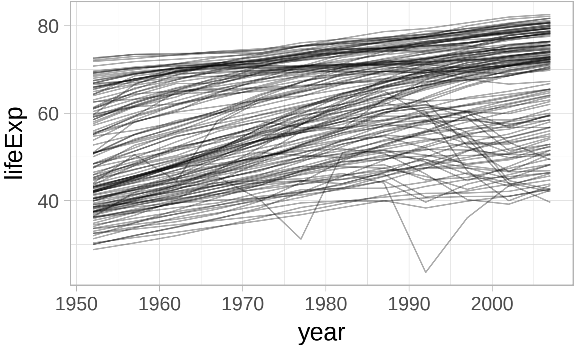
```r
library(gapminder)
gapminder
```

```
## # A tibble: 1,704 x 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.
## # ... with 1,694 more rows
```

Focus on three variables

How does life expectancy (`lifeExp`) change over time (`year`) for each country (`country`)?

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

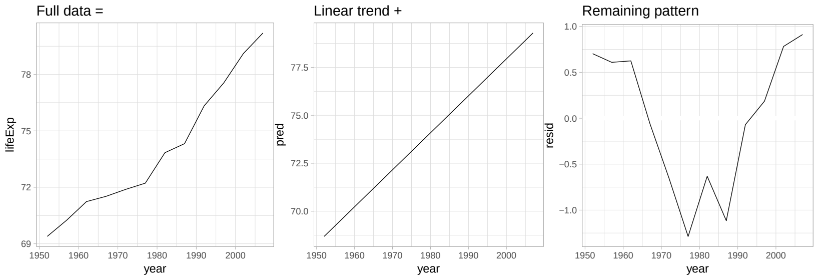


Model for a single country


```r
nz <- filter(gapminder, country == "New Zealand")
nz %>% ggplot(aes(year, lifeExp)) + geom_line() + ggtitle("Full data = ")

nz_mod <- lm(lifeExp ~ year, data = nz)
nz %>% add_predictions(nz_mod) %>%
  ggplot(aes(year, pred)) + geom_line() + ggtitle("Linear trend + ")

nz %>% add_residuals(nz_mod) %>%
  ggplot(aes(year, resid)) +
    geom_hline(yintercept = 0, colour = "white", size = 3) +
    geom_line() + ggtitle("Remaining pattern")
```



Nested data

```r
(by_country <- gapminder %>%
  group_by(country, continent) %>%
  nest())
```

```
## # A tibble: 142 x 3
##    country     continent data
##    <fct>       <fct>     <list>
##  1 Afghanistan Asia      <tibble [12 x 4]>
##  2 Albania     Europe    <tibble [12 x 4]>
##  3 Algeria     Africa    <tibble [12 x 4]>
##  4 Angola      Africa    <tibble [12 x 4]>
##  5 Argentina   Americas  <tibble [12 x 4]>
##  6 Australia   Oceania   <tibble [12 x 4]>
##  7 Austria     Europe    <tibble [12 x 4]>
##  8 Bahrain     Asia      <tibble [12 x 4]>
##  9 Bangladesh  Asia      <tibble [12 x 4]>
## 10 Belgium     Europe    <tibble [12 x 4]>
## # ... with 132 more rows
```

- In a grouped data frame, each row is an observation.
- In a nested data frame, each row is a group.

List-columns

A model-fitting function applied to every country:

```
country_model <- function(df) lm(lifeExp ~ year, data = df)
models <- map(by_country$data, country_model)
```

Or add an additional list-column:

```
(by_country <- by_country %>% mutate(model = map(data, country_model)))
```

```
## # A tibble: 142 x 4
##    country     continent data              model
##    <fct>       <fct>     <list>            <list>
##  1 Afghanistan Asia      <tibble [12 x 4]> <S3: lm>
##  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>
##  7 Austria     Europe    <tibble [12 x 4]> <S3: lm>
##  8 Bahrain     Asia      <tibble [12 x 4]> <S3: lm>
##  9 Bangladesh  Asia      <tibble [12 x 4]> <S3: lm>
## 10 Belgium     Europe    <tibble [12 x 4]> <S3: lm>
## # ... with 132 more rows
```

Why bother?

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- Avoid leaving the list of models as a free-floating object.
- No need to manually keep them in sync when using e.g. `filter` or `arrange`.

```
by_country %>% filter(continent == "Europe")
```

```
## # A tibble: 30 x 4
##    country                continent data              model
##    <fct>                  <fct>     <list>            <list>
##  1 Albania                Europe    <tibble [12 x 4]> <S3: lm>
##  2 Austria                Europe    <tibble [12 x 4]> <S3: lm>
##  3 Belgium                Europe    <tibble [12 x 4]> <S3: lm>
##  4 Bosnia and Herzegovina Europe    <tibble [12 x 4]> <S3: lm>
##  5 Bulgaria               Europe    <tibble [12 x 4]> <S3: lm>
##  6 Croatia                Europe    <tibble [12 x 4]> <S3: lm>
##  7 Czech Republic         Europe    <tibble [12 x 4]> <S3: lm>
##  8 Denmark                Europe    <tibble [12 x 4]> <S3: lm>
##  9 Finland                Europe    <tibble [12 x 4]> <S3: lm>
## 10 France                 Europe    <tibble [12 x 4]> <S3: lm>
## # ... with 20 more rows
```

Adding residuals


```
(by_country <- by_country %>%
  mutate(resids = map2(data, model, add_residuals)))
```

```
## # A tibble: 142 x 5
##    country     continent data              model    resids
##    <fct>       <fct>     <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]>
##  7 Austria     Europe    <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
##  8 Bahrain     Asia      <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
##  9 Bangladesh  Asia      <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
## 10 Belgium     Europe    <tibble [12 x 4]> <S3: lm> <tibble [12 x 5]>
## # ... with 132 more rows
```

Unnesting

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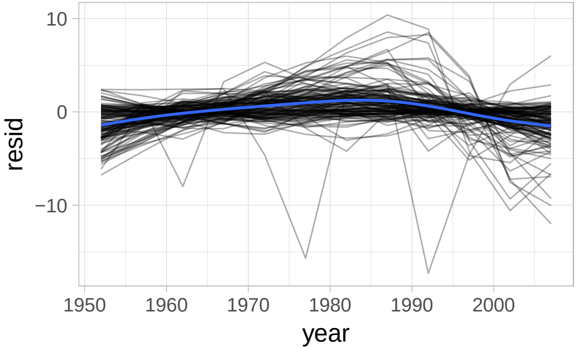
```r
resids <- unnest(by_country, resids)
resids
```

```
## # A tibble: 1,704 x 7
##    country     continent  year lifeExp      pop gdpPercap   resid
##    <fct>       <fct>     <int>   <dbl>    <int>     <dbl>   <dbl>
##  1 Afghanistan Asia       1952    28.8  8425333      779. -1.11
##  2 Afghanistan Asia       1957    30.3  9240934      821. -0.952
##  3 Afghanistan Asia       1962    32.0 10267083      853. -0.664
##  4 Afghanistan Asia       1967    34.0 11537966      836. -0.0172
##  5 Afghanistan Asia       1972    36.1 13079460      740.  0.674
##  6 Afghanistan Asia       1977    38.4 14880372      786.  1.65
##  7 Afghanistan Asia       1982    39.9 12881816      978.  1.69
##  8 Afghanistan Asia       1987    40.8 13867957      852.  1.28
##  9 Afghanistan Asia       1992    41.7 16317921      649.  0.754
## 10 Afghanistan Asia       1997    41.8 22227415      635. -0.534
## # ... with 1,694 more rows
```

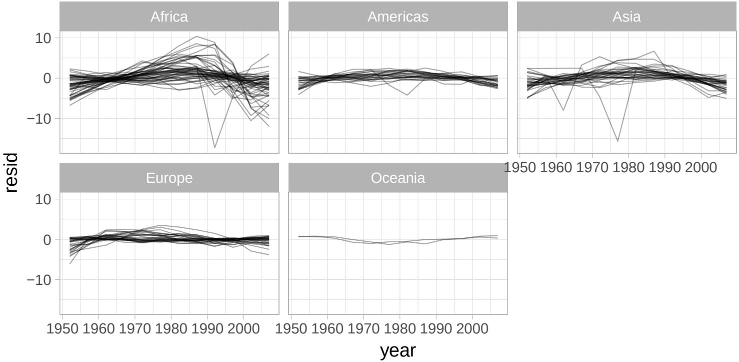
Visualizing the residuals


```r
resids %>%
  ggplot(aes(year, resid)) +
    geom_line(aes(group = country), alpha = 1 / 3) +
    geom_smooth(se = FALSE)
```



Visualizing the residuals cont'd

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



Model quality

```
broom::glance(nz_mod)
```

```
##   r.squared adj.r.squared     sigma statistic      p.value df
## 1 0.9535846     0.9489431 0.8043472  205.4459 5.407324e-08  2
##      logLik      AIC    BIC deviance df.residual
## 1 -13.32064 32.64128 34.096 6.469743          10
```

```
by_country %>% mutate(glance = map(model, glance)) %>% unnest(glance)
```

```
## # A tibble: 142 x 16
##    country continent data  model resids r.squared adj.r.squared sigma
##    <fct>   <fct>     <lis> <lis> <list>     <dbl>         <dbl> <dbl>
##  1 Afghan~ Asia      <tib~ <S3:~ <tibb~     0.948         0.942 1.22
##  2 Albania Europe    <tib~ <S3:~ <tibb~     0.911         0.902 1.98
##  3 Algeria Africa    <tib~ <S3:~ <tibb~     0.985         0.984 1.32
##  4 Angola  Africa    <tib~ <S3:~ <tibb~     0.888         0.877 1.41
##  5 Argent~ Americas  <tib~ <S3:~ <tibb~     0.996         0.995 0.292
##  6 Austra~ Oceania   <tib~ <S3:~ <tibb~     0.980         0.978 0.621
##  7 Austria Europe    <tib~ <S3:~ <tibb~     0.992         0.991 0.407
##  8 Bahrain Asia      <tib~ <S3:~ <tibb~     0.967         0.963 1.64
##  9 Bangla~ Asia      <tib~ <S3:~ <tibb~     0.989         0.988 0.977
## 10 Belgium Europe    <tib~ <S3:~ <tibb~     0.995         0.994 0.293
## # ... with 132 more rows, and 8 more variables: statistic <dbl>,
## #   p.value <dbl>, df <int>, logLik <dbl>, AIC <dbl>, BIC <dbl>,
## #   deviance <dbl>, df.residual <int>
```

Or better


```r
glance <- by_country %>%
  mutate(glance = 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
##    <fct>   <fct>         <dbl>         <dbl> <dbl>     <dbl>    <dbl>
##  1 Afghan~ Asia          0.948         0.942 1.22      181.  9.84e- 8
##  2 Albania Europe        0.911         0.902 1.98      102.  1.46e- 6
##  3 Algeria Africa        0.985         0.984 1.32      662.  1.81e-10
##  4 Angola  Africa        0.888         0.877 1.41       79.1 4.59e- 6
##  5 Argent~ Americas      0.996         0.995 0.292    2246.  4.22e-13
##  6 Austra~ Oceania       0.980         0.978 0.621     481.  8.67e-10
##  7 Austria Europe        0.992         0.991 0.407    1261.  7.44e-12
##  8 Bahrain Asia          0.967         0.963 1.64      291.  1.02e- 8
##  9 Bangla~ Asia          0.989         0.988 0.977     930.  3.37e-11
## 10 Belgium Europe        0.995         0.994 0.293    1822.  1.20e-12
## # ... with 132 more rows, and 6 more variables: df <int>,
## #   logLik <dbl>, AIC <dbl>, BIC <dbl>, deviance <dbl>,
## #   df.residual <int>
```

Which models don't fit well?

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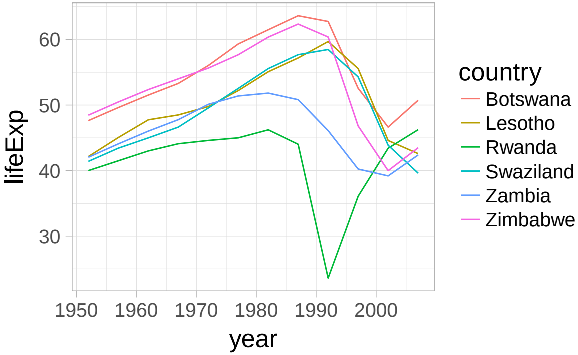
```r
glance %>%
  arrange(r.squared)
```

```
## # A tibble: 142 x 13
##    country  continent r.squared adj.r.squared sigma statistic p.value
##    <fct>    <fct>         <dbl>         <dbl> <dbl>     <dbl>   <dbl>
##  1 Rwanda   Africa       0.0172      -0.0811   6.56     0.175  0.685
##  2 Botswana Africa       0.0340      -0.0626   6.11     0.352  0.566
##  3 Zimbabwe Africa       0.0562      -0.0381   7.21     0.596  0.458
##  4 Zambia   Africa       0.0598      -0.0342   4.53     0.636  0.444
##  5 Swazila~ Africa       0.0682      -0.0250   6.64     0.732  0.412
##  6 Lesotho  Africa       0.0849      -0.00666  5.93     0.927  0.358
##  7 Cote d'~ Africa       0.283        0.212    3.93     3.95   0.0748
##  8 South A~ Africa       0.312        0.244    4.74     4.54   0.0588
##  9 Uganda   Africa       0.342        0.276    3.19     5.20   0.0457
## 10 Congo, ~ Africa       0.348        0.283    2.43     5.34   0.0434
## # ... with 132 more rows, and 6 more variables: df <int>,
## #   logLik <dbl>, AIC <dbl>, BIC <dbl>, deviance <dbl>,
## #   df.residual <int>
```

Visualize


```r
bad_fit <- filter(glance, r.squared < 0.25)

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



Outline

List-columns

```r
tibble(x = list(1:3, 3:5),
       y = c("1, 2", "3, 4, 5"))
```

```
## # A tibble: 2 x 2
##   x         y
##   <list>    <chr>
## 1 <int [3]> 1, 2
## 2 <int [3]> 3, 4, 5
```

```r
tribble(~x, ~y,
        1:3, "1, 2",
        3:5, "3, 4, 5")
```

```
## # A tibble: 2 x 2
##   x         y
##   <list>    <chr>
## 1 <int [3]> 1, 2
## 2 <int [3]> 3, 4, 5
```

An effective list-column pipeline

1. Create the list-column using one of `nest()`, `summarise()` + `list()`, or `mutate()` + a map function.
2. Create other intermediate list-columns by transforming existing list columns with `map()`, `map2()` or `pmap()`.
3. Simplify the list-column back down to a data frame or atomic vector.

Creating list-columns

1. With `nest()` to convert a grouped data frame into a nested data frame where you have list-column of data frames.
2. With `mutate()` and vectorised functions that return a list.
3. With `summarise()` and summary functions that return multiple results.

Create with nesting I


```
gapminder %>% group_by(country, continent) %>% nest()
```

```
## # A tibble: 142 x 3
##    country     continent data
##    <fct>       <fct>     <list>
##  1 Afghanistan Asia      <tibble [12 x 4]>
##  2 Albania     Europe    <tibble [12 x 4]>
##  3 Algeria     Africa    <tibble [12 x 4]>
##  4 Angola      Africa    <tibble [12 x 4]>
##  5 Argentina   Americas  <tibble [12 x 4]>
##  6 Australia   Oceania   <tibble [12 x 4]>
##  7 Austria     Europe    <tibble [12 x 4]>
##  8 Bahrain     Asia      <tibble [12 x 4]>
##  9 Bangladesh  Asia      <tibble [12 x 4]>
## 10 Belgium     Europe    <tibble [12 x 4]>
## # ... with 132 more rows
```

Create with nesting II

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```r
gapminder %>% nest(year:gdpPercap)
```

```
## # A tibble: 142 x 3
##    country     continent data
##    <fct>       <fct>     <list>
##  1 Afghanistan Asia      <tibble [12 x 4]>
##  2 Albania     Europe    <tibble [12 x 4]>
##  3 Algeria     Africa    <tibble [12 x 4]>
##  4 Angola      Africa    <tibble [12 x 4]>
##  5 Argentina   Americas  <tibble [12 x 4]>
##  6 Australia   Oceania   <tibble [12 x 4]>
##  7 Austria     Europe    <tibble [12 x 4]>
##  8 Bahrain     Asia      <tibble [12 x 4]>
##  9 Bangladesh  Asia      <tibble [12 x 4]>
## 10 Belgium     Europe    <tibble [12 x 4]>
## # ... with 132 more rows
```

Create from vectorized functions

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```
df <- tribble(~x1, "a,b,c", "d,e,f,g")

df %>% mutate(x2 = stringr::str_split(x1, ","))
```

```
## # A tibble: 2 x 2
##   x1      x2
##   <chr>   <list>
## 1 a,b,c   <chr [3]>
## 2 d,e,f,g <chr [4]>
```

```
sim <- tribble(~f,       ~params,
               "runif", list(min = -1, max = -1),
               "rnorm", list(sd = 5),
               "rpois", list(lambda = 10))

sim %>% mutate(sims = invoke_map(f, params, n = 10))
```

```
## # A tibble: 3 x 3
##   f     params     sims
##   <chr> <list>     <list>
## 1 runif <list [2]> <dbl [10]>
## 2 rnorm <list [1]> <dbl [10]>
## 3 rpois <list [1]> <int [10]>
```

Create from multivalued summaries II

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What's wrong here?

```
mtcars %>% group_by(cyl) %>% summarise(q = quantile(mpg))
```

```
## Error in summarise_impl(.data, dots): Column `q` must be length 1 (a summary
```

Use list-columns:

```
mtcars %>% group_by(cyl) %>% summarise(q = list(quantile(mpg)))
```

```
## # A tibble: 3 x 2
##     cyl q
##   <dbl> <list>
## 1    4. <dbl [5]>
## 2    6. <dbl [5]>
## 3    8. <dbl [5]>
```

Create from multivalued summaries II

```r
probs <- c(0.01, 0.25, 0.5, 0.75, 0.99)
mtcars %>% group_by(cyl) %>%
  summarise(p = list(probs), q = list(quantile(mpg, probs))) %>%
  unnest()
```

```
## # A tibble: 15 x 3
##      cyl      p     q
##    <dbl>  <dbl> <dbl>
##  1    4. 0.0100  21.4
##  2    4. 0.250   22.8
##  3    4. 0.500   26.0
##  4    4. 0.750   30.4
##  5    4. 0.990   33.8
##  6    6. 0.0100  17.8
##  7    6. 0.250   18.6
##  8    6. 0.500   19.7
##  9    6. 0.750   21.0
## 10    6. 0.990   21.4
## 11    8. 0.0100  10.4
## 12    8. 0.250   14.4
## 13    8. 0.500   15.2
## 14    8. 0.750   16.2
## 15    8. 0.990   19.1
```

Simplifying list-columns

1. If you want a single value, use `mutate()` with `map_lgl()`, `map_int()`, `map_dbl()`, and `map_chr()` to create an atomic vector.
2. If you want many values, use `unnest()` to convert list-columns back to regular columns, repeating the rows as many times as necessary.

List to vector

```
df <- tribble(~x, letters[1:5], 1:3, runif(5))

df %>% mutate(type = map_chr(x, typeof), length = map_int(x, length))
```

```
## # A tibble: 3 x 3
##   x         type      length
##   <list>    <chr>      <int>
## 1 <chr [5]> character      5
## 2 <int [3]> integer        3
## 3 <dbl [5]> double         5
```

Unnesting


```
tibble(x = 1:2, y = list(1:4, 1)) %>% unnest(y)
```

```
## # A tibble: 5 x 2
##       x     y
##   <int> <dbl>
## 1     1    1.
## 2     1    2.
## 3     1    3.
## 4     1    4.
## 5     2    1.
```

When columns contain different number of elements:

```
tribble(~x, ~y,           ~z,
        1, "a",           1:2,
        2, c("b", "c"), 3) %>% unnest(y, z)
```

```
## Error: All nested columns must have the same number of elements.
```

Making tidy data with broom

1. `broom::glance(model)`
   - A row for each model.
   - Columns give a model summary (measure of model quality, complexity, or combination of both).
2. `broom::tidy(model)`
   - A row for each coefficient in the model.
   - Columns give information about the estimate or its variability.
3. `broom::augment(model, data)`
   - A row for each row in `data`.
   - Adds extra values like residuals, and influence statistics.