Tidying data

Tidying data

- Data rarely come to us as we want to use them.
- Before we can do analysis, typically have organizing to do.
- This is typical of ANOVA-type data, "wide format":

```
pig feed1 feed2 feed3 feed4
  1  60.8  68.7  92.6  87.9
  2  57.0  67.7  92.1  84.2
  3  65.0  74.0  90.2  83.1
  4  58.6  66.3  96.5  85.7
  5  61.7  69.8  99.1  90.3
```

- 20 pigs randomly allocated to one of four feeds. At end of study, weight of each pig is recorded.
- Are any differences in mean weights among the feeds?
- Problem: want all weights in one column, with 2nd column labelling which feed. Untidy!

Tidy and untidy data (Wickham)

- Data set easier to deal with if:
  - each observation is one row
  - each variable is one column
  - each type of observation unit is one table
- Data arranged this way called "tidy"; otherwise called "untidy".
- For the pig data:
  - response variable is weight, but scattered over 4 columns, which are levels of a factor `feed`.
  - Want all the weights in one column, with a second column `feed` saying which feed that weight goes with.
  - Then we can run `aov`.

Packages for this section

```
library(tidyverse)
```

Reading in the pig data

```
my_url <- "http://ritsokiguess.site/datafiles/pigs1.txt"
pigs1 <- read_delim(my_url, " ")
pigs1
```

```
# A tibble: 5 x 5
    pig feed1 feed2 feed3 feed4
  <dbl> <dbl> <dbl> <dbl> <dbl>
1     1  60.8  68.7  92.6  87.9
2     2  57    67.7  92.1  84.2
3     3  65    74    90.2  83.1
4     4  58.6  66.3  96.5  85.7
5     5  61.7  69.8  99.1  90.3
```

Making it longer

- We wanted all the weights in one column, labelled by which feed they went with.
- This is a very common reorganization, and the magic "verb" is `pivot_longer`:

```
pigs1 %>% pivot_longer(feed1:feed4, names_to="feed",
                       values_to="weight") -> pigs2
pigs2
```

```
# A tibble: 20 x 3
     pig feed  weight
   <dbl> <chr>  <dbl>
 1     1 feed1   60.8
 2     1 feed2   68.7
 3     1 feed3   92.6
 4     1 feed4   87.9
 5     2 feed1   57
 6     2 feed2   67.7
 7     2 feed3   92.1
```

Alternatives

Any way of choosing the columns to pivot longer is good, eg:

```
pigs1 %>% pivot_longer(-pig, names_to="feed",
                              values_to="weight")
```

```
# A tibble: 20 x 3
     pig feed  weight
   <dbl> <chr>  <dbl>
 1     1 feed1   60.8
 2     1 feed2   68.7
 3     1 feed3   92.6
 4     1 feed4   87.9
 5     2 feed1   57
 6     2 feed2   67.7
 7     2 feed3   92.1
 8     2 feed4   84.2
 9     3 feed1   65
10     3 feed2   74
11     3 feed3   90.2
```

Comments

- `pigs2` now in "long" format, ready for analysis.
- Anatomy of `pivot_longer`:
  - columns to combine
  - a name for column that will contain groups ("names")
  - a name for column that will contain measurements ("values")

Identifying the pigs

- Values in pig identify pigs *within each group*: pig 1 is four different pigs!
- Create unique pig IDs by gluing pig number onto feed:

```
pigs2 %>% mutate(pig_id=str_c(feed, "_", pig)) -> pigs2
pigs2
```

```
# A tibble: 20 x 4
    pig feed  weight pig_id
  <dbl> <chr>  <dbl> <chr>
1     1 feed1   60.8 feed1_1
2     1 feed2   68.7 feed2_1
3     1 feed3   92.6 feed3_1
4     1 feed4   87.9 feed4_1
5     2 feed1   57   feed1_2
6     2 feed2   67.7 feed2_2
7     2 feed3   92.1 feed3_2
8     2 feed4   84.2 feed4_2
```

...and finally, the analysis

- which is just what we saw before:

```
weight.1 <- aov(weight ~ feed, data = pigs2)
summary(weight.1)
```

```
            Df Sum Sq Mean Sq F value   Pr(>F)    
feed         3   3521  1173.5   119.1 3.72e-11 ***
Residuals   16    158     9.8                     
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '
```

- The mean weights of pigs on the different feeds are definitely not all equal.
- So we run Tukey to see which ones differ (over).

Tukey

```r
TukeyHSD(weight.1)
```

```
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = weight ~ feed, data = pigs2)

$feed
             diff        lwr       upr     p adj
feed2-feed1  8.68   3.001038 14.358962 0.0024000
feed3-feed1 33.48  27.801038 39.158962 0.0000000
feed4-feed1 25.62  19.941038 31.298962 0.0000000
feed3-feed2 24.80  19.121038 30.478962 0.0000000
feed4-feed2 16.94  11.261038 22.618962 0.0000013
feed4-feed3 -7.86 -13.538962 -2.181038 0.0055599
```

All of the feeds differ!

Mean weights by feed

To find the best and worst, get mean weight by feed group. I borrowed an idea from earlier to put the means in descending order:

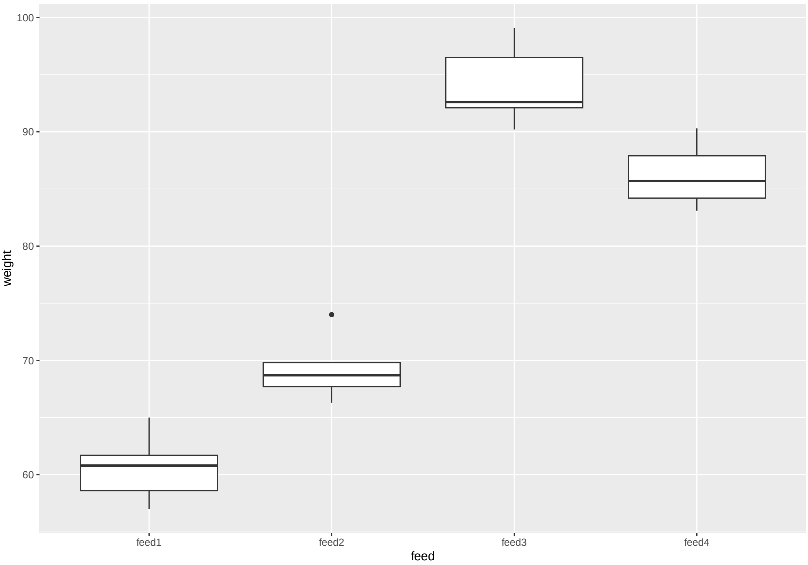
```
pigs2 %>%
  group_by(feed) %>%
  summarize(mean_weight = mean(weight))%>%
  arrange(desc(mean_weight))
```

```
# A tibble: 4 x 2
  feed  mean_weight
  <chr>       <dbl>
1 feed3        94.1
2 feed4        86.2
3 feed2        69.3
4 feed1        60.6
```

Feed 3 is best, feed 1 worst.

Should we have any concerns about the ANOVA?

```
ggplot(pigs2, aes(x = feed, y = weight)) + geom_boxplot()
```



Comments

- Feed 2 has an outlier
- But there are only 5 pigs in each group
- The conclusion is so clear that I am OK with this.

Tuberculosis

- The World Health Organization keeps track of number of cases of various diseases, eg. tuberculosis.
- Some data:

```
my_url <- "http://ritsokiguess.site/datafiles/tb.csv"
tb <- read_csv(my_url)
```

The data (randomly chosen rows)

```
tb %>% slice_sample(n = 10)
```

```
# A tibble: 10 x 22
   iso2   year   m04  m514  m014 m1524 m2534 m3544 m4554 m5
   <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <c
 1 ZW     1990    NA    NA    NA    NA    NA    NA    NA
 2 LR     2005    NA    NA    26   240   352   333   155
 3 PA     1984    NA    NA    NA    NA    NA    NA    NA
 4 BA     1999    NA    NA     2    44    76   113    89
 5 MN     1989    NA    NA    NA    NA    NA    NA    NA
 6 LK     2008    NA    NA    11   283   488   717   810
 7 PK     2004    NA    NA   363  3812  3309  2676  2329  2
 8 DK     1990    NA    NA    NA    NA    NA    NA    NA
 9 VC     1986    NA    NA    NA    NA    NA    NA    NA
10 MA     2006     4    69    73  2104  2373  1498  1036
# i 11 more variables: mu <dbl>, f04 <dbl>, f514 <dbl>, f0
#   f1524 <dbl>, f2534 <dbl>, f3544 <dbl>, f4554 <dbl>, f5
#   f65 <dbl>, fu <dbl>
```

What we have

- Variables: country (abbreviated), year. Then number of cases for each gender and age group, eg. `m1524` is males aged 15–24. Also `mu` and `fu`, where age is unknown.
- Lots of missings. Want to get rid of.
- Abbreviations here.

```
tb %>%
  pivot_longer(m04:fu, names_to = "genage",
                 values_to = "freq", values_drop_na = TRUE) -
```

- Code for `pivot_longer`:
  - columns to make longer
  - column to contain the names (categorical)
  - column to contain the values (quantitative)
  - drop missings in the values

Results (some)

```
tb2
```

```
# A tibble: 35,750 x 4
   iso2   year genage  freq
   <chr> <dbl> <chr>  <dbl>
 1 AD     1996 m014       0
 2 AD     1996 m1524      0
 3 AD     1996 m2534      0
 4 AD     1996 m3544      4
 5 AD     1996 m4554      1
 6 AD     1996 m5564      0
 7 AD     1996 m65        0
 8 AD     1996 f014       0
 9 AD     1996 f1524      1
10 AD     1996 f2534      1
# i 35,740 more rows
```

Separating

- 4 columns, but 5 variables, since genage contains both gender and age group. Split that up using separate.
- separate needs 3 things:
  - what to separate (no quotes needed),
  - what to separate into (here you do need quotes),
  - how to split.
- For "how to split", here "after first character":

```
tb2 %>% separate_wider_position(genage,
                                widths = c("gender" = 1, "a
                                too_few = "align_start") ->
tb3
```

```
# A tibble: 35,750 x 5
   iso2   year gender age    freq
   <chr> <dbl> <chr>  <chr> <dbl>
 1 AD     1996 m      014       0
 2 AD     1996 m      1524      0
 3 AD     1996 m      2534      0
```

Tidied tuberculosis data (some)

```
tb3
```

```
# A tibble: 35,750 x 5
   iso2   year gender age    freq
   <chr> <dbl> <chr>  <chr> <dbl>
 1 AD     1996 m      014       0
 2 AD     1996 m      1524      0
 3 AD     1996 m      2534      0
 4 AD     1996 m      3544      4
 5 AD     1996 m      4554      1
 6 AD     1996 m      5564      0
 7 AD     1996 m      65        0
 8 AD     1996 f      014       0
 9 AD     1996 f      1524      1
10 AD     1996 f      2534      1
# i 35,740 more rows
```

In practice...

- instead of doing the pipe one step at a time, you *debug* it one step at a time, and when you have each step working, you use that step's output as input to the next step, thus:

```
tb %>%
  pivot_longer(m04:fu, names_to = "genage",
               values_to = "freq", values_drop_na = TRUE) %
  separate_wider_position(genage,
                          widths = c("gender" = 1, "age" =
                          too_few = "align_start")
```

```
# A tibble: 35,750 x 5
   iso2   year gender age    freq
   <chr> <dbl> <chr>  <chr> <dbl>
 1 AD     1996 m      014       0
 2 AD     1996 m      1524      0
 3 AD     1996 m      2534      0
 4 AD     1996 m      3544      4
```

Total tuberculosis cases by year (some of the years)

```
tb3 %>%
  filter(between(year, 1991, 1998)) %>%
  group_by(year) %>% summarize(total=sum(freq))
```

```
# A tibble: 8 x 2
   year  total
  <dbl>  <dbl>
1  1991    544
2  1992    512
3  1993    492
4  1994    750
5  1995 513971
6  1996 635705
7  1997 733204
8  1998 840389
```

- Something very interesting happened between 1994 and 1995.

To find out what

- try counting up total cases by country:

```
tb3 %>% group_by(iso2) %>%
  summarize(total=sum(freq)) %>%
  arrange(desc(total))
```

```
# A tibble: 213 x 2
   iso2    total
   <chr>   <dbl>
 1 CN    4065174
 2 IN    3966169
 3 ID    1129015
 4 ZA     900349
 5 BD     758008
 6 VN     709695
 7 CD     603095
 8 PH     490040
 9 BR     440609
```

What years do I have for China?

China started recording in 1995, which is at least part of the problem:

```
tb3 %>% filter(iso2=="CN") %>%
  group_by(year) %>%
  summarize(total=sum(freq))
```

```
# A tibble: 14 x 2
    year  total
   <dbl>  <dbl>
 1  1995 131194
 2  1996 168270
 3  1997 195895
 4  1998 214404
 5  1999 212258
 6  2000 213766
 7  2001 212766
 8  2002 194972
```

First year of recording by country?

- A lot of countries started recording in about 1995, in fact:

```
tb3 %>% group_by(iso2) %>%
  summarize(first_year=min(year)) %>%
  count(first_year)
```

```
# A tibble: 14 x 2
   first_year     n
        <dbl> <int>
 1       1980     2
 2       1994     2
 3       1995   130
 4       1996    31
 5       1997    17
 6       1998     6
 7       1999    10
 8       2000     4
 9       2001     1
10       2002     3
```

Some Toronto weather data

```
my_url <-
  "http://ritsokiguess.site/STAC32/toronto_weather.csv"
weather <- read_csv(my_url)
weather
```

```
# A tibble: 24 x 35
   station   Year Month element   d01   d02   d03   d04   d0
   <chr>    <dbl> <chr> <chr>   <dbl> <dbl> <dbl> <dbl> <dbl
 1 TORONT~   2018 01    tmax     -7.9  -7.1  -5.3  -7.7 -14.
 2 TORONT~   2018 01    tmin    -18.6 -12.5 -11.2 -19.7 -20.
 3 TORONT~   2018 02    tmax      5.6  -8.6   0.4   1.8  -6.
 4 TORONT~   2018 02    tmin     -8.9 -15    -9.7  -8.8 -12
 5 TORONT~   2018 03    tmax     NA    NA    NA    NA    NA
 6 TORONT~   2018 03    tmin     NA    -0.5  NA    -3.1  NA
 7 TORONT~   2018 04    tmax      4.5   6.5   5     5.7   2.
 8 TORONT~   2018 04    tmin     -2.6  -1.2   2.4  -3.2  -3.
 9 TORONT~   2018 05    tmax     23.5  26.3  23    24    24.
10 TORONT~   2018 05    tmin      8.5  14.4  11.4   9.2   8.
```

The columns

- Daily weather records for “Toronto City” weather station in 2018:
  - `station`: identifier for this weather station (always same here)
  - `Year`, `Month`
  - `element`: whether temperature given was daily max or daily min
  - `d01`, `d02`,… `d31`: day of the month from 1st to 31st.

Off we go

Numbers in data frame all temperatures (for different days of the month), so first step is

```
weather %>%
  pivot_longer(d01:d31, names_to="day",
                values_to="temperature",
                values_drop_na = TRUE)
```

```
# A tibble: 703 x 6
   station       Year Month element day   temperature
   <chr>        <dbl> <chr> <chr>   <chr>       <dbl>
 1 TORONTO CITY  2018 01    tmax    d01          -7.9
 2 TORONTO CITY  2018 01    tmax    d02          -7.1
 3 TORONTO CITY  2018 01    tmax    d03          -5.3
 4 TORONTO CITY  2018 01    tmax    d04          -7.7
 5 TORONTO CITY  2018 01    tmax    d05         -14.7
 6 TORONTO CITY  2018 01    tmax    d06         -15.4
 7 TORONTO CITY  2018 01    tmax    d07          -1
```

Element

- Column `element` contains names of two different variables, that should each be in separate column.
- Distinct from eg. `m1524` in tuberculosis data, that contained levels of two different factors, handled by separate.
- Untangling names of variables handled by `pivot_wider`.

Handling element

```
weather %>%
  pivot_longer(d01:d31, names_to="day",
               values_to="temperature",
               values_drop_na = TRUE) %>%
  pivot_wider(names_from=element,
              values_from=temperature)
```

```
# A tibble: 355 x 6
   station      Year Month day    tmax  tmin
   <chr>       <dbl> <chr> <chr> <dbl> <dbl>
 1 TORONTO CITY  2018 01    d01     -7.9 -18.6
 2 TORONTO CITY  2018 01    d02     -7.1 -12.5
 3 TORONTO CITY  2018 01    d03     -5.3 -11.2
 4 TORONTO CITY  2018 01    d04     -7.7 -19.7
 5 TORONTO CITY  2018 01    d05    -14.7 -20.6
 6 TORONTO CITY  2018 01    d06    -15.4 -22.3
 7 TORONTO CITY  2018 01    d07     -1   -17.5
 8 TORONTO CITY  2018 01    d08      3    -1.7
```

Further improvements 1/2

- We have tidy data now, but can improve things further.
- `mutate` creates new columns from old (or assign back to change a variable).
- Would like numerical dates. `separate` works, or pull out number as below.
- `select` keeps columns (or drops, with minus). Station name has no value to us.

Further improvements 2/2

```
weather %>%
  pivot_longer(d01:d31, names_to="day",
               values_to="temperature", values_drop_na = T
  pivot_wider(names_from=element, values_from=temperature)
  mutate(Day = parse_number(day)) %>%
  select(-station)
```

```
# A tibble: 355 x 6
    Year Month day    tmax  tmin   Day
   <dbl> <chr> <chr> <dbl> <dbl> <dbl>
 1  2018 01    d01    -7.9 -18.6     1
 2  2018 01    d02    -7.1 -12.5     2
 3  2018 01    d03    -5.3 -11.2     3
 4  2018 01    d04    -7.7 -19.7     4
 5  2018 01    d05   -14.7 -20.6     5
 6  2018 01    d06   -15.4 -22.3     6
 7  2018 01    d07    -1   -17.5     7
 8  2018 01    d08     3    -1.7     8
```

Final step(s)

- Make year-month-day into proper date.
- Keep only date, tmax, tmin:

```
weather %>%
  pivot_longer(d01:d31, names_to="day",
               values_to="temperature", values_drop_na = T)
  pivot_wider(names_from=element, values_from=temperature)
  mutate(Day = parse_number(day)) %>%
  select(-station) %>%
  unite(datestr, c(Year, Month, Day), sep = "-") %>%
  mutate(date = as.Date(datestr)) %>%
  select(c(date, tmax, tmin)) -> weather_tidy
```

Our tidy data frame

```
weather_tidy
```

```
# A tibble: 355 x 3
   date        tmax  tmin
   <date>     <dbl> <dbl>
 1 2018-01-01  -7.9 -18.6
 2 2018-01-02  -7.1 -12.5
 3 2018-01-03  -5.3 -11.2
 4 2018-01-04  -7.7 -19.7
 5 2018-01-05 -14.7 -20.6
 6 2018-01-06 -15.4 -22.3
 7 2018-01-07  -1   -17.5
 8 2018-01-08   3    -1.7
 9 2018-01-09   1.6  -0.6
10 2018-01-10   5.9  -1.3
# i 345 more rows
```

Plotting the temperatures

- Plot temperature against date joined by lines, but with separate lines for max and min. `ggplot` requires something like

```
ggplot(..., aes(x = date, y = temperature)) + geom_point() +
  geom_line()
```

only we have two temperatures, one a max and one a min, that we want to keep separate.

- The trick: combine `tmax` and `tmin` together into one column, keeping track of what kind of temp they are. (This actually same format as untidy `weather`.) Are making `weather_tidy` untidy for purposes of drawing graph only.
- Then can do something like

```
ggplot(d, aes(x = date, y = temperature, colour = maxmin))
  + geom_point() + geom_line()
```

to distinguish max and min on graph.

Setting up plot

- Since we only need data frame for plot, we can do the column-creation and plot in a pipeline.
- For a `ggplot` in a pipeline, the initial data frame is omitted, because it is whatever came out of the previous step.
- To make those "one column"s: `pivot_longer`. I save the graph to show overleaf:

```
weather_tidy %>%
  pivot_longer(tmax:tmin, names_to="maxmin",
               values_to="temperature") %>%
  ggplot(aes(x = date, y = temperature, colour = maxmin)) +
    geom_line() -> g
```

The plot

```
g
```

temperature
20
0
−20
Jan 2018
Apr 2018
Jul 2018
Oct 2018
Jan 2019
date
maxmin
tmax
tmin

Summary of tidying “verbs”

Verb	Purpose
`pivot_longer`	Combine columns that measure same thing into one
`pivot_wider`	Take column that measures one thing under different conditions and put into multiple columns
`separate`	Turn a column that encodes several variables into several columns
`unite`	Combine several (related) variables into one “combination” variable

`pivot_longer` and `pivot_wider` are opposites; `separate` and `unite` are opposites.