

## 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
```

# 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 %>% slice_sample(n=7)
```

```
# A tibble: 7 x 4
```

		pig	feed	weight	pig_id
	<dbl>	<chr>	<dbl>	<chr>	
1	2	feed1	57	feed1_2	
2	4	feed1	58.6	feed1_4	
3	3	feed3	90.2	feed3_3	
4	1	feed4	87.9	feed4_1	
5	1	feed2	68.7	feed2_1	
6	5	feed2	69.8	feed2_5	
7	5	feed4	90.3	feed4_5	



## ...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 ' ' 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

```
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:

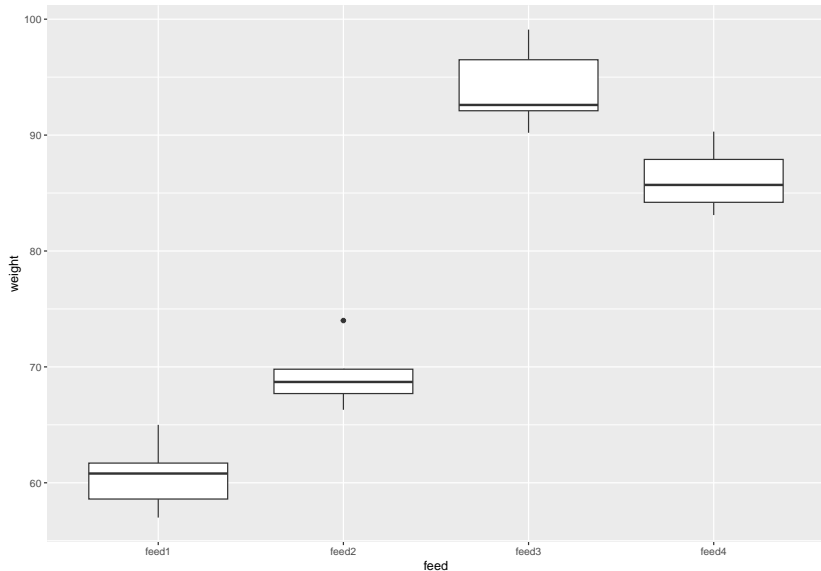
```
pigs2 %>%  
  group_by(feed) %>%  
  summarize(mean_weight = mean(weight))%>%  
  arrange(desc(mean_weight))
```

```
# 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>	<dbl>
1	MW	1989	NA	NA	NA	NA	NA	NA	NA	NA
2	SA	1989	NA	NA	NA	NA	NA	NA	NA	NA
3	IN	1982	NA	NA	NA	NA	NA	NA	NA	NA
4	QA	2001	NA	NA	1	2	0	3	4	4
5	BG	1998	NA	NA	NA	NA	NA	NA	NA	NA
6	PH	1984	NA	NA	NA	NA	NA	NA	NA	NA
7	ZA	2007	340	594	1909	10514	21948	20076	12164	4
8	CI	1986	NA	NA	NA	NA	NA	NA	NA	NA
9	TK	2001	NA	NA	NA	NA	NA	NA	NA	NA
10	BJ	1993	NA	NA	NA	NA	NA	NA	NA	NA

```
# i 11 more variables: mu <dbl>, f04 <dbl>, f514 <dbl>, f014 <dbl>,  
#   f1524 <dbl>, f2534 <dbl>, f3544 <dbl>, f4554 <dbl>, f514 <dbl>,  
#   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, "age" = 4),  
                                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
4	AD	1996	m	2544	4

## 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
5	AD	1996	m	4554	1

## 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
10	KE	431523

## 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
9	2003	267280

## 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	d05
	<chr>	<dbl>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	TORONT~	2018	01	tmax	-7.9	-7.1	-5.3	-7.7	-14.1
2	TORONT~	2018	01	tmin	-18.6	-12.5	-11.2	-19.7	-20.1
3	TORONT~	2018	02	tmax	5.6	-8.6	0.4	1.8	-6.1
4	TORONT~	2018	02	tmin	-8.9	-15	-9.7	-8.8	-12.1
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	2.1
8	TORONT~	2018	04	tmin	-2.6	-1.2	2.4	-3.2	-3.1
9	TORONT~	2018	05	tmax	23.5	26.3	23	24	24.1
10	TORONT~	2018	05	tmin	8.5	14.4	11.4	9.2	8.1

```
# i 14 more rows
```

# 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
8	TORONTO CITY	2018	01	tmax	d08	3

## 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
9	TORONTO CITY	2018	01	d09	1.6	0.6

## 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
9	2018	01	d09	1.6	-0.6	9

## 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.

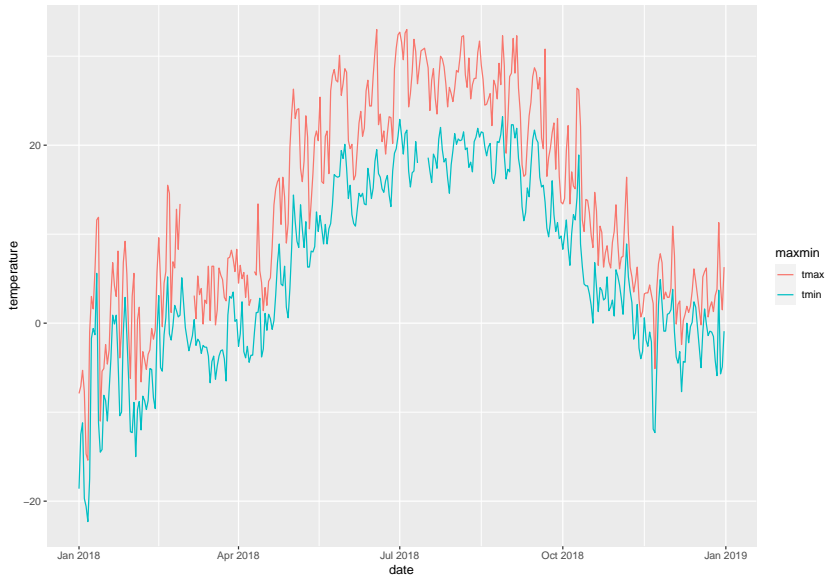
## Setting up plot

- ▶ 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

09



## Summary of tidying “verbs”

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

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