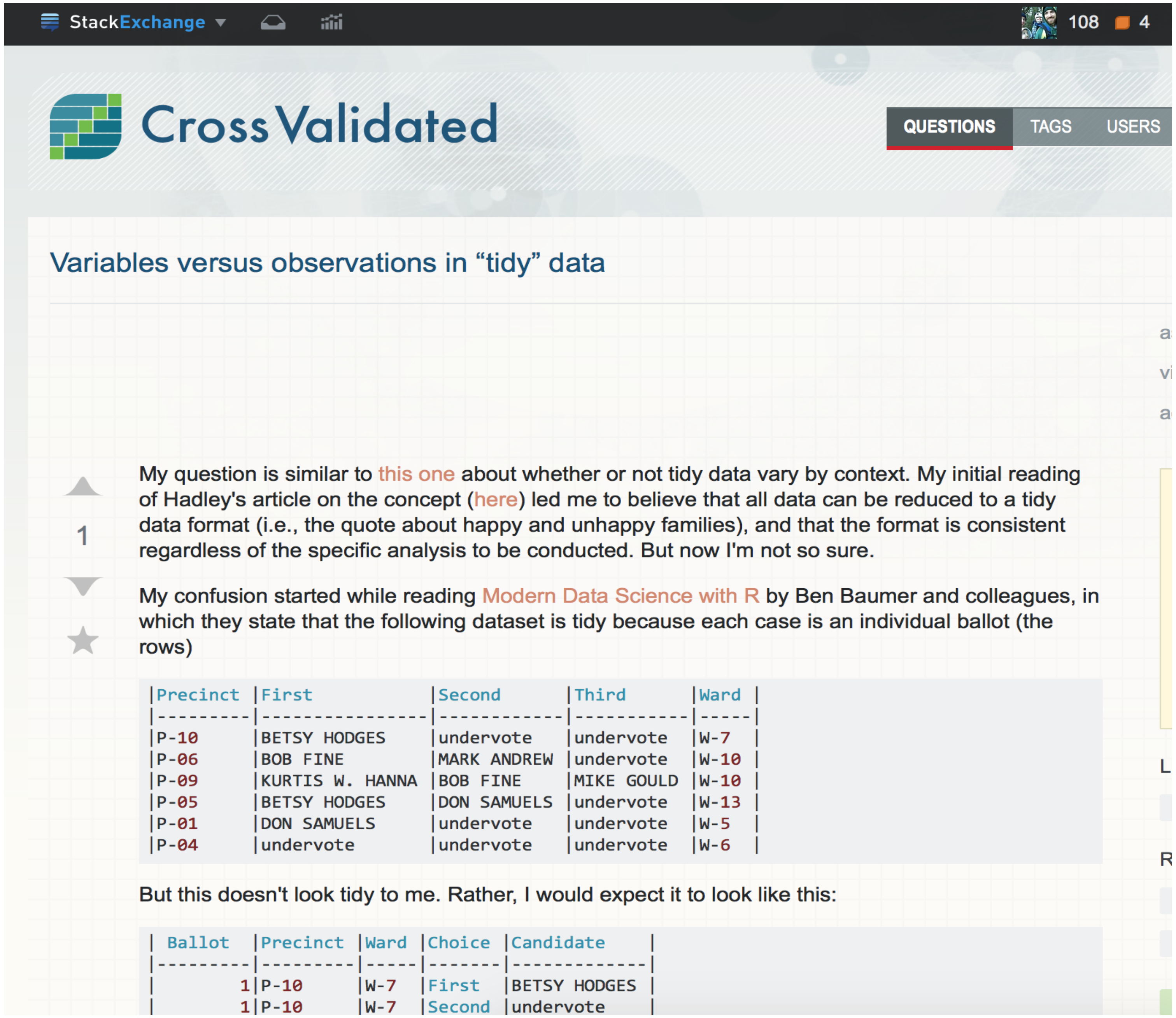
Intro to tidy data

Daniel Anderson

Agenda

- Introduce the concept of tidy data
- Tidy a simple dataset together with `tidyr`
- Summarize and transform tidy data with `dplyr`
- Fit a few models and look at some extensions (the `broom` package)
- Practice a bit, if time allows (it probably won't)

A little story first



Variables versus observations in “tidy” data

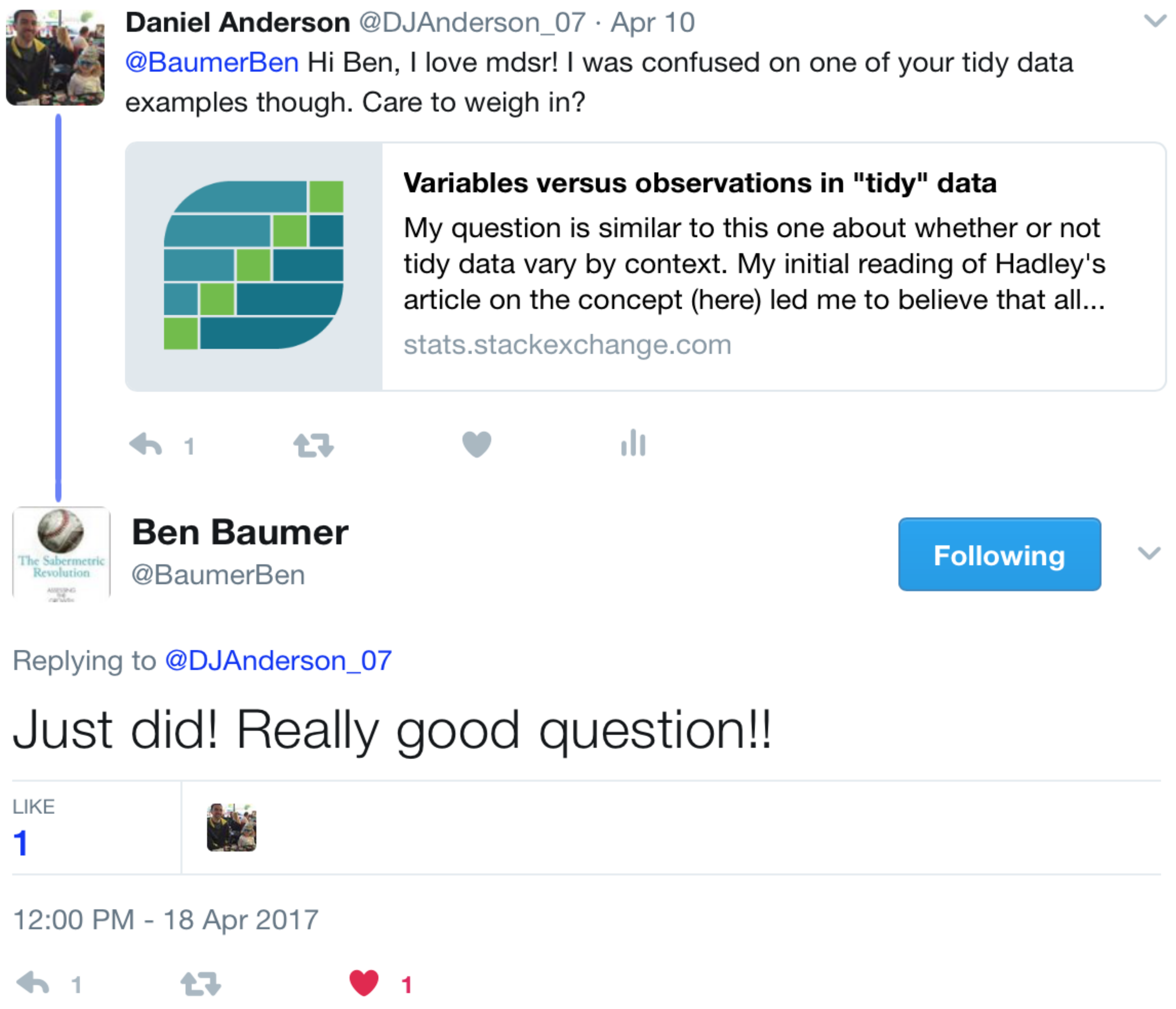
My question is similar to this one about whether or not tidy data vary by context. My initial reading of Hadley's article on the concept (here) led me to believe that all data can be reduced to a tidy data format (i.e., the quote about happy and unhappy families), and that the format is consistent regardless of the specific analysis to be conducted. But now I'm not so sure.

My confusion started while reading Modern Data Science with R by Ben Baumer and colleagues, in which they state that the following dataset is tidy because each case is an individual ballot (the rows)

```
|Precinct |First           |Second      |Third      |Ward |
|---------|----------------|------------|-----------|-----|
|P-10     |BETSY HODGES    |undervote   |undervote  |W-7  |
|P-06     |BOB FINE        |MARK ANDREW |undervote  |W-10 |
|P-09     |KURTIS W. HANNA |BOB FINE    |MIKE GOULD |W-10 |
|P-05     |BETSY HODGES    |DON SAMUELS |undervote  |W-13 |
|P-01     |DON SAMUELS     |undervote   |undervote  |W-5  |
|P-04     |undervote       |undervote   |undervote  |W-6  |
```

But this doesn't look tidy to me. Rather, I would expect it to look like this:

```
| Ballot  |Precinct |Ward |Choice |Candidate    |
|---------|---------|-----|-------|-------------|
|        1|P-10     |W-7  |First  |BETSY HODGES |
|        1|P-10     |W-7  |Second |undervote    |
```



Daniel Anderson @DJAnderson_07 · Apr 10

@BaumerBen Hi Ben, I love mdsr! I was confused on one of your tidy data examples though. Care to weigh in?

Variables versus observations in "tidy" data

My question is similar to this one about whether or not tidy data vary by context. My initial reading of Hadley's article on the concept (here) led me to believe that all...

stats.stackexchange.com

1

Ben Baumer

@BaumerBen

Following

Replying to @DJAnderson_07

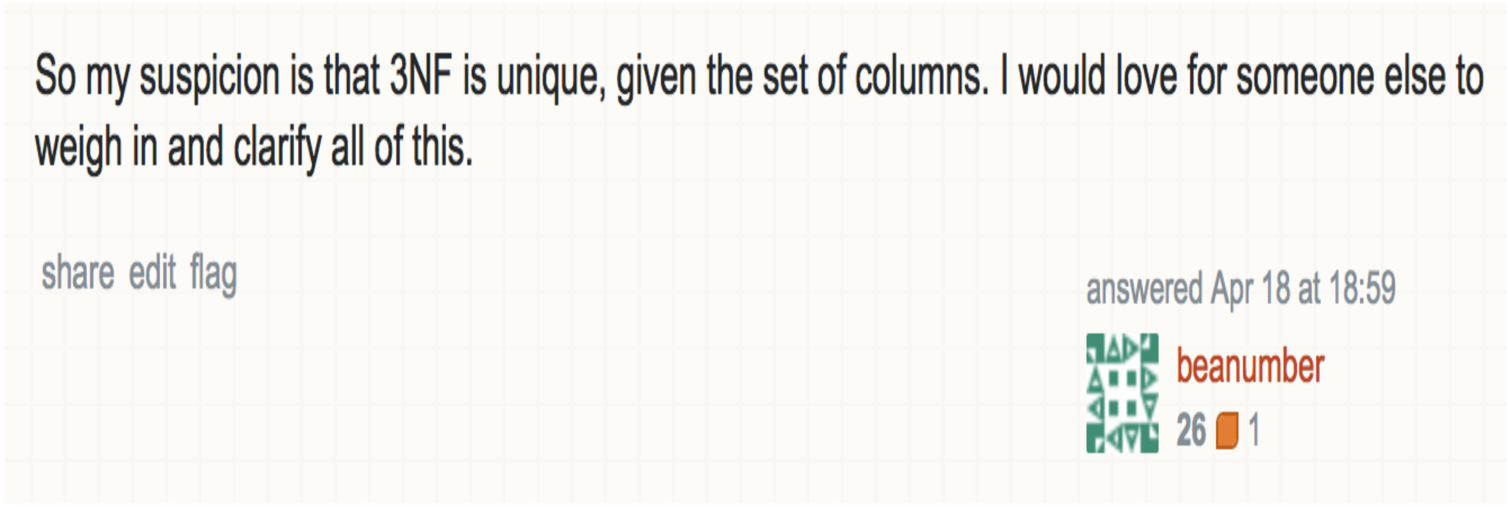
Just did! Really good question!!

LIKE

1

12:00 PM - 18 Apr 2017

1 1



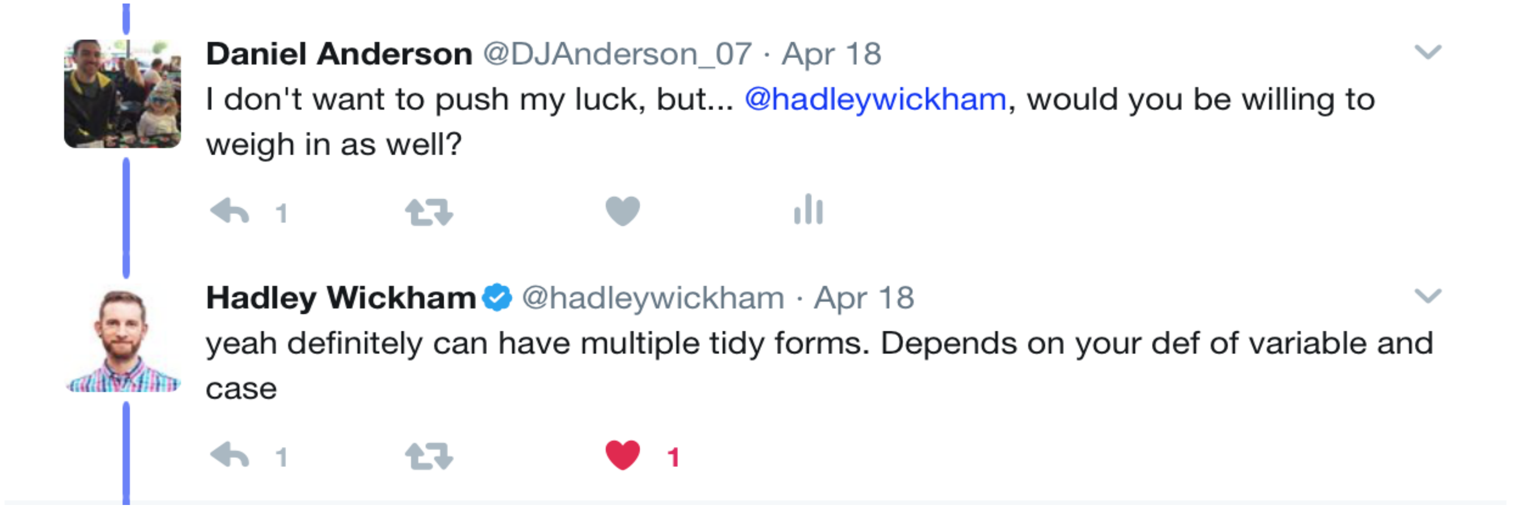
So my suspicion is that 3NF is unique, given the set of columns. I would love for someone else to weigh in and clarify all of this.

share edit flag

answered Apr 18 at 18:59

beanumber

26 🟧 1



Daniel Anderson @DJAnderson_07 · Apr 18

I don't want to push my luck, but... @hadleywickham, would you be willing to weigh in as well?

Hadley Wickham @hadleywickham · Apr 18

yeah definitely can have multiple tidy forms. Depends on your def of variable and case

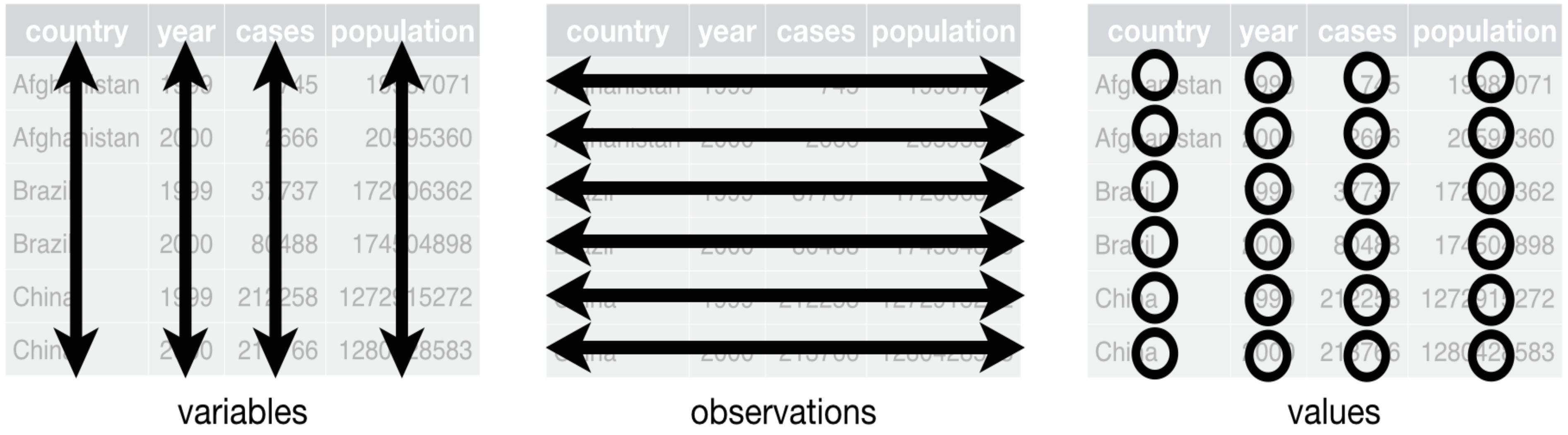
> “It is often said that 80% of data analysis is spent on the process of cleaning and preparing the data.”

- Persistent and varied challenge
- Little research on how to do it well
    - Enter Hadley Wickham

Tidy data

Definition

1. Each variable is a column
2. Each observation is a row
3. Each type of observational unit forms a table



Common ways rectangular datasets are "messy"

(We won't get into multiple data files and how they interact, i.e., relational databases)

- Column headers are values, not variable names
- Multiple variables stored in one column
- Variables are stored in both rows and columns

Some examples

(from the JSS paper)

RELIGION	<$10K	$10-20K	$20-30K	$30-40K	$40-50K	$50-75K	$75-100K	$100-150K	>150K	DON'T KNOW/REFUSED
Agnostic	27	34	60	81	76	137	122	109	84	96
Atheist	12	27	37	52	35	70	73	59	74	76
Buddhist	27	21	30	34	33	58	62	39	53	54
Catholic	418	617	732	670	638	1116	949	792	633	1489
Don’t know/refused	15	14	15	11	10	35	21	17	18	116
Evangelical Prot	575	869	1064	982	881	1486	949	723	414	1529
Hindu	1	9	7	9	11	34	47	48	54	37
Historically Black Prot	228	244	236	238	197	223	131	81	78	339
Jehovah's Witness	20	27	24	24	21	30	15	11	6	37
Jewish	19	19	25	25	30	95	69	87	151	162
Mainline Prot	289	495	619	655	651	1107	939	753	634	1328
Mormon	29	40	48	51	56	112	85	49	42	69

The tidied version

RELIGION	INCOME	FREQ
Agnostic	<$10k	27
Agnostic	$10-20k	34
Agnostic	$20-30k	60
Agnostic	$30-40k	81
Agnostic	$40-50k	76
Agnostic	$50-75k	137
Agnostic	$75-100k	122
Agnostic	$100-150k	109
Agnostic	>150k	84
Agnostic	Don't know/refused	96
Atheist	<$10k	12
Atheist	$10-20k	27

Yet another example

```
## Parsed with column specification:
## cols(
##   .default = col_integer(),
##   iso2 = col_character()
## )
```

```
## See spec(...) for full column specifications.
```

COUNTRY	YEAR	M014	M1524	M2534	M3544	M4554	MU	F014	F1524	F2534	F3544	F4554
AD	2000	0	0	1	0	0						
AE	2000	2	4	4	6	5		3	16	1	3	0
AF	2000	52	228	183	149	129		93	414	565	339	205
AG	2000	0	0	0	0	0		1	1	1	0	0
AL	2000	2	19	21	14	24		3	11	10	8	8
AM	2000	2	152	130	131	63		1	24	27	24	8
AN	2000	0	0	1	2	0		0	0	1	0	0
AO	2000	186	999	1003	912	482		247	1142	1091	844	417
AR	2000	97	278	594	402	419		121	544	479	262	230
AS	2000					1						1

Step one

COUNTRY	YEAR	VARIABLE	CASES
AD	2000	m014	0
AE	2000	m014	2
AF	2000	m014	52
AG	2000	m014	0
AL	2000	m014	2
AM	2000	m014	2
AN	2000	m014	0
AO	2000	m014	186
AR	2000	m014	97
AS	2000	m014	NA

Notice this is much closer to what we want, but we have a problem now in that we have **two variables stored in one column**.

Step two: Tidied data

COUNTRY	YEAR	SEX	AGE_RANGE	CASES
AD	2000	m	0-14	0
AD	2000	m	15-24	0
AD	2000	m	25-34	1
AD	2000	m	35-44	0
AD	2000	m	45-54	0
AD	2000	m	55-64	0
AD	2000	m	65+	0
AE	2000	m	0-14	2
AE	2000	m	15-24	4
AE	2000	m	25-34	4

Variables as rows and columns

ID	YEAR	MONTH	ELEMENT	D1	D2	D3	D4	D5	D6	D7	D8
MX17004	2010	1	tmax								
MX17004	2010	1	tmin								
MX17004	2010	2	tmax		27.3	24.1					
MX17004	2010	2	tmin		14.4	14.4					
MX17004	2010	3	tmax					32.1			
MX17004	2010	3	tmin					14.2			
MX17004	2010	4	tmax								
MX17004	2010	4	tmin								
MX17004	2010	5	tmax								
MX17004	2010	5	tmin								

Two Steps

Step 1

ID	YEAR	MONTH	ELEMENT	DAY_KEY	VALUE
MX17004	2010	12	tmax	d1	29.9
MX17004	2010	12	tmin	d1	13.8
MX17004	2010	2	tmax	d2	27.3
MX17004	2010	2	tmin	d2	14.4
MX17004	2010	11	tmax	d2	31.3
MX17004	2010	11	tmin	d2	16.3
MX17004	2010	2	tmax	d3	24.1
MX17004	2010	2	tmin	d3	14.4
MX17004	2010	7	tmax	d3	28.6
MX17004	2010	7	tmin	d3	17.5

Step 2

ID	DATE	TMAX	TMIN
MX17004	2010-01-01	27.8	14.5
MX17004	2010-02-02	29.7	13.4
MX17004	2010-02-02	27.3	14.4
MX17004	2010-02-02	29.9	10.7
MX17004	2010-02-02	24.1	14.4
MX17004	2010-03-03	34.5	16.8
MX17004	2010-03-03	31.1	17.6
MX17004	2010-03-03	32.1	14.2
MX17004	2010-04-04	36.3	16.7
MX17004	2010-05-05	33.2	18.2

The data that vexed me

Are the below tidy?

```
library(mdsr)
knitr::kable(head(Minneapolis2013))
```

PRECINCT	FIRST	SECOND	THIRD	WARD
P-10	BETSY HODGES	undervote	undervote	W-7
P-06	BOB FINE	MARK ANDREW	undervote	W-10
P-09	KURTIS W. HANNA	BOB FINE	MIKE GOULD	W-10
P-05	BETSY HODGES	DON SAMUELS	undervote	W-13
P-01	DON SAMUELS	undervote	undervote	W-5
P-04	undervote	undervote	undervote	W-6

I would have expected the data to look like this:

- Are both forms tidy? What's the difference?

PRECINCT	WARD	BALLOT	CHOICE	CANDIDATE
P-10	W-7	1	First	BETSY HODGES
P-10	W-7	1	Second	undervote
P-10	W-7	1	Third	undervote
P-06	W-10	2	First	BOB FINE
P-06	W-10	2	Second	MARK ANDREW
P-06	W-10	2	Third	undervote

Defining tidy data

Two rules essentially define tidy data

(from mdsr)

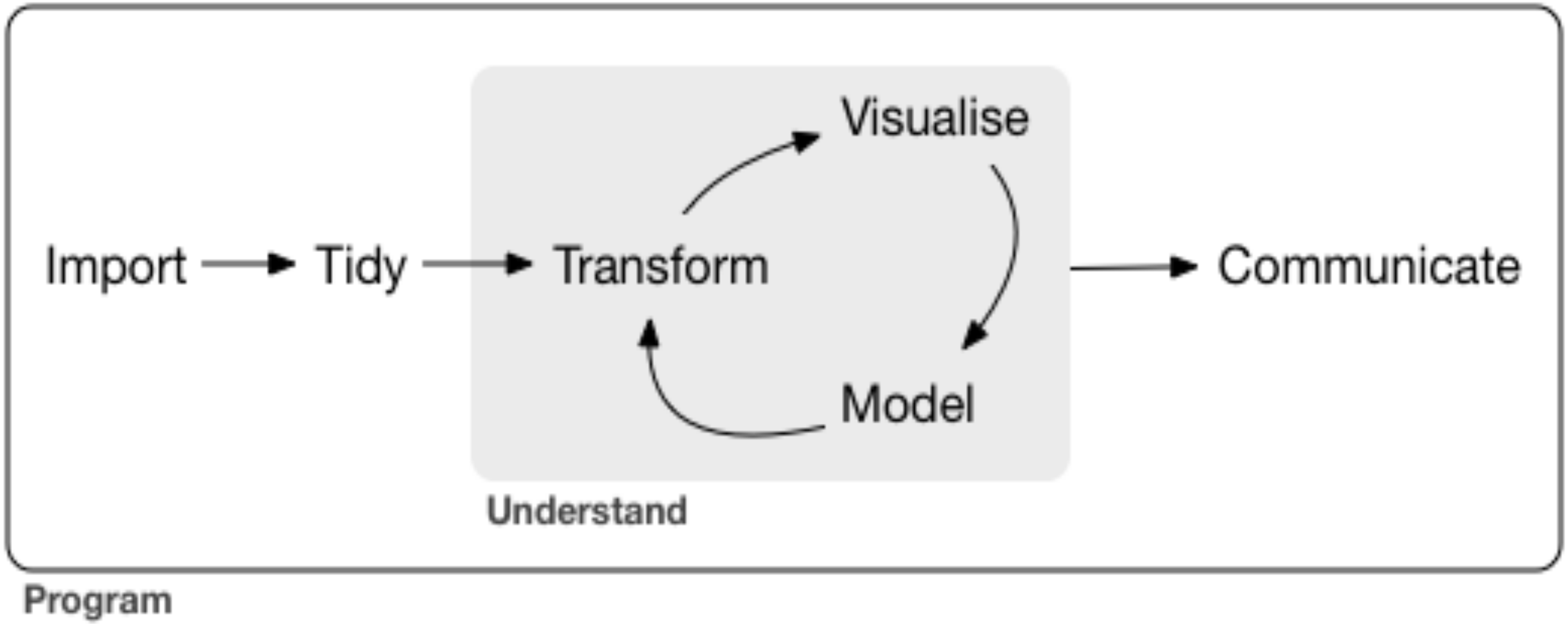
1. Each row is a case representing the same underlying attribute.
2. Each column is a variable containing the same type of value for each case.

The combination of rows and columns make each case (row) unique, even though cells may be repeated many times (e.g., student identifier).

A caveat

- There are many reasons why you might want to have messy data. However, tidy data is an extremely useful format generally, and particularly useful when applying tools within the .
- All packages within the tidyverse are designed to either help you get your data in a tidy format, or assume your data are already in a tidy format.
- Assuming a common data format leads to large jumps in efficiency, as the output from certain functions can be directly input into others.

The tidyverse data analysis philosophy



Load the data

```
library(tidyverse)
library(rio)
d <- import("./data/exam1.csv")
knitr::kable(head(d))
```

STU_NAME	GENDER	ITEM_1	ITEM_2	ITEM_3	ITEM_4	ITEM_5	ITEM_6	ITEM_7	ITEM_8	ITEM_9	ITEM_10	ITEM_1
Adam	M	1	1	1	1	1	1	1	0	0	0	0
Anne	F	1	1	1	1	1	1	1	1	1	1	0
Audrey	F	1	1	1	1	1	1	1	1	1	1	0
Barbara	F	1	1	1	1	0	0	1	0	0	1	0
Bert	M	1	1	1	1	1	0	1	0	1	1	0
Betty	F	1	1	1	1	1	1	1	1	1	0	0

Pop Quiz Time

Consider the item as the unit of analysis

- Are these data tidy?
- If not, what needs to happen to make them tidy?
- What are the variables? What are the values?

`dplyr` versus `tidyr`

- `dplyr`: Helps you manipulate your data (create, remove, summarize, etc.)
- `tidyr`: Helps you get your data into a tidy format

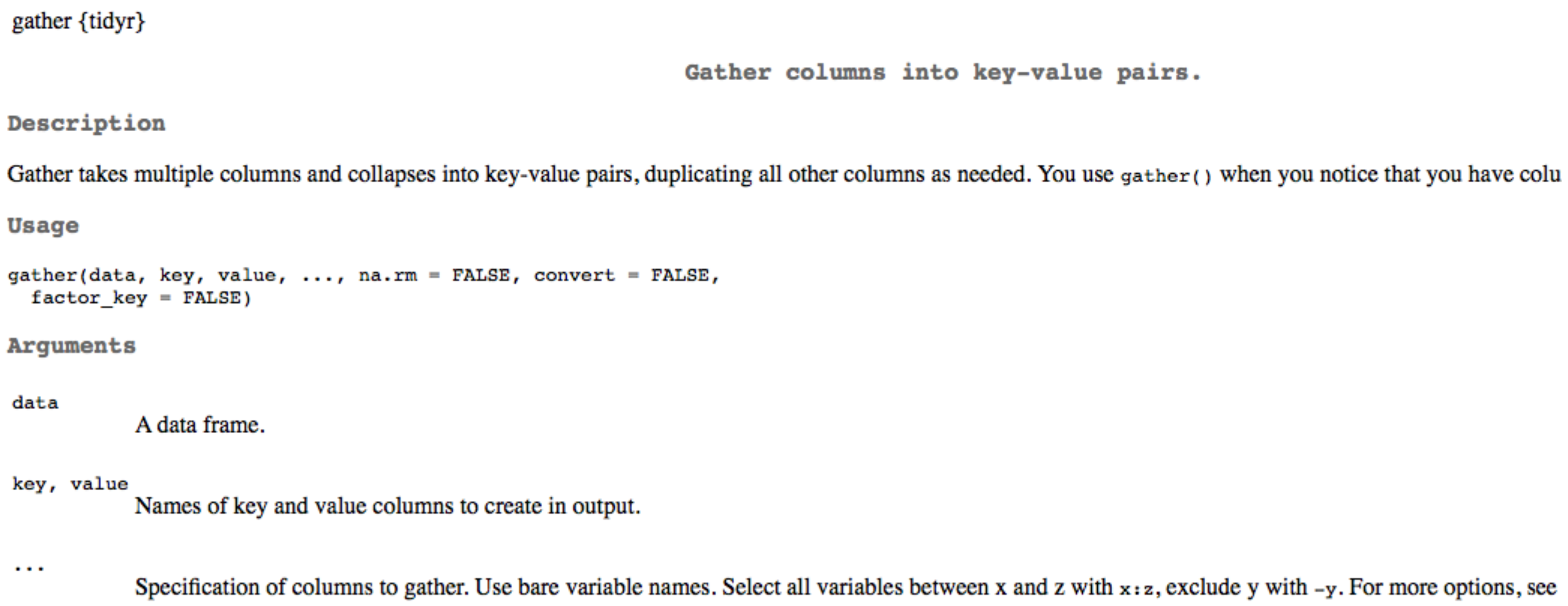
Verbs: `tidyr`

- `gather()`
- `spread()`
- `separate()` and `extract()`
- `unite()`
- `nest()`

What do you think each do?

Step 1: `gather` the item variables

- Change all item variables into two variables: `item` and `score`



gather {tidyr}

Gather columns into key-value pairs.

Description

Gather takes multiple columns and collapses into key-value pairs, duplicating all other columns as needed. You use `gather()` when you notice that you have colu

Usage

```
gather(data, key, value, ..., na.rm = FALSE, convert = FALSE,
  factor_key = FALSE)
```

Arguments

`data`	A data frame.
`key, value`	Names of key and value columns to create in output.
`...`	Specification of columns to gather. Use bare variable names. Select all variables between x and z with `x:z`, exclude y with `-y`. For more options, see

Try running the following code

```
d %>%
  gather(key = item, value = score, -1:-2)
```

- Third argument to `...` says we want to omit the first and second columns in when gathering.

/Users/Daniel/Teaching/exploring_data_r/slides/w4p1/w4p1.Rmd What do you get? Are these data tidy now?

- The code on the previous slide basically puts our data in a tidy format.
- To "clean up" some, could transform the `item` variable to numeric

Finish tidying the data

```
td <- d %>%
  gather(item, score, -1:-2) %>%
  mutate(item = parse_number(item))
```

- `parse_number()` comes from the package.

STU_NAME	GENDER	ITEM	SCORE
Adam	M	1	1
Anne	F	1	1
Audrey	F	1	1
Barbara	F	1	1
Bert	M	1	1
Betty	F	1	1

An alternative

(please run this code, following the explanation)

```
td <- d %>%
  gather(item, score, -1:-2) %>%
  separate(item, c("discard", "item"), sep = "_") %>%
  select(-discard)
```

Why are tidy data useful?

- When used in conjunction with `dplyr`, tidy data can result in large gains in efficiency.

For example, suppose we want to calculate the proportion of students responding correctly to each item.

```
td %>%
  group_by(item) %>%
  summarize(prop = mean(score))
```

```
## # A tibble: 18 x 2
##     item       prop
##    <chr>      <dbl>
##  1     1 1.00000000
##  2    10 0.68571429
##  3    11 0.34285714
##  4    12 0.17142857
##  5    13 0.20000000
##  6    14 0.08571429
##  7    15 0.02857143
##  8    16 0.02857143
##  9    17 0.02857143
## 10    18 0.00000000
## 11     2 1.00000000
## 12     3 1.00000000
## 13     4 0.91428571
## 14     5 0.88571429
## 15     6 0.85714286
## 16     7 0.88571429
## 17     8 0.77142857
## 18     9 0.85714286
```

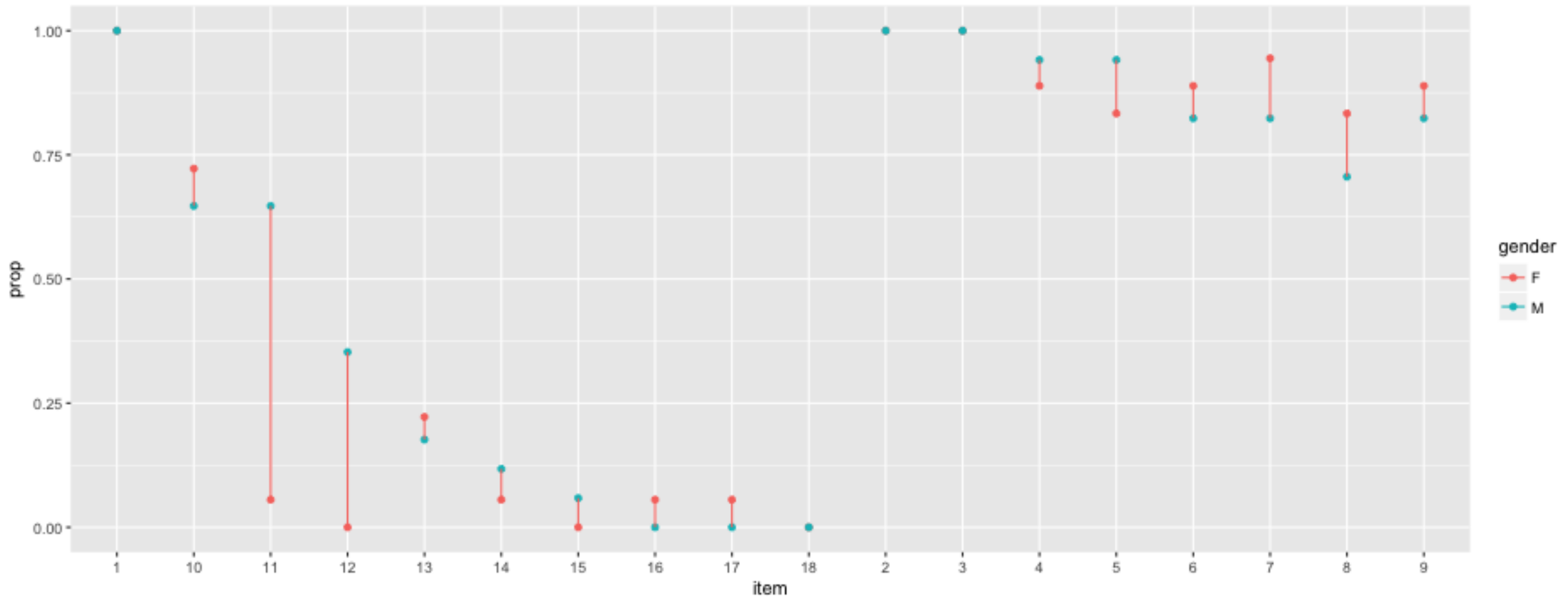
What if we also wanted to know the standard deviation?

```
td %>%
  group_by(item) %>%
  summarize(prop = mean(score),
            sd = sd(score))
```

```
## # A tibble: 18 x 3
##     item       prop        sd
##    <chr>      <dbl>     <dbl>
##  1     1 1.00000000 0.0000000
##  2    10 0.68571429 0.4710082
##  3    11 0.34285714 0.4815940
##  4    12 0.17142857 0.3823853
##  5    13 0.20000000 0.4058397
##  6    14 0.08571429 0.2840286
##  7    15 0.02857143 0.1690309
##  8    16 0.02857143 0.1690309
##  9    17 0.02857143 0.1690309
## 10    18 0.00000000 0.0000000
## 11     2 1.00000000 0.0000000
## 12     3 1.00000000 0.0000000
## 13     4 0.91428571 0.2840286
## 14     5 0.88571429 0.3228029
```

We can take the previous example further, by piping the output into a plot

```
td %>%
  group_by(item, gender) %>%
  summarize(prop = mean(score)) %>%
  mutate(gender = as.factor(gender)) %>%
  ggplot(aes(x = item, y = prop, color = gender)) +
  geom_point() +
  geom_line(aes(group = item))
```



But, probably better (clearer) to do it in two steps.

First produce the data

```r
pd <- td %>%
  group_by(item, gender) %>%
  summarize(prop = mean(score)) %>%
  mutate(gender = as.factor(gender))
```

Then produce the plot

```r
ggplot(pd, aes(x = item, y = prop, color = gender)) +
  geom_point() +
  geom_line(aes(group = item))
```

Challenge (work by yourself or with a neighbor)

Remember, the following code calculates the mean score for each item.

```
td %>%
  group_by(item) %>%
  summarize(prop = mean(score))
```

- Try to modify the above code to produce raw scores for every student.
- If you're successful, try to also calculate the percent correct.

Calculate Raw Scores

Modify the prior code to:

- `group_by` (rather than)
- `sum` score (rather than average it with `mean`)

```
td %>%
  group_by(stu_name) %>%
  summarize(raw_score = sum(score))
```

```
## # A tibble: 35 x 2
##    stu_name raw_score
##       <chr>     <int>
##  1     Adam         7
##  2     Anne        10
##  3   Audrey        11
##  4  Barbara         6
##  5     Bert         8
##  6    Betty         9
##  7   Blaise        13
##  8   Brenda        10
##  9  Britton         8
```

Calculate percent correct

```
td %>%
  group_by(stu_name) %>%
  summarize(total_poss = max(n()),
            raw_score = sum(score),
            pct_correct = raw_score / total_poss)
```

```
## # A tibble: 35 x 4
##    stu_name total_poss raw_score pct_correct
##       <chr>      <int>     <int>       <dbl>
##  1     Adam         18         7   0.3888889
##  2     Anne         18        10   0.5555556
##  3   Audrey         18        11   0.6111111
##  4  Barbara         18         6   0.3333333
##  5     Bert         18         8   0.4444444
##  6    Betty         18         9   0.5000000
##  7   Blaise         18        13   0.7222222
##  8   Brenda         18        10   0.5555556
##  9  Britton         18         8   0.4444444
## 10    Carol         18         6   0.3333333
## # ... with 25 more rows
```

Another common format with longitudinal data

Are these tidy? If not, what's wrong?

```
set.seed(100)
ld <- data_frame(sid = 1:5,
           wave_1_math = rnorm(5, 100, 10),
           wave_2_math = wave_1_math + rnorm(5, 3, 1.5),
           wave_3_math = wave_2_math + rnorm(5, 3, 1.5),
           wave_4_math = wave_3_math + rnorm(5, 3, 1.5),
           wave_1_rdg = rnorm(5, 100, 10),
           wave_2_rdg = wave_1_rdg + rnorm(5, 3, 1.5),
           wave_3_rdg = wave_2_rdg + rnorm(5, 3, 1.5),
           wave_4_rdg = wave_3_rdg + rnorm(5, 3, 1.5))
ld[ ,-1] <- lapply(ld[ ,-1], round)
ld
```

```
## # A tibble: 5 x 9
##      sid wave_1_math wave_2_math wave_3_math wave_4_math wave_1_rdg
##    <int>       <dbl>       <dbl>       <dbl>       <dbl>      <dbl>
## 1      1          95          98         102         105         96
## 2      2         101         103         107         109        108
## 3      3          99         103         106         110        103
```

Variable names include data

- wave
- subject
- Two steps
    - gather, separate

```
tidy_ld <- ld %>%
  gather(var, score, -1) %>%
  separate(var, c("dis", "wave", "subject"), sep = "_", convert = TRUE) %>%
  select(-dis)
tidy_ld %>%
  spread(subject, score)
```

```
## # A tibble: 20 x 4
##       sid  wave  math   rdg
##   * <int> <int> <dbl> <dbl>
##   1     1     1    95    96
##   2     1     2    98    98
##   3     1     3   102   101
##   4     1     4   105   103
##   5     2     1   101   108
```

Again - why so useful?

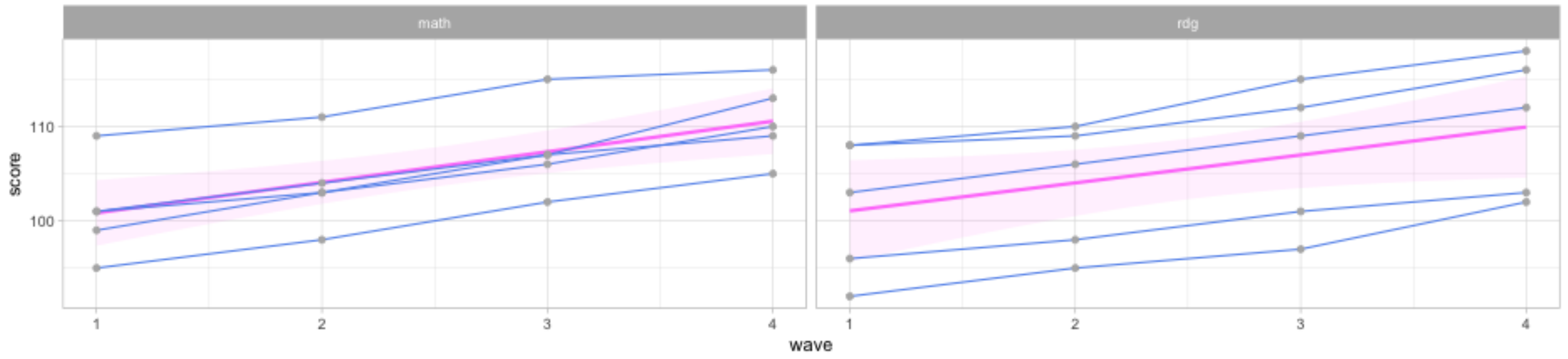
- summaries by wave and subject

```
tidy_ld %>%
  group_by(wave, subject) %>%
  summarize(n = n(),
            mean = mean(score),
            sd = sd(score)) %>%
  arrange(subject, wave)
```

```
## # A tibble: 8 x 5
## # Groups:   wave [4]
##    wave subject     n  mean       sd
##   <int>   <chr> <int> <dbl>    <dbl>
## 1     1    math     5 101.0 5.099020
## 2     2    math     5 103.8 4.658326
## 3     3    math     5 107.4 4.722288
## 4     4    math     5 110.6 4.159327
## 5     1     rdg     5 101.4 7.197222
## 6     2     rdg     5 103.6 6.730527
## 7     3     rdg     5 106.8 7.563068
## 8     4     rdg     5 110.2 7.362065
```

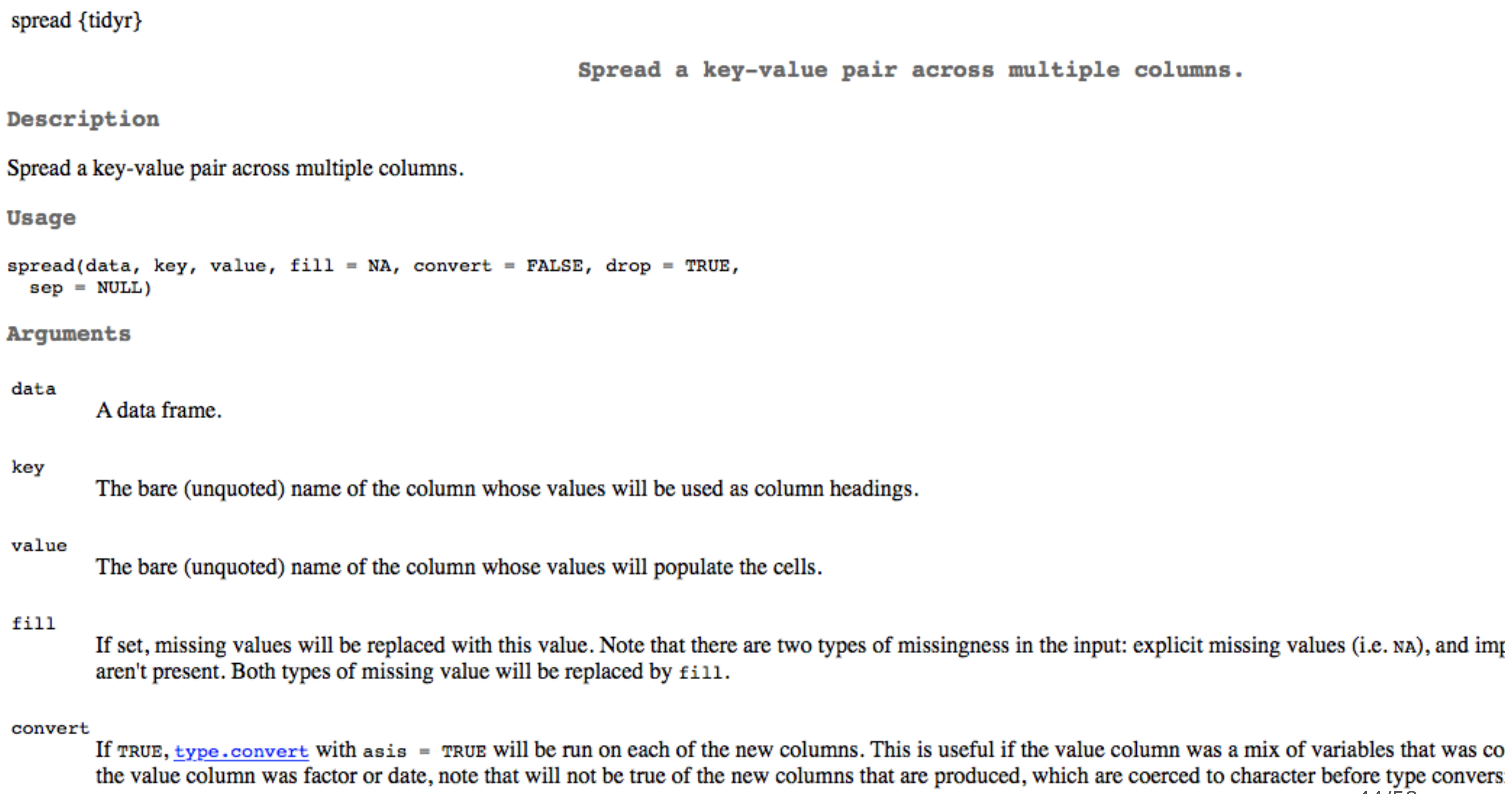
plotting

```
theme_set(theme_light())
ggplot(tidy_ld, aes(wave, score)) +
  geom_smooth(method = "lm",
              color = "orchid1",
              fill = "orchid1",
              alpha = 0.1) +
  geom_line(color = "cornflowerblue", aes(group = sid)) +
  geom_point(color = "gray70") +
  facet_wrap(~subject)
```



Spreading the data back out

Tidy data are great when conducting preliminary descriptives and for plotting the data. But if you're using other packages for analysis, it may need to be in a different format.



spread {tidyr}

Spread a key-value pair across multiple columns.

Description

Spread a key-value pair across multiple columns.

Usage

```
spread(data, key, value, fill = NA, convert = FALSE, drop = TRUE,
  sep = NULL)
```

Arguments

`data`
: A data frame.

`key`
: The bare (unquoted) name of the column whose values will be used as column headings.

`value`
: The bare (unquoted) name of the column whose values will populate the cells.

`fill`
: If set, missing values will be replaced with this value. Note that there are two types of missingness in the input: explicit missing values (i.e. `NA`), and imp
aren't present. Both types of missing value will be replaced by `fill`.

`convert`
: If `TRUE`, type.convert with `asis = TRUE` will be run on each of the new columns. This is useful if the value column was a mix of variables that was co
the value column was factor or date, note that will not be true of the new columns that are produced, which are coerced to character before type convers

Spread *td*

Reminder what the tidy data look like

STU_NAME	GENDER	ITEM	SCORE
Adam	M	1	1
Anne	F	1	1
Audrey	F	1	1

```
s_d <- td %>%
  spread(item, score)
```

STU_NAME	GENDER	1	10	11	12	13	14	15	16	17	18	2	3	4	5	6	7	8	9
Adam	M	1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0
Anne	F	1	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
Audrey	F	1	1	0	0	1	0	0	0	0	0	1	1	1	1	1	1	1	1

Fit model

We'll fit a 1PL IRT model.

- `ltm` package
- `rasch` function requires only item response data, with each column representing a unique item.

```
md <- s_d %>%
  select(-1:-3)

# install.packages("ltm")
library(ltm)
model <- rasch(md)
```

```r
summary(model)
```

```
##
## Call:
## rasch(data = md)
##
## Model Summary:
##    log.Lik      AIC     BIC
##  -156.3638 348.7277 376.724
##
## Coefficients:
##               value    std.err  z.vals
## Dffclt.10  -0.6313     0.3161 -1.9973
## Dffclt.11   0.5734     0.3035  1.8890
## Dffclt.12   1.3010     0.3802  3.4219
## Dffclt.13   1.1570     0.3601  3.2132
## Dffclt.14   1.8739     0.4872  3.8459
## Dffclt.15   2.6306     0.7249  3.6290
## Dffclt.16   2.6306     0.7249  3.6290
## Dffclt.17   2.6306     0.7249  3.6290
## Dffclt.18  14.0580 16370.4931  0.0009
## Dffclt.2  -14.0580 12394.3912 -0.0011
## Dffclt.3  -14.0580 12394.3912 -0.0011
```

More on spreading

- It's also common to have to `gather` beyond where you really need to, manipulate the variable, then spread it back out.

```
knitr::kable(d[1:3, 1:10])
```

SID	MALE_G6	MALE_G7	MALE_G8	ELL_G6	ELL_G7	ELL_G8	SPED_G6	SPED_G7	SPED_G8
1	0	0	0	0	0	0	0	0	0
2	1	1	1	0	0	0	0	0	0
3	1	1	1	1	1	1	0	0	0

```
knitr::kable(d[1:3, 11:ncol(d)])
```

PULLOUTS_G6	PULLOUTS_G7	PULLOUTS_G8	DISABILITY_G6	DISABILITY_G7	DISABILITY_G8	SCORE_G6	SCORE_G7
0	0	0	none	none	none	208.4344	212.5270
0	0	0	none	none	none	193.2352	200.9181
0	0	0	asd	asd	asd	196.0857	203.0576

First gather all vars

```
d %>%
    gather(var, val, -1)
```

```
## # A tibble: 1,800 x 3
##       SID     var   val
##     <int>   <chr> <chr>
##  1      1 male_g6     0
##  2      2 male_g6     1
##  3      3 male_g6     1
##  4      4 male_g6     1
##  5      5 male_g6     0
##  6      6 male_g6     1
##  7      7 male_g6     1
##  8      8 male_g6     0
##  9      9 male_g6     0
## 10     10 male_g6     1
## # ... with 1,790 more rows
```

Next, separate

```
d %>%
    gather(var, val, -1) %>%
    separate(var, c("var", "grade"), sep = "_")
```

```
## # A tibble: 1,800 x 4
##       SID   var grade   val
##   * <int> <chr> <chr> <chr>
## 1       1  male    g6     0
## 2       2  male    g6     1
## 3       3  male    g6     1
## 4       4  male    g6     1
## 5       5  male    g6     0
## 6       6  male    g6     1
## 7       7  male    g6     1
## 8       8  male    g6     0
## 9       9  male    g6     0
## 10     10  male    g6     1
## # ... with 1,790 more rows
```

Parse Numeric

```
d %>%
    gather(var, val, -1) %>%
    separate(var, c("var", "grade"), sep = "_") %>%
    mutate(grade = parse_number(grade))
```

```
## # A tibble: 1,800 x 4
##       SID   var grade   val
##     <int> <chr> <dbl> <chr>
##  1      1  male     6     0
##  2      2  male     6     1
##  3      3  male     6     1
##  4      4  male     6     1
##  5      5  male     6     0
##  6      6  male     6     1
##  7      7  male     6     1
##  8      8  male     6     0
##  9      9  male     6     0
## 10     10  male     6     1
## # ... with 1,790 more rows
```

spread for final produce

```
d %>%
    gather(var, val, -1) %>%
    separate(var, c("var", "grade"), sep = "_") %>%
    mutate(grade = parse_number(grade)) %>%
    spread(var, val)
```

```
## # A tibble: 300 x 8
##      SID grade disability   ell  male pullouts           score  sped
##  * <int> <dbl>      <chr> <chr> <chr>    <chr>           <chr> <chr>
## 1      1     6       none     0     0        0 208.434415681363     0
## 2      1     7       none     0     0        0  212.52698033647     0
## 3      1     8       none     0     0        0 219.999423463527     0
## 4      2     6       none     0     1        0 193.235211343351     0
## 5      2     7       none     0     1        0 200.918088606708     0
## 6      2     8       none     0     1        0 205.561434813331     0
## 7      3     6        asd     1     1        0 196.085670969229     0
## 8      3     7        asd     1     1        0  203.05758537086     0
## 9      3     8        asd     1     1        0 210.530524529609     0
## 10     4     6       none     0     1        0 204.049406440706     0
## # ... with 290 more rows
```

Same thing with our longitudinal data from before

Say we wanted a wave column, but wanted separate columns by subject

```
tidy_ld %>%
  spread(subject, score)
```

```
## # A tibble: 20 x 4
##       sid  wave  math   rdg
##   * <int> <int> <dbl> <dbl>
##   1     1     1    95    96
##   2     1     2    98    98
##   3     1     3   102   101
##   4     1     4   105   103
##   5     2     1   101   108
##   6     2     2   103   110
##   7     2     3   107   115
##   8     2     4   109   118
##   9     3     1    99   103
##  10     3     2   103   106
##  11     3     3   106   109
##  12     3     4   110   112
##  13     4     1   109   108
```

One last note

For many models, you can get tidy output using the package (part of the)

```
lmd <- td %>%
  group_by(stu_name, gender) %>%
  summarize(raw_score = sum(score)) %>%
  ungroup() %>%
  mutate(gender = as.factor(gender))

mod <- lm(raw_score ~ gender, data = lmd)
arm::display(mod, detail = TRUE)
```

```
## lm(formula = raw_score ~ gender, data = lmd)
##             coef.est coef.se t value Pr(>|t|)
## (Intercept)  9.44     0.57   16.64    0.00
## genderM      0.61     0.81    0.75    0.46
## ---
## n = 35, k = 2
## residual sd = 2.41, R-Squared = 0.02
```

```r
library(broom)
tidy(mod, conf.int = TRUE)
```

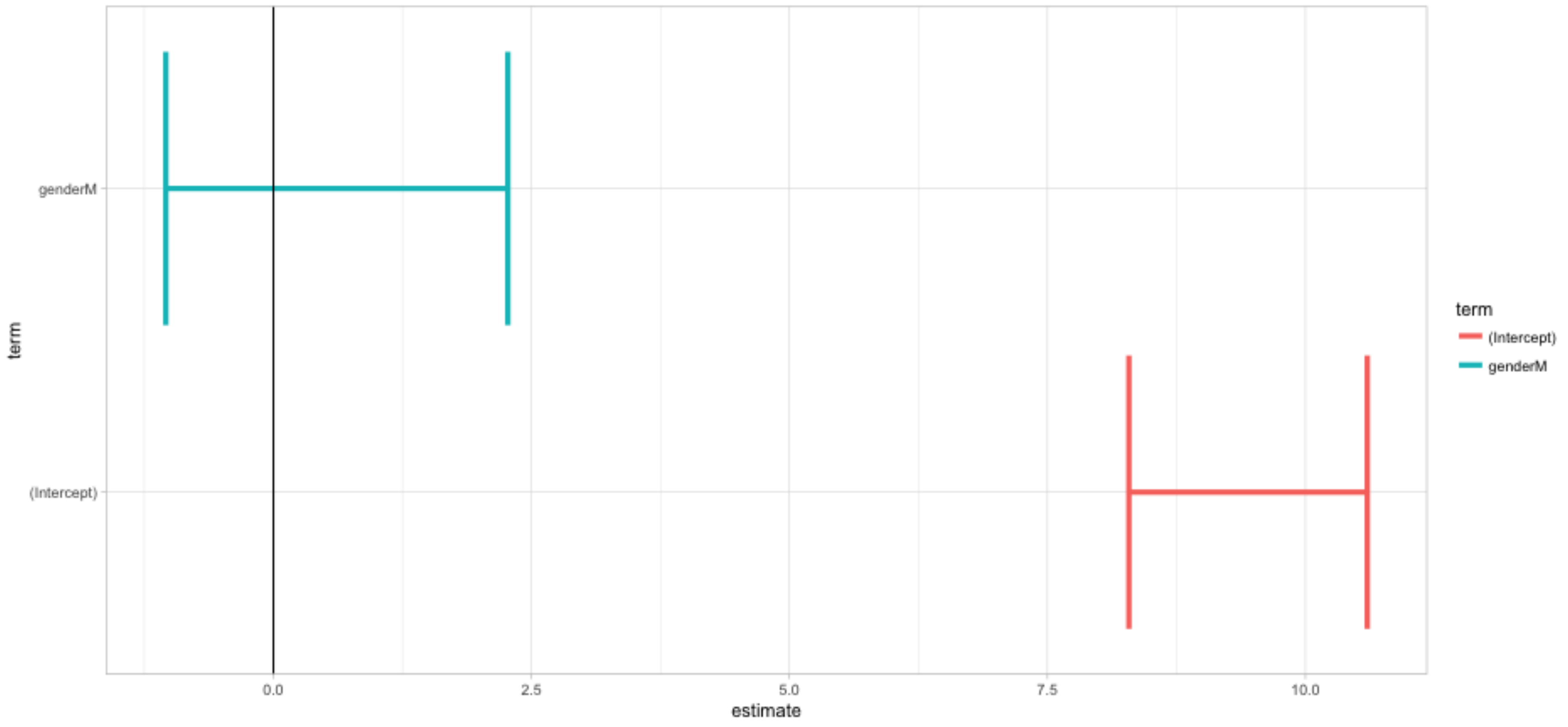
```
##          term  estimate std.error statistic      p.value  conf.low
## 1 (Intercept) 9.4444444 0.5676249 16.638531 1.300394e-17  8.289603
## 2     genderM 0.6143791 0.8144623  0.754337 4.559964e-01 -1.042657
##   conf.high
## 1 10.599286
## 2  2.271415
```

```r
glance(mod)
```

```
##    r.squared adj.r.squared    sigma statistic   p.value df    logLik
## 1 0.01695088   -0.01283849 2.408228 0.5690244 0.4559964  2 -79.39434
##        AIC      BIC deviance df.residual
## 1 164.7887 169.4547 191.3856          33
```

Broom is particularly useful for things like plotting. The below code will work for any linear model (with any number of predictors)

```r
tidy_mod <- tidy(mod, conf.int = TRUE)
ggplot(tidy_mod, aes(estimate, term, color = term)) +
  geom_errorbarh(aes(xmin = conf.low, xmax = conf.high), size = 1.5) +
    geom_vline(xintercept = 0)
```



Practice

Create these data

- Read in and tidy the dataset and compute means and standard deviations by year and sex