Tidy data

Data Wrangling, Session 4

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Code Horizons

July 19, 2024

Tidy data with tidyr

Load the packages, as always

```r
library(here)       # manage file paths
library(socviz)     # data and some useful functions
```

```r
library(tidyverse) # your friend and mine
library(gapminder) # gapminder data

## Quieten dplyr summarise chatter (with an 's')!
options(dplyr.summarise.inform = FALSE)
```

Tidy data is data in long format

The Tidyverse wants to be fed tidy data

Get your data into long format

Very, very often, the solution to some data-wrangling problem in Tidyverse-focused workflow is:

Get the data in long format

Then do the recoding thing that you want.

Then transform it back to something wider if needed.

This isn't an *iron* rule

As we'll see later, `dplyr` *is* able to do "rowwise" operations if you need them.

It is a pretty good rule though

Tidy data

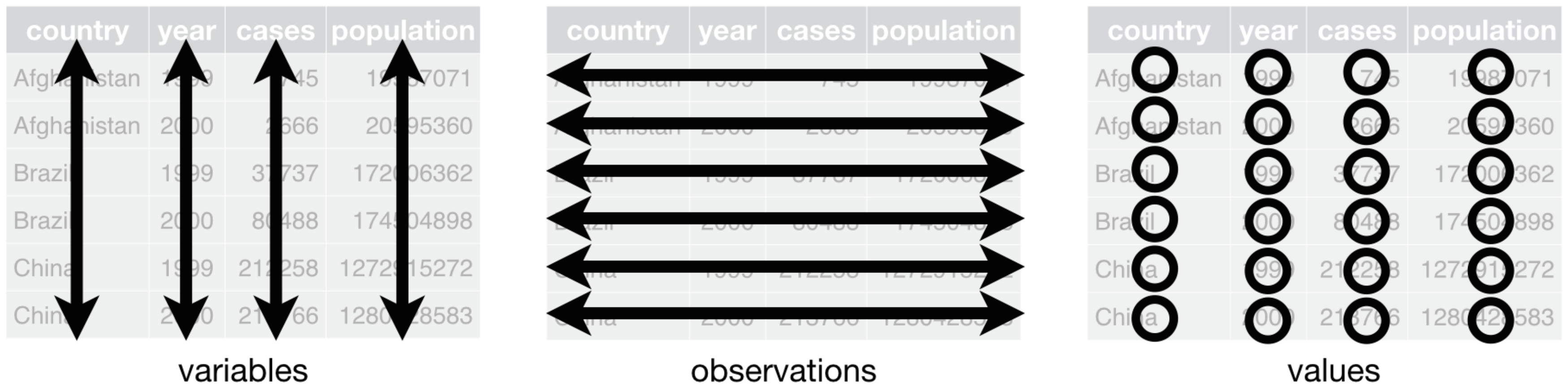
```
gapminder
```

```
# 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
```

Tidy data

gdp	lifexp	pop	continent
340	65	31	Euro
227	51	200	Amer
909	81	80	Euro
126	40	20	Asia

Tidy data



Grolemund & Wickham (2017)

Tidy data

Each variable has its own column.
Each observation has its own row.
Each value has its own cell.
When data is tidy in this way, the vectorized character of R’s way of doing things works best.

Untidy data: common for good reasons

Table A-1. Years of School Completed by People 25 Years and Over, by Age and Sex: Selected Years 1940 to 2016

(Numbers in thousands. Noninstitutionalized population except where otherwise specified.)

Age, sex, and years	Total	Years of School Completed						
		Elementary		High school		College		Median
		0 to 4 years	5 to 8 years	1 to 3 years	4 years	1 to 3 years	4 years or more	
25 YEARS AND OLDER								
Male								
2016	103,372	1,183	3,513	7,144	30,780	26,468	34,283	(NA)
2015	101,887	1,243	3,669	7,278	30,997	25,778	32,923	(NA)
2014	100,592	1,184	3,761	7,403	30,718	25,430	32,095	(NA)
2013	99,305	1,127	3,836	7,314	30,014	25,283	31,731	(NA)
2012	98,119	1,237	3,879	7,388	30,216	24,632	30,766	(NA)
2011	97,220	1,234	3,883	7,443	30,370	24,319	29,971	(NA)
2010	96,325	1,279	3,931	7,705	30,682	23,570	29,158	(NA)
2009	95,518	1,372	4,027	7,754	30,025	23,634	28,706	(NA)
2008	94,470	1,310	4,136	7,853	29,491	23,247	28,433	(NA)
2007	93,421	1,458	4,249	8,294	29,604	22,219	27,596	(NA)
2006	92,233	1,472	4,395	7,940	29,380	22,136	26,910	(NA)
2005	90,899	1,505	4,402	7,787	29,151	21,794	26,259	(NA)

Untidy data: common for good reasons

Storing data in long form is often *inefficient*

```
library(covdata)
covus |>
  filter(state == "NY") |>
  select(date:fips, measure:count)
```

```
# A tibble: 11,872 × 5
   date       state fips  measure                    count
   <date>     <chr> <chr> <chr>                      <dbl>
 1 2021-03-07 NY    36    positive                 1681169
 2 2021-03-07 NY    36    probable_cases                NA
 3 2021-03-07 NY    36    negative                      NA
 4 2021-03-07 NY    36    pending                       NA
 5 2021-03-07 NY    36    hospitalized_currently      4789
 6 2021-03-07 NY    36    hospitalized_cumulative       NA
 7 2021-03-07 NY    36    in_icu_currently             999
 8 2021-03-07 NY    36    in_icu_cumulative             NA
 9 2021-03-07 NY    36    on_ventilator_currently      682
10 2021-03-07 NY    36    on_ventilator_cumulative      NA
# ℹ 11,862 more rows
```

Untidy data: common for good reasons

Storing data in wide form is *easier to display* in a printed table

```r
library(palmerpenguins)
penguins |>
  group_by(species, island, year) |>
  summarize(bill = round(mean(bill_length_mm, na.rm = TRUE),2)) |>
  knitr::kable()
```

species	island	year	bill
Adelie	Biscoe	2007	38.32
Adelie	Biscoe	2008	38.70
Adelie	Biscoe	2009	39.69
Adelie	Dream	2007	39.10
Adelie	Dream	2008	38.19
Adelie	Dream	2009	38.15
Adelie	Torgersen	2007	38.80
Adelie	Torgersen	2008	38.77
Adelie	Torgersen	2009	39.31
Chinstrap	Dream	2007	48.72
Chinstrap	Dream	2008	48.70
Chinstrap	Dream	2009	49.05

Untidy data: common for good reasons

Storing data in wide form is *easier to display* in a printed table

```
penguins |>
  group_by(species, island, year) |>
  summarize(bill = round(mean(bill_length_mm, na.rm = TRUE), 2)) |>
  pivot_wider(names_from = year, values_from = bill) |>
  knitr::kable()
```

species	island	2007	2008	2009
Adelie	Biscoe	38.32	38.70	39.69
Adelie	Dream	39.10	38.19	38.15
Adelie	Torgersen	38.80	38.77	39.31
Chinstrap	Dream	48.72	48.70	49.05
Gentoo	Biscoe	47.01	46.94	48.50

Again, these tables are made directly in R with the code you see here.

It’s also common for *less* good reasons

State

A	B	C	D	E	F	G	H	I	J	K	L	M	N	P	Q
State	CD#	2018 Cook PVI Score	2018 Winner	Party	Dem Votes	GOP Votes	Other Votes	Dem %	GOP %	Other %	Dem Margin	2016 Clinton Margin	Swing vs. 2016 Prez	Raw Votes vs. 2016	Final?
New House Breakdown: 235D, 199R, 1 Not Certified				**D**	**60,619,428**	**50,896,244**	**1,978,795**	**53.4%**	**44.8%**	**1.7%**	**8.6%**	**2.1%**	**6.5%**	**83.3%**	
Compiled by: David Wasserman & Ally Flinn, Cook Political Report. @Redistrict/@CookPolitical. *Italics* denotes freshman, **Bold** denotes party change.															
Alabama	1	R+15	Bradley Byrne	R	89,226	153,228	163	36.8%	63.2%	0.1%	-26.4%	-29.2%	2.8%	79.3%	x
Alabama	2	R+16	Martha Roby	R	86,931	138,879	420	38.4%	61.4%	0.2%	-23.0%	-31.7%	8.7%	78.7%	x
Alabama	3	R+16	Mike Rogers	R	83,996	147,770	149	36.2%	63.7%	0.1%	-27.5%	-33.0%	5.5%	79.6%	x
Alabama	4	R+30	Robert Aderholt	R	46,492	184,255	222	20.1%	79.8%	0.1%	-59.6%	-62.5%	2.9%	78.9%	x
Alabama	5	R+18	Mo Brooks	R	101,388	159,063	222	38.9%	61.0%	0.1%	-22.1%	-32.9%	10.8%	82.8%	x
Alabama	6	R+26	Gary Palmer	R	85,644	192,542	142	30.8%	69.2%	0.1%	-38.4%	-43.8%	5.4%	82.8%	x
Alabama	7	D+20	Terri Sewell	D	185,010	0	4,153	97.8%	0.0%	2.2%	97.8%	41.2%	N/A	64.2%	x
Alaska	AL	R+9	Don Young	R	131,199	149,779	1,188	46.5%	53.1%	0.4%	-6.6%	-14.7%	8.1%	88.6%	x
Arizona	1	R+2	Tom O'Halleran	D	143,240	122,784	65	53.8%	46.1%	0.0%	7.7%	-1.1%	8.8%	92.0%	x
Arizona	2	R+1	***Ann Kirkpatrick***	***D***	161,000	133,102	50	54.7%	45.2%	0.0%	9.5%	4.8%	4.7%	91.5%	x
Arizona	3	D+13	Raul Grijalva	D	114,650	64,868	0	63.9%	36.1%	0.0%	27.7%	29.5%	-1.8%	84.8%	x
Arizona	4	R+21	Paul Gosar	R	84,521	188,842	3,672	30.5%	68.2%	1.3%	-37.7%	-39.4%	1.7%	91.1%	x
Arizona	5	R+15	Andy Biggs	R	127,027	186,037	0	40.6%	59.4%	0.0%	-18.8%	-20.5%	1.7%	91.7%	x
Arizona	6	R+9	David Schweikert	R	140,559	173,140	0	44.8%	55.2%	0.0%	-10.4%	-9.8%	-0.6%	91.2%	x
Arizona	7	D+23	Ruben Gallego	D	113,044	301	18,706	85.6%	0.2%	14.2%	85.4%	48.3%	N/A	79.0%	x
Arizona	8	R+13	Debbie Lesko	R	135,569	168,835	13	44.5%	55.5%	0.0%	-10.9%	-20.8%	9.9%	91.5%	x
Arizona	9	D+4	*Greg Stanton*	*D*	159,583	101,662	0	61.1%	38.9%	0.0%	22.2%	15.9%	6.3%	90.0%	x
Arkansas	1	R+17	Rick Crawford	R	57,907	138,757	4,581	28.8%	68.9%	2.3%	-40.2%	-34.8%	-5.4%	77.2%	x
Arkansas	2	R+7	French Hill	R	116,135	132,125	5,193	45.8%	52.1%	2.0%	-6.3%	-10.7%	4.4%	82.6%	x
Arkansas	3	R+19	Steve Womack	R	74,952	148,717	6,039	32.6%	64.7%	2.6%	-32.1%	-31.4%	-0.7%	78.6%	x
Arkansas	4	R+17	Bruce Westerman	R	63,984	136,740	4,168	31.2%	66.7%	2.0%	-35.5%	-32.8%	-2.7%	75.7%	x
California	1	R+11	Doug LaMalfa	R	131,506	160,006	0	45.1%	54.9%	0.0%	-9.8%	-19.4%	9.6%	91.6%	
California	2	D+22	Jared Huffman	D	243,051	72,541	0	77.0%	23.0%	0.0%	54.0%	45.2%	8.8%	90.5%	
California	3	D+5	John Garamendi	D	132,983	96,106	0	58.0%	42.0%	0.0%	16.1%	12.5%	3.6%	86.8%	
California	4	R+10	Tom McClintock	R	156,253	184,401	0	45.9%	54.1%	0.0%	-8.3%	-14.5%	6.2%	94.6%	
California	5	D+21	Mike Thompson	D	203,012	0	53,836	79.0%	0.0%	21.0%	79.0%	44.6%	N/A	83.8%	
California	6	D+21	Doris Matsui	D	201,939	0	0	100.0%	0.0%	0.0%	100.0%	44.0%	N/A	81.4%	
California	7	D+3	Ami Bera	D	155,016	126,601	0	55.0%	45.0%	0.0%	10.1%	11.2%	-1.1%	91.0%	
California	8	R+9	Paul Cook	R	0	170,785	0	0.0%	100.0%	0.0%	-100.0%	-15.1%	N/A	73.3%	
California	9	D+8	Jerry McNerney	D	113,240	87,263	0	56.5%	43.5%	0.0%	13.0%	18.2%	-5.2%	82.4%	

It’s also common for *less* good reasons

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Arkansas	3	R+19	Steve Womack	R	74,952	148,717	6,039	32.6%	64.7%	2.6%	-32.1%	-31.4%	-0.7%	78.6%	x
Arkansas	4	R+17	Bruce Westerman	R	63,984	136,740	4,168	31.2%	66.7%	2.0%	-35.5%	-32.8%	-2.7%	75.7%	x
California	1	R+11	Doug LaMalfa	R	131,506	160,006	0	45.1%	54.9%	0.0%	-9.8%	-19.4%	9.6%	91.6%	
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California	3	D+5	John Garamendi	D	132,983	96,106	0	58.0%	42.0%	0.0%	16.1%	12.5%	3.6%	86.8%	
California	4	R+10	Tom McClintock	R	156,253	184,401	0	45.9%	54.1%	0.0%	-8.3%	-14.5%	6.2%	94.6%	
California	5	D+21	Mike Thompson	D	203,012	0	53,836	79.0%	0.0%	21.0%	79.0%	44.6%	N/A	83.8%	
California	6	D+21	Doris Matsui	D	201,939	0	0	100.0%	0.0%	0.0%	100.0%	44.0%	N/A	81.4%	
California	7	D+3	Ami Bera	D	155,016	126,601	0	55.0%	45.0%	0.0%	10.1%	11.2%	-1.1%	91.0%	
California	8	R+9	Paul Cook	R	0	170,785	0	0.0%	100.0%	0.0%	-100.0%	-15.1%	N/A	73.3%	
California	9	D+8	Jerry McNerney	D	113,240	87,263	0	56.5%	43.5%	0.0%	13.0%	18.2%	-5.2%	82.4%	

More than one header row

Mixed data types in some columns

Color and typography used to encode variables and their values

Fix it **before** you import it

Prevention is better than cure!

Broman KW, Woo KH (2018) "Data organization in spreadsheets." *The American Statistician* 78:2–10

THE AMERICAN STATISTICIAN
2018, VOL. 72, NO. 1, 2–10
https://doi.org/10.1080/00031305.2017.1375989

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Data Organization in Spreadsheets

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ABSTRACT
Spreadsheets are widely used software tools for data entry, storage, analysis, and visualization. Focusing on the data entry and storage aspects, this article offers practical recommendations for organizing spreadsheet data to reduce errors and ease later analyses. The basic principles are: be consistent, write dates like YYYY-MM-DD, do not leave any cells empty, put just one thing in a cell, organize the data as a single rectangle (with subjects as rows and variables as columns, and with a single header row), create a data dictionary, do not include calculations in the raw data files, do not use font color or highlighting as data, choose good names for things, make backups, use data validation to avoid data entry errors, and save the data in plain text files.

ARTICLE HISTORY
Received June 2017
Revised August 2017

KEYWORDS
Data management; Data organization; Microsoft Excel; Spreadsheets

Key points from Broman & Woo

	A	B	C
1	Date	Assay date	Weight
2		12/9/05	54.9
3		12/9/05	45.3
4	12/6/2005	e	47
5		e	45.7
6		e	52.9
7		1/11/2006	46.1
8		1/11/2006	38.6

Figure 1. A spreadsheet with inconsistent date formats. This spreadsheet does not adhere to our recommendations for consistency of date format.

Use a consistent date format

ISO 8601
YYYY-MM-DD

The one true year-month-day format

Key points from Broman & Woo

A

	A	B	C
1	id	date	glucose
2	101	2015–06–14	149.3
3	102		95.3
4	103	2015–06–18	97.5
5	104		117.0
6	105		108.0
7	106	2015–06–20	149.0
8	107		169.4

B

	A	B	C	D	E	F	G	H	I
1		1 min				5 min			
2	strain	normal		mutant		normal		mutant	
3	A	147	139	166	179	334	354	451	474
4	B	246	240	178	172	514	611	412	447

No empty cells.

Use one row of headers only.

Key points from Broman & Woo

	A	B	C	D	E
1	strain	genotype	min	replicate	response
2	A	normal	1	1	147
3	A	normal	1	2	139
4	B	normal	1	1	246
5	B	normal	1	2	240
6	A	mutant	1	1	166
7	A	mutant	1	2	179
8	B	mutant	1	1	178
9	B	mutant	1	2	172
10	A	normal	5	1	334
11	A	normal	5	2	354
12	B	normal	5	1	514
13	B	normal	5	2	611
14	A	mutant	5	1	451
15	A	mutant	5	2	474
16	B	mutant	5	1	412
17	B	mutant	5	2	447

Tidied version

Key points from Broman & Woo

A

	A	B	C	D	E	F
1						
2		101	102	103	104	105
3	sex	Male	Female	Male	Male	Male
4						
5		101	102	103	104	105
6	glucose	134.1	120.0	124.8	83.1	105.2
7						
8		101	102	103	104	105
9	insulin	0.60	1.18	1.23	1.16	0.73

B

	A	B	C	D	E	F	G
1	1MIN						
2			Normal			Mutant	
3	B6	146.6	138.6	155.6	166	179.3	186.9
4	BTBR	245.7	240	243.1	177.8	171.6	188.1
5							
6	5MIN						
7			Normal			Mutant	
8	B6	333.6	353.6	408.8	450.6	474.4	423.8
9	BTBR	514.4	610.6	597.9	412.1	447.4	446.5

C

	A	B	C	D	E	F	G
1							
2	Date	11/3/14					
3	Days on diet	126					
4	Mouse #	43					
5	sex	f					
6	experiment		values			mean	SD
7	control		0.186	0.191	1.081	0.49	0.52
8	treatment A		7.414	1.468	2.254	3.71	3.23
9	treatment B		9.811	9.259	11.296	10.12	1.05
10							
11	fold change		values			mean	SD
12	treatment A		15.26	3.02	4.64	7.64	6.65
13	treatment B		20.19	19.05	23.24	20.83	2.17

D

	A	B	C	D	E	F
1		GTT date	GTT weight	time	glucose mg/dl	insulin ng/ml
2	321	2/9/15	24.5	0	99.2	lo off curve
3				5	349.3	0.205
4				15	286.1	0.129
5				30	312	0.175
6				60	99.9	0.122
7				120	217.9	lo off curve
8	322	2/9/15	18.9	0	185.8	0.251
9				5	297.4	2.228
10				15	439	2.078
11				30	362.3	0.775
12				60	232.7	0.5
13				120	260.7	0.523
14	323	2/9/15	24.7	0	198.5	0.151
15				5	530.6	off curve lo

Rectangle your data

Key points from Broman & Woo

A

	A	B	C
1	id	GTT date	GTT weight
2	321	2/9/15	24.5
3	322	2/9/15	18.9
4	323	2/9/15	24.7

B

	A	B	C	D	E
1	id	GTT time	glucose mg/dl	insulin ng/ml	note
2	321	0	99.2	NA	insulin below curve
3	321	5	349.3	0.205	
4	321	15	286.1	0.129	
5	321	30	312	0.175	
6	321	60	99.9	0.122	
7	321	120	217.9	NA	insulin below curve
8	322	0	185.8	0.251	
9	322	5	297.4	2.228	
10	322	15	439	2.078	
11	322	30	362.3	0.775	
12	322	60	232.7	0.5	
13	322	120	260.7	0.523	
14	323	0	198.5	0.151	
15	323	5	530.6	NA	insulin below curve

Use more than one table if needed. We can join them later.

Key points from Broman & Woo

	A	B	C	D	E	F	G	H	I	J	K
1			week 4			week 6			week 8		
2	Mouse ID	SEX	date	weight	glucose	date	weight	glucose	date	weight	glucose
3	3005	M	3/30/2007	19.3	635	4/11/2007	31	460.7	4/27/2007	39.6	530.2
4	3017	M	10/6/2006	25.9	202.4	10/19/2006	45.1	384.7	11/3/2006	57.2	458.7
5	3434	F	11/22/2006	26.6	238.9	12/6/2006	45.9	378	12/22/2006	56.2	409.8
6	3449	M	1/5/2007	27.5	121	1/19/2007	42.9	191.3	2/2/2007	56.7	182.5
7	3499	F	1/5/2007	19.8	220.2	1/19/2007	36.6	556.9	2/2/2007	43.6	446

Needs a single header row and a consistent naming scheme.

Key points from Broman & Woo

	A	B	C	D	E	F
1	mouse_id	sex	week	date	glucose	weight
2	3005	M	4	3/30/2007	19.3	635
3	3005	M	6	4/11/2007	31	460.7
4	3005	M	8	4/27/2007	39.6	530.2
5	3017	M	4	10/6/2006	25.9	202.4
6	3017	M	6	10/19/2006	45.1	384.7
7	3017	M	8	11/3/2006	57.2	458.7
8	3434	F	4	11/22/2006	26.6	238.9
9	3434	F	6	12/6/2006	45.9	378
10	3434	F	8	12/22/2006	56.2	409.8
11	3449	M	4	1/5/2007	27.5	121
12	3449	M	6	1/19/2007	42.9	191.3
13	3449	M	8	2/2/2007	56.7	182.5
14	3499	F	4	1/5/2007	19.8	220.2
15	3499	F	6	1/19/2007	36.6	556.9
16	3499	F	8	2/2/2007	43.6	446

Tidied version.

The most common `tidyr` operation

Pivoting:

```
edu
```

```
# A tibble: 366 × 11
   age   sex    year total elem4 elem8   hs3   hs4 coll3 coll4 median
   <chr> <chr> <int> <int> <int> <int> <dbl> <dbl> <dbl> <dbl>  <dbl>
 1 25-34 Male   2016 21845   116   468  1427  6386  6015  7432     NA
 2 25-34 Male   2015 21427   166   488  1584  6198  5920  7071     NA
 3 25-34 Male   2014 21217   151   512  1611  6323  5910  6710     NA
 4 25-34 Male   2013 20816   161   582  1747  6058  5749  6519     NA
 5 25-34 Male   2012 20464   161   579  1707  6127  5619  6270     NA
 6 25-34 Male   2011 20985   190   657  1791  6444  5750  6151     NA
 7 25-34 Male   2010 20689   186   641  1866  6458  5587  5951     NA
 8 25-34 Male   2009 20440   184   695  1806  6495  5508  5752     NA
 9 25-34 Male   2008 20210   172   714  1874  6356  5277  5816     NA
10 25-34 Male   2007 20024   246   757  1930  6361  5137  5593     NA
# ℹ 356 more rows
```

The “Level of Schooling Attained” measure is spread across the columns, from `elem4` to `coll4`.

This is fine for a compact table, but for us it should be a single measure, say, “education”.

Wide to long with `pivot_longer()`

We're going to put the columns `elem4:coll4` into a new column, creating a new categorical measure named `education`. The numbers currently under each column will become a new `value` column corresponding to that level of education.

```r
edu |>
  pivot_longer(elem4:coll4, names_to = "education")
```

```
# A tibble: 2,196 × 7
   age   sex    year total median education value
   <chr> <chr> <int> <int>  <dbl> <chr>     <dbl>
 1 25-34 Male   2016 21845     NA elem4       116
 2 25-34 Male   2016 21845     NA elem8       468
 3 25-34 Male   2016 21845     NA hs3        1427
 4 25-34 Male   2016 21845     NA hs4        6386
 5 25-34 Male   2016 21845     NA coll3      6015
 6 25-34 Male   2016 21845     NA coll4      7432
 7 25-34 Male   2015 21427     NA elem4       166
 8 25-34 Male   2015 21427     NA elem8       488
 9 25-34 Male   2015 21427     NA hs3        1584
10 25-34 Male   2015 21427     NA hs4        6198
# ℹ 2,186 more rows
```

Wide to long with `pivot_longer()`

We can name the value column to whatever we like. Here it's a number of people.

```
edu |>
  pivot_longer(elem4:coll4, names_to = "education", values_to = "n")
```

```
# A tibble: 2,196 × 7
   age   sex    year total median education     n
   <chr> <chr> <int> <int>  <dbl> <chr>     <dbl>
 1 25-34 Male   2016 21845     NA elem4       116
 2 25-34 Male   2016 21845     NA elem8       468
 3 25-34 Male   2016 21845     NA hs3        1427
 4 25-34 Male   2016 21845     NA hs4        6386
 5 25-34 Male   2016 21845     NA coll3      6015
 6 25-34 Male   2016 21845     NA coll4      7432
 7 25-34 Male   2015 21427     NA elem4       166
 8 25-34 Male   2015 21427     NA elem8       488
 9 25-34 Male   2015 21427     NA hs3        1584
10 25-34 Male   2015 21427     NA hs4        6198
# ℹ 2,186 more rows
```

Let’s recode() it while we’re here

```
edu |>
  pivot_longer(elem4:coll4, names_to = "education", values_to = "n") |>
  mutate(education = recode(education,
                            elem4 = "Elementary 4", elem8 = "Elementary 8",
                            hs3 = "High School 3", hs4 = "High School 4",
                            coll3 = "College 3", coll4 = "College 4"))
```

```
# A tibble: 2,196 × 7
   age   sex    year total median education         n
   <chr> <chr> <int> <int>  <dbl> <chr>         <dbl>
 1 25-34 Male   2016 21845     NA Elementary 4    116
 2 25-34 Male   2016 21845     NA Elementary 8    468
 3 25-34 Male   2016 21845     NA High School 3  1427
 4 25-34 Male   2016 21845     NA High School 4  6386
 5 25-34 Male   2016 21845     NA College 3      6015
 6 25-34 Male   2016 21845     NA College 4      7432
 7 25-34 Male   2015 21427     NA Elementary 4    166
 8 25-34 Male   2015 21427     NA Elementary 8    488
 9 25-34 Male   2015 21427     NA High School 3  1584
10 25-34 Male   2015 21427     NA High School 4  6198
# ℹ 2,186 more rows
```

The argument order of `recode()` is inconsistent with other tidyverse functions and it may be superceded in the future.

pivot_longer() implies pivot_wider()

```r
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
```

pivot_longer() implies pivot_wider()

```
gapminder ▷
  select(country, continent, year, lifeExp) ▷
  pivot_wider(names_from = year, values_from = lifeExp)
```

```
# A tibble: 142 × 14
   country     continent `1952` `1957` `1962` `1967` `1972` `1977` `1982` `1987`
   <fct>       <fct>      <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>
 1 Afghanistan Asia        28.8   30.3   32.0   34.0   36.1   38.4   39.9   40.8
 2 Albania     Europe      55.2   59.3   64.8   66.2   67.7   68.9   70.4   72  
 3 Algeria     Africa      43.1   45.7   48.3   51.4   54.5   58.0   61.4   65.8
 4 Angola      Africa      30.0   32.0   34     36.0   37.9   39.5   39.9   39.9
 5 Argentina   Americas    62.5   64.4   65.1   65.6   67.1   68.5   69.9   70.8
 6 Australia   Oceania     69.1   70.3   70.9   71.1   71.9   73.5   74.7   76.3
 7 Austria     Europe      66.8   67.5   69.5   70.1   70.6   72.2   73.2   74.9
 8 Bahrain     Asia        50.9   53.8   56.9   59.9   63.3   65.6   69.1   70.8
 9 Bangladesh  Asia        37.5   39.3   41.2   43.5   45.3   46.9   50.0   52.8
10 Belgium     Europe      68     69.2   70.2   70.9   71.4   72.8   73.9   75.4
# ℹ 132 more rows
# ℹ 4 more variables: `1992` <dbl>, `1997` <dbl>, `2002` <dbl>, `2007` <dbl>
```

What about *multiple* columns?

This is a pretty common problem. A first thought (“Just don’t mention the other columns”) isn’t it:

```
gapminder |>
  pivot_wider(names_from = year, values_from = lifeExp)
```

```
# A tibble: 1,704 × 16
   country  continent     pop gdpPercap `1952` `1957` `1962` `1967` `1972` `1977`
   <fct>    <fct>       <int>     <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>
 1 Afghani… Asia       8.43e6      779.   28.8   NA     NA     NA     NA     NA
 2 Afghani… Asia       9.24e6      821.   NA     30.3   NA     NA     NA     NA
 3 Afghani… Asia       1.03e7      853.   NA     NA     32.0   NA     NA     NA
 4 Afghani… Asia       1.15e7      836.   NA     NA     NA     34.0   NA     NA
 5 Afghani… Asia       1.31e7      740.   NA     NA     NA     NA     36.1   NA
 6 Afghani… Asia       1.49e7      786.   NA     NA     NA     NA     NA     38.4
 7 Afghani… Asia       1.29e7      978.   NA     NA     NA     NA     NA     NA
 8 Afghani… Asia       1.39e7      852.   NA     NA     NA     NA     NA     NA
 9 Afghani… Asia       1.63e7      649.   NA     NA     NA     NA     NA     NA
10 Afghani… Asia       2.22e7      635.   NA     NA     NA     NA     NA     NA
# ℹ 1,694 more rows
# ℹ 6 more variables: `1982` <dbl>, `1987` <dbl>, `1992` <dbl>, `1997` <dbl>,
#   `2002` <dbl>, `2007` <dbl>
```

`pop` and `gdpPercap` are still long, and now our table is really sparse

What about *multiple* columns?

We need to specify that we want values from more than one column.

```
gapminder |>
  select(country, continent, year, lifeExp, gdpPercap) |>
  pivot_wider(names_from = year, values_from = c(lifeExp, gdpPercap))
```

```
# A tibble: 142 × 26
   country     continent lifeExp_1952 lifeExp_1957 lifeExp_1962 lifeExp_1967
   <fct>       <fct>            <dbl>        <dbl>        <dbl>        <dbl>
 1 Afghanistan Asia              28.8         30.3         32.0         34.0
 2 Albania     Europe            55.2         59.3         64.8         66.2
 3 Algeria     Africa            43.1         45.7         48.3         51.4
 4 Angola      Africa            30.0         32.0         34           36.0
 5 Argentina   Americas          62.5         64.4         65.1         65.6
 6 Australia   Oceania           69.1         70.3         70.9         71.1
 7 Austria     Europe            66.8         67.5         69.5         70.1
 8 Bahrain     Asia              50.9         53.8         56.9         59.9
 9 Bangladesh  Asia              37.5         39.3         41.2         43.5
10 Belgium     Europe            68           69.2         70.2         70.9
# ℹ 132 more rows
# ℹ 20 more variables: lifeExp_1972 <dbl>, lifeExp_1977 <dbl>,
#   lifeExp_1982 <dbl>, lifeExp_1987 <dbl>, lifeExp_1992 <dbl>,
#   lifeExp_1997 <dbl>, lifeExp_2002 <dbl>, lifeExp_2007 <dbl>,
#   gdpPercap_1952 <dbl>, gdpPercap_1957 <dbl>, gdpPercap_1962 <dbl>,
#   gdpPercap_1967 <dbl>, gdpPercap_1972 <dbl>, gdpPercap_1977 <dbl>,
#   gdpPercap_1982 <dbl>, gdpPercap_1987 <dbl>, gdpPercap_1992 <dbl>, …
```

This will give us a very wide table, but it's what we wanted.

```
# Some made-up data
dfstrat <- read_csv(here::here("data", "dfstrat.csv"))
dfstrat
```

Pivot wider while summarizing

```r
dfstrat ← read_csv(here::here("data", "dfstrat.csv"))
```

Pivot wider while summarizing

```r
dfstrat <- read_csv(here::here("data", "dfstrat.csv"))
dfstrat
```

```
# A tibble: 1,000 × 5
   stratum sex   race  educ  income
     <dbl> <chr> <chr> <chr>  <dbl>
 1       6 F     W     HS      83.7
 2       5 F     W     BA     128.
 3       3 F     B     HS      66.3
 4       3 F     W     HS     111.
 5       6 M     W     BA     116.
 6       7 M     B     HS     159.
 7       8 M     W     BA     131.
 8       3 M     W     BA      94.4
 9       7 F     B     HS     146.
10       2 F     W     BA      88.8
# ℹ 990 more rows
```

Pivot wider while summarizing

```r
dfstrat <- read_csv(here::here("data", "dfstrat.csv"))
dfstrat |>
    group_by(sex, race, stratum, educ)
```

```
# A tibble: 1,000 × 5
# Groups:   sex, race, stratum, educ [64]
   stratum sex   race  educ  income
     <dbl> <chr> <chr> <chr>  <dbl>
 1       6 F     W     HS      83.7
 2       5 F     W     BA     128.
 3       3 F     B     HS      66.3
 4       3 F     W     HS     111.
 5       6 M     W     BA     116.
 6       7 M     B     HS     159.
 7       8 M     W     BA     131.
 8       3 M     W     BA      94.4
 9       7 F     B     HS     146.
10       2 F     W     BA      88.8
# ℹ 990 more rows
```

Pivot wider while summarizing

```
dfstrat <- read_csv(here::here("data", "dfstrat.csv"))
dfstrat |>
    group_by(sex, race, stratum, educ) |>
    summarize(mean_inc = mean(income),
              n = n())
```

```
# A tibble: 64 × 6
# Groups:   sex, race, stratum [32]
   sex   race  stratum educ  mean_inc     n
   <chr> <chr>   <dbl> <chr>    <dbl> <int>
 1 F     B           1 BA        93.8    19
 2 F     B           1 HS        99.3     6
 3 F     B           2 BA        89.7    11
 4 F     B           2 HS        93.0    16
 5 F     B           3 BA       112.     13
 6 F     B           3 HS        95.0    16
 7 F     B           4 BA       108.     14
 8 F     B           4 HS        96.1    15
 9 F     B           5 BA        91.0    11
10 F     B           5 HS        92.6    15
# ℹ 54 more rows
```

Pivot wider while summarizing

```r
dfstrat <- read_csv(here::here("data", "dfstrat.csv"))
dfstrat |>
    group_by(sex, race, stratum, educ) |>
    summarize(mean_inc = mean(income),
              n = n()) |>
    pivot_wider(names_from = (educ),
                values_from = c(mean_inc, n))
```

```
# A tibble: 32 × 7
# Groups:   sex, race, stratum [32]
   sex   race  stratum mean_inc_BA mean_inc_HS  n_BA  n_HS
   <chr> <chr>   <dbl>       <dbl>       <dbl> <int> <int>
 1 F     B           1        93.8        99.3    19     6
 2 F     B           2        89.7        93.0    11    16
 3 F     B           3       112.         95.0    13    16
 4 F     B           4       108.         96.1    14    15
 5 F     B           5        91.0        92.6    11    15
 6 F     B           6        93.0       116.     15    15
 7 F     B           7       102.        121.     13    13
 8 F     B           8       105.         88.3    14     8
 9 F     W           1        92.6       110.     19    13
10 F     W           2        98.5       101.     15    19
# ℹ 22 more rows
```

Pivot wider while summarizing

```r
dfstrat <- read_csv(here::here("data", "dfstrat.csv"))
dfstrat |>
    group_by(sex, race, stratum, educ) |>
    summarize(mean_inc = mean(income),
              n = n()) |>
    pivot_wider(names_from = (educ),
                values_from = c(mean_inc, n)) |>
    ungroup()
```

```
# A tibble: 32 × 7
   sex   race  stratum mean_inc_BA mean_inc_HS  n_BA  n_HS
   <chr> <chr>   <dbl>       <dbl>       <dbl> <int> <int>
 1 F     B           1        93.8        99.3    19     6
 2 F     B           2        89.7        93.0    11    16
 3 F     B           3       112.         95.0    13    16
 4 F     B           4       108.         96.1    14    15
 5 F     B           5        91.0        92.6    11    15
 6 F     B           6        93.0       116.     15    15
 7 F     B           7       102.        121.     13    13
 8 F     B           8       105.         88.3    14     8
 9 F     W           1        92.6       110.     19    13
10 F     W           2        98.5       101.     15    19
# ℹ 22 more rows
```

Here we end up with sex-by-race-by-stratum in the rows, and the income-by-education means, and income-by-education Ns, in their own columns.

Separate and Unite

separate() and unite() columns

```r
## tribble() lets you make tibbles by hand
df <- tribble(
  ~name, ~occupation,
  "Nero.Wolfe", "Private Detective",
  "Archie.Goodwin", "Personal Assistant",
  "Fritz.Brenner", "Cook and Butler",
  "Theodore.Horstmann", "Orchid Expert"
)

df
```

```
# A tibble: 4 × 2
  name               occupation
  <chr>              <chr>
1 Nero.Wolfe         Private Detective
2 Archie.Goodwin     Personal Assistant
3 Fritz.Brenner      Cook and Butler
4 Theodore.Horstmann Orchid Expert
```

separate() and unite() columns

```
## tribble() lets you make tibbles by hand
df <- tribble(
  ~name, ~occupation,
  "Nero.Wolfe", "Private Detective",
  "Archie.Goodwin", "Personal Assistant",
  "Fritz.Brenner", "Cook and Butler",
  "Theodore.Horstmann", "Orchid Expert"
)

df
```

```
# A tibble: 4 × 2
  name               occupation
  <chr>              <chr>
1 Nero.Wolfe         Private Detective
2 Archie.Goodwin     Personal Assistant
3 Fritz.Brenner      Cook and Butler
4 Theodore.Horstmann Orchid Expert
```

Separate and unite

```r
df
```

```
# A tibble: 4 × 2
  name               occupation
  <chr>              <chr>
1 Nero.Wolfe         Private Detective
2 Archie.Goodwin     Personal Assistant
3 Fritz.Brenner      Cook and Butler
4 Theodore.Horstmann Orchid Expert
```

Separate and unite

```r
df |>
  separate(name, into = c("first", "last"))
```

```
# A tibble: 4 × 3
  first    last      occupation
  <chr>    <chr>     <chr>
1 Nero     Wolfe     Private Detective
2 Archie   Goodwin   Personal Assistant
3 Fritz    Brenner   Cook and Butler
4 Theodore Horstmann Orchid Expert
```

Separate and unite

```r
df |>
  separate(name, into = c("first", "last")) |>
  unite("full_name", first:last, sep = " ")
```

```
# A tibble: 4 × 2
  full_name          occupation
  <chr>              <chr>
1 Nero Wolfe         Private Detective
2 Archie Goodwin     Personal Assistant
3 Fritz Brenner      Cook and Butler
4 Theodore Horstmann Orchid Expert
```

Separate and unite

```r
df ▷
  separate(name, into = c("first", "last")) ▷
  unite("full_name", first:last, sep = " ") ▷
  unite("both_together", full_name:occupation,
        sep = ", ", remove = FALSE)
```

```
# A tibble: 4 × 3
  both_together                         full_name          occupation
  <chr>                                 <chr>              <chr>
1 Nero Wolfe, Private Detective         Nero Wolfe         Private Detective
2 Archie Goodwin, Personal Assistant    Archie Goodwin     Personal Assistant
3 Fritz Brenner, Cook and Butler        Fritz Brenner      Cook and Butler
4 Theodore Horstmann, Orchid Expert     Theodore Horstmann Orchid Expert
```

Separate and unite

```r
df |>
  separate(name, into = c("first", "last")) |>
  unite("full_name", first:last, sep = " ") |>
  unite("both_together", full_name:occupation,
        sep = ", ", remove = FALSE)
```

```
# A tibble: 4 × 3
  both_together                        full_name          occupation
  <chr>                                <chr>              <chr>
1 Nero Wolfe, Private Detective        Nero Wolfe         Private Detective
2 Archie Goodwin, Personal Assistant   Archie Goodwin     Personal Assistant
3 Fritz Brenner, Cook and Butler       Fritz Brenner      Cook and Butler
4 Theodore Horstmann, Orchid Expert    Theodore Horstmann Orchid Expert
```

Separate and unite

```r
df
```

```
# A tibble: 4 × 2
  name                occupation
  <chr>               <chr>
1 Nero.Wolfe          Private Detective
2 Archie.Goodwin      Personal Assistant
3 Fritz.Brenner       Cook and Butler
4 Theodore.Horstmann  Orchid Expert
```

Separate and unite

```r
df |>
  separate(name, into = c("first", "last"))
```

```
# A tibble: 4 × 3
  first    last      occupation
  <chr>    <chr>     <chr>
1 Nero     Wolfe     Private Detective
2 Archie   Goodwin   Personal Assistant
3 Fritz    Brenner   Cook and Butler
4 Theodore Horstmann Orchid Expert
```

Separate and unite

```r
df |>
  separate(name, into = c("first", "last")) |>
  unite("full_name", first:last)
```

```
# A tibble: 4 × 2
  full_name          occupation
  <chr>              <chr>
1 Nero_Wolfe         Private Detective
2 Archie_Goodwin     Personal Assistant
3 Fritz_Brenner      Cook and Butler
4 Theodore_Horstmann Orchid Expert
```

Separate and unite

```r
df |>
  separate(name, into = c("first", "last")) |>
  unite("full_name", first:last) |>
  separate(full_name, into = c("first", "last"))
```

```
# A tibble: 4 × 3
  first    last      occupation
  <chr>    <chr>     <chr>
1 Nero     Wolfe     Private Detective
2 Archie   Goodwin   Personal Assistant
3 Fritz    Brenner   Cook and Butler
4 Theodore Horstmann Orchid Expert
```

Separate and unite

```r
df ▷
  separate(name, into = c("first", "last")) ▷
  unite("full_name", first:last) ▷
  separate(full_name, into = c("first", "last"))
```

```
# A tibble: 4 × 3
  first    last      occupation
  <chr>    <chr>     <chr>
1 Nero     Wolfe     Private Detective
2 Archie   Goodwin   Personal Assistant
3 Fritz    Brenner   Cook and Butler
4 Theodore Horstmann Orchid Expert
```

The underscore, `_`, is the default uniting character.

Separate and unite

```
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>,
```

Separate and unite

```r
gss_sm |>
    select(race, degree)
```

```
# A tibble: 2,867 × 2
   race  degree
   <fct> <fct>
 1 White Bachelor
 2 White High School
 3 White Bachelor
 4 White High School
 5 White Graduate
 6 White Junior College
 7 White High School
 8 Other High School
 9 Black High School
10 White Junior College
# ℹ 2,857 more rows
```

Separate and unite

```r
gss_sm |>
    select(race, degree) |>
    mutate(racedeg = interaction(race, degree))
```

```
# A tibble: 2,867 × 3
   race  degree         racedeg
   <fct> <fct>          <fct>
 1 White Bachelor       White.Bachelor
 2 White High School    White.High School
 3 White Bachelor       White.Bachelor
 4 White High School    White.High School
 5 White Graduate       White.Graduate
 6 White Junior College White.Junior College
 7 White High School    White.High School
 8 Other High School    Other.High School
 9 Black High School    Black.High School
10 White Junior College White.Junior College
# ℹ 2,857 more rows
```

Separate and unite

```r
gss_sm |>
    select(race, degree) |>
    mutate(racedeg = interaction(race, degree)) |>
    group_by(racedeg)
```

```
# A tibble: 2,867 × 3
# Groups:   racedeg [16]
   race  degree         racedeg
   <fct> <fct>          <fct>
 1 White Bachelor       White.Bachelor
 2 White High School    White.High School
 3 White Bachelor       White.Bachelor
 4 White High School    White.High School
 5 White Graduate       White.Graduate
 6 White Junior College White.Junior College
 7 White High School    White.High School
 8 Other High School    Other.High School
 9 Black High School    Black.High School
10 White Junior College White.Junior College
# ℹ 2,857 more rows
```

Separate and unite

```
gss_sm ▷
    select(race, degree) ▷
    mutate(racedeg = interaction(race, degree)) ▷
    group_by(racedeg) ▷
    tally()
```

```
# A tibble: 16 × 2
   racedeg                   n
   <fct>                 <int>
 1 White.Lt High School    197
 2 Black.Lt High School     60
 3 Other.Lt High School     71
 4 White.High School      1057
 5 Black.High School       292
 6 Other.High School       112
 7 White.Junior College    166
 8 Black.Junior College     33
 9 Other.Junior College     17
10 White.Bachelor          426
11 Black.Bachelor           71
12 Other.Bachelor           39
13 White.Graduate          250
14 Black.Graduate           31
15 Other.Graduate           37
16 <NA>                      8
```

Separate and unite

```
gss_sm ▷
    select(race, degree) ▷
    mutate(racedeg = interaction(race, degree)) ▷
    group_by(racedeg) ▷
    tally() ▷
    separate(racedeg, sep = "\\.", into = c("race", "degree"))
```

```
# A tibble: 16 × 3
   race  degree             n
   <chr> <chr>          <int>
 1 White Lt High School   197
 2 Black Lt High School    60
 3 Other Lt High School    71
 4 White High School     1057
 5 Black High School      292
 6 Other High School      112
 7 White Junior College   166
 8 Black Junior College    33
 9 Other Junior College    17
10 White Bachelor         426
11 Black Bachelor          71
12 Other Bachelor          39
13 White Graduate         250
14 Black Graduate          31
15 Other Graduate          37
16 <NA>  <NA>               8
```

This one is a bit trickier, and our first glimpse of a *regular expression*.

We have to tell `separate()` to split on the period, not the space.