Week 7: Data cleaning & joins

EMSE 4197 | John Paul Helveston | February 26, 2020

Stragies for when variables encode 2 things

1. Divide & conquer

2. Gather, separate, spread

Example:

Winners of Nathan's hot dog eating contest

	A	B	C	D	E	F	G
1	Year	Mens	Dogs eaten	Country	Womens	Dogs eaten	Country
2	1980	Paul Siederman & Joe Baldini	9.1	United States			
3	1981	Thomas DeBerry	11	United States			
4	1982	Steven Abrams	11	United States			
5	1983	Luis Llamas	19.5	Mexico			
6	1984	Birgit Felden	9.5	Germany			
7	1985	Oscar Rodriguez	11.75	United States			
8	1986	Mark Heller	15.5	United States			
9	1987	Don Wolfman	12	United States			
10	1988	Jay Green	14	United States			
11	1989	Jay Green	13	United States			
12	1990	Mike DeVito	16	United States			
13	1991	Frank Dellarosa	21.5*	United States			
14	1992	Frank Dellarosa	19	United States			
15	1993	Mike DeVito	17	United States			
16	1994	Mike DeVito	20	United States			
17	1995	Edward Krachie	19.5	United States			
18	1996	Edward Krachie	22.25*	United States			
19	1997	Hirofumi Nakajima	24.5*	Japan			
20	1998	Hirofumi Nakajima	19	Japan			
21	1999	Steve Keiner	20.25	United States			
22	2000	Kazutoyo Arai	25.13*	Japan			
23	2001	Takeru Kobayashi	50*	Japan			
24	2002	Takeru Kobayashi	50.5*	Japan			
25	2003	Takeru Kobayashi	44.5	Japan			
26	2004	Takeru Kobayashi	53.5*	Japan			
27	2005	Takeru Kobayashi	49	Japan			
28	2006	Takeru Kobayashi	53.75*	Japan			
29	2007	Joey Chestnut	66*	United States			
30	2008	Joey Chestnut	59	United States			
31	2009	Joey Chestnut	68*	United States			
32	2010	Joey Chestnut	54	United States			
33	2011	Joey Chestnut	62	United States	Sonya Thomas	40*	United States
34	2012	Joey Chestnut	68	United States	Sonya Thomas	45*	United States
35	2013	Joey Chestnut	69*	United States	Sonya Thomas	36.75	United States
36	2014	Joey Chestnut	61	United States	Miki Sudo	34	United States
37	2015	Matt Stonie	62	United States	Miki Sudo	38	United States
38	2016	Joey Chestnut	70*	United States	Miki Sudo	38.5	United States
39	2017	Joey Chestnut	72*	United States	Miki Sudo	41	United States
40	2018	Joey Chestnut	74*	United States	Miki Sudo	37	United States
41	2019	Joey Chestnut	71	United States	Miki Sudo	31	United States
42							
43	Notes: * means new record						

Strategy 1: divide & conquer

Steps:

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table

```
hot_dogs <- read_excel(
    here::here('data', 'hot_dog_winners.xlsx'),
    sheet = 'hot_dog_winners') %>%
    clean_names() %>%
    dplyr::filter(!is.na(mens))

glimpse(hot_dogs)
```

```
## Observations: 40
## Variables: 7
## $ year         <chr> "1980", "1981", "1982", "1983", "19
## $ mens         <chr> "Paul Siederman & Joe Baldini", "Th
## $ dogs_eaten_3 <chr> "9.1", "11", "11", "19.5", "9.5", "
## $ country_4    <chr> "United States", "United States", "
## $ womens       <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ dogs_eaten_6 <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ country_7    <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA,
```

Strategy 1: divide & conquer

Steps

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table
4. **Split data into two competitions with the same variable names**
5. **Create new variable in each data frame: `competition`**

```
hot_dogs_m <- hot_dogs %>%
    select(
        year,
        competitor = mens,
        dogs_eaten = dogs_eaten_3,
        country    = country_4) %>%
    mutate(competition = 'Mens')

hot_dogs_w <- hot_dogs %>%
    select(
        year,
        competitor = womens,
        dogs_eaten = dogs_eaten_6,
        country    = country_7) %>%
    mutate(competition = 'Womens') %>%
    dplyr::filter(!is.na(competitor))
```

Strategy 1: divide & conquer

Steps

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table
4. Split data into two competitions **with the same variable names**
5. Create new variable in each data frame: `competition`
6. **Merge data together with `bind_rows()`**
7. **Clean up final data frame**

```
hot_dogs <- bind_rows(hot_dogs_m, hot_dogs_w) %>%
    mutate(
        new_record = str_detect(dogs_eaten, "\\*"),
        dogs_eaten = parse_number(dogs_eaten),
        year       = as.numeric(year))

glimpse(hot_dogs)
```

```
## Observations: 49
## Variables: 6
## $ year        <dbl> 1980, 1981, 1982, 1983, 1984, 1985,
## $ competitor  <chr> "Paul Siederman & Joe Baldini", "Tho
## $ dogs_eaten  <dbl> 9.10, 11.00, 11.00, 19.50, 9.50, 11.
## $ country     <chr> "United States", "United States", "U
## $ competition <chr> "Mens", "Mens", "Mens", "Mens", "Mer
## $ new_record  <lgl> FALSE, FALSE, FALSE, FALSE, FALSE, F
```

Strategy 2: gather, separate, spread

Steps:

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table

```r
hot_dogs <- read_excel(
    here::here('data', 'hot_dog_winners.xlsx'),
    sheet = 'hot_dog_winners') %>%
    clean_names() %>%
    dplyr::filter(!is.na(mens))

glimpse(hot_dogs)
```

```
## Observations: 40
## Variables: 7
## $ year          <chr> "1980", "1981", "1982", "1983", "19
## $ mens          <chr> "Paul Siederman & Joe Baldini", "Th
## $ dogs_eaten_3  <chr> "9.1", "11", "11", "19.5", "9.5", "
## $ country_4     <chr> "United States", "United States", "
## $ womens        <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ dogs_eaten_6  <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ country_7     <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA,
```

Strategy 2: gather, separate, spread

Steps:

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table
4. **Rename variables**
5. **Gather all the "joint" variables**

```
hot_dogs <- hot_dogs %>%
    select(
        year,
        competitor.mens   = mens,
        competitor.womens = womens,
        dogs_eaten.mens   = dogs_eaten_3,
        dogs_eaten.womens = dogs_eaten_6,
        country.mens      = country_4,
        country.womens    = country_7) %>%
    gather(key = 'variable', value = 'value',
           competitor.mens:country.womens)

head(hot_dogs, 3)
```

```
## # A tibble: 3 x 3
##   year  variable        value
##   <chr> <chr>           <chr>
## 1 1980  competitor.mens Paul Siederman & Joe Baldini
## 2 1981  competitor.mens Thomas DeBerry
## 3 1982  competitor.mens Steven Abrams
```

Strategy 2: gather, separate, spread

Steps:

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table
4. Rename variables
5. Gather all the "joint" variables
6. **Separate "joint" variables into components**

```
hot_dogs <- hot_dogs %>%
    separate(variable, into = c('variable', 'competition'),
             sep = '\\.')

head(hot_dogs)
```

```
## # A tibble: 6 x 4
##   year  variable   competition value
##   <chr> <chr>      <chr>       <chr>
## 1 1980  competitor mens        Paul Siederman & Joe Baldini
## 2 1981  competitor mens        Thomas DeBerry
## 3 1982  competitor mens        Steven Abrams
## 4 1983  competitor mens        Luis Llamas
## 5 1984  competitor mens        Birgit Felden
## 6 1985  competitor mens        Oscar Rodriguez
```

Strategy 2: gather, separate, spread

Steps:

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table
4. Rename variables
5. Gather all the "joint" variables
6. Separate "joint" variables into components
7. **Spread variable and value back to columns**
8. **Clean up final data frame**

```
hot_dogs <- hot_dogs %>%
    spread(key = variable, value = value) %>%
    mutate(
        new_record = str_detect(dogs_eaten, "\\*"),
        dogs_eaten = parse_number(dogs_eaten),
        year       = as.numeric(year))

glimpse(hot_dogs)
```

```
## Observations: 80
## Variables: 6
## $ year        <dbl> 1980, 1980, 1981, 1981, 1982, 1982, 1983, 1983
## $ competition <chr> "mens", "womens", "mens", "womens", "mens", "w
## $ competitor  <chr> "Paul Siederman & Joe Baldini", NA, "Thomas De
## $ country     <chr> "United States", NA, "United States", NA, "Uni
## $ dogs_eaten  <dbl> 9.10, NA, 11.00, NA, 11.00, NA, 19.50, NA, 9.5
## $ new_record  <lgl> FALSE, NA, FALSE, NA, FALSE, NA, FALSE, NA, FA
```

Divide & conquer

```r
hot_dogs <- read_excel(
    here::here('data', 'hot_dog_winners.xlsx'),
    sheet = 'hot_dog_winners') %>%
    clean_names() %>%
    dplyr::filter(!is.na(mens))

# Divide
hot_dogs_m <- hot_dogs %>%
    select(
        year,
        competitor = mens,
        dogs_eaten = dogs_eaten_3,
        country    = country_4) %>%
    mutate(competition = 'Mens')

hot_dogs_w <- hot_dogs %>%
    select(
        year,
        competitor = womens,
        dogs_eaten = dogs_eaten_6,
        country    = country_7) %>%
    mutate(competition = 'Womens') %>%
    dplyr::filter(!is.na(competitor))

# Merge and finish cleaning
hot_dogs <- bind_rows(hot_dogs_m, hot_dogs_w) %>%
    mutate(
        new_record = str_detect(dogs_eaten, "\\*"),
        dogs_eaten = parse_number(dogs_eaten),
        year       = as.numeric(year))
```

Gather, separate, spread

```r
hot_dogs <- read_excel(
    here::here('data', 'hot_dog_winners.xlsx'),
    sheet = 'hot_dog_winners') %>%
    clean_names() %>%
    dplyr::filter(!is.na(mens)) %>%
    # Rename variables
    select(
        year,
        competitor.mens   = mens,
        competitor.womens = womens,
        dogs_eaten.mens   = dogs_eaten_3,
        dogs_eaten.womens = dogs_eaten_6,
        country.mens      = country_4,
        country.womens    = country_7) %>%
    # Gather "joint" variables
    gather(key = 'variable', value = 'value',
           competitor.mens:country.womens) %>%
    # Separate "joint" variables
    separate(variable, into = c('variable', 'competition'),
             sep = '\\.') %>%
    # Spread "joint" variables
    spread(key = variable, value = value) %>%
    # Finish cleaning
    mutate(
        new_record = str_detect(dogs_eaten, "\\*"),
        dogs_eaten = parse_number(dogs_eaten),
        year       = as.numeric(year))
```

Strategies for dealing with sub-headers

Example:

OICA passenger car sales data

OICA

NEW PC REGISTRATIONS OR SALES

Estimated figures

REGIONS/COUNTRIES	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
EUROPE	**17,906,455**	**18,685,556**	**19,618,588**	**18,821,599**	**16,608,761**	**16,499,863**	**17,167,600**	**16,191,269**	**15,942,273**	**16,154,279**	**16,410,563**	**17,291,819**	**17,974,281**	**17,912,336**
EU 28 countries + EFTA	**15,622,035**	**15,961,138**	**16,147,274**	**14,911,880**	**14,533,115**	**13,830,694**	**13,642,659**	**12,567,903**	**12,344,415**	**13,061,461**	**14,287,881**	**15,160,239**	**15,631,283**	**15,626,509**
EU 15 countries + EFTA	**14,565,695**	**14,820,182**	**14,842,186**	**13,602,038**	**13,668,808**	**12,984,549**	**12,815,435**	**11,773,281**	**11,555,153**	**12,148,648**	**13,261,258**	**13,971,468**	**14,320,223**	**14,210,016**
AUSTRIA	307,915	308,594	298,182	293,697	319,403	328,563	356,145	336,010	319,035	303,318	308,555	329,604	353,320	341,068
BELGIUM	480,088	526,141	524,795	535,947	476,194	547,340	572,211	486,737	486,065	482,939	501,066	539,519	546,558	549,632
DENMARK	148,819	156,936	162,686	150,199	112,454	153,858	170,036	170,763	182,086	189,055	207,717	222,924	221,821	218,566
FINLAND	148,161	145,700	125,608	139,669	90,574	111,968	126,123	111,251	103,455	106,237	108,819	118,991	120,480	120,480
FRANCE	2,118,042	2,045,745	2,109,672	2,091,369	2,302,398	2,251,669	2,204,229	1,898,760	1,790,456	1,795,885	1,917,226	2,015,177	2,110,748	2,173,481
GERMANY	3,319,259	3,467,961	3,148,163	3,090,040	3,807,175	2,916,259	3,173,634	3,082,504	2,952,431	3,036,773	3,206,042	3,351,607	3,441,262	3,435,778
GREECE	269,728	267,669	279,745	267,295	219,730	141,501	97,680	58,482	58,694	71,218	75,805	78,873	88,083	103,431
ICELAND	18,060	17,129	15,942	9,033	2,113	3,106	5,038	7,902	7,274	9,537	14,004	18,442	21,324	17,976
IRELAND	171,742	178,484	186,325	151,607	57,453	88,446	89,911	79,498	74,367	96,284	124,804	146,600	131,332	125,557
ITALY	2,244,108	2,335,462	2,494,115	2,161,359	2,159,465	1,961,580	1,749,740	1,403,010	1,304,648	1,360,578	1,575,737	1,824,968	1,970,497	1,910,025
LUXEMBOURG	48,517	50,837	51,332	52,359	47,265	49,726	49,881	50,398	46,624	49,793	46,473	50,561	52,775	52,786
NETHERLANDS	465,196	483,999	504,300	499,980	387,699	482,531	555,812	502,454	417,036	387,553	449,350	382,825	414,306	443,531
NORWAY	109,907	109,164	129,195	110,617	98,675	127,754	138,345	137,967	142,151	144,202	150,686	154,603	158,650	147,929
PORTUGAL	206,488	194,702	201,816	213,389	161,013	223,464	153,404	95,309	105,921	142,826	178,503	207,345	222,129	228,327
SPAIN	1,528,877	1,634,608	1,614,835	1,161,176	952,772	982,015	808,051	699,589	722,689	890,125	1,094,077	1,147,007	1,234,932	1,321,438
SWEDEN	274,301	282,766	306,794	253,982	213,408	289,684	304,984	279,899	269,599	303,948	345,108	372,318	379,393	353,729
SWITZERLAND (+FL)	266,770	269,421	284,674	288,525	266,018	294,239	318,958	328,139	307,885	301,942	323,783	317,318	311,996	299,135
UNITED KINGDOM	2,439,717	2,344,864	2,404,007	2,131,795	1,994,999	2,030,846	1,941,253	2,044,609	2,264,737	2,476,435	2,633,503	2,692,786	2,540,617	2,367,147
EUROPE NEW MEMBERS	**1,056,340**	**1,140,956**	**1,305,088**	**1,309,842**	**864,307**	**846,145**	**827,224**	**794,622**	**789,262**	**912,813**	**1,026,623**	**1,188,771**	**1,311,060**	**1,416,493**
BULGARIA*	25,956	36,455	43,521	45,143	22,869	16,257	19,250	19,419	19,352	20,359	23,500	26,370	33,265	37,506
CROATIA	70,541	78,775	82,664	88,265	44,918	38,587	41,561	31,360	27,802	33,962	35,715	44,106	50,769	60,041
CYPRUS	17,687	18,639	22,878	22,241	14,981	14,088	13,480	10,123	7,102	8,276	10,344	12,643	13,127	13,135
CZECH REPUBLIC	151,699	156,686	174,456	182,554	167,708	169,580	173,595	174,009	164,736	192,314	230,857	259,693	271,595	261,437
ESTONIA	19,640	25,363	30,912	24,579	9,946	10,295	17,070	19,424	19,694	20,969	20,347	22,429	25,618	26,297
HUNGARY	198,982	187,676	171,661	153,278	60,189	43,476	45,094	53,059	56,139	67,476	77,171	96,552	116,265	136,601
LATVIA	10,467	14,234	21,606	22,217	7,515	7,970	13,234	10,665	10,636	12,452	13,765	16,359	16,698	16,878
LITHUANIA	16,602	25,582	32,771	19,831	5,367	6,365	10,980	12,165	12,163	14,503	17,085	20,320	25,836	32,382
MALTA	6,552	6,745	6,240	5,423	5,894	4,056	5,428	5,884	5,749	6,451	7,121	7,333	7,825	8,128
POLAND	207,007	224,728	277,427	319,190	276,220	315,855	277,427	272,719	289,913	327,709	354,975	416,123	486,352	531,889
ROMANIA	214,967	247,411	312,533	285,506	116,016	94,441	81,709	66,436	57,710	82,809	98,325	115,004	105,083	129,004
SLOVAKIA	56,916	59,084	59,700	70,040	74,717	64,033	68,203	69,268	65,998	72,237	77,968	88,165	96,105	98,080
SLOVENIA	59,324	59,578	68,719	71,575	57,967	61,142	60,193	50,091	52,268	53,296	59,450	63,674	62,522	65,115
RUSSIA, TURKEY & OTHER EUROPE	**2,284,420**	**2,724,418**	**3,471,314**	**3,909,719**	**2,075,646**	**2,669,169**	**3,524,941**	**3,623,366**	**3,597,858**	**3,092,818**	**2,122,682**	**2,131,580**	**2,342,998**	**2,285,827**

Strategies for dealing with sub-headers

Steps:

1. Read in the data, skipping first 5 rows
2. Clean the names

```
pc_sales <- read_excel(
    here::here('data', 'pc_sales_2018.xlsx'),
    sheet = 'pc_sales', skip = 5) %>%
    clean_names() %>%
    rename(country = regions_countries)

glimpse(pc_sales)
```

```
## Observations: 160
## Variables: 18
## $ country <chr> NA, "EUROPE", "EU 28 countries + EFTA",
## $ x2      <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ x3      <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ x4      <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ x2005   <dbl> NA, 17906455, 15622035, 14565695, 307915
## $ x2006   <dbl> NA, 18685556, 15961138, 14820182, 308594
## $ x2007   <dbl> NA, 19618588, 16147274, 14842186, 298182
## $ x2008   <dbl> NA, 18821599, 14911880, 13602038, 293697
## $ x2009   <dbl> NA, 16608761, 14533115, 13668808, 319403
## $ x2010   <dbl> NA, 16499863, 13830694, 12984549, 328563
## $ x2011   <dbl> NA, 17167600, 13642659, 12815435, 356145
```

Strategies for dealing with sub-headers

Steps:

1. Read in the data, skipping first 5 rows
2. Clean the names
3. **Filter out bad columns**
4. **Filter out bad rows**

Use **datapasta** to get rows to drop

```
drop <- c(
    'EUROPE', 'EU 28 countries + EFTA',
    'EU 15 countries + EFTA', 'EUROPE NEW MEMBERS',
    'RUSSIA, TURKEY & OTHER EUROPE', 'AMERICA',
    'NAFTA', 'CENTRAL & SOUTH AMERICA',
    'ASIA/OCEANIA/MIDDLE EAST', 'AFRICA', 'ALL COUNTRIES')

pc_sales <- pc_sales %>%
    select(-c(x2:x4)) %>%       # Drop bad columns
    filter(! country %in% drop, # Drop bad rows
           ! is.na(country))

head(pc_sales)
```

```
## # A tibble: 6 x 15
##   country  x2005  x2006  x2007  x2008  x2009  x2010  x2011
##   <chr>    <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>
## 1 AUSTRIA 307915 308594 298182 293697 319403 328563 356145
## 2 BELGIUM 480088 526141 524795 535947 476194 547340 572211
## 3 DENMARK 148819 156936 162686 150199 112454 153858 170036
## 4 FINLAND 148161 145700 125608 139669  90574 111968 12617
```

Strategies for dealing with sub-headers

Steps:

1. Read in the data, skipping first 5 rows
2. Clean the names
3. Filter out bad columns
4. Filter out bad rows
5. **Gather the year variables**

```
pc_sales <- pc_sales %>%
    gather(key = 'year', value = 'num_cars', x2005:x2018)

head(pc_sales)
```

```
## # A tibble: 6 x 3
##   country year  num_cars
##   <chr>   <chr>    <dbl>
## 1 AUSTRIA x2005   307915
## 2 BELGIUM x2005   480088
## 3 DENMARK x2005   148819
## 4 FINLAND x2005   148161
## 5 FRANCE  x2005  2118042
## 6 GERMANY x2005  3319259
```

Strategies for dealing with sub-headers

Steps:

1. Read in the data, skipping first 5 rows
2. Clean the names
3. Filter out bad columns
4. Filter out bad rows
5. Gather the year variables
6. **Separate the "x" from the year**

```
pc_sales <- pc_sales %>%
    separate(year, into = c('drop', 'year'), sep = 'x',
             convert = TRUE)

head(pc_sales)
```

```
## # A tibble: 6 x 4
##   country drop   year num_cars
##   <chr>   <lgl> <int>    <dbl>
## 1 AUSTRIA NA     2005   307915
## 2 BELGIUM NA     2005   480088
## 3 DENMARK NA     2005   148819
## 4 FINLAND NA     2005   148161
## 5 FRANCE  NA     2005  2118042
## 6 GERMANY NA     2005  3319259
```

Strategies for dealing with sub-headers

Steps:

1. Read in the data, skipping first 5 rows
2. Clean the names
3. Filter out bad columns
4. Filter out bad rows
5. Gather the year variables
6. Separate the "x" from the year
7. **Finish cleaning**

```
pc_sales <- pc_sales %>%
    select(-drop) %>%
    mutate(
        country  = str_to_title(country),
        num_cars = num_cars / 10^6)

head(pc_sales)
```

```
## # A tibble: 6 x 3
##   country  year num_cars
##   <chr>   <int>    <dbl>
## 1 Austria  2005    0.308
## 2 Belgium  2005    0.480
## 3 Denmark  2005    0.149
## 4 Finland  2005    0.148
## 5 France   2005    2.12
## 6 Germany  2005    3.32
```

Your turn: `weather` case study

Follow along as we:

1. Import the data
2. Gather columns that are values
3. Spread values that are variable names
4. Clean up dates
5. Re-arrange the column order
6. Convert strings to numbers
7. Re-name columns
8. Deal with missing values
9. Fix errors in the data

Extra practice: `pv_cells` case study

Read in the `pv_cell_production.xlsx` file and format it to produce this data frame.

```
pv_cells %>%
    distinct(country)
```

```
## # A tibble: 8 x 1
##   country
##   <chr>
## 1 China
## 2 Taiwan
## 3 Japan
## 4 Malaysia
## 5 Germany
## 6 South Korea
## 7 United States
## 8 Others
```

```
head(pv_cells)
```

```
## # A tibble: 6 x 3
##    year country     n
##   <dbl> <chr>   <dbl>
## 1  1995 China     NA
## 2  1996 China     NA
## 3  1997 China     NA
## 4  1998 China     NA
## 5  1999 China     NA
## 6  2000 China      2.5
```

```
tail(pv_cells)
```

```
## # A tibble: 6 x 3
##    year country     n
##   <dbl> <chr>   <dbl>
## 1  2008 Others   709.
## 2  2009 Others   664.
## 3  2010 Others  1443.
## 4  2011 Others  1834.
## 5  2012 Others  1475.
## 6  2013 Others  1453.
```

Data cleaning & joins

1. Joins
2. Re-typing variables
3. Re-naming variables
4. Re-coding variables
5. Data cleaning strategies

Data cleaning & joins

1. Joins
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Joins

1. `inner_join()`
2. `left_join()` / `right_join()`
3. `full_join()`

Example: `band_members` & `band_instruments`

```
band_members
```

```
## # A tibble: 3 x 2
##   name  band
##   <chr> <chr>
## 1 Mick  Stones
## 2 John  Beatles
## 3 Paul  Beatles
```

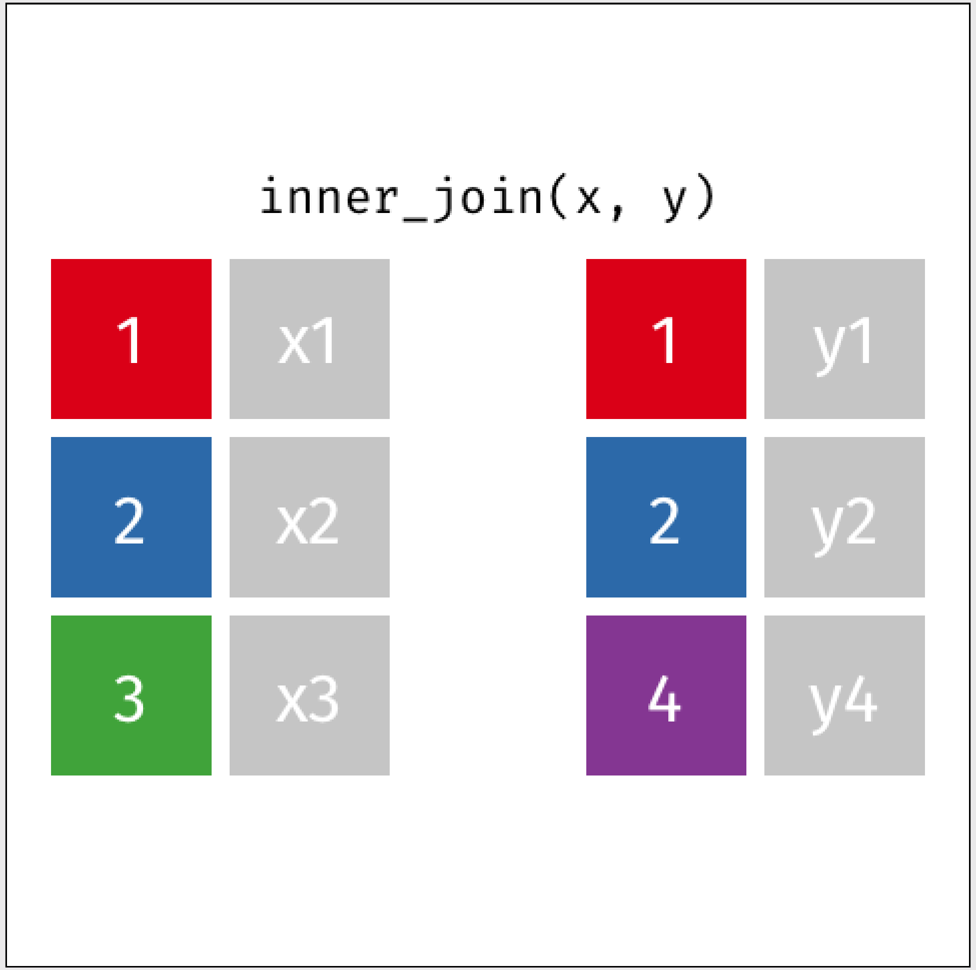
```
band_instruments
```

```
## # A tibble: 3 x 2
##   name  plays
##   <chr> <chr>
## 1 John  guitar
## 2 Paul  bass
## 3 Keith guitar
```

inner_join()

```
band_members %>%
    inner_join(band_instruments)
```

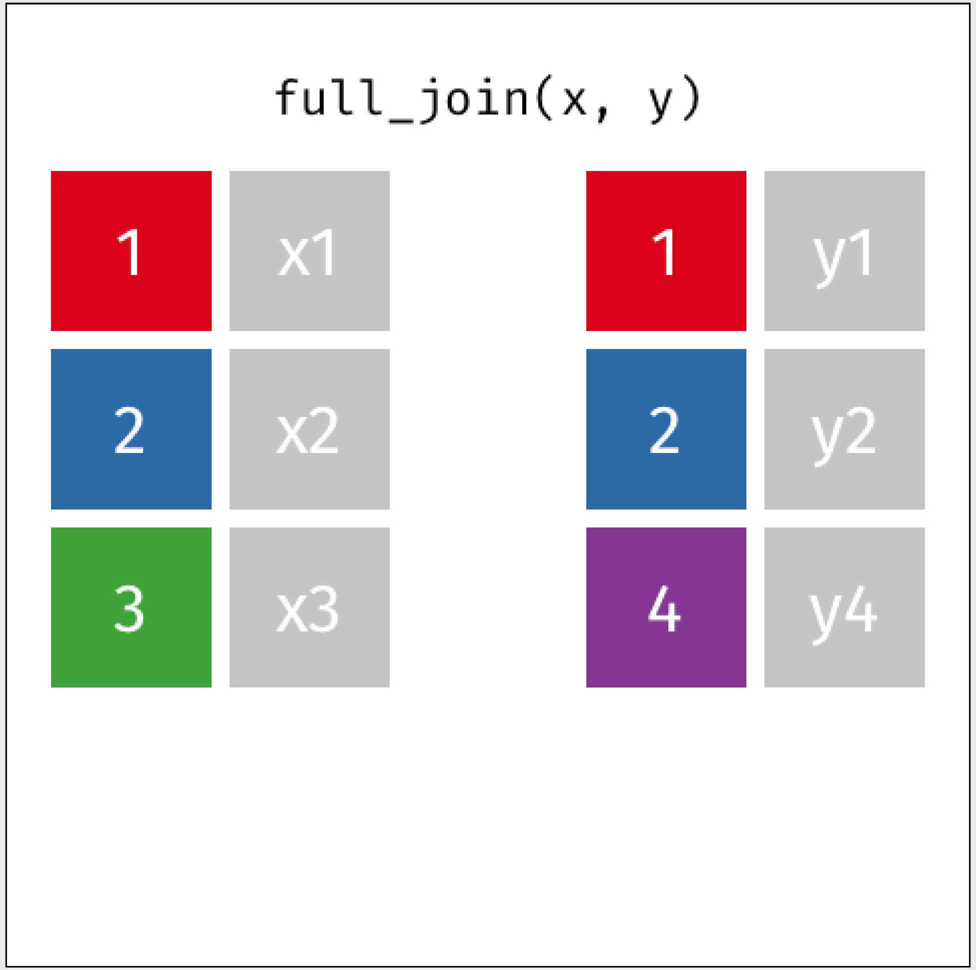
```
## # A tibble: 2 x 3
##   name  band    plays
##   <chr> <chr>   <chr>
## 1 John  Beatles guitar
## 2 Paul  Beatles bass
```



`full_join()`

```
band_members %>%
    full_join(band_instruments)
```

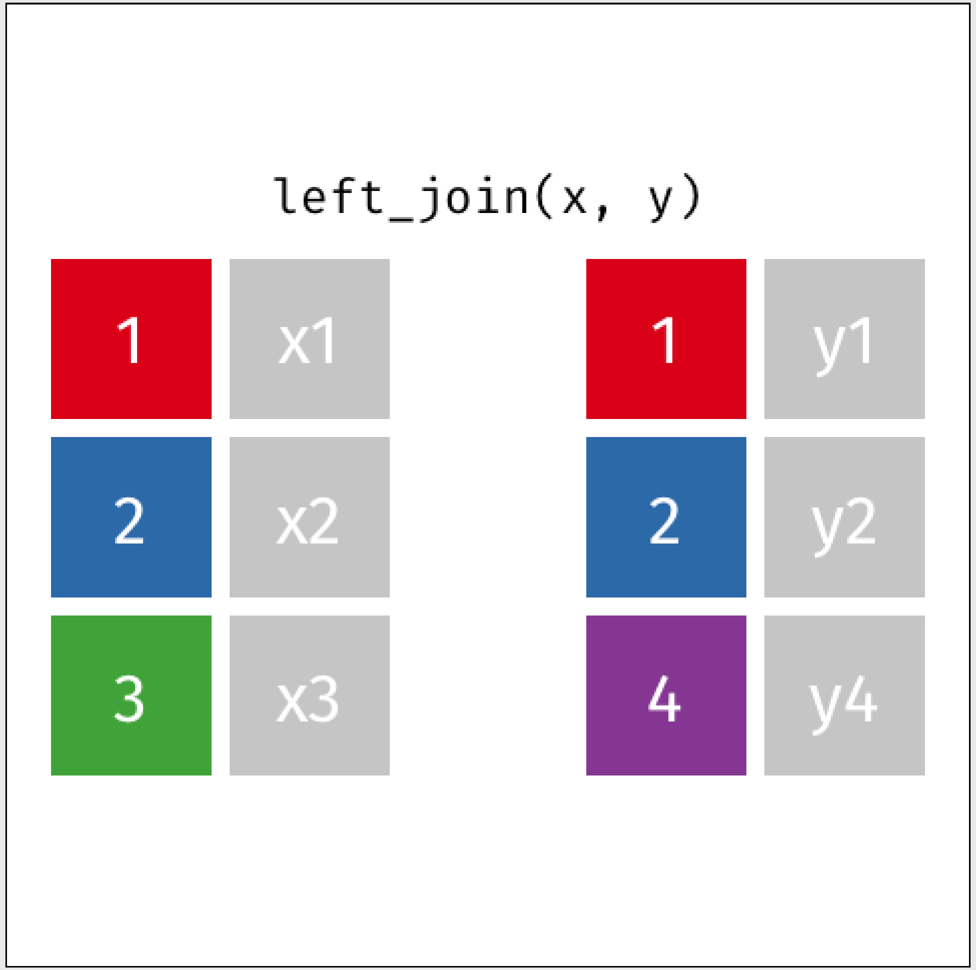
```
## # A tibble: 4 x 3
##   name  band    plays
##   <chr> <chr>   <chr>
## 1 Mick  Stones  <NA>
## 2 John  Beatles guitar
## 3 Paul  Beatles bass
## 4 Keith <NA>    guitar
```



left_join()

```
band_members %>%
    left_join(band_instruments)
```

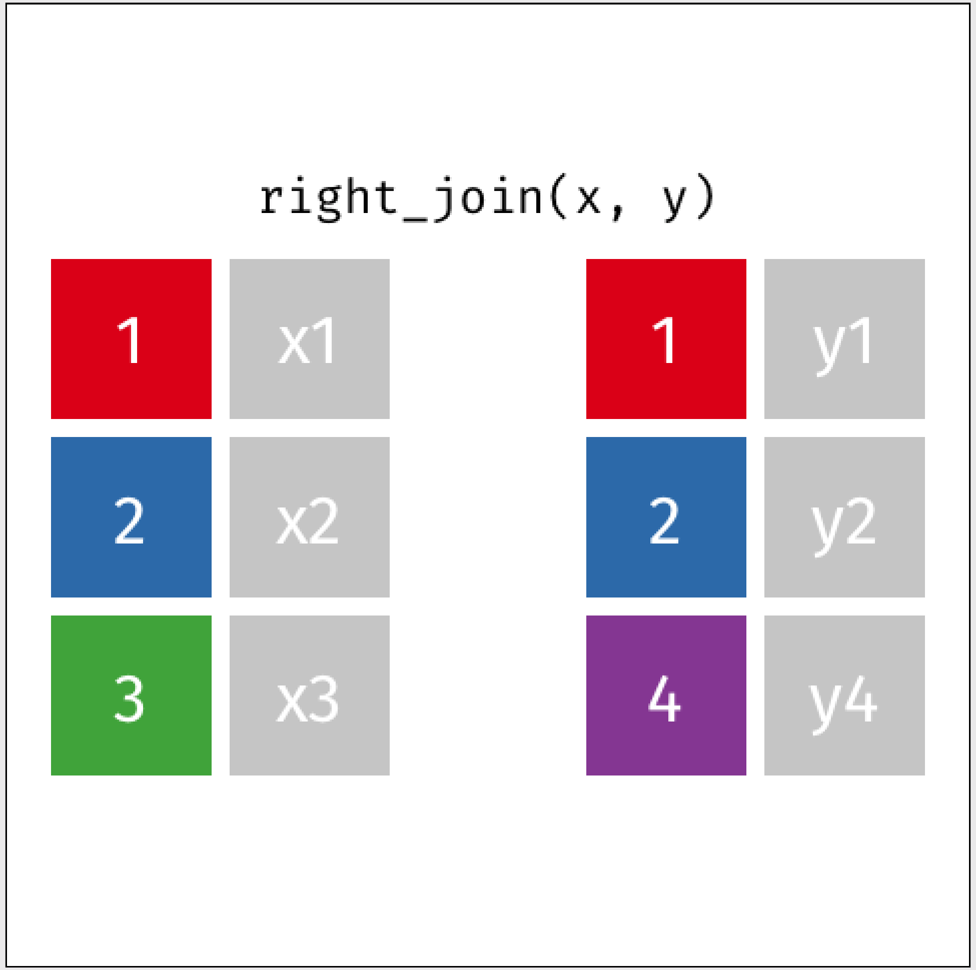
```
## # A tibble: 3 x 3
##   name  band    plays
##   <chr> <chr>   <chr>
## 1 Mick  Stones  <NA>
## 2 John  Beatles guitar
## 3 Paul  Beatles bass
```



right_join()

```r
band_members %>%
    right_join(band_instruments)
```

```
## # A tibble: 3 x 3
##   name  band    plays
##   <chr> <chr>   <chr>
## 1 John  Beatles guitar
## 2 Paul  Beatles bass
## 3 Keith <NA>    guitar
```



Specify the joining variable name

```
band_members %>%
    left_join(band_instruments)
```

```
## # A tibble: 3 x 3
##   name  band    plays
##   <chr> <chr>   <chr>
## 1 Mick  Stones  <NA>
## 2 John  Beatles guitar
## 3 Paul  Beatles bass
```

```
band_members %>%
    left_join(band_instruments,
              by = 'name')
```

```
## # A tibble: 3 x 3
##   name  band    plays
##   <chr> <chr>   <chr>
## 1 Mick  Stones  <NA>
## 2 John  Beatles guitar
## 3 Paul  Beatles bass
```

Specify the joining variable name

If the names differ, use `by = c("left_name" = "joining_name")`

```r
band_members
```

```
## # A tibble: 3 x 2
##   name  band
##   <chr> <chr>
## 1 Mick  Stones
## 2 John  Beatles
## 3 Paul  Beatles
```

```r
band_instruments2
```

```
## # A tibble: 3 x 2
##   artist plays
##   <chr>  <chr>
## 1 John   guitar
## 2 Paul   bass
## 3 Keith  guitar
```

```r
band_members %>%
    left_join(band_instruments2,
              by = c("name" = "artist"))
```

```
## # A tibble: 3 x 3
##   name  band    plays
##   <chr> <chr>   <chr>
## 1 Mick  Stones  <NA>
## 2 John  Beatles guitar
## 3 Paul  Beatles bass
```

Your turn

1) Create a data frame called `state_data`:

a) Join the `states_abbs` data frame to the `milk_production` data frame.

b) Select the three variables `region`, `state_name`, `state_abb`.

```
head(state_data)
```

```
## # A tibble: 6 x 3
##   region    state_name    state_abb
##   <chr>     <chr>         <chr>
## 1 Northeast Maine         ME
## 2 Northeast New Hampshire NH
## 3 Northeast Vermont       VT
## 4 Northeast Massachusetts MA
## 5 Northeast Rhode Island  RI
## 6 Northeast Connecticut   CT
```

15:00

2) Create the data frame `wildlife_impacts2` by joining the `state_data` data frame to the `wildlife_impacts` data frame, adding the variables `region` and `state_name`.

```
glimpse(wildlife_impacts2)
```

```
## Observations: 56,978
## Variables: 24
## $ incident_date         <dttm> 2018-12-31, 2018-12-29, 2018-12-29, 2018-12-27…
## $ state_abb             <chr> "FL", "IN", NA, NA, NA, "FL", "FL", NA, NA, "FL…
## $ airport_id            <chr> "KMIA", "KIND", "ZZZZ", "ZZZZ", "ZZZZ", "KMIA",…
## $ airport               <chr> "MIAMI INTL", "INDIANAPOLIS INTL ARPT", "UNKNOW…
## $ operator              <chr> "AMERICAN AIRLINES", "AMERICAN AIRLINES", "AMER…
## $ atype                 <chr> "B-737-800", "B-737-800", "UNKNOWN", "B-737-900…
## $ type_eng              <chr> "D", "D", NA, "D", "D", "D", "D", "D", "D", "D"…
## $ species_id            <chr> "UNKBL", "R", "R2004", "N5205", "J2139", "UNKB"…
## $ species               <chr> "Unknown bird - large", "Owls", "Short-eared ow…
## $ damage                <chr> "M?", "N", NA, "M?", "M?", "N", "N", "N", "N", …
## $ num_engs              <dbl> 2, 2, NA, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2…
## $ incident_month        <dbl> 12, 12, 12, 12, 12, 12, 12, 12, 12, 12, 12, 12,…
## $ incident_year         <dbl> 2018, 2018, 2018, 2018, 2018, 2018, 2018, 2018,…
## $ time_of_day           <chr> "Day", "Night", NA, NA, NA, "Day", "Night", NA,…
## $ time                  <dbl> 1207, 2355, NA, NA, NA, 955, 948, NA, NA, 1321,…
## $ height                <dbl> 700, 0, NA, NA, NA, NA, 600, NA, NA, 0, NA, 0, …
## $ speed                 <dbl> 200, NA, NA, NA, NA, NA, 145, NA, NA, 130, NA, …
## $ phase_of_flt          <chr> "departure", "arrival", "other", "other", "othe…
## $ sky                   <chr> "Some Cloud", NA, NA, NA, NA, NA, "Some Cloud",…
## $ precip                <chr> "None", NA, NA, NA, NA, NA, "None", NA, NA, "No…
## $ cost_repairs_infl_adj <dbl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,…
## $ weekday_name          <ord> Mon, Sat, Sat, Thu, Thu, Thu, Thu, Wed, Sun, Su…
## $ region                <chr> "Southeast", "Corn Belt", NA, NA, NA, "Southeas…
## $ state_name            <chr> "Florida", "Indiana", NA, NA, NA, "Florida", "F…
```

Data cleaning & joins

1. Joins
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Using the `col_types` argument

- You can change the column type when reading in data
- Different syntax for **readxl** and **readr**

readxl

`col_types` must be a vector describing each column type

```
wind <- read_excel(
    here::here('data',
               'US_State_Wind_Energy_Facts_2018.xlsx'))

glimpse(wind)
```

```
## Observations: 50
## Variables: 7
## $ Ranking                       <chr> "1.0", "2.0", "3
## $ State                         <chr> "TEXAS", "OKLAHO
## $ `Installed Capacity (MW)`     <dbl> 23262, 7495, 731
## $ `Equivalent Homes Powered`    <chr> "6235000.0", "22
## $ `Total Investment ($ Millions)` <chr> "42000.0", "1370
## $ `Wind Projects Online`        <dbl> 136, 45, 107, 10
## $ `# of Wind Turbines`          <chr> "12750.0", "3717
```

readxl

`col_types` must be a vector describing each column type

How it is in Excel	How it will be in R	How to request in `col_types`
anything	*non-existent*	`"skip"`
empty	`logical`, but all NA	*you cannot request this*
boolean	`logical`	`"logical"`
numeric	`numeric`	`"numeric"`
datetime	`POSIXct`	`"date"`
text	`character`	`"text"`
anything	`list`	`"list"`

```r
columns <- c('numeric', 'text', rep('numeric', 5))
columns
```

```
## [1] "numeric" "text"    "numeric" "numeric" "numeric" "r
```

```r
wind <- read_excel(
    here::here('data',
               'US_State_Wind_Energy_Facts_2018.xlsx'),
    col_types = columns)

glimpse(wind)
```

```
## Observations: 50
## Variables: 7
## $ Ranking                        <dbl> 1, 2, 3, 4, 5, 6
## $ State                          <chr> "TEXAS", "OKLAHO
## $ `Installed Capacity (MW)`      <dbl> 23262, 7495, 731
## $ `Equivalent Homes Powered`     <dbl> 6235000, 2268000
## $ `Total Investment ($ Millions)` <dbl> 42000, 13700, 14
## $ `Wind Projects Online`         <dbl> 136, 45, 107, 10
## $ `# of Wind Turbines`           <dbl> 12750, 3717, 414
```

readr

`col_types` describes individual variables by name using `cols()`

```
milk <- read_csv(
    here::here('data', 'milk_production.csv'),
    col_types = cols(year = col_character()))

glimpse(milk)
```

```
## Observations: 2,400
## Variables: 4
## $ region        <chr> "Northeast", "Northeast", "Northea
## $ state         <chr> "Maine", "New Hampshire", "Vermont
## $ year          <chr> "1970", "1970", "1970", "1970", "1
## $ milk_produced <dbl> 6.1900e+08, 3.5600e+08, 1.9700e+09
```

readr

`col_types` describes individual variables by name using `cols()`

Type	dplyr::glimpse()	readr::parse_*()	readr::col_*()
Logical	<lgl>	parse_logical()	col_logical()
Numeric	<int> *or* <dbl>	parse_number()	col_number()
Character	<chr>	parse_character()	col_character()
Factor	<fct>	parse_factor(levels)	col_factor(levels)
Date	<date>	parse_date(format)	col_date(format)

Data cleaning & joins

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Renaming made easy

`janitor::clean_names()`

```r
wind <- read_excel(
    here::here('data',
               'US_State_Wind_Energy_Facts_2018.xlsx'))

glimpse(wind)
```

```
## Observations: 50
## Variables: 7
## $ Ranking                        <chr> "1.0", "2.0", "3.0",
## $ State                          <chr> "TEXAS", "OKLAHOMA",
## $ `Installed Capacity (MW)`      <dbl> 23262, 7495, 7312, 56
## $ `Equivalent Homes Powered`     <chr> "6235000.0", "2268000
## $ `Total Investment ($ Millions)` <chr> "42000.0", "13700.0",
## $ `Wind Projects Online`         <dbl> 136, 45, 107, 104, 35
## $ `# of Wind Turbines`           <chr> "12750.0", "3717.0",
```

Renaming made easy

`janitor::clean_names()`

```r
wind <- read_excel(
    here::here('data',
               'US_State_Wind_Energy_Facts_2018.xlsx')) %>%
    clean_names()

glimpse(wind)
```

```
## Observations: 50
## Variables: 7
## $ ranking                   <chr> "1.0", "2.0", "3.0", "4.0",
## $ state                     <chr> "TEXAS", "OKLAHOMA", "IOWA"
## $ installed_capacity_mw     <dbl> 23262, 7495, 7312, 5686, 51
## $ equivalent_homes_powered  <chr> "6235000.0", "2268000.0", "
## $ total_investment_millions <chr> "42000.0", "13700.0", "1420
## $ wind_projects_online      <dbl> 136, 45, 107, 104, 35, 49,
## $ number_of_wind_turbines   <chr> "12750.0", "3717.0", "4145.
```

Renaming made easy

`janitor::clean_names()`

```
wind <- read_excel(
    here::here('data',
               'US_State_Wind_Energy_Facts_2018.xlsx')) %>%
    clean_names(case = 'lower_camel')

glimpse(wind)
```

```
## Observations: 50
## Variables: 7
## $ ranking                <chr> "1.0", "2.0", "3.0", "4.0", "
## $ state                  <chr> "TEXAS", "OKLAHOMA", "IOWA",
## $ installedCapacityMw    <dbl> 23262, 7495, 7312, 5686, 5110
## $ equivalentHomesPowered <chr> "6235000.0", "2268000.0", "19
## $ totalInvestmentMillions <chr> "42000.0", "13700.0", "14200.
## $ windProjectsOnline     <dbl> 136, 45, 107, 104, 35, 49, 98
## $ numberOfWindTurbines   <chr> "12750.0", "3717.0", "4145.0"
```

`select()`: more powerful than you probably thought

Use `select()` to choose which columns to **keep**

```
msleep %>%
    select(name:order, sleep_total:sleep_cycle) %>%
    glimpse()
```

```
## Observations: 83
## Variables: 7
## $ name        <chr> "Cheetah", "Owl monkey", "Mounta
## $ genus       <chr> "Acinonyx", "Aotus", "Aplodontia
## $ vore        <chr> "carni", "omni", "herbi", "omni"
## $ order       <chr> "Carnivora", "Primates", "Rodent
## $ sleep_total <dbl> 12.1, 17.0, 14.4, 14.9, 4.0, 14.
## $ sleep_rem   <dbl> NA, 1.8, 2.4, 2.3, 0.7, 2.2, 1.4
## $ sleep_cycle <dbl> NA, NA, NA, 0.1333333, 0.6666667
```

Use `select()` to choose which columns to **drop**

```
msleep %>%
    select(-(name:order)) %>%
    glimpse()
```

```
## Observations: 83
## Variables: 7
## $ conservation <chr> "lc", NA, "nt", "lc", "domestic
## $ sleep_total  <dbl> 12.1, 17.0, 14.4, 14.9, 4.0, 14
## $ sleep_rem    <dbl> NA, 1.8, 2.4, 2.3, 0.7, 2.2, 1.
## $ sleep_cycle  <dbl> NA, NA, NA, 0.1333333, 0.666666
## $ awake        <dbl> 11.9, 7.0, 9.6, 9.1, 20.0, 9.6,
## $ brainwt      <dbl> NA, 0.01550, NA, 0.00029, 0.423
## $ bodywt       <dbl> 50.000, 0.480, 1.350, 0.019, 60
```

Select columns based on partial column names

Select columns that start with "sleep":

```
msleep %>%
    select(name, starts_with("sleep")) %>%
    glimpse()
```

```
## Observations: 83
## Variables: 4
## $ name        <chr> "Cheetah", "Owl monkey", "Mounta
## $ sleep_total <dbl> 12.1, 17.0, 14.4, 14.9, 4.0, 14.
## $ sleep_rem   <dbl> NA, 1.8, 2.4, 2.3, 0.7, 2.2, 1.4
## $ sleep_cycle <dbl> NA, NA, NA, 0.1333333, 0.6666667
```

Select columns that contain "eep" and end with "wt":

```
msleep %>%
    select(contains("eep"), ends_with("wt")) %>%
    glimpse()
```

```
## Observations: 83
## Variables: 5
## $ sleep_total <dbl> 12.1, 17.0, 14.4, 14.9, 4.0, 14.
## $ sleep_rem   <dbl> NA, 1.8, 2.4, 2.3, 0.7, 2.2, 1.4
## $ sleep_cycle <dbl> NA, NA, NA, 0.1333333, 0.6666667
## $ brainwt     <dbl> NA, 0.01550, NA, 0.00029, 0.4230
## $ bodywt      <dbl> 50.000, 0.480, 1.350, 0.019, 600
```

Select columns based on their data type

Select only numeric columns:

```
msleep %>%
    select_if(is.numeric) %>%
    glimpse()
```

```
## Observations: 83
## Variables: 6
## $ sleep_total <dbl> 12.1, 17.0, 14.4, 14.9, 4.0, 14.4, 8
## $ sleep_rem   <dbl> NA, 1.8, 2.4, 2.3, 0.7, 2.2, 1.4, NA
## $ sleep_cycle <dbl> NA, NA, NA, 0.1333333, 0.6666667, 0.
## $ awake       <dbl> 11.9, 7.0, 9.6, 9.1, 20.0, 9.6, 15.3
## $ brainwt     <dbl> NA, 0.01550, NA, 0.00029, 0.42300, N
## $ bodywt      <dbl> 50.000, 0.480, 1.350, 0.019, 600.000
```

Use `select()` to reorder variables

```
msleep %>%
    select(everything()) %>%
    glimpse()
```

```
## Observations: 83
## Variables: 11
## $ name         <chr> "Cheetah", "Owl monkey",
## $ genus        <chr> "Acinonyx", "Aotus", "Apl
## $ vore         <chr> "carni", "omni", "herbi",
## $ order        <chr> "Carnivora", "Primates",
## $ conservation <chr> "lc", NA, "nt", "lc", "do
## $ sleep_total  <dbl> 12.1, 17.0, 14.4, 14.9, 4
## $ sleep_rem    <dbl> NA, 1.8, 2.4, 2.3, 0.7, 2
## $ sleep_cycle  <dbl> NA, NA, NA, 0.1333333, 0.
## $ awake        <dbl> 11.9, 7.0, 9.6, 9.1, 20.0
## $ brainwt      <dbl> NA, 0.01550, NA, 0.00029,
## $ bodywt       <dbl> 50.000, 0.480, 1.350, 0.0
```

```
msleep %>%
    select(conservation, sleep_total, everything()) %>%
    glimpse()
```

```
## Observations: 83
## Variables: 11
## $ conservation <chr> "lc", NA, "nt", "lc", "domesticated"
## $ sleep_total  <dbl> 12.1, 17.0, 14.4, 14.9, 4.0, 14.4, 8
## $ name         <chr> "Cheetah", "Owl monkey", "Mountain b
## $ genus        <chr> "Acinonyx", "Aotus", "Aplodontia", "
## $ vore         <chr> "carni", "omni", "herbi", "omni", "h
## $ order        <chr> "Carnivora", "Primates", "Rodentia",
## $ sleep_rem    <dbl> NA, 1.8, 2.4, 2.3, 0.7, 2.2, 1.4, NA
## $ sleep_cycle  <dbl> NA, NA, NA, 0.1333333, 0.6666667, 0.
## $ awake        <dbl> 11.9, 7.0, 9.6, 9.1, 20.0, 9.6, 15.3
## $ brainwt      <dbl> NA, 0.01550, NA, 0.00029, 0.42300, N
## $ bodywt       <dbl> 50.000, 0.480, 1.350, 0.019, 600.000
```

Use `select()` to **rename** variables

Use `rename()` to just change the name

```
msleep %>%
    rename(animal = name,
           extinction_threat = conservation) %>%
    glimpse()
```

```
## Observations: 83
## Variables: 11
## $ animal            <chr> "Cheetah", "Owl monkey", "
## $ genus             <chr> "Acinonyx", "Aotus", "Aplo
## $ vore              <chr> "carni", "omni", "herbi",
## $ order             <chr> "Carnivora", "Primates", "
## $ extinction_threat <chr> "lc", NA, "nt", "lc", "dom
## $ sleep_total       <dbl> 12.1, 17.0, 14.4, 14.9, 4.
## $ sleep_rem         <dbl> NA, 1.8, 2.4, 2.3, 0.7, 2.
## $ sleep_cycle       <dbl> NA, NA, NA, 0.1333333, 0.6
## $ awake             <dbl> 11.9, 7.0, 9.6, 9.1, 20.0,
## $ brainwt           <dbl> NA, 0.01550, NA, 0.00029,
## $ bodywt            <dbl> 50.000, 0.480, 1.350, 0.01
```

Use `select()` to change the name **and drop everything else**

```
msleep %>%
    select(animal = name,
           extinction_threat = conservation) %>%
    glimpse()
```

```
## Observations: 83
## Variables: 2
## $ animal            <chr> "Cheetah", "Owl monkey", "
## $ extinction_threat <chr> "lc", NA, "nt", "lc", "dom
```

Your turn

Read in the `hot_dog_winners.xlsx` file and adjust the variable names and types to the following:

```
## Observations: 42
## Variables: 7
## $ year              <dbl> 1980, 1981
## $ competitor.mens   <chr> "Paul Sied
## $ competitor.womens <chr> NA, NA, NA
## $ dogs_eaten.mens   <dbl> 9.10, 11.0
## $ dogs_eaten.womens <dbl> NA, NA, NA
## $ country.mens      <chr> "United St
## $ country.womens    <chr> NA, NA, NA
```

	A	B	C	D	E	F	G
1	Year	Mens	Dogs eaten	Country	Womens	Dogs eaten	Country
2	1980	Paul Siederman & Joe Baldini	9.1	United States			
3	1981	Thomas DeBerry	11	United States			
4	1982	Steven Abrams	11	United States			
5	1983	Luis Llamas	19.5	Mexico			
6	1984	Birgit Felden	9.5	Germany			
7	1985	Oscar Rodriguez	11.75	United States			
8	1986	Mark Heller	15.5	United States			
9	1987	Don Wolfman	12	United States			
10	1988	Jay Green	14	United States			
11	1989	Jay Green	13	United States			
12	1990	Mike DeVito	16	United States			
13	1991	Frank Dellarosa	21.5*	United States			
14	1992	Frank Dellarosa	19	United States			
15	1993	Mike DeVito	17	United States			
16	1994	Mike DeVito	20	United States			
17	1995	Edward Krachie	19.5	United States			
18	1996	Edward Krachie	22.25*	United States			
19	1997	Hirofumi Nakajima	24.5*	Japan			
20	1998	Hirofumi Nakajima	19	Japan			
21	1999	Steve Keiner	20.25	United States			
22	2000	Kazutoyo Arai	25.13*	Japan			
23	2001	Takeru Kobayashi	50*	Japan			
24	2002	Takeru Kobayashi	50.5*	Japan			
25	2003	Takeru Kobayashi	44.5	Japan			
26	2004	Takeru Kobayashi	53.5*	Japan			
27	2005	Takeru Kobayashi	49	Japan			
28	2006	Takeru Kobayashi	53.75*	Japan			
29	2007	Joey Chestnut	66*	United States			
30	2008	Joey Chestnut	59	United States			
31	2009	Joey Chestnut	68*	United States			
32	2010	Joey Chestnut	54	United States			
33	2011	Joey Chestnut	62	United States	Sonya Thomas	40*	United States
34	2012	Joey Chestnut	68	United States	Sonya Thomas	45*	United States
35	2013	Joey Chestnut	69*	United States	Sonya Thomas	36.75	United States
36	2014	Joey Chestnut	61	United States	Miki Sudo	34	United States
37	2015	Matt Stonie	62	United States	Miki Sudo	38	United States
38	2016	Joey Chestnut	70*	United States	Miki Sudo	38.5	United States
39	2017	Joey Chestnut	72*	United States	Miki Sudo	41	United States
40	2018	Joey Chestnut	74*	United States	Miki Sudo	37	United States
41	2019	Joey Chestnut	71	United States	Miki Sudo	31	United States
42							
43	Notes: * means new record						

15:00

5 minute break!

Stand up

Move around

Stretch!

05:00

Data cleaning & joins

1. Joins
2. Re-typing variables
3. Re-naming variables
4. Re-coding variables
5. Data cleaning strategies

Recoding with `if_else()`

Example: Create a variable, `cost_high`, that is `TRUE` if the repair costs were greater than the median costs and `FALSE` otherwise.

```
wildlife_impacts1 <- wildlife_impacts %>%
    rename(cost = cost_repairs_infl_adj) %>%
    dplyr::filter(! is.na(cost)) %>%
    mutate(cost_high = if_else(cost > median(cost), TRUE, FALSE))

wildlife_impacts1 %>%
    select(cost, cost_high) %>%
    head()
```

```
## # A tibble: 6 x 2
##      cost cost_high
##     <dbl> <lgl>
## 1    1000 FALSE
## 2     200 FALSE
## 3   10000 FALSE
## 4  100000 TRUE
## 5   20000 FALSE
## 6  487000 TRUE
```

Recoding with **nested** `if_else()`

Example:

Create a variable, `season`, based on the `incident_month` variable.

```
wildlife_impacts2 <- wildlife_impacts %>%
    mutate(season = if_else(
        incident_month %in% c(3, 4, 5), 'spring', if_else(
        incident_month %in% c(6, 7, 8), 'summer', if_else(
        incident_month %in% c(9, 10, 11), 'fall', 'winter'))))

wildlife_impacts2 %>%
    distinct(incident_month, season) %>%
    head()
```

```
## # A tibble: 6 x 2
##   incident_month season
##            <dbl> <chr>
## 1             12 winter
## 2             11 fall
## 3             10 fall
## 4              9 fall
## 5              8 summer
## 6              7 summer
```

Recoding with `case_when()`

Example:

Create a variable, `season`, based on the `incident_month` variable.

```
wildlife_impacts2 <- wildlife_impacts %>%
    mutate(season = case_when(
        incident_month %in% c(3, 4, 5) ~ 'spring',
        incident_month %in% c(6, 7, 8) ~ 'summer',
        incident_month %in% c(9, 10, 11) ~ 'fall',
        TRUE ~ 'winter'))

wildlife_impacts2 %>%
    distinct(incident_month, season) %>%
    head()
```

```
## # A tibble: 6 x 2
##   incident_month season
##            <dbl> <chr>
## 1             12 winter
## 2             11 fall
## 3             10 fall
## 4              9 fall
## 5              8 summer
## 6              7 summer
```

Recoding with `case_when()`

Example:

Create a variable, `season`, based on the `incident_month` variable.

```r
wildlife_impacts2 <- wildlife_impacts %>%
    mutate(season = case_when(
        between(incident_month, 3, 5) ~ 'spring',
        between(incident_month, 6, 8) ~ 'summer',
        between(incident_month, 9, 11) ~ 'fall',
        TRUE ~ 'winter'))

wildlife_impacts2 %>%
    distinct(incident_month, season) %>%
    head()
```

```
## # A tibble: 6 x 2
##   incident_month season
##            <dbl> <chr>
## 1             12 winter
## 2             11 fall
## 3             10 fall
## 4              9 fall
## 5              8 summer
## 6              7 summer
```

`case_when()` is a bit "cleaner" than `if_else()`

Example:

Convert the `num_engs` variable into a string of the number.

`if_else()`

```
wildlife_impacts3 <- wildlife_impacts %>%
    mutate(num_engs = if_else(
        num_engs == 1, 'one', if_else(
        num_engs == 2, 'two', if_else(
        num_engs == 3, 'three', if_else(
        num_engs == 4, 'four', as.character(num_engs))))))

unique(wildlife_impacts3$num_engs)
```

```
## [1] "two"    NA       "three" "four"   "one"
```

`case_when()`

```
wildlife_impacts3 <- wildlife_impacts %>%
    mutate(num_engs = case_when(
        num_engs == 1 ~ 'one',
        num_engs == 2 ~ 'two',
        num_engs == 3 ~ 'three',
        num_engs == 4 ~ 'four'))

unique(wildlife_impacts3$num_engs)
```

```
## [1] "two"    NA       "three" "four"   "one"
```

Break a single variable into two with `separate()`

```
tuberculosis_rates
```

```
## # A tibble: 6 x 3
##   country      year rate
## * <chr>       <int> <chr>
## 1 Afghanistan  1999 745/19987071
## 2 Afghanistan  2000 2666/20595360
## 3 Brazil       1999 37737/172006362
## 4 Brazil       2000 80488/174504898
## 5 China        1999 212258/1272915272
## 6 China        2000 213766/1280428583
```

```
tuberculosis_rates %>%
  separate(rate, into = c("cases", "population"))
```

```
## # A tibble: 6 x 4
##   country      year cases  population
##   <chr>       <int> <chr>  <chr>
## 1 Afghanistan  1999 745    19987071
## 2 Afghanistan  2000 2666   20595360
## 3 Brazil       1999 37737  172006362
## 4 Brazil       2000 80488  174504898
## 5 China        1999 212258 1272915272
## 6 China        2000 213766 1280428583
```

Break a single variable into two with `separate()`

```r
tuberculosis_rates
```

```
## # A tibble: 6 x 3
##   country      year rate
## * <chr>       <int> <chr>
## 1 Afghanistan  1999 745/19987071
## 2 Afghanistan  2000 2666/20595360
## 3 Brazil       1999 37737/172006362
## 4 Brazil       2000 80488/174504898
## 5 China        1999 212258/1272915272
## 6 China        2000 213766/1280428583
```

```r
tuberculosis_rates %>%
  separate(rate, into = c("cases", "population"),
           sep = "/")
```

```
## # A tibble: 6 x 4
##   country      year cases  population
##   <chr>       <int> <chr>  <chr>
## 1 Afghanistan  1999 745    19987071
## 2 Afghanistan  2000 2666   20595360
## 3 Brazil       1999 37737  172006362
## 4 Brazil       2000 80488  174504898
## 5 China        1999 212258 1272915272
## 6 China        2000 213766 1280428583
```

Break a single variable into two with `separate()`

```
tuberculosis_rates
```

```
## # A tibble: 6 x 3
##   country      year rate
## * <chr>       <int> <chr>
## 1 Afghanistan  1999 745/19987071
## 2 Afghanistan  2000 2666/20595360
## 3 Brazil       1999 37737/172006362
## 4 Brazil       2000 80488/174504898
## 5 China        1999 212258/1272915272
## 6 China        2000 213766/1280428583
```

```
tuberculosis_rates %>%
  separate(rate, into = c("cases", "population"),
                    sep = "/", convert = TRUE)
```

```
## # A tibble: 6 x 4
##   country      year  cases population
##   <chr>       <int>  <int>      <int>
## 1 Afghanistan  1999    745   19987071
## 2 Afghanistan  2000   2666   20595360
## 3 Brazil       1999  37737  172006362
## 4 Brazil       2000  80488  174504898
## 5 China        1999 212258 1272915272
## 6 China        2000 213766 1280428583
```

You can also break up a variable by an index

```r
tuberculosis_rates
```

```
## # A tibble: 6 x 3
##   country      year rate
## * <chr>       <int> <chr>
## 1 Afghanistan  1999 745/19987071
## 2 Afghanistan  2000 2666/20595360
## 3 Brazil       1999 37737/172006362
## 4 Brazil       2000 80488/174504898
## 5 China        1999 212258/1272915272
## 6 China        2000 213766/1280428583
```

```r
tuberculosis_rates %>%
  separate(year, into = c("century", "year"),
           sep = 1)
```

```
## # A tibble: 6 x 4
##   country     century year  rate
##   <chr>       <chr>   <chr> <chr>
## 1 Afghanistan 1       999   745/19987071
## 2 Afghanistan 2       000   2666/20595360
## 3 Brazil      1       999   37737/172006362
## 4 Brazil      2       000   80488/174504898
## 5 China       1       999   212258/1272915272
## 6 China       2       000   213766/1280428583
```

`unite()`: The opposite of `separate()`

```r
tuberculosis_rates
```

```
## # A tibble: 6 x 3
##   country      year rate
## * <chr>       <int> <chr>
## 1 Afghanistan  1999 745/19987071
## 2 Afghanistan  2000 2666/20595360
## 3 Brazil       1999 37737/172006362
## 4 Brazil       2000 80488/174504898
## 5 China        1999 212258/1272915272
## 6 China        2000 213766/1280428583
```

```r
tuberculosis_rates %>%
  separate(year, into = c("century", "year"),
           sep = 1) %>%
  unite(year_new, century, year)
```

```
## # A tibble: 6 x 3
##   country     year_new rate
##   <chr>       <chr>    <chr>
## 1 Afghanistan 1_999    745/19987071
## 2 Afghanistan 2_000    2666/20595360
## 3 Brazil      1_999    37737/172006362
## 4 Brazil      2_000    80488/174504898
## 5 China       1_999    212258/1272915272
## 6 China       2_000    213766/1280428583
```

`unite()`: The opposite of `separate()`

```r
tuberculosis_rates
```

```
## # A tibble: 6 x 3
##   country      year rate
## * <chr>       <int> <chr>
## 1 Afghanistan  1999 745/19987071
## 2 Afghanistan  2000 2666/20595360
## 3 Brazil       1999 37737/172006362
## 4 Brazil       2000 80488/174504898
## 5 China        1999 212258/1272915272
## 6 China        2000 213766/1280428583
```

```r
tuberculosis_rates %>%
  separate(year, into = c("century", "year"),
           sep = 2) %>%
  unite(year_new, century, year,
        sep = "")
```

```
## # A tibble: 6 x 3
##   country     year_new rate
##   <chr>       <chr>    <chr>
## 1 Afghanistan 1999     745/19987071
## 2 Afghanistan 2000     2666/20595360
## 3 Brazil      1999     37737/172006362
## 4 Brazil      2000     80488/174504898
## 5 China       1999     212258/1272915272
## 6 China       2000     213766/1280428583
```

Dates


What is your idea of a perfect date?
YYYY/MM/DD, other formats can be really confusing
You will die single.
?

Create dates from strings - **order is the ONLY thing that matters!**

```r
library(lubridate)
```

Year-Month-Day

```r
ymd('2020-02-26')
```

```
## [1] "2020-02-26"
```

```r
ymd('2020 Feb 26')
```

```
## [1] "2020-02-26"
```

```r
ymd('2020 Feb. 26')
```

```
## [1] "2020-02-26"
```

```r
ymd('2020 february 26')
```

```
## [1] "2020-02-26"
```

Month-Day-Year

```r
mdy('February 26, 2020')
```

```
## [1] "2020-02-26"
```

```r
mdy('Feb. 26, 2020')
```

```
## [1] "2020-02-26"
```

```r
mdy('Feb 26 2020')
```

```
## [1] "2020-02-26"
```

Day-Month-Year

```r
dmy('26 February 2020')
```

```
## [1] "2020-02-26"
```

```r
dmy('26 Feb. 2020')
```

```
## [1] "2020-02-26"
```

```r
dmy('26 Feb, 2020')
```

```
## [1] "2020-02-26"
```

Manipulate dates

```r
date <- today()
date
```

```
## [1] "2020-02-26"
```

```r
# Get the year
year(date)
```

```
## [1] 2020
```

```r
# Get the month
month(date)
```

```
## [1] 2
```

```r
# Get the month name
month(date, label = TRUE, abbr = FALSE)
```

```
## [1] February
## 12 Levels: January < February < March < April < May
```

```r
# Get the day
day(date)
```

```
## [1] 26
```

```r
# Get the weekday
wday(date)
```

```
## [1] 4
```

```r
# Get the weekday name
wday(date, label = TRUE, abbr = TRUE)
```

```
## [1] Wed
## Levels: Sun < Mon < Tue < Wed < Thu < Fri < Sat
```

Modify elements of the date

```r
date <- today()
date
```

```
## [1] "2020-02-26"
```

```r
# Change the year
year(date) <- 2016
date
```

```
## [1] "2016-02-26"
```

```r
# Change the day
day(date) <- 30
```

```r
date
```

```
## [1] "2016-03-01"
```

Your turn

20:00

1) Use `case_when()` to modify the `phase_of_flt` variable in the `wildlife_impacts` data:

- The values `'approach'`, `'arrival'`, `'descent'`, and `'landing roll'` should be merged into a single value called `'arrival'`.
- The values `'climb'`, `'departure'`, and `'take-off run'` should be merged into a single value called `'departure'`.
- All other values should be called `'other'`.

Before:

```
unique(str_to_lower(wildlife_impacts$phase_of_flt))
```

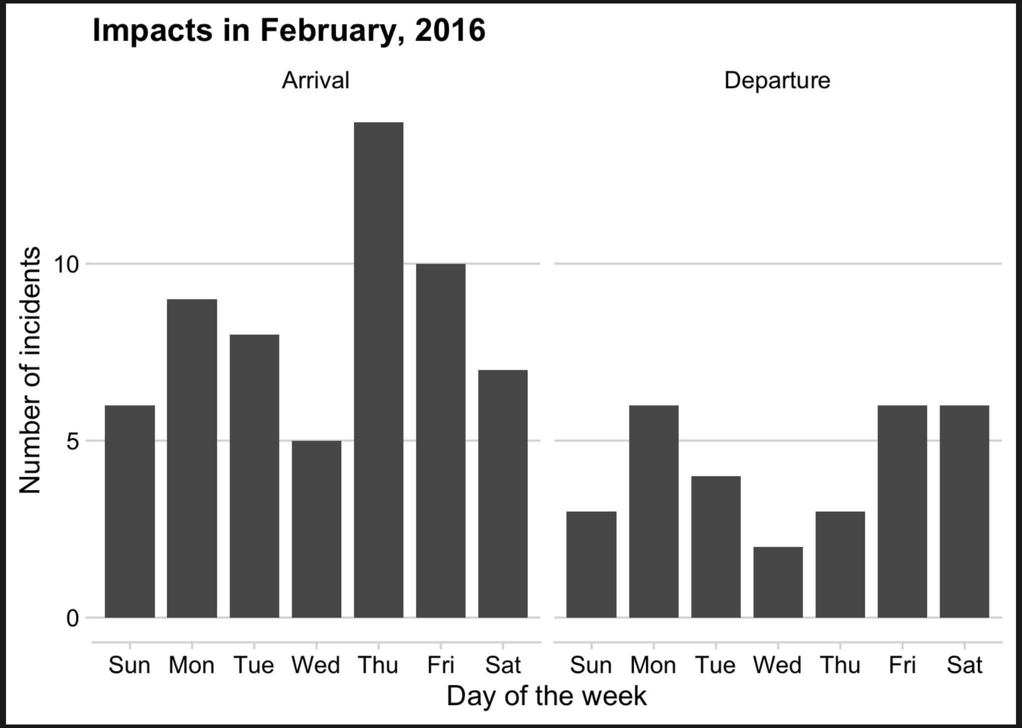
```
##  [1] "climb"        "landing roll" NA             "approach"
##  [6] "departure"    "arrival"      "descent"      "local"
## [11] "unknown"      "en route"     "parked"
```

After:

```
## [1] "departure" "arrival"   "other"
```

2) Use the **lubridate** package to create a new variable, `weekday_name`, from the `incident_date` variable in the `wildlife_impacts` data.

3) Use `weekday_name` and `phase_of_flt` to make this plot of "arrival" and "departure" impacts from **Feb. 2016**.



Data cleaning & joins

1. Joins
2. Re-typing variables
3. Re-naming variables
4. Re-coding variables
5. Data cleaning strategies

Stragies for when variables encode 2 things

1. Divide & conquer

2. Gather, separate, spread

Example:

Winners of Nathan's hot dog eating contest

	A	B	C	D	E	F	G
1	Year	Mens	Dogs eaten	Country	Womens	Dogs eaten	Country
2	1980	Paul Siederman & Joe Baldini	9.1	United States			
3	1981	Thomas DeBerry	11	United States			
4	1982	Steven Abrams	11	United States			
5	1983	Luis Llamas	19.5	Mexico			
6	1984	Birgit Felden	9.5	Germany			
7	1985	Oscar Rodriguez	11.75	United States			
8	1986	Mark Heller	15.5	United States			
9	1987	Don Wolfman	12	United States			
10	1988	Jay Green	14	United States			
11	1989	Jay Green	13	United States			
12	1990	Mike DeVito	16	United States			
13	1991	Frank Dellarosa	21.5*	United States			
14	1992	Frank Dellarosa	19	United States			
15	1993	Mike DeVito	17	United States			
16	1994	Mike DeVito	20	United States			
17	1995	Edward Krachie	19.5	United States			
18	1996	Edward Krachie	22.25*	United States			
19	1997	Hirofumi Nakajima	24.5*	Japan			
20	1998	Hirofumi Nakajima	19	Japan			
21	1999	Steve Keiner	20.25	United States			
22	2000	Kazutoyo Arai	25.13*	Japan			
23	2001	Takeru Kobayashi	50*	Japan			
24	2002	Takeru Kobayashi	50.5*	Japan			
25	2003	Takeru Kobayashi	44.5	Japan			
26	2004	Takeru Kobayashi	53.5*	Japan			
27	2005	Takeru Kobayashi	49	Japan			
28	2006	Takeru Kobayashi	53.75*	Japan			
29	2007	Joey Chestnut	66*	United States			
30	2008	Joey Chestnut	59	United States			
31	2009	Joey Chestnut	68*	United States			
32	2010	Joey Chestnut	54	United States			
33	2011	Joey Chestnut	62	United States	Sonya Thomas	40*	United States
34	2012	Joey Chestnut	68	United States	Sonya Thomas	45*	United States
35	2013	Joey Chestnut	69*	United States	Sonya Thomas	36.75	United States
36	2014	Joey Chestnut	61	United States	Miki Sudo	34	United States
37	2015	Matt Stonie	62	United States	Miki Sudo	38	United States
38	2016	Joey Chestnut	70*	United States	Miki Sudo	38.5	United States
39	2017	Joey Chestnut	72*	United States	Miki Sudo	41	United States
40	2018	Joey Chestnut	74*	United States	Miki Sudo	37	United States
41	2019	Joey Chestnut	71	United States	Miki Sudo	31	United States
42							
43	Notes: * means new record						

Strategy 1: divide & conquer

Steps:

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table

```
hot_dogs <- read_excel(
    here::here('data', 'hot_dog_winners.xlsx'),
    sheet = 'hot_dog_winners') %>%
    clean_names() %>%
    dplyr::filter(!is.na(mens))

glimpse(hot_dogs)
```

```
## Observations: 40
## Variables: 7
## $ year         <chr> "1980", "1981", "1982", "1983", "19
## $ mens         <chr> "Paul Siederman & Joe Baldini", "Th
## $ dogs_eaten_3 <chr> "9.1", "11", "11", "19.5", "9.5", "
## $ country_4    <chr> "United States", "United States", "
## $ womens       <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ dogs_eaten_6 <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ country_7    <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA,
```

Strategy 1: divide & conquer

Steps

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table
4. **Split data into two competitions with the same variable names**
5. **Create new variable in each data frame:** `competition`

```
hot_dogs_m <- hot_dogs %>%
    select(
        year,
        competitor = mens,
        dogs_eaten = dogs_eaten_3,
        country    = country_4) %>%
    mutate(competition = 'Mens')

hot_dogs_w <- hot_dogs %>%
    select(
        year,
        competitor = womens,
        dogs_eaten = dogs_eaten_6,
        country    = country_7) %>%
    mutate(competition = 'Womens') %>%
    dplyr::filter(!is.na(competitor))
```

Strategy 1: divide & conquer

Steps

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table
4. Split data into two competitions **with the same variable names**
5. Create new variable in each data frame: `competition`
6. **Merge data together with `bind_rows()`**
7. **Clean up final data frame**

```
hot_dogs <- bind_rows(hot_dogs_m, hot_dogs_w) %>%
    mutate(
        new_record = str_detect(dogs_eaten, "\\*"),
        dogs_eaten = parse_number(dogs_eaten),
        year       = as.numeric(year))

glimpse(hot_dogs)
```

```
## Observations: 49
## Variables: 6
## $ year        <dbl> 1980, 1981, 1982, 1983, 1984, 1985,
## $ competitor  <chr> "Paul Siederman & Joe Baldini", "Tho
## $ dogs_eaten  <dbl> 9.10, 11.00, 11.00, 19.50, 9.50, 11.
## $ country     <chr> "United States", "United States", "U
## $ competition <chr> "Mens", "Mens", "Mens", "Mens", "Men
## $ new_record  <lgl> FALSE, FALSE, FALSE, FALSE, FALSE, F
```

Strategy 2: gather, separate, spread

Steps:

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table

```
hot_dogs <- read_excel(
    here::here('data', 'hot_dog_winners.xlsx'),
    sheet = 'hot_dog_winners') %>%
    clean_names() %>%
    dplyr::filter(!is.na(mens))

glimpse(hot_dogs)
```

```
## Observations: 40
## Variables: 7
## $ year         <chr> "1980", "1981", "1982", "1983", "19
## $ mens         <chr> "Paul Siederman & Joe Baldini", "Th
## $ dogs_eaten_3 <chr> "9.1", "11", "11", "19.5", "9.5", "
## $ country_4    <chr> "United States", "United States", "
## $ womens       <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ dogs_eaten_6 <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ country_7    <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA,
```

Strategy 2: gather, separate, spread

Steps:

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table
4. **Rename variables**
5. **Gather all the "joint" variables**

```
hot_dogs <- hot_dogs %>%
    select(
        year,
        competitor.mens   = mens,
        competitor.womens = womens,
        dogs_eaten.mens   = dogs_eaten_3,
        dogs_eaten.womens = dogs_eaten_6,
        country.mens      = country_4,
        country.womens    = country_7) %>%
    gather(key = 'variable', value = 'value',
           competitor.mens:country.womens)

head(hot_dogs, 3)
```

```
## # A tibble: 3 x 3
##   year  variable        value
##   <chr> <chr>           <chr>
## 1 1980  competitor.mens Paul Siederman & Joe Baldini
## 2 1981  competitor.mens Thomas DeBerry
## 3 1982  competitor.mens Steven Abrams
```

Strategy 2: gather, separate, spread

Steps:

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table
4. Rename variables
5. Gather all the "joint" variables
6. **Separate "joint" variables into components**

```
hot_dogs <- hot_dogs %>%
    separate(variable, into = c('variable', 'competition'),
             sep = '\\.')

head(hot_dogs)
```

```
## # A tibble: 6 x 4
##   year  variable   competition value
##   <chr> <chr>      <chr>       <chr>
## 1 1980  competitor mens        Paul Siederman & Joe Baldini
## 2 1981  competitor mens        Thomas DeBerry
## 3 1982  competitor mens        Steven Abrams
## 4 1983  competitor mens        Luis Llamas
## 5 1984  competitor mens        Birgit Felden
## 6 1985  competitor mens        Oscar Rodriguez
```

Strategy 2: gather, separate, spread

Steps:

1. Read in the data
2. Clean the names
3. Remove `*` note at bottom of table
4. Rename variables
5. Gather all the "joint" variables
6. Separate "joint" variables into components
7. **Spread variable and value back to columns**
8. **Clean up final data frame**

```
hot_dogs <- hot_dogs %>%
    spread(key = variable, value = value) %>%
    mutate(
        new_record = str_detect(dogs_eaten, "\\*"),
        dogs_eaten = parse_number(dogs_eaten),
        year       = as.numeric(year))

glimpse(hot_dogs)
```

```
## Observations: 80
## Variables: 6
## $ year        <dbl> 1980, 1980, 1981, 1981, 1982, 1982, 1983, 1983
## $ competition <chr> "mens", "womens", "mens", "womens", "mens", "w
## $ competitor  <chr> "Paul Siederman & Joe Baldini", NA, "Thomas De
## $ country     <chr> "United States", NA, "United States", NA, "Uni
## $ dogs_eaten  <dbl> 9.10, NA, 11.00, NA, 11.00, NA, 19.50, NA, 9.5
## $ new_record  <lgl> FALSE, NA, FALSE, NA, FALSE, NA, FALSE, NA, FA
```

Divide & conquer

```r
hot_dogs <- read_excel(
    here::here('data', 'hot_dog_winners.xlsx'),
    sheet = 'hot_dog_winners') %>%
    clean_names() %>%
    dplyr::filter(!is.na(mens))

# Divide
hot_dogs_m <- hot_dogs %>%
    select(
        year,
        competitor = mens,
        dogs_eaten = dogs_eaten_3,
        country    = country_4) %>%
    mutate(competition = 'Mens')

hot_dogs_w <- hot_dogs %>%
    select(
        year,
        competitor = womens,
        dogs_eaten = dogs_eaten_6,
        country    = country_7) %>%
    mutate(competition = 'Womens') %>%
    dplyr::filter(!is.na(competitor))

# Merge and finish cleaning
hot_dogs <- bind_rows(hot_dogs_m, hot_dogs_w) %>%
    mutate(
        new_record = str_detect(dogs_eaten, "\\*"),
        dogs_eaten = parse_number(dogs_eaten),
        year       = as.numeric(year))
```

Gather, separate, spread

```r
hot_dogs <- read_excel(
    here::here('data', 'hot_dog_winners.xlsx'),
    sheet = 'hot_dog_winners') %>%
    clean_names() %>%
    dplyr::filter(!is.na(mens)) %>%
    # Rename variables
    select(
        year,
        competitor.mens   = mens,
        competitor.womens = womens,
        dogs_eaten.mens   = dogs_eaten_3,
        dogs_eaten.womens = dogs_eaten_6,
        country.mens      = country_4,
        country.womens    = country_7) %>%
    # Gather "joint" variables
    gather(key = 'variable', value = 'value',
           competitor.mens:country.womens) %>%
    # Separate "joint" variables
    separate(variable, into = c('variable', 'competition'),
             sep = '\\.') %>%
    # Spread "joint" variables
    spread(key = variable, value = value) %>%
    # Finish cleaning
    mutate(
        new_record = str_detect(dogs_eaten, "\\*"),
        dogs_eaten = parse_number(dogs_eaten),
        year       = as.numeric(year))
```

Strategies for dealing with sub-headers

Example:

OICA passenger car sales data

OICA

NEW PC REGISTRATIONS OR SALES

Estimated figures

	A	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
6	REGIONS/COUNTRIES	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
7															
8	**EUROPE**	**17,906,455**	**18,685,556**	**19,618,588**	**18,821,599**	**16,608,761**	**16,499,863**	**17,167,600**	**16,191,269**	**15,942,273**	**16,154,279**	**16,410,563**	**17,291,819**	**17,974,281**	**17,912,336**
9	**EU 28 countries + EFTA**	**15,622,035**	**15,961,138**	**16,147,274**	**14,911,880**	**14,533,115**	**13,830,694**	**13,642,659**	**12,567,903**	**12,344,415**	**13,061,461**	**14,287,881**	**15,160,239**	**15,631,283**	**15,626,509**
10	**EU 15 countries + EFTA**	**14,565,695**	**14,820,182**	**14,842,186**	**13,602,038**	**13,668,808**	**12,984,549**	**12,815,435**	**11,773,281**	**11,555,153**	**12,148,648**	**13,261,258**	**13,971,468**	**14,320,223**	**14,210,016**
11	AUSTRIA	307,915	308,594	298,182	293,697	319,403	328,563	356,145	336,010	319,035	303,318	308,555	329,604	353,320	341,068
12	BELGIUM	480,088	526,141	524,795	535,947	476,194	547,340	572,211	486,737	486,065	482,939	501,066	539,519	546,558	549,632
13	DENMARK	148,819	156,936	162,686	150,199	112,454	153,858	170,036	170,763	182,086	189,055	207,717	222,924	221,821	218,566
14	FINLAND	148,161	145,700	125,608	139,669	90,574	111,968	126,123	111,251	103,455	106,237	108,819	118,991	120,480	120,480
15	FRANCE	2,118,042	2,045,745	2,109,672	2,091,369	2,302,398	2,251,669	2,204,229	1,898,760	1,790,456	1,795,885	1,917,226	2,015,177	2,110,748	2,173,481
16	GERMANY	3,319,259	3,467,961	3,148,163	3,090,040	3,807,175	2,916,259	3,173,634	3,082,504	2,952,431	3,036,773	3,206,042	3,351,607	3,441,262	3,435,778
17	GREECE	269,728	267,669	279,745	267,295	219,730	141,501	97,680	58,482	58,694	71,218	75,805	78,873	88,083	103,431
18	ICELAND	18,060	17,129	15,942	9,033	2,113	3,106	5,038	7,902	7,274	9,537	14,004	18,442	21,324	17,976
19	IRELAND	171,742	178,484	186,325	151,607	57,453	88,446	89,911	79,498	74,367	96,284	124,804	146,600	131,332	125,557
20	ITALY	2,244,108	2,335,462	2,494,115	2,161,359	2,159,465	1,961,580	1,749,740	1,403,010	1,304,648	1,360,578	1,575,737	1,824,968	1,970,497	1,910,025
21	LUXEMBOURG	48,517	50,837	51,332	52,359	47,265	49,726	49,881	50,398	46,624	49,793	46,473	50,561	52,775	52,786
22	NETHERLANDS	465,196	483,999	504,300	499,980	387,699	482,531	555,812	502,454	417,036	387,553	449,350	382,825	414,306	443,531
23	NORWAY	109,907	109,164	129,195	110,617	98,675	127,754	138,345	137,967	142,151	144,202	150,686	154,603	158,650	147,929
24	PORTUGAL	206,488	194,702	201,816	213,389	161,013	223,464	153,404	95,309	105,921	142,826	178,503	207,345	222,129	228,327
25	SPAIN	1,528,877	1,634,608	1,614,835	1,161,176	952,772	982,015	808,051	699,589	722,689	890,125	1,094,077	1,147,007	1,234,932	1,321,438
26	SWEDEN	274,301	282,766	306,794	253,982	213,408	289,684	304,984	279,899	269,599	303,948	345,108	372,318	379,393	353,729
27	SWITZERLAND (+FL)	266,770	269,421	284,674	288,525	266,018	294,239	318,958	328,139	307,885	301,942	323,783	317,318	311,996	299,135
28	UNITED KINGDOM	2,439,717	2,344,864	2,404,007	2,131,795	1,994,999	2,030,846	1,941,253	2,044,609	2,264,737	2,476,435	2,633,503	2,692,786	2,540,617	2,367,147
29	**EUROPE NEW MEMBERS**	**1,056,340**	**1,140,956**	**1,305,088**	**1,309,842**	**864,307**	**846,145**	**827,224**	**794,622**	**789,262**	**912,813**	**1,026,623**	**1,188,771**	**1,311,060**	**1,416,493**
30	BULGARIA*	25,956	36,455	43,521	45,143	22,869	16,257	19,250	19,419	19,352	20,359	23,500	26,370	33,265	37,506
31	CROATIA	70,541	78,775	82,664	88,265	44,918	38,587	41,561	31,360	27,802	33,962	35,715	44,106	50,769	60,041
32	CYPRUS	17,687	18,639	22,878	22,241	14,981	14,088	13,480	10,123	7,102	8,276	10,344	12,643	13,127	13,135
33	CZECH REPUBLIC	151,699	156,686	174,456	182,554	167,708	169,580	173,595	174,009	164,736	192,314	230,857	259,693	271,595	261,437
34	ESTONIA	19,640	25,363	30,912	24,579	9,946	10,295	17,070	19,424	19,694	20,969	20,347	22,429	25,618	26,297
35	HUNGARY	198,982	187,676	171,661	153,278	60,189	43,476	45,094	53,059	56,139	67,476	77,171	96,552	116,265	136,601
36	LATVIA	10,467	14,234	21,606	22,217	7,515	7,970	13,234	10,665	10,636	12,452	13,765	16,359	16,698	16,878
37	LITHUANIA	16,602	25,582	32,771	19,831	5,367	6,365	10,980	12,165	12,163	14,503	17,085	20,320	25,836	32,382
38	MALTA	6,552	6,745	6,240	5,423	5,894	4,056	5,428	5,884	5,749	6,451	7,121	7,333	7,825	8,128
39	POLAND	207,007	224,728	277,427	319,190	276,220	315,855	277,427	272,719	289,913	327,709	354,975	416,123	486,352	531,889
40	ROMANIA	214,967	247,411	312,533	285,506	116,016	94,441	81,709	66,436	57,710	82,809	98,325	115,004	105,083	129,004
41	SLOVAKIA	56,916	59,084	59,700	70,040	74,717	64,033	68,203	69,268	65,998	72,237	77,968	88,165	96,105	98,080
42	SLOVENIA	59,324	59,578	68,719	71,575	57,967	61,142	60,193	50,091	52,268	53,296	59,450	63,674	62,522	65,115
43	**RUSSIA, TURKEY & OTHER EUROPE**	**2,284,420**	**2,724,418**	**3,471,314**	**3,909,719**	**2,075,646**	**2,669,169**	**3,524,941**	**3,623,366**	**3,597,858**	**3,092,818**	**2,122,682**	**2,131,580**	**2,342,998**	**2,285,827**

Strategies for dealing with sub-headers

Steps:

1. Read in the data, skipping first 5 rows
2. Clean the names

```
pc_sales <- read_excel(
    here::here('data', 'pc_sales_2018.xlsx'),
    sheet = 'pc_sales', skip = 5) %>%
    clean_names() %>%
    rename(country = regions_countries)

glimpse(pc_sales)
```

```
## Observations: 160
## Variables: 18
## $ country <chr> NA, "EUROPE", "EU 28 countries + EFTA",
## $ x2      <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ x3      <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ x4      <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
## $ x2005   <dbl> NA, 17906455, 15622035, 14565695, 307915
## $ x2006   <dbl> NA, 18685556, 15961138, 14820182, 308594
## $ x2007   <dbl> NA, 19618588, 16147274, 14842186, 298182
## $ x2008   <dbl> NA, 18821599, 14911880, 13602038, 293697
## $ x2009   <dbl> NA, 16608761, 14533115, 13668808, 319403
## $ x2010   <dbl> NA, 16499863, 13830694, 12984549, 328563
## $ x2011   <dbl> NA, 17167600, 13642659, 12815435, 356145
```

Strategies for dealing with sub-headers

Steps:

1. Read in the data, skipping first 5 rows
2. Clean the names
3. **Filter out bad columns**
4. **Filter out bad rows**

Use **datapasta** to get rows to drop

```
drop <- c(
    'EUROPE', 'EU 28 countries + EFTA',
    'EU 15 countries + EFTA', 'EUROPE NEW MEMBERS',
    'RUSSIA, TURKEY & OTHER EUROPE', 'AMERICA',
    'NAFTA', 'CENTRAL & SOUTH AMERICA',
    'ASIA/OCEANIA/MIDDLE EAST', 'AFRICA', 'ALL COUNTRIES')

pc_sales <- pc_sales %>%
    select(-c(x2:x4)) %>%       # Drop bad columns
    filter(! country %in% drop, # Drop bad rows
           ! is.na(country))

head(pc_sales)
```

```
## # A tibble: 6 x 15
##   country  x2005  x2006  x2007  x2008  x2009  x2010  x2011
##   <chr>    <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>
## 1 AUSTRIA 307915 308594 298182 293697 319403 328563 356145
## 2 BELGIUM 480088 526141 524795 535947 476194 547340 572211
## 3 DENMARK 148819 156936 162686 150199 112454 153858 170036
## 4 FINLAND 148161 145700 125608 139669  90574 111968 126123
```

Strategies for dealing with sub-headers

Steps:

1. Read in the data, skipping first 5 rows
2. Clean the names
3. Filter out bad columns
4. Filter out bad rows
5. **Gather the year variables**

```
pc_sales <- pc_sales %>%
    gather(key = 'year', value = 'num_cars', x2005:x2018)

head(pc_sales)
```

```
## # A tibble: 6 x 3
##   country year  num_cars
##   <chr>   <chr>    <dbl>
## 1 AUSTRIA x2005   307915
## 2 BELGIUM x2005   480088
## 3 DENMARK x2005   148819
## 4 FINLAND x2005   148161
## 5 FRANCE  x2005  2118042
## 6 GERMANY x2005  3319259
```

Strategies for dealing with sub-headers

Steps:

1. Read in the data, skipping first 5 rows
2. Clean the names
3. Filter out bad columns
4. Filter out bad rows
5. Gather the year variables
6. **Separate the "x" from the year**

```
pc_sales <- pc_sales %>%
    separate(year, into = c('drop', 'year'), sep = 'x',
             convert = TRUE)

head(pc_sales)
```

```
## # A tibble: 6 x 4
##   country drop   year num_cars
##   <chr>   <lgl> <int>    <dbl>
## 1 AUSTRIA NA     2005   307915
## 2 BELGIUM NA     2005   480088
## 3 DENMARK NA     2005   148819
## 4 FINLAND NA     2005   148161
## 5 FRANCE  NA     2005  2118042
## 6 GERMANY NA     2005  3319259
```

Strategies for dealing with sub-headers

Steps:

1. Read in the data, skipping first 5 rows
2. Clean the names
3. Filter out bad columns
4. Filter out bad rows
5. Gather the year variables
6. Separate the "x" from the year
7. **Finish cleaning**

```
pc_sales <- pc_sales %>%
    select(-drop) %>%
    mutate(
        country  = str_to_title(country),
        num_cars = num_cars / 10^6)

head(pc_sales)
```

```
## # A tibble: 6 x 3
##   country  year num_cars
##   <chr>   <int>    <dbl>
## 1 Austria  2005    0.308
## 2 Belgium  2005    0.480
## 3 Denmark  2005    0.149
## 4 Finland  2005    0.148
## 5 France   2005    2.12
## 6 Germany  2005    3.32
```

Your turn: `weather` case study

Follow along as we:

1. Import the data
2. Gather columns that are values
3. Spread values that are variable names
4. Clean up dates
5. Re-arrange the column order
6. Convert strings to numbers
7. Re-name columns
8. Deal with missing values
9. Fix errors in the data

Extra practice:

`pv_cells` case study

Read in the `pv_cell_production.xlsx` file and format it to produce this data frame.

```
pv_cells %>%
    distinct(country)
```

```
## # A tibble: 8 x 1
##   country
##   <chr>
## 1 China
## 2 Taiwan
## 3 Japan
## 4 Malaysia
## 5 Germany
## 6 South Korea
## 7 United States
## 8 Others
```

```
head(pv_cells)
```

```
## # A tibble: 6 x 3
##    year country     n
##   <dbl> <chr>   <dbl>
## 1  1995 China     NA
## 2  1996 China     NA
## 3  1997 China     NA
## 4  1998 China     NA
## 5  1999 China     NA
## 6  2000 China      2.5
```

```
tail(pv_cells)
```

```
## # A tibble: 6 x 3
##    year country     n
##   <dbl> <chr>   <dbl>
## 1  2008 Others   709.
## 2  2009 Others   664.
## 3  2010 Others  1443.
## 4  2011 Others  1834.
## 5  2012 Others  1475.
## 6  2013 Others  1453.
```

If you haven't already, now would be a good time to start working on your projects

You have 2 weeks until proposals are due

Writing a research question

Following these guidelines, your question should be:

- **Clear**: your audience can easily understand its purpose without additional explanation.
- **Focused**: it is narrow enough that it can be addressed thoroughly with the data available and within the limits of the final project report.
- **Concise**: it is expressed in the fewest possible words.
- **Complex**: it is not answerable with a simple "yes" or "no," but rather requires synthesis and analysis of data.
- **Arguable**: its potential answers are open to debate rather than accepted facts (do others care about it?)

This is an iterative process