

# Manipulating tables with `dplyr`

*Data Wrangling, Session 3 (contd)*

Kieran Healy

Code Horizons

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# Manipulating Tables with dplyr (contd)

# Window functions and moving averages

# Load our libraries

```
library(here)      # manage file paths  
library(socviz)    # data and some useful functions  
library(tidyverse) # your friend and mine
```

# dplyr's window functions

Ranking and cumulation within groups.

```
## Data on COVID-19  
library(covdata)
```

```
covnat_weekly
```

```
# A tibble: 4,966 × 11
```

	date	year_week	cname	iso3	pop	cases	deaths	cu_cases	cu_deaths
	<date>	<chr>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	2019-12-30	2020-01	Austria	AUT	8932664	NA	NA	NA	NA
2	2020-01-06	2020-02	Austria	AUT	8932664	NA	NA	NA	NA
3	2020-01-13	2020-03	Austria	AUT	8932664	NA	NA	NA	NA
4	2020-01-20	2020-04	Austria	AUT	8932664	NA	NA	NA	NA
5	2020-01-27	2020-05	Austria	AUT	8932664	NA	NA	NA	NA
6	2020-02-03	2020-06	Austria	AUT	8932664	NA	NA	NA	NA
7	2020-02-10	2020-07	Austria	AUT	8932664	NA	NA	NA	NA
8	2020-02-17	2020-08	Austria	AUT	8932664	NA	NA	NA	NA
9	2020-02-24	2020-09	Austria	AUT	8932664	12	0	12	0
10	2020-03-02	2020-10	Austria	AUT	8932664	115	0	127	0

```
# i 4,956 more rows
```

```
# i 2 more variables: r14_cases <dbl>, r14_deaths <dbl>
```

# dplyr's window functions

**cumsum()** gives cumulative sums

```
covnat_weekly >
  filter(iso3 == "FRA") >
  select(date, cname, iso3, cases) >
  mutate(cases = ifelse(is.na(cases), 0, cases), # convert NA vals in `cases` to 0
         cumulative = cumsum(cases))
```

```
# A tibble: 159 × 5
   date      cname iso3  cases cumulative
<date>    <chr> <chr> <dbl>      <dbl>
1 2019-12-30 France FRA      0          0
2 2020-01-06 France FRA      0          0
3 2020-01-13 France FRA      0          0
4 2020-01-20 France FRA      3          3
5 2020-01-27 France FRA      3          6
6 2020-02-03 France FRA      6         12
7 2020-02-10 France FRA      0         12
8 2020-02-17 France FRA      4         16
9 2020-02-24 France FRA     133        149
10 2020-03-02 France FRA     981       1130
# i 149 more rows
```

# dplyr's window functions

`cume_dist()` gives the proportion of values less than or equal to the current value.

```
covnat_weekly >
  select(date, cname, iso3, deaths) >
  filter(iso3 = "FRA") >
  filter(cume_dist(desc(deaths)) < 0.1) # i.e. Top 10%
```

```
# A tibble: 15 × 4
  date      cname iso3 deaths
<date>    <chr> <chr> <dbl>
1 2020-04-06 France FRA    3348
2 2020-10-26 France FRA    3517
3 2020-11-02 France FRA    5281
4 2020-11-09 France FRA    6018
5 2020-11-16 France FRA    6208
6 2020-11-23 France FRA    5215
7 2020-11-30 France FRA    4450
8 2020-12-07 France FRA    4257
9 2020-12-14 France FRA    3786
10 2020-12-21 France FRA    3560
11 2021-01-04 France FRA    3851
12 2021-01-11 France FRA    3833
13 2021-01-18 France FRA    3754
14 2021-01-25 France FRA    3535
15 2021-02-01 France FRA    3431
```

The dplyr window functions is good.

# An application

```
covus >
  filter(measure == "death") >
  group_by(state) >
  arrange(state, desc(date)) >
  filter(state %in% "NY")
```

```
# A tibble: 371 × 7
```

```
# Groups:   state [1]
```

	date	state	fips	data_quality_grade	measure	count	measure_label
	<date>	<chr>	<chr>	<lgl>	<chr>	<dbl>	<chr>
1	2021-03-07	NY	36	NA	death	39029	Deaths
2	2021-03-06	NY	36	NA	death	38970	Deaths
3	2021-03-05	NY	36	NA	death	38891	Deaths
4	2021-03-04	NY	36	NA	death	38796	Deaths
5	2021-03-03	NY	36	NA	death	38735	Deaths
6	2021-03-02	NY	36	NA	death	38660	Deaths
7	2021-03-01	NY	36	NA	death	38577	Deaths
8	2021-02-28	NY	36	NA	death	38497	Deaths
9	2021-02-27	NY	36	NA	death	38407	Deaths
10	2021-02-26	NY	36	NA	death	38321	Deaths

```
# i 361 more rows
```

Here the **count** measure is *cumulative* deaths. What if we want to recover the daily count for all the states in the data?



# An application

`dplyr` has `lead()` and `lag()` functions. These allow you to access the previous and next values in a vector. You can calculate offsets this way.

```
my_vec ← c(1:20)
my_vec
```

```
[1] 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
```

```
lag(my_vec) # first element has no lag
```

```
[1] NA 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19
```

```
my_vec - lag(my_vec)
```

```
[1] NA 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

# An application

We can write the expression directly:

```
covus ▷  
  select(-data_quality_grade) ▷  
  filter(measure = "death") ▷  
  group_by(state) ▷  
  arrange(date) ▷  
  mutate(deaths_daily = count - lag(count, order_by = date)) ▷  
  arrange(state, desc(date)) ▷  
  filter(state %in% "NY")
```

```
# A tibble: 371 × 7  
# Groups:   state [1]  
   date      state fips  measure  count measure_label deaths_daily  
   <date>    <chr> <chr> <chr>    <dbl> <chr>          <dbl>  
1 2021-03-07 NY     36    death  39029 Deaths        59  
2 2021-03-06 NY     36    death  38970 Deaths        79  
3 2021-03-05 NY     36    death  38891 Deaths        95  
4 2021-03-04 NY     36    death  38796 Deaths        61  
5 2021-03-03 NY     36    death  38735 Deaths        75  
6 2021-03-02 NY     36    death  38660 Deaths        83  
7 2021-03-01 NY     36    death  38577 Deaths        80  
8 2021-02-28 NY     36    death  38497 Deaths        90  
9 2021-02-27 NY     36    death  38407 Deaths        86  
10 2021-02-26 NY     36    death  38321 Deaths        94  
# i 361 more rows
```

# Writing our own functions

We write functions using the special `function()` function.\*

```
my_fun ← function(x) {  
  x + 1  
}
```

```
my_fun # we've created the function; it's just an object
```

```
function(x) {  
  x + 1  
}
```

```
my_fun(x = 1) # But we can supply it with an input!
```

```
[1] 2
```

```
my_fun(10)
```

```
[1] 11
```

\*Nerds love this sort of stuff.

# Writing our own functions

We write our function. It's just the expression we originally wrote, wrapped up.

```
get_daily_count ← function(count, date){  
  count - lag(count, order_by = date)  
}
```

This function has no generality, error-handling, or anything else. It's a once-off.

# Writing our own functions

Now we can use it like any other:

```
covus >
  filter(measure = "death") >
  select(-data_quality_grade) >
  group_by(state) >
  arrange(date) >
  mutate(deaths_daily = get_daily_count(count, date)) >
  arrange(state, desc(date)) >
  filter(state %in% "NY")
```

```
# A tibble: 371 × 7
# Groups:   state [1]
   date       state fips  measure  count measure_label deaths_daily
  <date>    <chr> <chr> <chr>    <dbl> <chr>          <dbl>
1 2021-03-07 NY      36    death  39029 Deaths        59
2 2021-03-06 NY      36    death  38970 Deaths        79
3 2021-03-05 NY      36    death  38891 Deaths        95
4 2021-03-04 NY      36    death  38796 Deaths        61
5 2021-03-03 NY      36    death  38735 Deaths        75
6 2021-03-02 NY      36    death  38660 Deaths        83
7 2021-03-01 NY      36    death  38577 Deaths        80
8 2021-02-28 NY      36    death  38497 Deaths        90
9 2021-02-27 NY      36    death  38407 Deaths        86
10 2021-02-26 NY      36    death  38321 Deaths        94
# i 361 more rows
```

# The slider package

# Tidy moving averages with **slider**

**dplyr**'s window functions don't include moving averages.

There are several options, notably **RcppRoll**

We'll use the **slider** package.

```
# install.packages("slider")  
library(slider)
```

# Tidy moving averages with **slider**

```
covus >
  filter(measure == "death") >
  select(-data_quality_grade) >
  group_by(state) >
  arrange(date) >
  mutate(
    deaths_daily = get_daily_count(count, date),
    deaths7 = slide_mean(deaths_daily,
                        before = 7,
                        na_rm = TRUE)) >
  arrange(state, desc(date)) >
  filter(state %in% "NY")
```

# A tibble: 371 × 8

# Groups: state [1]

	date	state	fips	measure	count	measure_label	deaths_daily	deaths7
	<date>	<chr>	<chr>	<chr>	<dbl>	<chr>	<dbl>	<dbl>
1	2021-03-07	NY	36	death	39029	Deaths	59	77.8
2	2021-03-06	NY	36	death	38970	Deaths	79	81.1
3	2021-03-05	NY	36	death	38891	Deaths	95	83
4	2021-03-04	NY	36	death	38796	Deaths	61	82.6
5	2021-03-03	NY	36	death	38735	Deaths	75	88
6	2021-03-02	NY	36	death	38660	Deaths	83	89.9
7	2021-03-01	NY	36	death	38577	Deaths	80	90.8
8	2021-02-28	NY	36	death	38497	Deaths	90	90.1
9	2021-02-27	NY	36	death	38407	Deaths	86	91.5
10	2021-02-26	NY	36	death	38321	Deaths	94	95.6

# : 361 more rows



# Tidy moving averages with **slider**

```
deaths7 = slide_mean(deaths_daily,  
                      before = 7,  
                      na_rm = TRUE)) ▶
```

Notice the Tidyverse-style **na\_rm** argument rather than the usual base **na.rm**

The package provides a lot of different functions, from general-purpose **slide\_max()**, **slide\_min()** to more specialized sliding functions. In particular note e.g. **slide\_index\_mean()** that addresses some subtleties in averaging over dates with gaps.

# Move columns with `relocate()`

```
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>, madeg <fct>,
# partyid <fct>, polviews <fct>, happy <fct>, partners <fct>, grass <fct>,
# zodiac <fct>, pres12 <labelled>, wtssall <dbl>, income_rc <fct>,
# agegrp <fct>, ageq <fct>, siblings <fct>, kids <fct>, religion <fct>,
# bigregion <fct>, partners_rc <fct>, obama <dbl>
```

# Shuffle columns around

```
gss_sm
```

```
# A tibble: 2,867 × 32
  year   id ballot age child 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>, madeg <fct>,
# partyid <fct>, polviews <fct>, happy <fct>, partners <fct>, grass <fct>,
# zodiac <fct>, pres12 <labelled>, wtssall <dbl>, income_rc <fct>,
# agegrp <fct>, ageq <fct>, siblings <fct>, kids <fct>, religion <fct>,
# bigregion <fct>, partners_rc <fct>, obama <dbl>
```

# Shuffle columns around

```
gss_sm ►  
  select(region, bigregion, year,  
         id:region,  
         starts_with("p"),  
         contains("income"))
```

```
# A tibble: 2,867 × 19  
  region    bigregion  year   id ballot  age childs sibs degree race  sex  
  <fct>      <fct>    <dbl> <dbl> <labe> <dbl> <dbl> <lab> <fct> <fct> <fct>  
1 New Engla... Northeast  2016     1  1      47     3  2  Bache... White Male  
2 New Engla... Northeast  2016     2  2      61     0  3  High ... White Male  
3 New Engla... Northeast  2016     3  3      72     2  3  Bache... White Male  
4 New Engla... Northeast  2016     4  1      43     4  3  High ... White Fema...  
5 New Engla... Northeast  2016     5  3      55     2  2  Gradu... White Fema...  
6 New Engla... Northeast  2016     6  2      53     2  2  Junio... White Fema...  
7 New Engla... Northeast  2016     7  1      50     2  2  High ... White Male  
8 Middle At... Northeast  2016     8  3      23     3  6  High ... Other Fema...  
9 Middle At... Northeast  2016     9  1      45     3  5  High ... Black Male  
10 Middle At... Northeast  2016    10  3      71     4  1  Junio... White Male  
# i 2,857 more rows  
# i 8 more variables: padeg <fct>, partyid <fct>, polviews <fct>,  
#   partners <fct>, pres12 <labelled>, partners_rc <fct>, income16 <fct>,  
#   income_rc <fct>
```

# Shuffle columns around

```
gss_sm ►  
  select(region, bigregion, year,  
         id:region,  
         starts_with("p"),  
         contains("income")) ►  
  rename(children = childs,  
         siblings = sibs)
```

```
# A tibble: 2,867 × 19  
  region      bigregion  year   id ballot  age children siblings degree race  
  <fct>      <fct>    <dbl> <dbl> <labs> <dbl>    <dbl> <labell> <fct> <fct>  
1 New England Northeast  2016     1 1      47         3 2      Bache... White  
2 New England Northeast  2016     2 2      61         0 3      High ... White  
3 New England Northeast  2016     3 3      72         2 3      Bache... White  
4 New England Northeast  2016     4 1      43         4 3      High ... White  
5 New England Northeast  2016     5 3      55         2 2      Gradu... White  
6 New England Northeast  2016     6 2      53         2 2      Junio... White  
7 New England Northeast  2016     7 1      50         2 2      High ... White  
8 Middle Atl... Northeast  2016     8 3      23         3 6      High ... Other  
9 Middle Atl... Northeast  2016     9 1      45         3 5      High ... Black  
10 Middle Atl... Northeast  2016    10 3      71         4 1      Junio... White  
# i 2,857 more rows  
# i 9 more variables: sex <fct>, padeg <fct>, partyid <fct>, polviews <fct>,  
#   partners <fct>, pres12 <labelled>, partners_rc <fct>, income16 <fct>,  
#   income_rc <fct>
```

# Shuffle columns around

```
gss_sm ►  
  select(region, bigregion, year,  
         id:region,  
         starts_with("p"),  
         contains("income")) ►  
  rename(children = child_s,  
         siblings = sib_s) ►  
  relocate(id)
```

```
# A tibble: 2,867 × 19  
   id region      bigregion year ballot age children siblings degree race  
   <dbl> <fct>      <fct>    <dbl> <lab> <dbl>    <dbl> <labell> <fct> <fct>  
1     1 New England Northeast  2016 1     47      3 2     Bache... White  
2     2 New England Northeast  2016 2     61      0 3     High ... White  
3     3 New England Northeast  2016 3     72      2 3     Bache... White  
4     4 New England Northeast  2016 1     43      4 3     High ... White  
5     5 New England Northeast  2016 3     55      2 2     Gradu... White  
6     6 New England Northeast  2016 2     53      2 2     Junio... White  
7     7 New England Northeast  2016 1     50      2 2     High ... White  
8     8 Middle Atl... Northeast  2016 3     23      3 6     High ... Other  
9     9 Middle Atl... Northeast  2016 1     45      3 5     High ... Black  
10    10 Middle Atl... Northeast  2016 3     71      4 1     Junio... White  
# i 2,857 more rows  
# i 9 more variables: sex <fct>, padeg <fct>, partyid <fct>, polviews <fct>,  
#   partners <fct>, pres12 <labelled>, partners_rc <fct>, income16 <fct>,  
#   income_rc <fct>
```

# Shuffle columns around

```
gss_sm ►  
  select(region, bigregion, year,  
         id:region,  
         starts_with("p"),  
         contains("income")) ►  
  rename(children = child_s,  
         siblings = sibs) ►  
  relocate(id) ►  
  select(-ballot)
```

```
# A tibble: 2,867 × 18  
   id region bigregion year age children siblings degree race sex padeg  
   <dbl> <fct> <fct>      <dbl> <dbl>      <dbl> <labell> <fct> <fct> <fct> <fct>  
1     1 New E... Northeast 2016  47         3 2      Bache... White Male Grad...  
2     2 New E... Northeast 2016  61         0 3      High ... White Male Lt H...  
3     3 New E... Northeast 2016  72         2 3      Bache... White Male High...  
4     4 New E... Northeast 2016  43         4 3      High ... White Fema... <NA>  
5     5 New E... Northeast 2016  55         2 2      Gradu... White Fema... Bach...  
6     6 New E... Northeast 2016  53         2 2      Junio... White Fema... <NA>  
7     7 New E... Northeast 2016  50         2 2      High ... White Male High...  
8     8 Middl... Northeast 2016  23         3 6      High ... Other Fema... Lt H...  
9     9 Middl... Northeast 2016  45         3 5      High ... Black Male Lt H...  
10    10 Middl... Northeast 2016  71         4 1      Junio... White Male High...  
# i 2,857 more rows  
# i 7 more variables: partyid <fct>, polviews <fct>, partners <fct>,  
#   pres12 <labelled>, partners_rc <fct>, income16 <fct>, income_rc <fct>
```

# Shuffle columns around

```
gss_sm ▷  
  select(region, bigregion, year,  
         id:region,  
         starts_with("p"),  
         contains("income")) ▷  
  rename(children = child_s,  
         siblings = sibs) ▷  
  relocate(id) ▷  
  select(-ballot) ▷  
  relocate(where(is.numeric),  
           .before = where(is.factor))
```

```
# A tibble: 2,867 × 18  
   id year age children siblings pres12 region bigregion degree race  
   <dbl> <dbl> <dbl>   <dbl> <labelled> <labelled> <fct> <fct> <fct> <fct>  
1     1  2016  47       3 2         3    New E... Northeast Bache... White  
2     2  2016  61       0 3         1    New E... Northeast High ... White  
3     3  2016  72       2 3         2    New E... Northeast Bache... White  
4     4  2016  43       4 3         2    New E... Northeast High ... White  
5     5  2016  55       2 2         1    New E... Northeast Gradu... White  
6     6  2016  53       2 2         1    New E... Northeast Junio... White  
7     7  2016  50       2 2        NA    New E... Northeast High ... White  
8     8  2016  23       3 6        NA    Middl... Northeast High ... Other  
9     9  2016  45       3 5        NA    Middl... Northeast High ... Black  
10    10  2016  71       4 1         2    Middl... Northeast Junio... White  
# i 2,857 more rows  
# i 8 more variables: sex <fct>, padeg <fct>, partyid <fct>, polviews <fct>,  
#   partners <fct>, partners_rc <fct>, income16 <fct>, income_rc <fct>
```



# Shuffle columns around

```
gss_sm ▷  
  select(region, bigregion, year,  
         id:region,  
         starts_with("p"),  
         contains("income")) ▷  
  rename(children = child_s,  
         siblings = sibs) ▷  
  relocate(id) ▷  
  select(-ballot) ▷  
  relocate(where(is.numeric),  
           .before = where(is.factor)) ▷  
  relocate(contains("region"),  
           .after = year)
```

```
# A tibble: 2,867 × 18  
   id year region    bigregion age children siblings pres12 degree race  
   <dbl> <dbl> <fct>      <fct>    <dbl>   <dbl> <labell> <labe> <fct> <fct>  
1     1   2016 New England Northeast    47     3 2      3    Bache... White  
2     2   2016 New England Northeast    61     0 3      1    High ... White  
3     3   2016 New England Northeast    72     2 3      2    Bache... White  
4     4   2016 New England Northeast    43     4 3      2    High ... White  
5     5   2016 New England Northeast    55     2 2      1    Gradu... White  
6     6   2016 New England Northeast    53     2 2      1    Junio... White  
7     7   2016 New England Northeast    50     2 2     NA    High ... White  
8     8   2016 Middle Atl... Northeast    23     3 6     NA    High ... Other  
9     9   2016 Middle Atl... Northeast    45     3 5     NA    High ... Black  
10    10   2016 Middle Atl... Northeast    71     4 1      2    Junio... White  
# i 2,857 more rows  
# i 8 more variables: sex <fct>, padeg <fct>, partyid <fct>, polviews <fct>,  
# partners <fct>, partners_rc <fct>, income16 <fct>, income_rc <fct>
```

# Example: UK Election Data

```
library(ukelection2019)
```

```
ukvote2019
```

```
# A tibble: 3,320 × 13
  cid      constituency electorate party_name candidate votes vote_share_percent
  <chr>    <chr>           <int> <chr>      <chr>      <int>      <dbl>
1 W07000... Aberavon           50747 Labour    Stephen ... 17008        53.8
2 W07000... Aberavon           50747 Conservat... Charlott... 6518         20.6
3 W07000... Aberavon           50747 The Brexi... Glenda D... 3108          9.8
4 W07000... Aberavon           50747 Plaid Cym... Nigel Hu... 2711          8.6
5 W07000... Aberavon           50747 Liberal D... Sheila K... 1072          3.4
6 W07000... Aberavon           50747 Independe... Captain ... 731           2.3
7 W07000... Aberavon           50747 Green       Giorgia ... 450           1.4
8 W07000... Aberconwy         44699 Conservat... Robin Mi... 14687         46.1
9 W07000... Aberconwy         44699 Labour      Emily Ow... 12653         39.7
10 W07000... Aberconwy         44699 Plaid Cym... Lisa Goo... 2704          8.5
# i 3,310 more rows
# i 6 more variables: vote_share_change <dbl>, total_votes_cast <int>,
#   vranks <int>, turnout <dbl>, fname <chr>, lname <chr>
```

# Example: UK Election Data

Use `sample_n()` to sample `n` rows of your tibble.

```
library(ukelection2019)
```

```
ukvote2019 >  
  sample_n(10)
```

```
# A tibble: 10 × 13
```

	cid	constituency	electorate	party_name	candidate	votes	vote_share_percent
	<chr>	<chr>	<int>	<chr>	<chr>	<int>	<dbl>
1	W07000...	Newport West	66657	Plaid Cym...	Jonathan...	1187	2.7
2	E14001...	Wentworth &...	74536	The Brexi...	Stephen ...	7019	16.9
3	W07000...	Cardiff Cen...	64037	Independe...	Akil Kata	119	0.3
4	E14000...	Gedling	71438	Green	Jim Norr...	1097	2.2
5	S14000...	Dunbartonsh...	66517	Green	Peter Co...	867	1.9
6	S14000...	Linlithgow ...	87044	Scottish ...	Martyn D...	25551	44.2
7	E14001...	Walsall Nor...	67177	Labour	Gill Ogi...	11369	31.1
8	E14000...	Durham, Cit...	71271	Green	Jonathan...	1635	3.3
9	E14000...	Burnley	64343	Green	Laura Fi...	739	1.9
10	E14000...	Southampton...	72293	Green	Osman Se...	1040	2.2

```
# i 6 more variables: vote_share_change <dbl>, total_votes_cast <int>,
```

```
#   vranks <int>, turnout <dbl>, fname <chr>, lname <chr>
```

# Example: UK Election Data

A vector of unique constituency names

```
ukvote2019 ▶  
distinct(constituency)
```

```
# A tibble: 650 × 1  
  constituency  
  <chr>  
1 Aberavon  
2 Aberconwy  
3 Aberdeen North  
4 Aberdeen South  
5 Aberdeenshire West & Kincardine  
6 Airdrie & Shotts  
7 Aldershot  
8 Aldridge-Brownhills  
9 Altrincham & Sale West  
10 Alyn & Deeside  
# i 640 more rows
```

# Example: UK Election Data

Tally them up

```
ukvote2019 ▶  
  distinct(constituency) ▶  
  tally()
```

```
# A tibble: 1 × 1  
      n  
  <int>  
1    650
```

```
# Base R / non-pipeline version
```

```
length(unique(ukvote2019$constituency))
```

```
[1] 650
```

# Example: UK Election Data

Which parties fielded the most candidates?

```
ukvote2019 ▶  
  count(party_name) ▶  
  arrange(desc(n))
```

```
# A tibble: 69 × 2  
  party_name      n  
  <chr>         <int>  
1 Conservative    636  
2 Labour          631  
3 Liberal Democrat 611  
4 Green           497  
5 The Brexit Party 275  
6 Independent      224  
7 Scottish National Party 59  
8 UKIP             44  
9 Plaid Cymru      36  
10 Christian Peoples Alliance 29  
# i 59 more rows
```

# Example: UK Election Data

## Top 5

```
ukvote2019 >  
  count(party_name) >  
  slice_max(order_by = n, n = 5)
```

```
# A tibble: 5 × 2  
  party_name      n  
  <chr>         <int>  
1 Conservative    636  
2 Labour          631  
3 Liberal Democrat 611  
4 Green           497  
5 The Brexit Party 275
```

# Example: UK Election Data

## Top 5

```
ukvote2019 ▶  
  count(party_name) ▶  
  slice_max(order_by = n, n = 5)
```

```
# A tibble: 5 × 2  
  party_name      n  
  <chr>      <int>  
1 Conservative    636  
2 Labour          631  
3 Liberal Democrat 611  
4 Green           497  
5 The Brexit Party 275
```

## Bottom 5

```
ukvote2019 ▶  
  count(party_name) ▶  
  slice_min(order_by = n, n = 5)
```

```
# A tibble: 25 × 2  
  party_name      n  
  <chr>      <int>  
1 Ashfield Independents    1  
2 Best for Luton           1  
3 Birkenhead Social Justice Party    1  
4 British National Party    1  
5 Burnley & Padiham Independent Party 1  
6 Church of the Militant Elvis Party  1  
7 Citizens Movement Party UK    1  
8 CumbriaFirst              1  
9 Heavy Woollen District Independents 1  
10 Independent Network       1  
# i 15 more rows
```



# Example: UK Election Data

How many constituencies are there?

```
ukvote2019 ▶  
  count(constituency)
```

```
# A tibble: 650 × 2  
  constituency      n  
  <chr>          <int>  
1 Aberavon        7  
2 Aberconwy        4  
3 Aberdeen North   6  
4 Aberdeen South   4  
5 Aberdeenshire West & Kincardine 4  
6 Airdrie & Shotts  5  
7 Aldershot        4  
8 Aldridge-Brownhills 5  
9 Altrincham & Sale West 6  
10 Alyn & Deeside   5  
# i 640 more rows
```

```
ukvote2019 ▶  
  distinct(constituency) ▶  
  count()
```

```
# A tibble: 1 × 1  
  n  
  <int>  
1  650
```

```
# Base R style ...  
length(unique(ukvote2019$constituency))
```

```
[1] 650
```

# Counting Twice Over

```
ukvote2019 ▶  
  count(constituency) ▶  
  count(n)
```

```
# A tibble: 8 × 2  
      n      nn  
  <int> <int>  
1     3     21  
2     4    194  
3     5    226  
4     6    139  
5     7     49  
6     8     18  
7     9      2  
8    12      1
```

# Counting Twice Over

```
ukvote2019
```

```
# A tibble: 3,320 × 13
  cid constituency electorate party_name candidate votes
<dbl> <chr> <chr> <int> <chr> <chr> <int>
1 W07000... Aberavon 50747 Labour Stephen ... 17008
53.8
2 W07000... Aberavon 50747 Conservat... Charlott... 6518
20.6
3 W07000... Aberavon 50747 The Brexi... Glenda D... 3108
9.8
4 W07000... Aberavon 50747 Plaid Cym... Nigel Hu... 2711
8.6
5 W07000... Aberavon 50747 Liberal D... Sheila K... 1072
3.4
6 W07000... Aberavon 50747 Independe... Captain ... 731
2.3
7 W07000... Aberavon 50747 Green Giorgia ... 450
1.4
8 W07000... Aberconwy 44699 Conservat... Robin Mi... 14687
46.1
9 W07000... Aberconwy 44699 Labour Emily Ow... 12653
39.7
10 W07000... Aberconwy 44699 Plaid Cym... Lisa Goo... 2704
8.5
# i 3,310 more rows
# i 6 more variables: vote_share_change <dbl>, total_votes_cast <int>,
```

# Counting Twice Over

```
ukvote2019 ▶  
count(constituency, name = "n_cands")
```

```
# A tibble: 650 × 2  
  constituency n_cands  
    <chr>      <int>  
1 Aberavon          7  
2 Aberconwy         4  
3 Aberdeen North    6  
4 Aberdeen South    4  
5 Aberdeenshire West & Kincardine 4  
6 Airdrie & Shotts   5  
7 Aldershot         4  
8 Aldridge-Brownhills 5  
9 Altrincham & Sale West 6  
10 Alyn & Deeside    5  
# i 640 more rows
```

# Counting Twice Over

```
ukvote2019 >  
count(constituency, name = "n_cands") >  
count(n_cands, name = "n_const")
```

```
# A tibble: 8 × 2  
  n_cands n_const  
    <int>    <int>  
1       3      21  
2       4     194  
3       5     226  
4       6     139  
5       7      49  
6       8      18  
7       9       2  
8      12       1
```

# Recap and Looking Ahead

# Recap and Looking Ahead

**Coding as gardening**

**Working in RStudio with RMarkdown documents**

# Core `dplyr` verbs

Subset your table: `filter()` rows, `select()` columns

Logically `group_by()` one or more columns

Add columns with `mutate()`

Summarize (by group, or the whole table) with `summarize()`



# Expand your `dplyr` actions

Count up rows with `n()`, `tally()` or `count()`

Calculate quantities with `sum()`, `mean()`, `min()`, etc

Subset rows with logical expressions or `slice` functions

Conditionally select columns by name directly, with `%in%` or `%nin%`, or with tidy selectors like `starts_with()`, `ends_with()`, `contains()`

Conditionally select columns by *type* with `where()` and some criterion, e.g. `where(is.numeric)`

Conditionally select and then *act* on columns with `across(where(<condition>), <action>)`

# Expand your `dplyr` actions

Tidy up columns with `relocate()` and `rename()`

Tidy up rows with `arrange()`

**A dplyr shortcut**

# A dplyr shortcut

So far we have been writing, e.g.,

```
gss_sm >
  group_by(bigregion, religion) >
  summarize(total = n())
```

```
# A tibble: 24 × 3
# Groups:   bigregion [4]
  bigregion religion  total
  <fct>      <fct>    <int>
1 Northeast Protestant  158
2 Northeast Catholic   162
3 Northeast Jewish     27
4 Northeast None      112
5 Northeast Other      28
6 Northeast <NA>        1
7 Midwest   Protestant 325
8 Midwest   Catholic   172
9 Midwest   Jewish      3
10 Midwest   None      157
# i 14 more rows
```

# A dplyr shortcut

Or

```
gss_sm ►  
  group_by(bigregion, religion) ►  
  tally()
```

```
# A tibble: 24 × 3  
# Groups:   bigregion [4]  
  bigregion religion      n  
  <fct>      <fct>    <int>  
1 Northeast Protestant  158  
2 Northeast Catholic    162  
3 Northeast Jewish      27  
4 Northeast None       112  
5 Northeast Other       28  
6 Northeast <NA>        1  
7 Midwest   Protestant  325  
8 Midwest   Catholic    172  
9 Midwest   Jewish       3  
10 Midwest   None       157  
# i 14 more rows
```

# A dplyr shortcut

Or

```
gss_sm ►  
  count(bigregion, religion)
```

```
# A tibble: 24 × 3  
  bigregion religion      n  
  <fct>      <fct>    <int>  
1 Northeast Protestant  158  
2 Northeast Catholic    162  
3 Northeast Jewish      27  
4 Northeast None       112  
5 Northeast Other       28  
6 Northeast <NA>         1  
7 Midwest   Protestant  325  
8 Midwest   Catholic    172  
9 Midwest   Jewish       3  
10 Midwest   None       157  
# i 14 more rows
```

With this last one the final result is *ungrouped*, no matter how many levels of grouping there are going in.

# A dplyr shortcut

But we can also write this:

```
gss_sm ►  
  summarize(total = n(), .by = c(bigregion, religion))
```

```
# A tibble: 24 × 3  
  bigregion religion    total  
  <fct>      <fct>    <int>  
1 Northeast None       112  
2 Northeast Catholic    162  
3 Northeast Protestant  158  
4 Northeast Other        28  
5 Northeast Jewish       27  
6 West      Jewish       10  
7 West      None       180  
8 West      Other        48  
9 West      Protestant  238  
10 West     Catholic    155  
# i 14 more rows
```

By default the result is an *ungrouped* tibble, whereas with `group_by() ... summarize()` the result would still be grouped by `bigregion` at the end. To prevent unexpected results, you can't use `.by` on tibble that's already grouped.

# Data as implicitly first

This code:

```
gss_sm ►  
  summarize(total = n(), .by = c(bigregion, religion))
```

```
# A tibble: 24 × 3  
  bigregion religion    total  
  <fct>      <fct>      <int>  
1 Northeast None         112  
2 Northeast Catholic      162  
3 Northeast Protestant   158  
4 Northeast Other         28  
5 Northeast Jewish        27  
6 West      Jewish         10  
7 West      None         180  
8 West      Other          48  
9 West      Protestant    238  
10 West     Catholic      155  
# i 14 more rows
```



# Data as implicitly first

... is equivalent to this:

```
summarize(gss_sm, total = n(), .by = c(bigregion, religion))
```

```
# A tibble: 24 × 3
  bigregion religion  total
  <fct>      <fct>    <int>
1 Northeast None      112
2 Northeast Catholic   162
3 Northeast Protestant 158
4 Northeast Other      28
5 Northeast Jewish     27
6 West      Jewish     10
7 West      None     180
8 West      Other      48
9 West      Protestant 238
10 West     Catholic   155
# i 14 more rows
```

This is true of Tidyverse pipelines in general. Let's look at the help for `summarize()` to see why.

Two dplyr gotchas

# Comparisons filtering on proportions

Let's say you are working with proportions ...

```
df
```

```
# A tibble: 4 × 3
  id    prop1 prop2
<chr> <dbl> <dbl>
1 A      0.1   0.2
2 B      0.1   0.21
3 C      0.11  0.2
4 D      0.1   0.1
```

# Comparisons filtering on proportions

And you want to focus on cases where `prop1` *plus* `prop2` is greater than 0.3:

```
df >
  filter(prop1 + prop2 > 0.3)
```

```
# A tibble: 3 × 3
  id    prop1 prop2
<chr> <dbl> <dbl>
1 A      0.1   0.2
2 B      0.1   0.21
3 C      0.11  0.2
```

The row with `id A` shouldn't have been included there.

This is not dplyr's fault. It's our floating point friend again.

# Comparisons filtering on proportions

```
df >  
  filter(prop1 + prop2 == 0.3)
```

```
# A tibble: 0 × 3  
#   id prop1 prop2  
#   <chr> <dbl> <dbl>
```

The row with **id A** *should* have been included here!

# Comparisons filtering on proportions

This won't give the right behavior either:

```
df >
  mutate(prop3 = prop1 + prop2) >
  filter(prop3 == 0.3)
```

```
# A tibble: 0 × 4
```

```
# i 4 variables: id <chr>, prop1 <dbl>, prop2 <dbl>, prop3 <dbl>
```

# Comparisons filtering on proportions

So, beware.

```
df ▶  
  filter(prop1*100 + prop2*100 == 0.3*100)
```

```
# A tibble: 1 × 3  
  id    prop1 prop2  
  <chr> <dbl> <dbl>  
1 A      0.1   0.2
```

Better:

```
df ▶  
  filter(near(prop1 + prop2, 0.3))
```

```
# A tibble: 1 × 3  
  id    prop1 prop2  
  <chr> <dbl> <dbl>  
1 A      0.1   0.2
```

# Zero Counts in dplyr

```
df ← read_csv(here("data", "first_terms.csv"))
```

```
df
```

```
# A tibble: 280 × 4
```

	pid	start_year	party	sex
	<dbl>	<date>	<chr>	<chr>
1	3160	2013-01-03	Republican	M
2	3161	2013-01-03	Democrat	F
3	3162	2013-01-03	Democrat	M
4	3163	2013-01-03	Republican	M
5	3164	2013-01-03	Democrat	M
6	3165	2013-01-03	Republican	M
7	3166	2013-01-03	Republican	M
8	3167	2013-01-03	Democrat	F
9	3168	2013-01-03	Republican	M
10	3169	2013-01-03	Democrat	M

```
# i 270 more rows
```



# Zero Counts in dplyr

```
df >
  group_by(start_year, party, sex) >
  summarize(N = n()) >
  mutate(freq = N / sum(N))
```

```
# A tibble: 14 × 5
```

```
# Groups:   start_year, party [8]
```

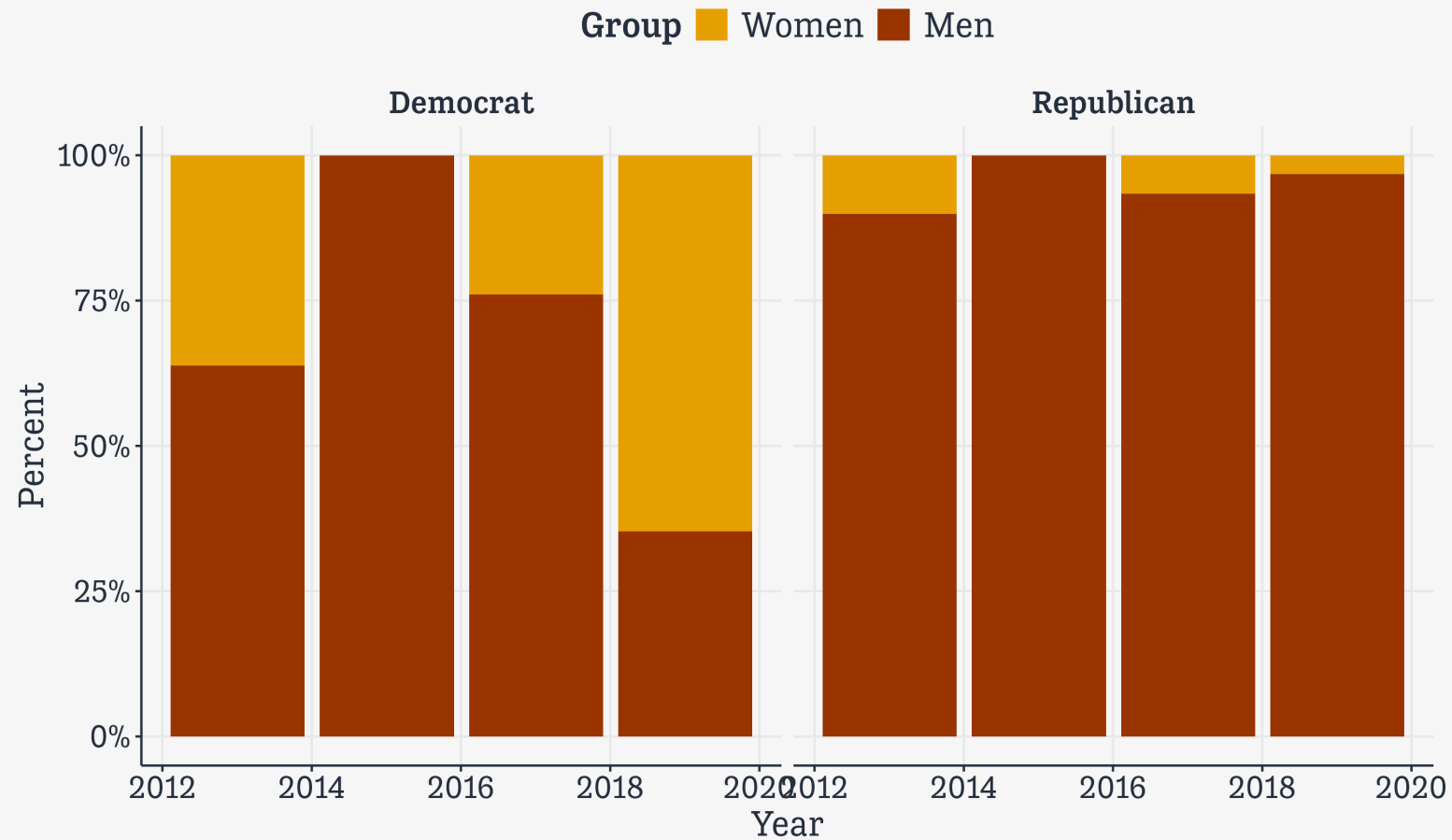
	start_year	party	sex	N	freq
	<date>	<chr>	<chr>	<int>	<dbl>
1	2013-01-03	Democrat	F	21	0.362
2	2013-01-03	Democrat	M	37	0.638
3	2013-01-03	Republican	F	8	0.101
4	2013-01-03	Republican	M	71	0.899
5	2015-01-03	Democrat	M	1	1
6	2015-01-03	Republican	M	5	1
7	2017-01-03	Democrat	F	6	0.24
8	2017-01-03	Democrat	M	19	0.76
9	2017-01-03	Republican	F	2	0.0667
10	2017-01-03	Republican	M	28	0.933
11	2019-01-03	Democrat	F	33	0.647
12	2019-01-03	Democrat	M	18	0.353
13	2019-01-03	Republican	F	1	0.0323
14	2019-01-03	Republican	M	30	0.968

# Zero Counts in dplyr

```
p_col ← df ▷  
  group_by(start_year, party, sex) ▷  
  summarize(N = n()) ▷  
  mutate(freq = N / sum(N)) ▷  
  ggplot(aes(x = start_year,  
             y = freq,  
             fill = sex)) +  
  geom_col() +  
  scale_y_continuous(labels = scales::percent) +  
  scale_fill_manual(values = sex_colors, labels = c("Women", "Men")) +  
  labs(x = "Year", y = "Percent", fill = "Group") +  
  facet_wrap(~ party)
```

# Zero Counts in dplyr

```
p_col
```

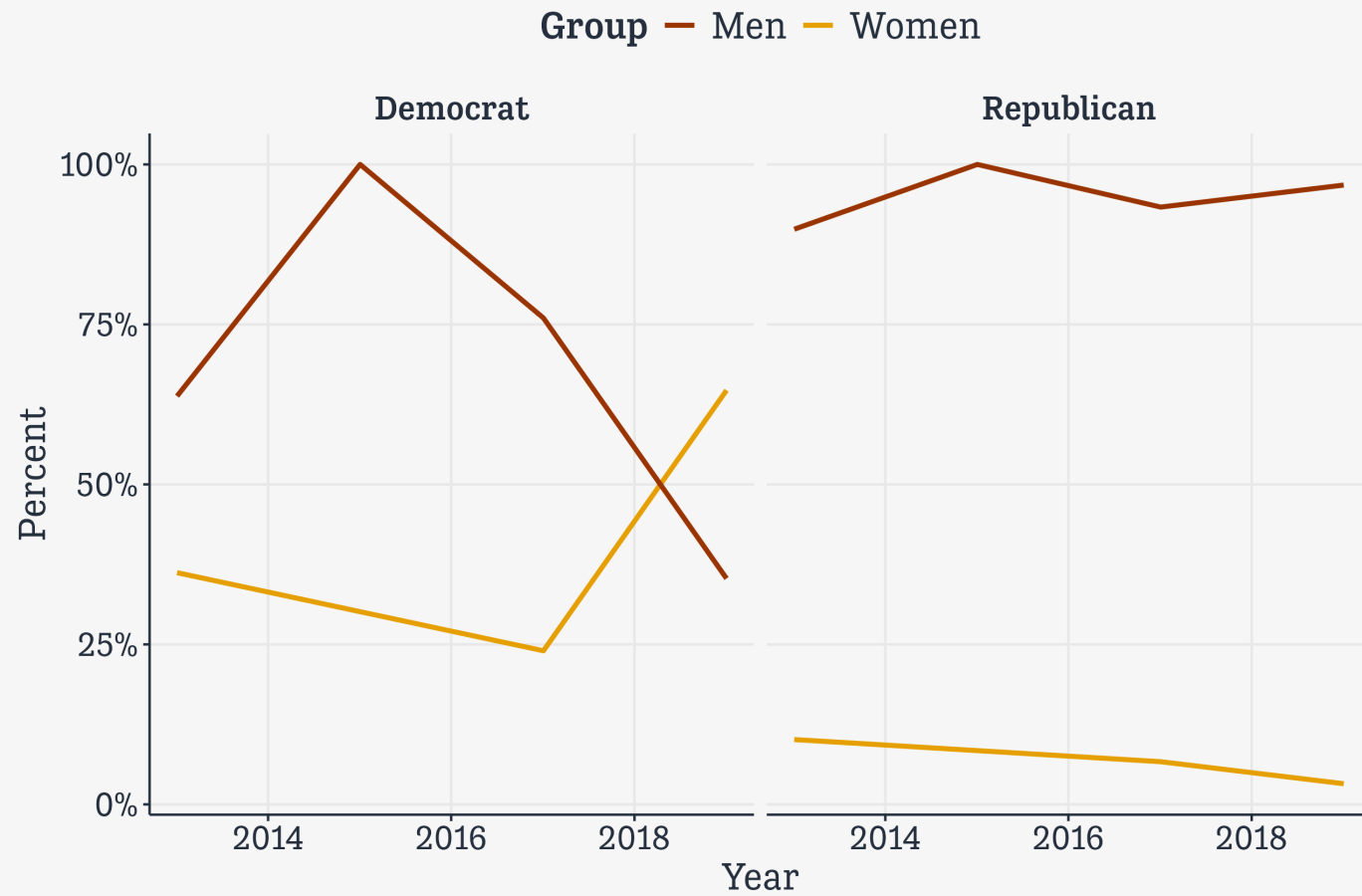


## 2. Zero Counts in dplyr

```
p_line ← df ▷  
  group_by(start_year, party, sex) ▷  
  summarize(N = n()) ▷  
  mutate(freq = N / sum(N)) ▷  
  ggplot(aes(x = start_year,  
             y = freq,  
             color = sex)) +  
  geom_line(size = 1.1) +  
  scale_y_continuous(labels = scales::percent) +  
  scale_color_manual(values = sex_colors, labels = c("Women", "Men")) +  
  guides(color = guide_legend(reverse = TRUE)) +  
  labs(x = "Year", y = "Percent", color = "Group") +  
  facet_wrap(~ party)
```

# Zero Counts in dplyr

```
p_line
```



# Option 1: factors and `.drop`

Factors are for categorical variables and are stored differently from characters.

This can matter when modeling, and also now.

```
df_f <- df %>%  
  mutate(party_f = factor(party))
```

```
df_f
```

```
# A tibble: 280 × 5  
  pid start_year party    sex party_f  
  <dbl> <date>    <chr>  <chr> <fct>  
1  3160 2013-01-03 Republican M    Republican  
2  3161 2013-01-03 Democrat  F    Democrat  
3  3162 2013-01-03 Democrat  M    Democrat  
4  3163 2013-01-03 Republican M    Republican  
5  3164 2013-01-03 Democrat  M    Democrat  
6  3165 2013-01-03 Republican M    Republican  
7  3166 2013-01-03 Republican M    Republican  
8  3167 2013-01-03 Democrat  F    Democrat  
9  3168 2013-01-03 Republican M    Republican  
10 3169 2013-01-03 Democrat  M    Democrat  
# i 270 more rows
```

# Option 1: **factors** and **.drop**

```
df_f >
  group_by(party_f) >
  tally()
```

```
# A tibble: 2 × 2
  party_f      n
  <fct>    <int>
1 Democrat    135
2 Republican  145
```

Factors are integer values with named labels, or *levels*:

```
typeof(df_f$party_f)
```

```
[1] "integer"
```

```
levels(df_f$party_f)
```

```
[1] "Democrat"  "Republican"
```

# Option 1: **factors** and **.drop**

By default, unused levels won't display:

```
df_f <- df >
mutate(party_f = factor(party,
                        levels = c("Democrat",
                                   "Republican",
                                   "Libertarian")))

df_f >
group_by(party_f) >
tally()
```

```
# A tibble: 2 × 2
  party_f      n
  <fct>    <int>
1 Democrat    135
2 Republican   145
```

```
levels(df_f$party_f)
```

```
[1] "Democrat" "Republican" "Libertarian"
```



# Option 1: factors and `.drop`

By default, unused levels won't display:

```
df >
  mutate(across(where(is.character), as_factor)) >
  group_by(start_year, party, sex) >
  summarize(N = n()) >
  mutate(freq = N / sum(N))
```

```
# A tibble: 14 × 5
```

```
# Groups:   start_year, party [8]
```

	start_year	party	sex	N	freq
	<date>	<fct>	<fct>	<int>	<dbl>
1	2013-01-03	Republican	M	71	0.899
2	2013-01-03	Republican	F	8	0.101
3	2013-01-03	Democrat	M	37	0.638
4	2013-01-03	Democrat	F	21	0.362
5	2015-01-03	Republican	M	5	1
6	2015-01-03	Democrat	M	1	1
7	2017-01-03	Republican	M	28	0.933
8	2017-01-03	Republican	F	2	0.0667
9	2017-01-03	Democrat	M	19	0.76
10	2017-01-03	Democrat	F	6	0.24
11	2019-01-03	Republican	M	30	0.968
12	2019-01-03	Republican	F	1	0.0323
13	2019-01-03	Democrat	M	18	0.353
14	2019-01-03	Democrat	F	33	0.647

# Option 1: **factors** and **.drop**

You can make **dplyr** keep empty factor levels though:

```
df >
  mutate(across(where(is.character), as_factor)) >
  group_by(start_year, party, sex, .drop = FALSE) >
  summarize(N = n()) >
  mutate(freq = N / sum(N))
```

```
# A tibble: 16 × 5
# Groups:   start_year, party [8]
  start_year party      sex      N  freq
  <date>      <fct>      <fct> <int> <dbl>
1 2013-01-03 Republican M        71 0.899
2 2013-01-03 Republican F         8 0.101
3 2013-01-03 Democrat  M        37 0.638
4 2013-01-03 Democrat  F        21 0.362
5 2015-01-03 Republican M         5 1
6 2015-01-03 Republican F         0 0
7 2015-01-03 Democrat  M         1 1
8 2015-01-03 Democrat  F         0 0
9 2017-01-03 Republican M        28 0.933
10 2017-01-03 Republican F         2 0.0667
11 2017-01-03 Democrat  M        19 0.76
12 2017-01-03 Democrat  F         6 0.24
13 2019-01-03 Republican M        30 0.968
14 2019-01-03 Republican F         1 0.0323
15 2019-01-03 Democrat  M        18 0.353
```

## Option 2: **ungroup()** and **complete()**

Maybe you don't want to deal with factors.

```
df_c <- df ▷  
  group_by(start_year, party, sex) ▷  
  summarize(N = n()) ▷  
  mutate(freq = N / sum(N)) ▷  
  ungroup() ▷  
  complete(start_year, party, sex,  
            fill = list(N = 0, freq = 0))
```

# Option 2: `ungroup()` and `complete()`

```
df_c
```

```
# A tibble: 16 × 5
  start_year party    sex      N  freq
  <date>    <chr>  <chr> <int> <dbl>
1 2013-01-03 Democrat F      21 0.362
2 2013-01-03 Democrat M      37 0.638
3 2013-01-03 Republican F       8 0.101
4 2013-01-03 Republican M      71 0.899
5 2015-01-03 Democrat F       0 0
6 2015-01-03 Democrat M       1 1
7 2015-01-03 Republican F       0 0
8 2015-01-03 Republican M       5 1
9 2017-01-03 Democrat F       6 0.24
10 2017-01-03 Democrat M      19 0.76
11 2017-01-03 Republican F       2 0.0667
12 2017-01-03 Republican M      28 0.933
13 2019-01-03 Democrat F      33 0.647
14 2019-01-03 Democrat M      18 0.353
15 2019-01-03 Republican F       1 0.0323
16 2019-01-03 Republican M      30 0.968
```

## Option 2: `ungroup()` and `complete()`

```
p_out <- df_c >
  ggplot(aes(x = start_year,
             y = freq,
             color = sex)) +
  geom_line(size = 1.1) +
  scale_y_continuous(labels = scales::percent) +
  scale_color_manual(values = sex_colors, labels = c("Women", "Men")) +
  guides(color = guide_legend(reverse = TRUE)) +
  labs(x = "Year", y = "Percent", color = "Group") +
  facet_wrap(~ party)
```

# Option 2: `ungroup()` and `complete()`

`p_out`

