

Manipulating tables with `dplyr`

Data Wrangling, Session 3 (contd)

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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      NA
2 2020-01-06 2020-02 Austria AUT 8932664    NA     NA     NA      NA      NA
3 2020-01-13 2020-03 Austria AUT 8932664    NA     NA     NA      NA      NA
4 2020-01-20 2020-04 Austria AUT 8932664    NA     NA     NA      NA      NA
5 2020-01-27 2020-05 Austria AUT 8932664    NA     NA     NA      NA      NA
6 2020-02-03 2020-06 Austria AUT 8932664    NA     NA     NA      NA      NA
7 2020-02-10 2020-07 Austria AUT 8932664    NA     NA     NA      NA      NA
8 2020-02-17 2020-08 Austria AUT 8932664    NA     NA     NA      NA      NA
9 2020-02-24 2020-09 Austria AUT 8932664    12      0     12      0      0
10 2020-03-02 2020-10 Austria AUT 8932664   115      0    127      0      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 \leq 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` vignette on 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> <dbl> <lgcl>        <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 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> <dbl> <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
```

Not super-useful quite yet, but if our task had more steps ...

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> <dbl> <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     83.0  
4 2021-03-04 NY     36 death    38796 Deaths           61     82.6  
5 2021-03-03 NY     36 death    38735 Deaths           75     88.0  
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  
# i 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 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  Bach... 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  Bach... 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>, padege <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 childs sibs degree race sex   region income16
  <dbl> <dbl> <labelled> <dbl> <dbl> <labe> <fct> <fct> <fct> <fct>
1 2016     1 1           47     3 2  Bach... 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  Bach... 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> <label> <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> <label> <dbl>    <dbl> <label> <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 = childs,  
         siblings = sibs) ▷  
  relocate(id)
```

```
# A tibble: 2,867 × 19  
      id region     bigregion   year ballot    age children siblings degree race  
      <dbl> <fct>       <fct>     <dbl> <labe> <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 = childs,  
         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 = childs,  
         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> <labelle> <fct>   <fct>   <fct>  <fct>  
 1     1  2016    47       3 2        3 New E.. Northeast Bach... White  
 2     2  2016    61       0 3        1 New E.. Northeast High ... White  
 3     3  2016    72       2 3        2 New E.. Northeast Bach... 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 = childs,  
         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
# ... with 6 more variables: vote_share_change <dbl>,
#   total_votes_cast <int>, vrank <int>, turnout <dbl>,
#   fname <chr>, lname <chr>
# ... with 13 variables: cid <chr>, constituency <chr>,
#   electorate <int>, party_name <chr>, candidate <chr>,
#   votes <int>, vote_share_percent <dbl>, ...
```

cid	constituency	electorate	party_name	candidate	votes	vote_share_percent
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	Independen...	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

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 E14000... Norfolk Sou...     78455 Green     Pallavi ...  1645            3.2
2 E14000... Norfolk Sou...     78455 Liberal D... Josie Ra...  4166            8.1
3 E14000... Stafford        72572 Conservat... Theo Cla... 29992           58.6
4 E14001... Wycombe         78094 Green     Peter Si...  1454            2.7
5 S14000... East Kilbri...    81224 UKIP      David Ma...  559             1
6 E14000... High Peak       74343 Green     Robert H...  1148            2.1
7 E14000... Hammersmith    74759 Liberal D... Jessie V...  6947           13.4
8 E14001... Wansbeck        63339 Liberal D... Stephen ...  2539            6.3
9 E14000... Bosworth        81537 Liberal D... Michael ...  9096           16.1
10 E14000... Crewe & Nan...  80321 Labour     Laura Sm... 20196           37.4
# ℹ 6 more variables: vote_share_change <dbl>, total_votes_cast <int>,
#   vrank <int>, turnout <dbl>, fname <chr>, lname <chr>
```

Example: UK Election Data

A one-column tibble 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				
	vote_share_percent				
<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	Independen...	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					

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
```

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  
# i 3 variables: id <chr>, prop1 <dbl>, prop2 <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 Democratic F
3 3162 2013-01-03 Democratic M
4 3163 2013-01-03 Republican M
5 3164 2013-01-03 Democratic M
6 3165 2013-01-03 Republican M
7 3166 2013-01-03 Republican M
8 3167 2013-01-03 Democratic F
9 3168 2013-01-03 Republican M
10 3169 2013-01-03 Democratic M
# i 270 more rows
```

Zero Counts in dplyr

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

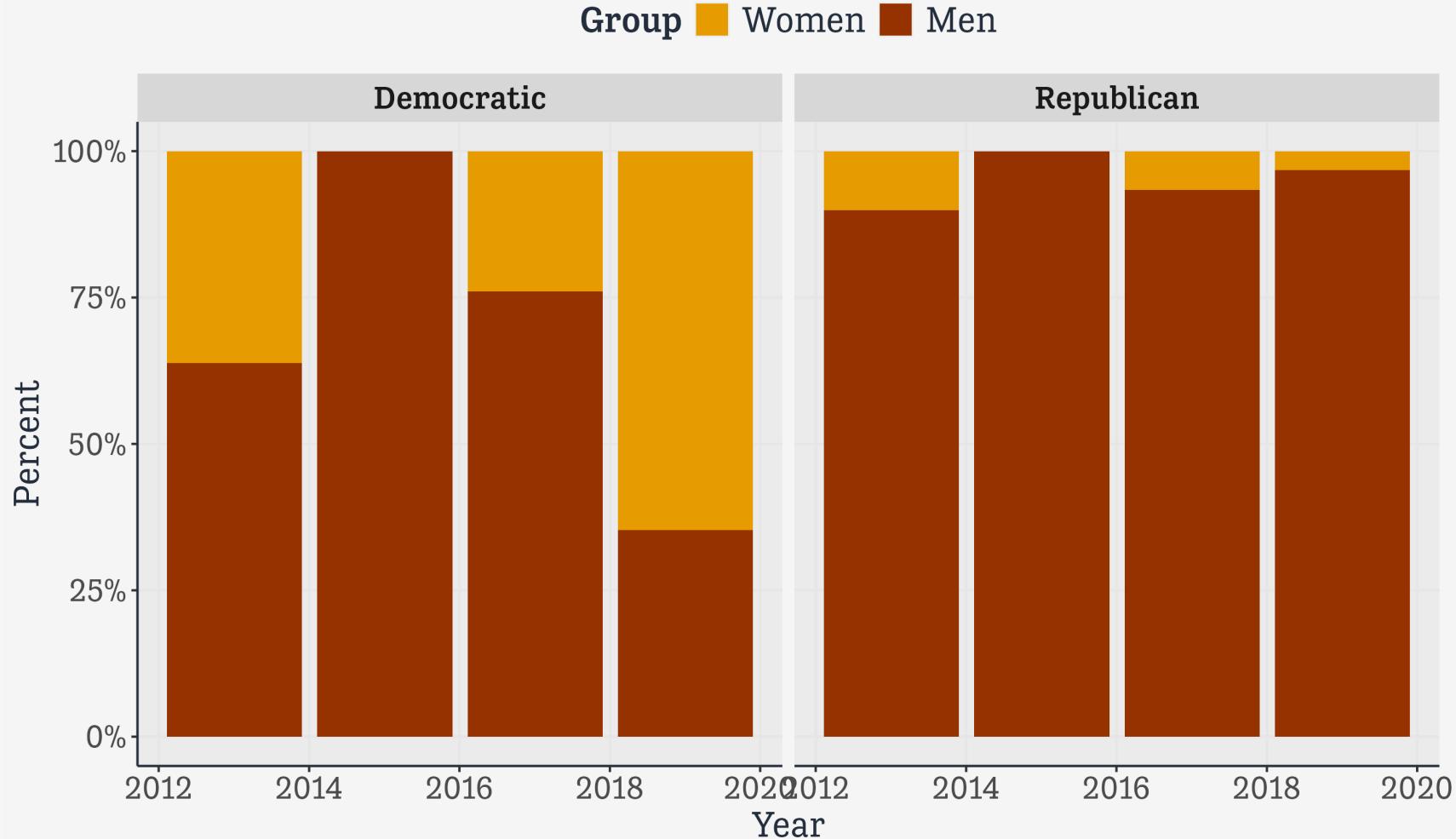
# A tibble: 14 × 5
# Groups:   start_year, party [8]
  start_year party     sex     N   freq
  <date>    <chr>    <chr> <int> <dbl>
1 2013-01-03 Democratic F      21 0.362
2 2013-01-03 Democratic M     37 0.638
3 2013-01-03 Republican F     8 0.101
4 2013-01-03 Republican M    71 0.899
5 2015-01-03 Democratic M     1 1
6 2015-01-03 Republican M     5 1
7 2017-01-03 Democratic F     6 0.24
8 2017-01-03 Democratic 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 Democratic F    33 0.647
12 2019-01-03 Democratic 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

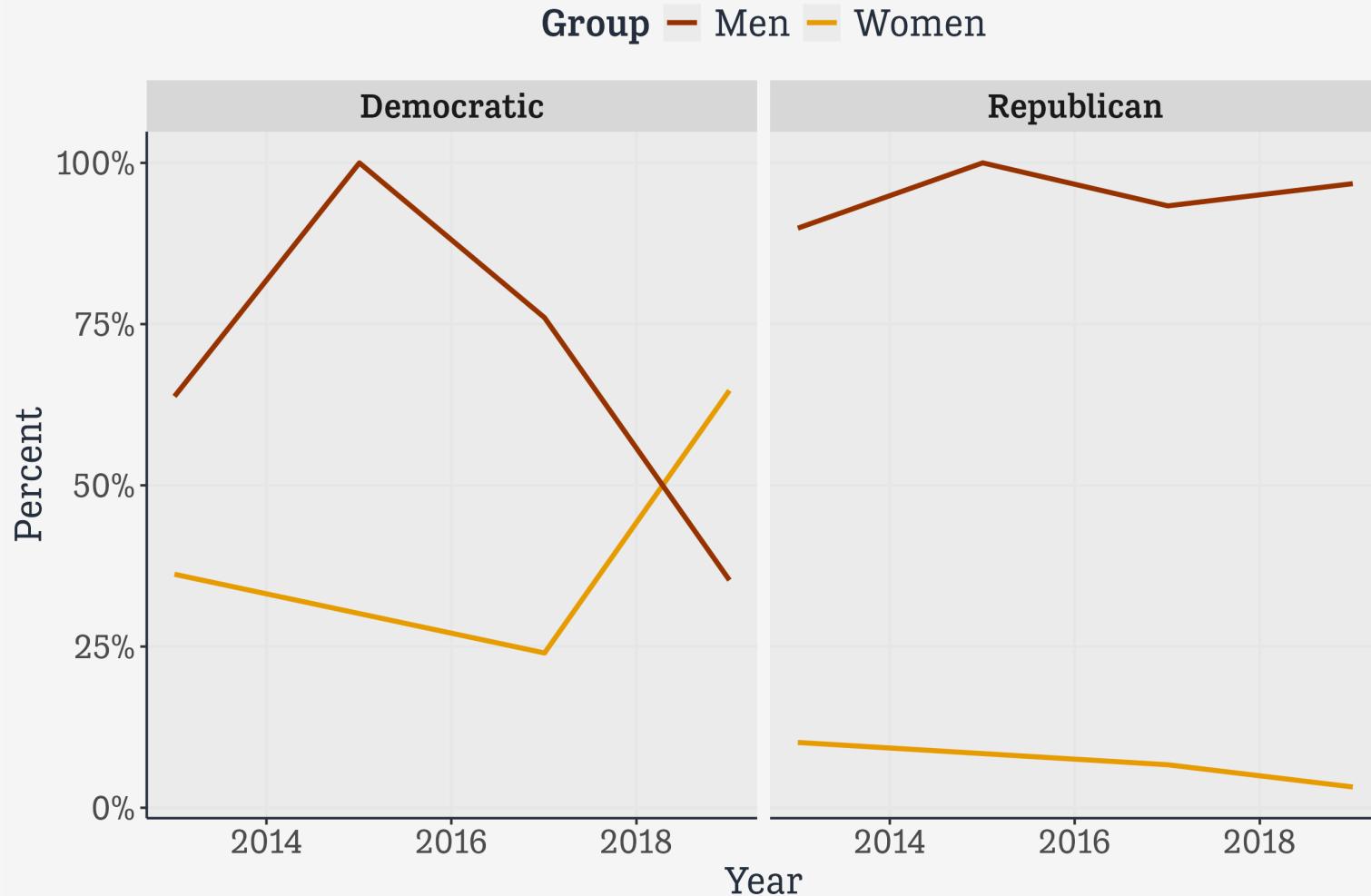


2. Zero Counts in dplyr

```
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 Democratic F   Democratic  
3 3162 2013-01-03 Democratic M   Democratic  
4 3163 2013-01-03 Republican M   Republican  
5 3164 2013-01-03 Democratic M   Democratic  
6 3165 2013-01-03 Republican M   Republican  
7 3166 2013-01-03 Republican M   Republican  
8 3167 2013-01-03 Democratic F   Democratic  
9 3168 2013-01-03 Republican M   Republican  
10 3169 2013-01-03 Democratic M  Democratic  
# 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 Democratic   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] "Democratic" "Republican"
```

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

By default, unused levels won't display:

```
df_f <- df ▷  
  mutate(party_f = factor(party,  
                          levels = c("Democratic",  
                                    "Republican",  
                                    "Libertarian")))  
df_f ▷  
  group_by(party_f) ▷  
  tally()
```

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

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

```
[1] "Democratic"  "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 Democratic M     37 0.638  
4 2013-01-03 Democratic F     21 0.362  
5 2015-01-03 Republican M      5 1  
6 2015-01-03 Democratic 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 Democratic M     19 0.76  
10 2017-01-03 Democratic 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 Democratic M     18 0.353  
14 2019-01-03 Democratic 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 Democratic M     37 0.638
4 2013-01-03 Democratic F     21 0.362
5 2015-01-03 Republican M      5 1
6 2015-01-03 Republican F      0 0
7 2015-01-03 Democratic M      1 1
8 2015-01-03 Democratic 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 Democratic M     19 0.76
12 2017-01-03 Democratic 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 Democratic 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 Democratic F     21 0.362
2 2013-01-03 Democratic 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 Democratic F    0 0
6 2015-01-03 Democratic M    1 1
7 2015-01-03 Republican F    0 0
8 2015-01-03 Republican M    5 1
9 2017-01-03 Democratic F    6 0.24
10 2017-01-03 Democratic 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 Democratic F   33 0.647
14 2019-01-03 Democratic 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

