Manipulating Tables with dplyr (contd)

Data Wrangling: Session 3

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Window functions and moving averages

Load our libraries

```r
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.

```r
## 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.

```r
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

```r
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  1
```

An application

We can write the expression directly:

```r
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**

But we could also write a function to do this.

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 ...

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.

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

Tidy moving averages with `slider`

```r
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
## # ℹ 361 more rows
```

Tidy moving averages with `slider`

```r
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.

Tidy up after yourself 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

```r
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 ▷
  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> <labe> <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

```r
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 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

```r
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

```r
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>,
## #   vrank <int>, turnout <dbl>, fname <chr>, lname <chr>
```

Example: UK Election Data

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

```r
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… Sheffield H…      72763 Labour     Olivia B… 19709               34.6
##  2 E14000… Brigg & Goo…      65939 Green      Jo Baker   1281                3
##  3 E14000… Reading West      74623 Conservat… Alok Sha… 24393               48.4
##  4 S14000… Ochil & Sou…      78776 Conservat… Luke Gra… 22384               38.7
##  5 E14000… Bradford We…      70694 Conservat… Mohammed…  6717               15.2
##  6 E14000… Salford & E…      82202 Labour     Rebecca … 28755               56.8
##  7 W07000… Newport East      58554 The Brexi… Julie Pr…  2454                6.8
##  8 E14000… Arundel & S…      81726 Liberal D… Alison B… 13045               21.2
##  9 S14000… Orkney & Sh…      34211 Conservat… Jennifer…  2287                9.9
## 10 E14000… Folkestone …      88273 Young Peo… Rohen Ka…    80                0.1
## # 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 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

```r
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

```r
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

```r
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
```

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

```r
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>,
## #   vrank <int>, turnout <dbl>, fname <chr>, lname <chr>
```

Counting Twice Over

```r
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
```

Recapping Yesterday and Looking Ahead

Data Wrangling

Kieran Healy
Statistical Horizons, October 2023

Recapping and Looking Ahead

Coding as gardening

Working in RStudio with RMarkdown documents

Recapping and Looking Ahead

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()`

Recapping and Looking Ahead

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>)`

Recapping and Looking Ahead

Expand your `dplyr` actions

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

Tidy up rows with `arrange()`

Recapping and Looking Ahead

Today's sessions

A dplyr shortcut

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

```r
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
```

Notice that 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.

The data is implicitly the first argument

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
```

The data is implicitly the first argument

... is also 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

1. 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 
```

1. Comparisons filtering on proportions

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

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.

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 dlpyr's fault. It's our floating point friend again.

1. Comparisons filtering on proportions

```r
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!

1. 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>
```

1. 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
```

2. Zero Counts in dplyr

```r
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
```

2. Zero Counts in dplyr

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

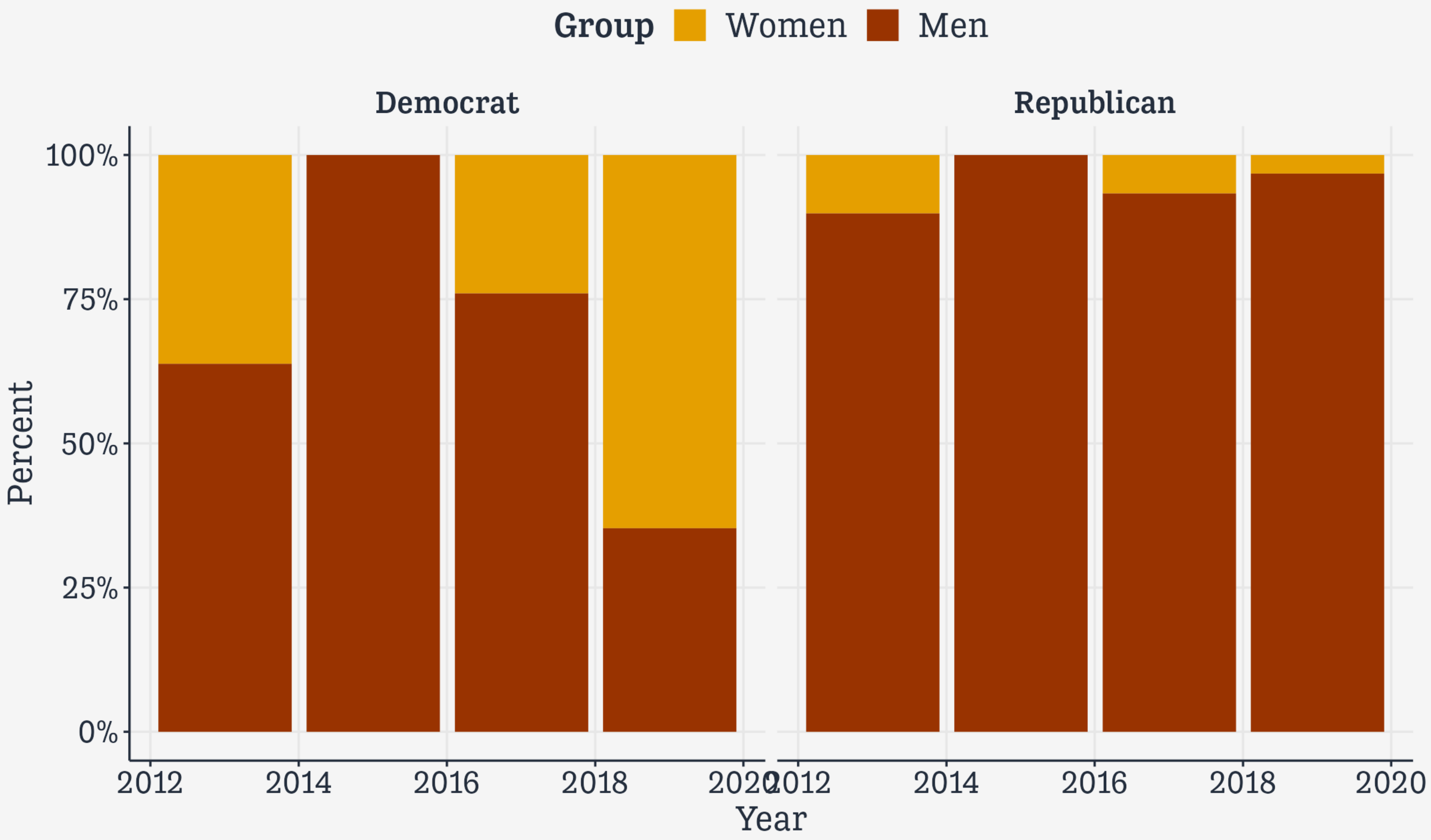
```
## # A tibble: 14 × 5
## # Groups:   start_year, party [8]
##    start_year party      sex       N   freq
##    <date>     <chr>      <chr> <int>  <dbl>
##  1 2013-01-03 Democrat   F        21 0.362
##  2 2013-01-03 Democrat   M        37 0.638
##  3 2013-01-03 Republican F         8 0.101
##  4 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
```

2. Zero Counts in dplyr

```r
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)
```

2. Zero Counts in dplyr

```
p_col
```

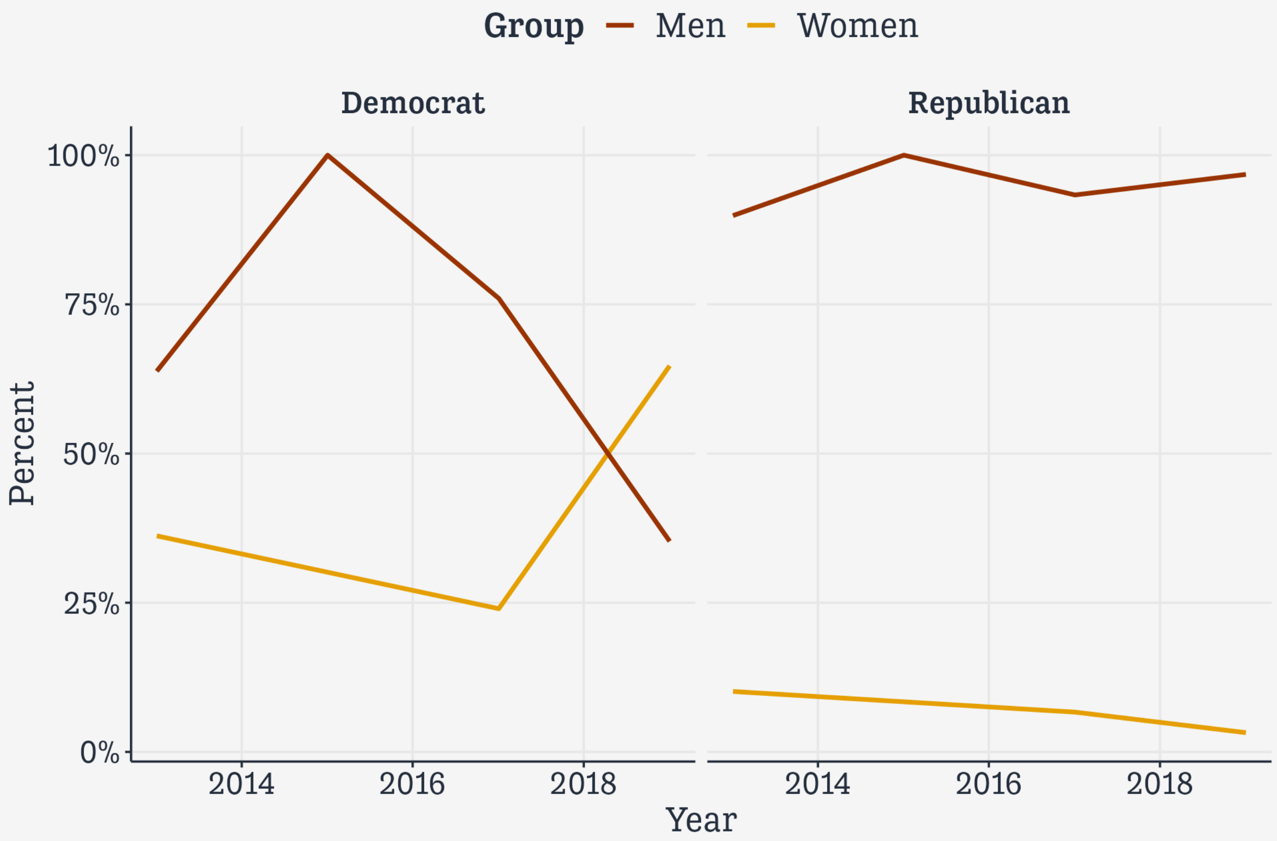


Zero Counts in dplyr

```r
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)
```

2. 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:

```r
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
```

```r
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:

```r
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
## 16 2019-01-03 Democrat   F        33 0.647
```

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()

```r
df_c
```

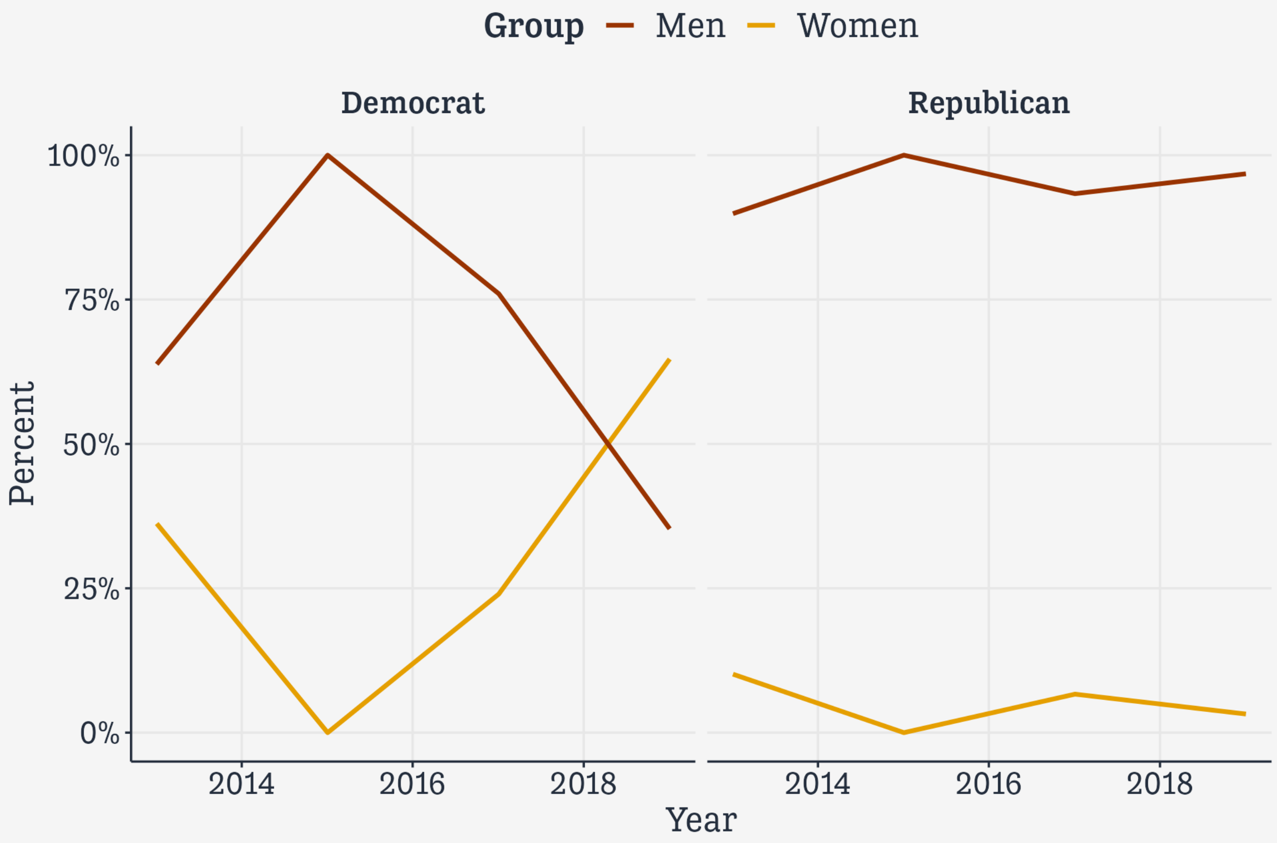
```
## # A tibble: 16 × 5
##    start_year party      sex       N   freq
##    <date>     <chr>      <chr> <int>  <dbl>
##  1 2013-01-03 Democrat   F        21 0.362
##  2 2013-01-03 Democrat   M        37 0.638
##  3 2013-01-03 Republican F         8 0.101
##  4 2013-01-03 Republican M        71 0.899
##  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
```


Group
Men
Women
Democrat
Republican
Percent
Year