AE 03: Joining prognosticators

Suggested answers

APPLICATION EXERCISE ANSWERS

MODIFIED

September 13, 2024

> **Important**
>
> These are suggested answers. This document should be used as reference only, it's not designed to be an exhaustive key.

```r
library(tidyverse)
library(scales)

seers <- read_csv("data/prognosticators.csv")
weather <- read_csv("data/weather-region.csv")
```

Prognosticator success

We previously examined the accuracy rate of Groundhog Day prognosticators.[1] Today we want to work with the original dataset to understand how those accuracy metrics were generated and answer the question: **How does prognosticator accuracy vary by climatic region?**

[1] See ae-01

Let's start by looking at the `seers` data frame.

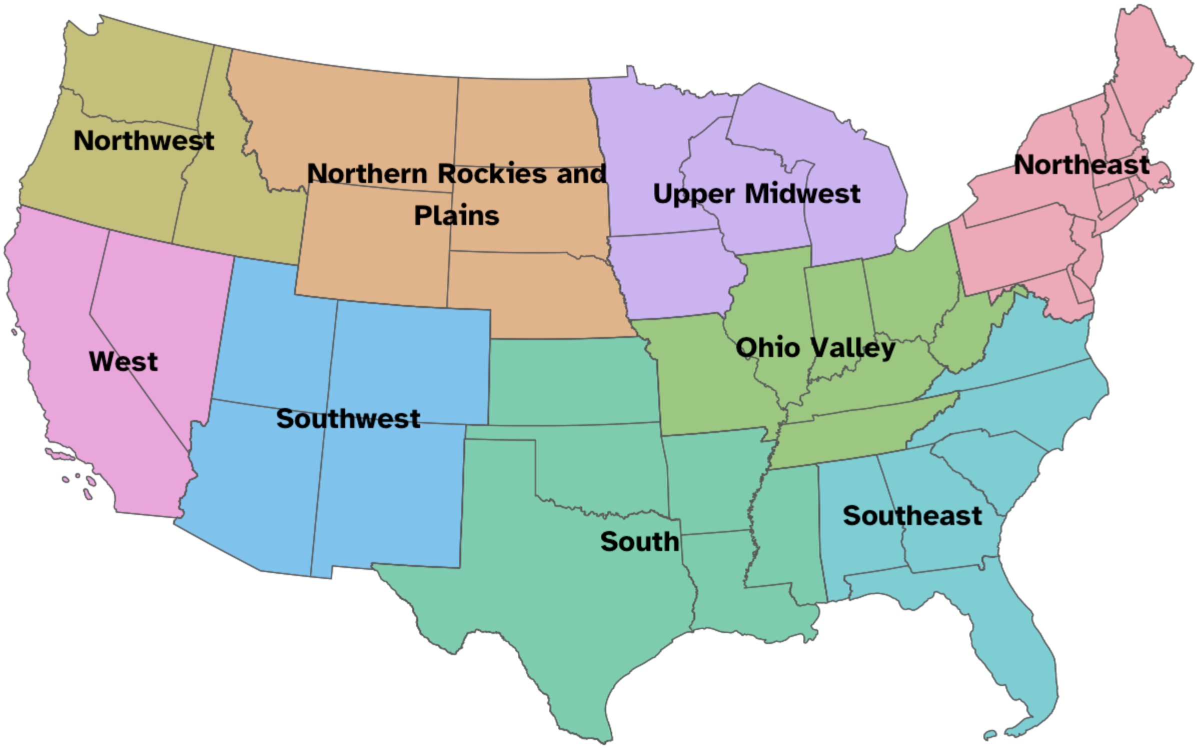
```r
glimpse(seers)
```

```
Rows: 1,710
Columns: 7
$ name            <chr> "Punxsutawney Phil", "Punxsutawney Phil", "Punxsutawne…
$ forecaster_type <chr> "Groundhog", "Groundhog", "Groundhog", "Groundhog", "G…
$ alive           <lgl> TRUE, TRUE, TRUE, TRUE, TRUE, TRUE, TRUE, TRUE, TRUE, …
$ town            <chr> "Punxsutawney", "Punxsutawney", "Punxsutawney", "Punxs…
$ state           <chr> "PA", "PA", "PA", "PA", "PA", "PA", "PA", "PA", "PA", …
$ year            <dbl> 2024, 2023, 2022, 2021, 2020, 2019, 2018, 2017, 2016, …
$ prediction      <chr> "Early Spring", "Late Winter", "Late Winter", "Late Wi…
```

We have the predictions, but our goal is to make a visualization by climate region.[2]

[2] Source: National Weather Service Climate Prediction Center

Climatic regions in the United States



Source: National Climatic Data Center

Join the data frames

Let’s take a look at the weather data frame.

```
glimpse(weather)
```

```
Rows: 5,568
Columns: 13
$ region        <chr> "Northeast", "Northeast", "Northeast", "Northeast", "No…
$ state_abb     <chr> "CT", "CT", "CT", "CT", "CT", "CT", "CT", "CT", "CT", "…
$ id            <dbl> 101, 101, 101, 101, 101, 101, 101, 101, 101, 101, 101, …
$ year          <dbl> 1909, 1910, 1911, 1912, 1913, 1914, 1915, 1916, 1917, 1…
$ avg_temp      <dbl> 28.00, 29.20, 24.90, 23.15, 28.05, 22.05, 27.50, 21.55,…
$ temp_hist     <dbl> 25.58333, 26.09000, 26.16667, 25.85667, 25.63333, 25.52…
$ temp_hist_sd  <dbl> 4.245360, 4.241218, 4.103158, 4.124311, 3.907804, 4.016…
$ temp_sd       <dbl> 4.154767, 4.154767, 4.154767, 4.154767, 4.154767, 4.154…
$ precip        <dbl> 4.005, 2.520, 2.810, 3.570, 3.765, 2.920, 2.330, 3.425,…
$ precip_hist   <dbl> 3.476667, 3.526667, 3.378000, 3.411000, 3.446333, 3.352…
$ precip_hist_sd <dbl> 1.1784719, 1.2081292, 1.1442431, 1.1620681, 1.2039309, …
$ precip_sd      <dbl> 0.9715631, 0.9715631, 0.9715631, 0.9715631, 0.9715631, …
$ outcome        <chr> "Early Spring", "Early Spring", "Early Spring", "Late W…
```

- **Your turn (2 minutes):**
  - Which variable(s) will we use to join the `seers` and `weather` data frames?
  - We want to keep all rows and columns from `seers` and add columns for corresponding weather data. Which join function should we use?
- **Demo:** Join the two data frames and assign the joined data frame to `seers_weather`.

```
seers_weather <- inner_join(
  x = seers, y = weather,
  by = join_by(state == state_abb, year)
)
```

Calculate the variables

- **Demo:** Take a look at the updated `seers` data frame. First we need to calculate for each prediction whether or not the prognostication was correct.

```
seers_weather <- seers_weather |>
  mutate(correct_pred = prediction == outcome)
```

- **Demo:** Calculate the accuracy rate (we'll call it `preds_rate`) for weather predictions using the `summarize()` function in **dplyr**. Note that the function for calculating the mean is `mean()` in R.

```
seers_weather |> # start with seers data frame
  group_by(region) |> # group by region
  summarize(preds_rate = mean(correct_pred)) # calculate accuracy rate
```

```
# A tibble: 9 × 2
  region                      preds_rate
  <chr>                            <dbl>
1 Northeast                        0.491
2 Northern Rockies and Plains      0.574
3 Northwest                        0.442
4 Ohio Valley                      0.557
5 South                            0.506
6 Southeast                        0.568
7 Southwest                        0.667
8 Upper Midwest                    0.5
9 West                             0.286
```

- **Your turn (5 minutes):** Now expand your calculations to also calculate the number of predictions in each region and the standard error of accuracy rate. Store this data frame as `seers_summary`. Recall the formula for the standard error of a sample proportion:

$$SE(\hat{p}) \approx \sqrt{\frac{(\hat{p})(1-\hat{p})}{n}}$$

```r
seers_summary <- seers_weather |>
  group_by(region) |>
  summarize(
    preds_rate = mean(correct_pred),
    preds_n = n(),
    preds_se = sqrt((preds_rate * (1 - preds_rate)) / preds_n)
  )
seers_summary
```

```
# A tibble: 9 × 4
  region                      preds_rate preds_n preds_se
  <chr>                            <dbl>   <int>    <dbl>
1 Northeast                        0.491     696   0.0189
2 Northern Rockies and Plains      0.574      47   0.0721
3 Northwest                        0.442      52   0.0689
4 Ohio Valley                      0.557     280   0.0297
5 South                            0.506      79   0.0562
6 Southeast                        0.568     176   0.0373
7 Southwest                        0.667      36   0.0786
8 Upper Midwest                    0.5       104   0.0490
9 West                             0.286       7   0.171
```

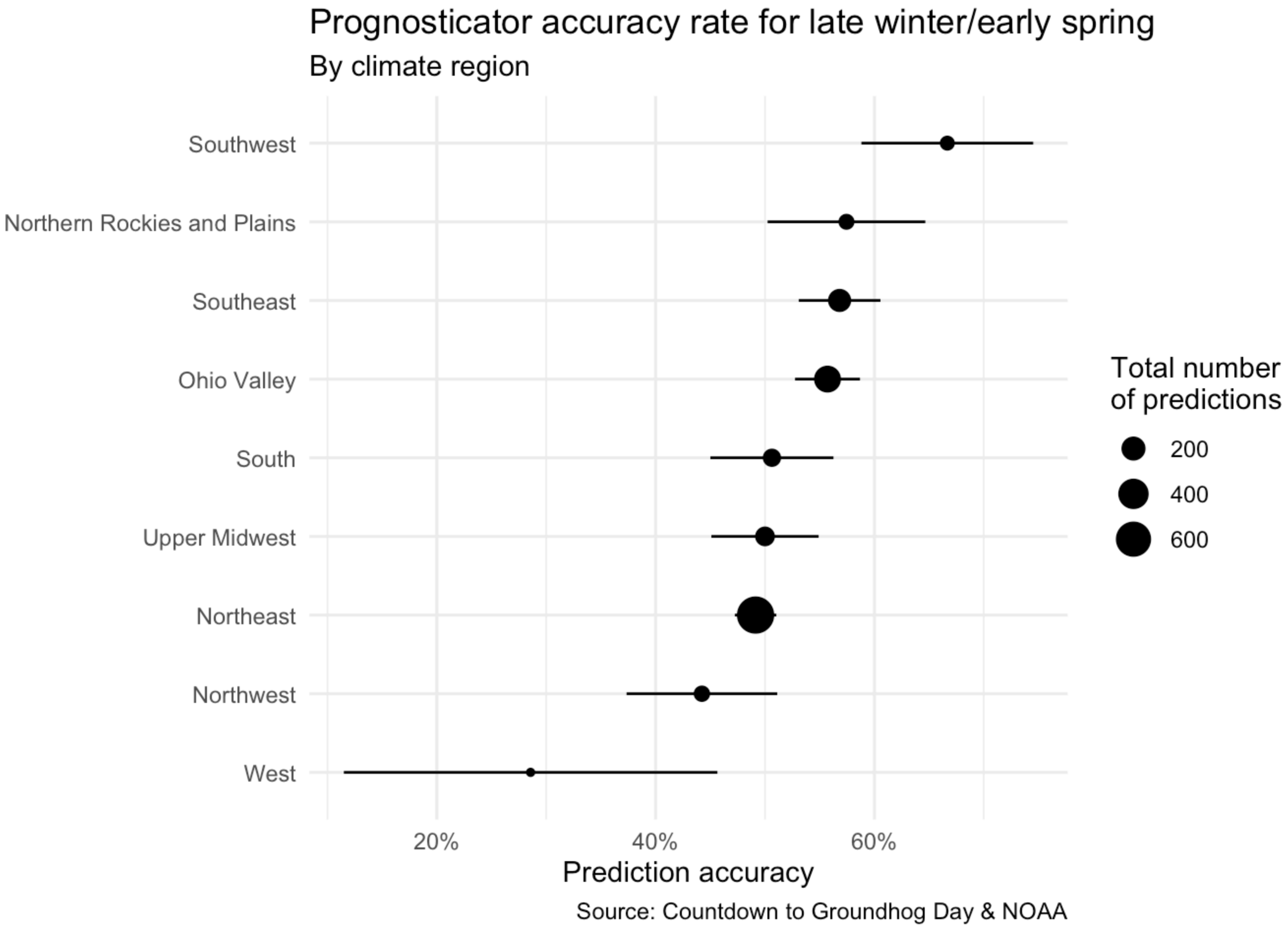
- **Demo:** Take the `seers_summary` data frame and order the results in descending order of accuracy rate.

```r
seers_summary |> # start with seers_summary data frame
  arrange(desc(preds_rate)) # order in descending order of preds_rate
```

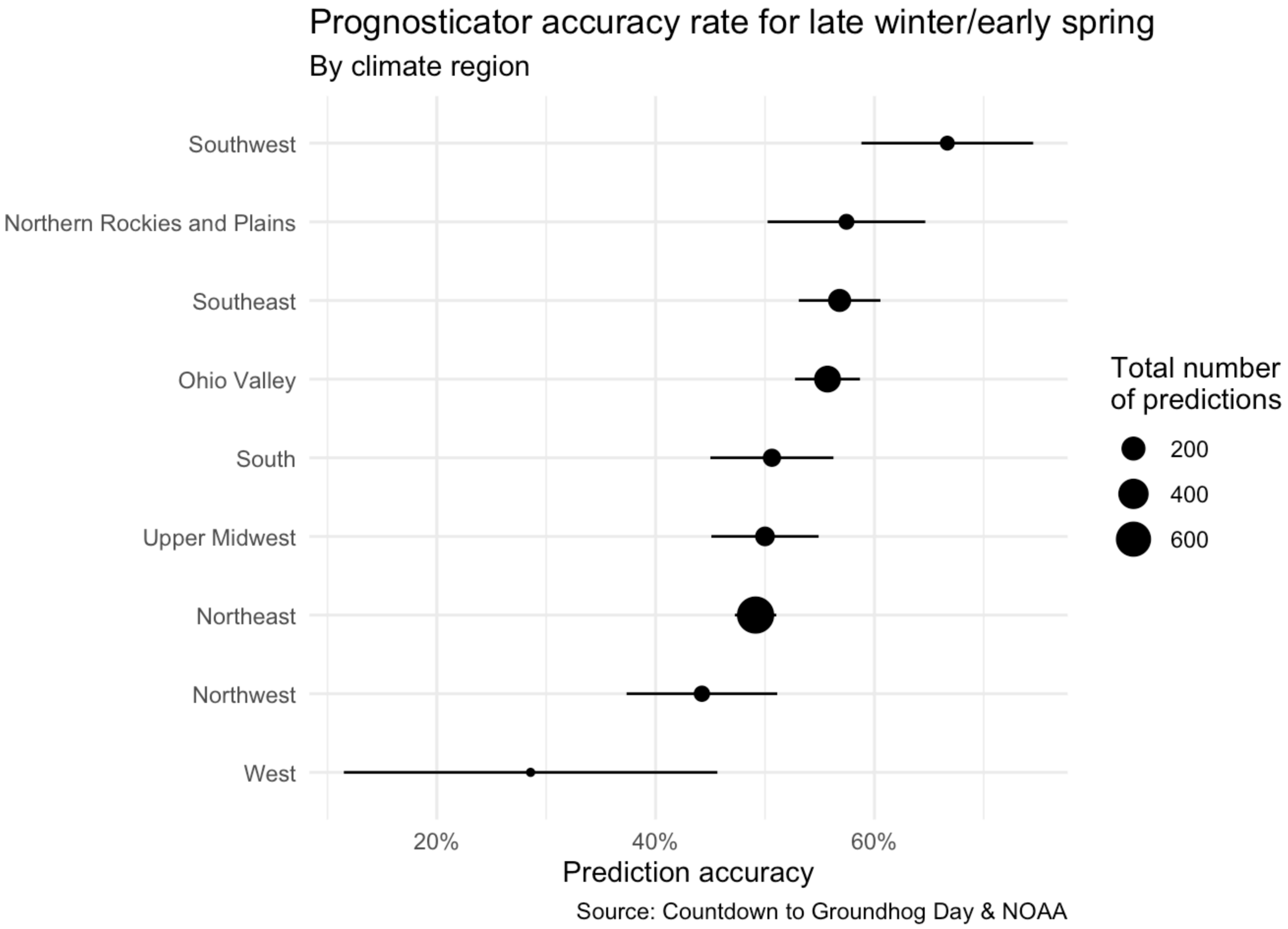
```
# A tibble: 9 × 4
  region                      preds_rate preds_n preds_se
  <chr>                            <dbl>   <int>    <dbl>
1 Southwest                        0.667      36   0.0786
2 Northern Rockies and Plains      0.574      47   0.0721
3 Southeast                        0.568     176   0.0373
4 Ohio Valley                      0.557     280   0.0297
5 South                            0.506      79   0.0562
6 Upper Midwest                    0.5       104   0.0490
7 Northeast                        0.491     696   0.0189
8 Northwest                        0.442      52   0.0689
9 West                             0.286       7   0.171
```

Recreate the plot

- **Demo:** Recreate the following plot using the data frame you have developed so far.



```
seers_summary |>
  mutate(region = fct_reorder(.f = region, .x = preds_rate)) |>
  ggplot(mapping = aes(x = preds_rate, y = region)) +
  geom_point(mapping = aes(size = preds_n)) +
  geom_linerange(mapping = aes(
    xmin = preds_rate - preds_se,
    xmax = preds_rate + preds_se
  )) +
  scale_x_continuous(labels = label_percent()) +
  labs(
    title = "Prognosticator accuracy rate for late winter/early spring",
    subtitle = "By climate region",
    x = "Prediction accuracy",
    y = NULL,
    size = "Total number\nof predictions",
    caption = "Source: Countdown to Groundhog Day & NOAA"
  ) +
  theme_minimal()
```



- **Your turn (time permitting):** Make any other changes you would like to improve it.

```
# add your code here
```

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