Polling and ML Concepts

GOV 1347 Lab: Week III

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Check-In

- Any questions or feedback?

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- Cross-validation
- Elastic-net regularization: Parsimony of a model reduces out-of-sample error
- Bottom-line: An $R^2 > 0.9$ might actually be *bad* for prediction

This Week's Goal

Main Question: How can we best use polls to predict election outcomes?

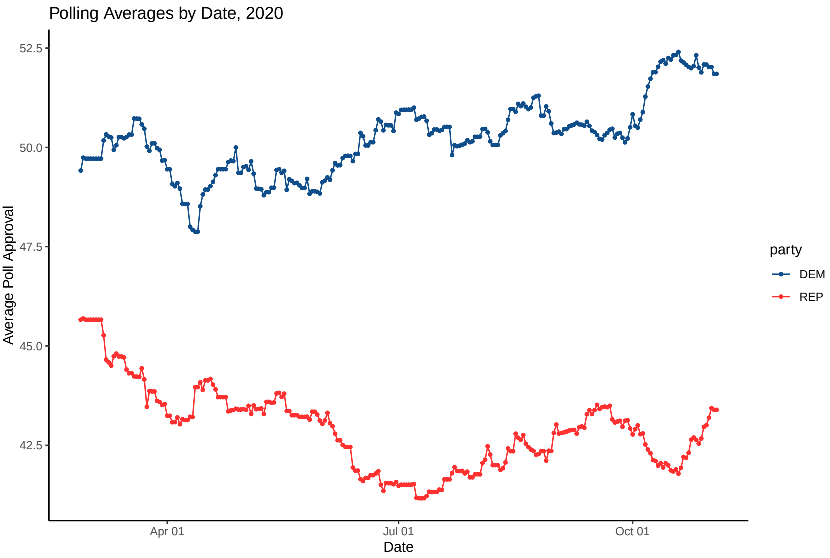
1. **Visualizing Poll Variation Over Time.**
2. **Regularization.**
3. **Regularized Regression with Polling Data.**
4. **(Time Allowing. . .) Ensemble Learning, Model Ensembling, and Combining Predictions.**

FiveThirtyEight Polling Data

Section 1

Visualizing Poll Variation Over Time

How Do Polls Fluctuate Over Time? 2020



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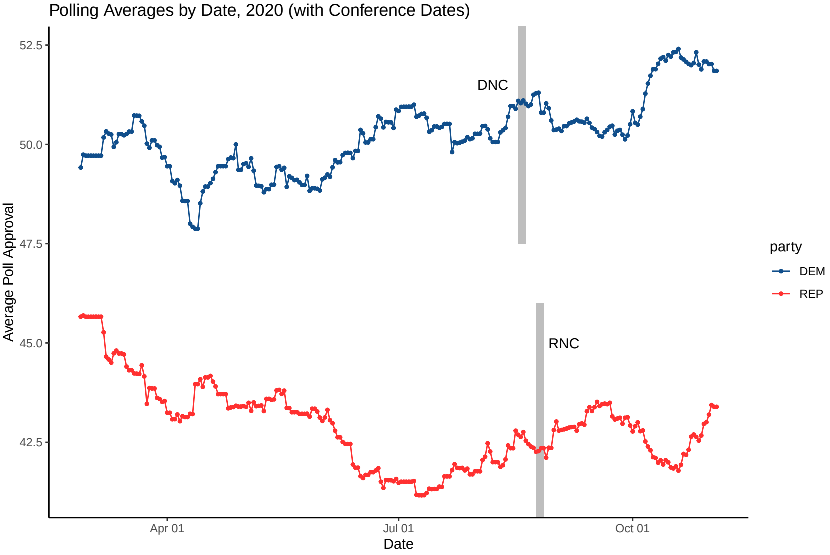

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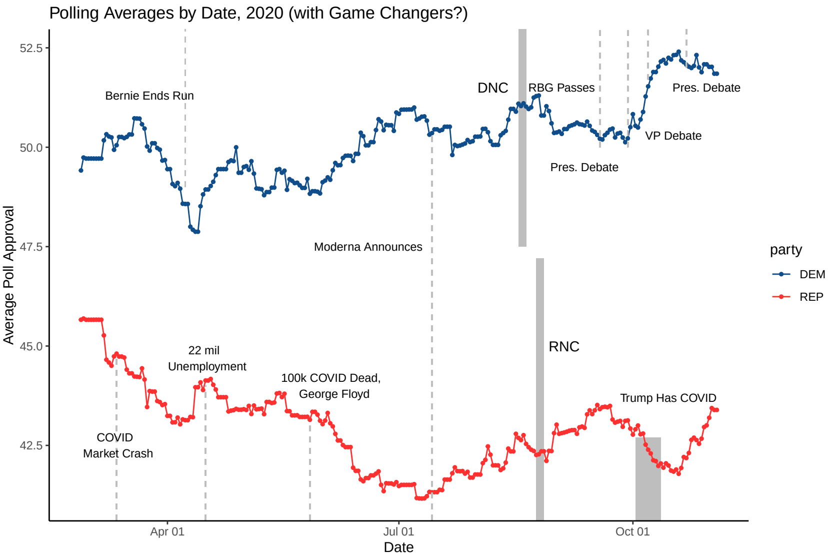

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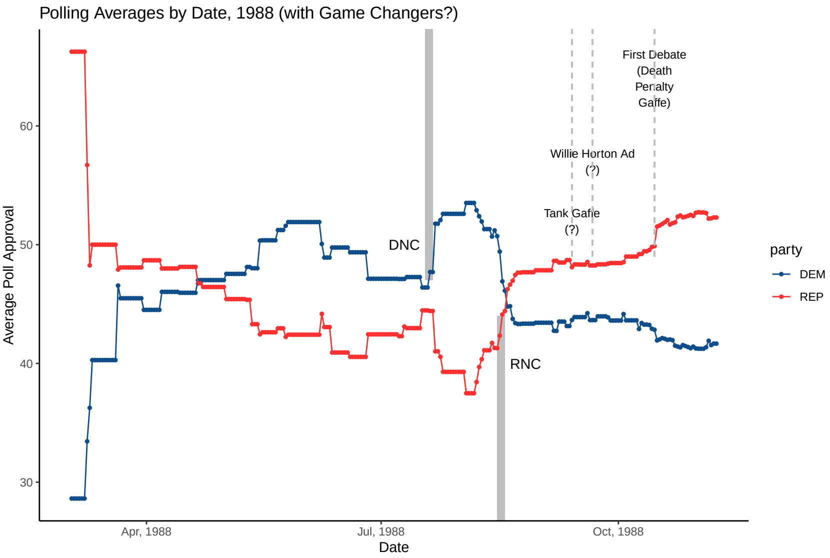
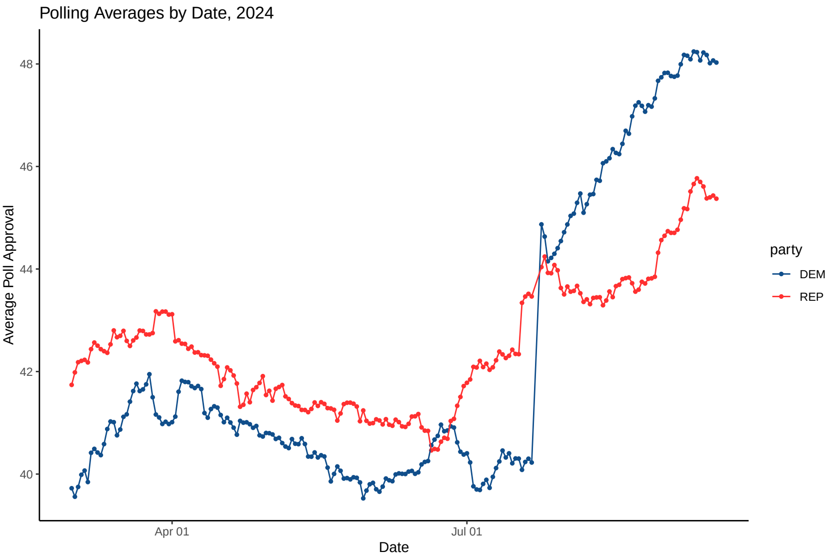


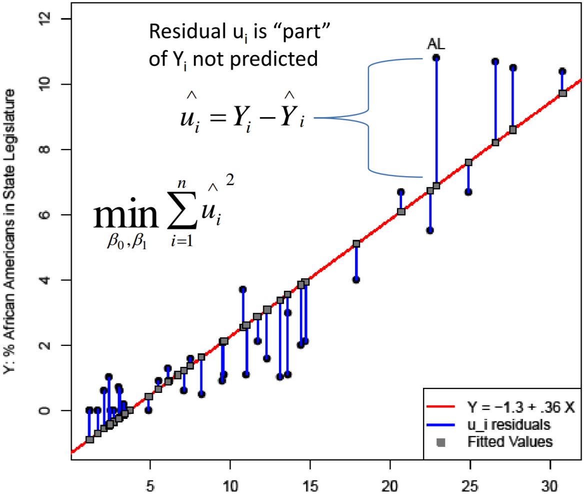
How Do Polls Fluctuate Over Time? 2024



Section 2

Regularization 101

Review of OLS Objective



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- Number of features is less than number of observations ($p < n$).

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  - If we wanted to include all (or, at least $n + 1$) features in our model, OLS will have infinite solutions.
- Bet on sparsity principle: smaller subset of features in model exhibit the strongest effects.

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- Selects for features that are particularly important.

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With complexity (a.k.a. tuning) parameter $\lambda \geq 0$ times the L^2 (Euclidean) norm:

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As $\lambda \to \infty, \beta_j \to 0$. As $\lambda \to 0, \beta_j \to \hat{\beta}_j^{OLS}$. And there are other methods like . . .

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- *Key difference* from Ridge: LASSO coefficients can be exactly zero.

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- If $\alpha = 0$, Elastic-Net is Ridge. If $\alpha = 1$, Elastic-Net is LASSO.

Section 3

Regularized Regression with Polling Data

Using November Polls Average to Predict National Popular Vote

```r
# OLS: Party-stacked pv2p on November polling average.
ols.nov.2 <- lm(pv2p ~ nov_poll,
                data = d_poll_nov)
```

```
##
## Call:
## lm(formula = pv2p ~ nov_poll, data = d_poll_nov)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.6190 -1.6523 -0.5808  1.3629  6.0220
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 17.92577    4.15543   4.314 0.000205 ***
## nov_poll     0.70787    0.09099   7.780 2.97e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.75 on 26 degrees of freedom
```

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- In fact, OLS with 31 weekly polls is inestimable.

What If We Want to Use Weekly Poll Averages Throughout the Election Year?

```
##
## Call:
## lm(formula = paste0("pv2p ~ ", paste0("poll_weeks_left_", 0:30,
##     collapse = " + ")), data = d_poll_weeks_train)
##
## Residuals:
## ALL 28 residuals are 0: no residual degrees of freedom!
##
## Coefficients: (4 not defined because of singularities)
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         28.25534        NaN     NaN      NaN
## poll_weeks_left_0    3.24113        NaN     NaN      NaN
## poll_weeks_left_1    0.02516        NaN     NaN      NaN
## poll_weeks_left_2   -8.87360        NaN     NaN      NaN
## poll_weeks_left_3    7.91455        NaN     NaN      NaN
## poll_weeks_left_4    0.74573        NaN     NaN      NaN
## poll_weeks_left_5    1.41567        NaN     NaN      NaN
## poll_weeks_left_6   -4.58444        NaN     NaN      NaN
## poll_weeks_left_7    4.63361        NaN     NaN      NaN
## poll_weeks_left_8   -0.95121        NaN     NaN      NaN
## poll_weeks_left_9   -1.55307        NaN     NaN      NaN
## poll_weeks_left_10 -1.38062        NaN     NaN      NaN
## poll_weeks_left_11  1.74881        NaN     NaN      NaN
## poll_weeks_left_12 -1.28871        NaN     NaN      NaN
## poll_weeks_left_13 -0.08482        NaN     NaN      NaN
## poll_weeks_left_14  0.87498        NaN     NaN      NaN
## poll_weeks_left_15 -0.16310        NaN     NaN      NaN
## poll_weeks_left_16 -0.34501        NaN     NaN      NaN
## poll_weeks_left_17 -0.38689        NaN     NaN      NaN
## poll_weeks_left_18 -0.06281        NaN     NaN      NaN
## poll_weeks_left_19 -0.17204        NaN     NaN      NaN
## poll_weeks_left_20  1.52230        NaN     NaN      NaN
## poll_weeks_left_21 -0.72487        NaN     NaN      NaN
## poll_weeks_left_22 -2.76531        NaN     NaN      NaN
```

Ridge Regression Using Weekly Poll Averages

```
# Separate data into X and Y for training.
x.train <- d_poll_weeks_train |>
  ungroup() |>
  select(all_of(starts_with("poll_weeks_left_"))) |>
  as.matrix()
y.train <- d_poll_weeks_train$pv2p

# Ridge.
ridge.pollsweeks <- glmnet(x = x.train, y = y.train, alpha = 0)
  # Set ridge using alpha = 0.
```

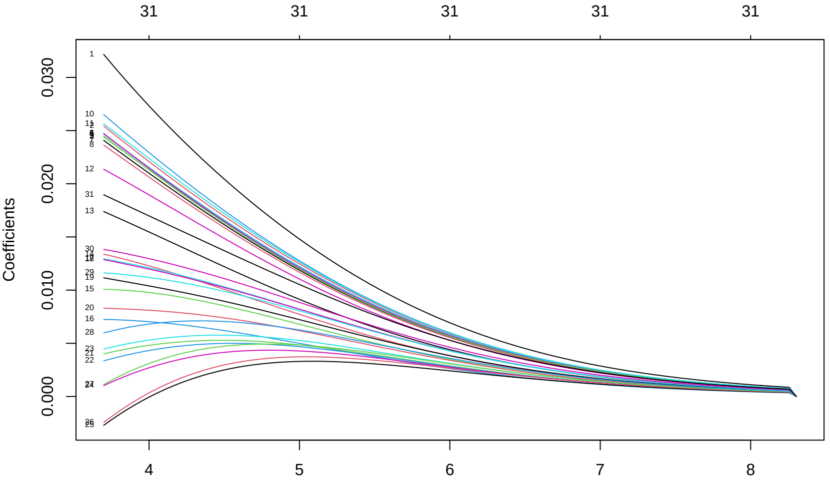
Ridge Regression Using Weekly Poll Averages

```r
# Get particular coefficients.
coef(ridge.pollsweeks, s = 0.1)
```

```
## 32 x 1 sparse Matrix of class "dgCMatrix"
##                              s1
## (Intercept)         29.951147799
## poll_weeks_left_0    0.032163983
## poll_weeks_left_1    0.025440084
## poll_weeks_left_2    0.024404320
## poll_weeks_left_3    0.024688870
## poll_weeks_left_4    0.024695646
## poll_weeks_left_5    0.024725772
## poll_weeks_left_6    0.024080438
## poll_weeks_left_7    0.023636908
## poll_weeks_left_8    0.024487501
## poll_weeks_left_9    0.026498950
## poll_weeks_left_10   0.025642838
## poll_weeks_left_11   0.021361476
## poll_weeks_left_12   0.017386999
## poll_weeks_left_13   0.013378030
## poll_weeks_left_14   0.010078675
## poll_weeks_left_15   0.007248494
## poll_weeks_left_16   0.012943440
## poll_weeks_left_17   0.012879654
## poll_weeks_left_18   0.011157452
## poll_weeks_left_19   0.008302783
## poll_weeks_left_20   0.004012987
## poll_weeks_left_21   0.003350434
## poll_weeks_left_22   0.004458406
## poll_weeks_left_23   0.001019583
## poll_weeks_left_24  -0.002711193
## poll_weeks_left_25  -0.002447895
## poll_weeks_left_26   0.001121142
## poll_weeks_left_27   0.005975853
## poll_weeks_left_28   0.011623984
## poll_weeks_left_29   0.013833925
## poll_weeks_left_30   0.018964139
```

Ridge Shrinkage Visualization

```r
# Visualize shrinkage.
plot(ridge.pollsweeks, xvar = "lambda", label = TRUE)
```



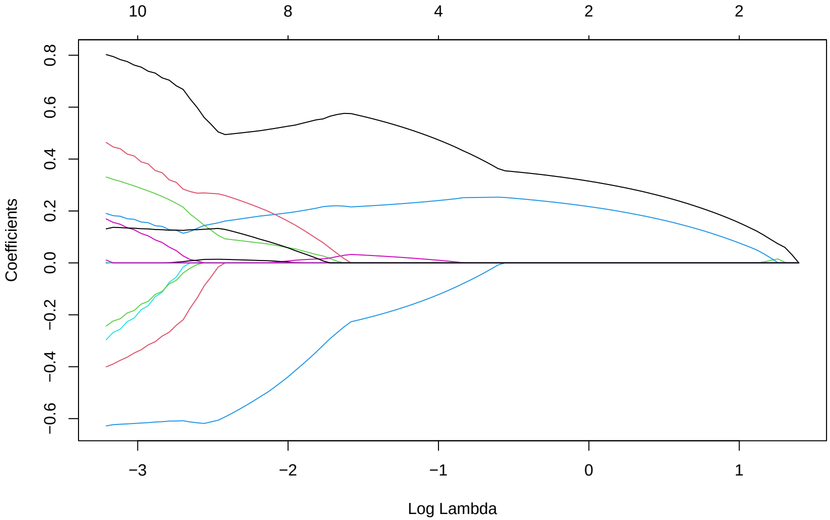
LASSO Using Weekly Poll Averages

```
# Lasso.
lasso.pollsweeks <- glmnet(x = x.train, y = y.train, alpha = 1) # Se
```

```
## 32 x 1 sparse Matrix of class "dgCMatrix"
##                             s1
## (Intercept)        24.57897724
## poll_weeks_left_0   0.50149421
## poll_weeks_left_1   .
## poll_weeks_left_2   .
## poll_weeks_left_3   .
## poll_weeks_left_4   .
## poll_weeks_left_5   0.08461518
## poll_weeks_left_6   .
## poll_weeks_left_7   .
## poll_weeks_left_8   .
## poll_weeks_left_9   0.17064525
## poll_weeks_left_10  .
## poll_weeks_left_11  .
## poll_weeks_left_12  .
## poll_weeks_left_13  .
## poll_weeks_left_14  .
## poll_weeks_left_15  0.01147512
## poll_weeks_left_16  .
## poll_weeks_left_17  .
## poll_weeks_left_18  0.23694416
## poll_weeks_left_19  .
## poll_weeks_left_20  .
## poll_weeks_left_21  .
## poll_weeks_left_22  .
## poll_weeks_left_23  .
## poll_weeks_left_24  .
## poll_weeks_left_25 -0.55693209
## poll_weeks_left_26  .
## poll_weeks_left_27  .
```

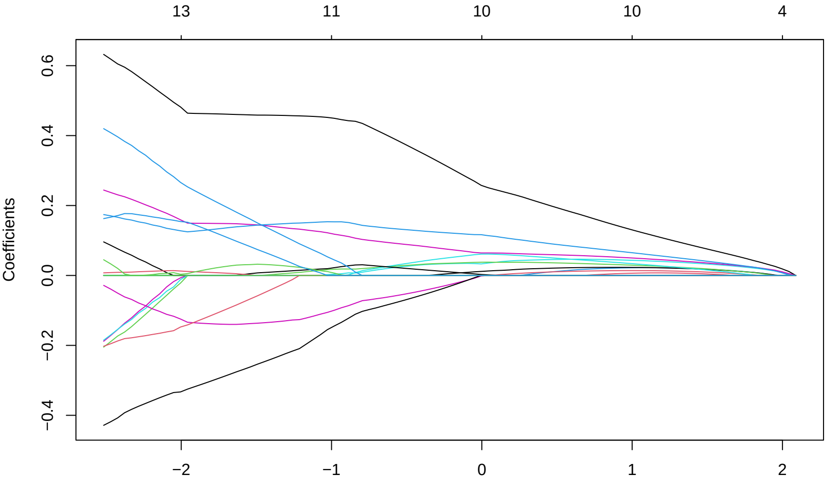
LASSO Shrinkage Visualization

```
plot(lasso.pollsweeks, xvar = "lambda")
```



Elastic-Net Using Weekly Poll Averages

```
# Elastic net.
enet.pollsweeks <- glmnet(x = x.train, y = y.train, alpha = 0.5) # S
```



Cross-Validated Regularized Regression

```
# Can use cross-validated versions to find the optimal values of lambda that minimiz
cv.ridge.pollweeks <- cv.glmnet(x = x.train, y = y.train, alpha = 0)
cv.lasso.pollweeks <- cv.glmnet(x = x.train, y = y.train, alpha = 1)
cv.enet.pollweeks <- cv.glmnet(x = x.train, y = y.train, alpha = 0.5)

# Get minimum lambda values
lambda.min.ridge <- cv.ridge.pollweeks$lambda.min
lambda.min.lasso <- cv.lasso.pollweeks$lambda.min
lambda.min.enet <- cv.enet.pollweeks$lambda.min

# Predict on training data using lambda values that minimize MSE.
(mse.ridge <- mean((predict(ridge.pollsweeks, s = lambda.min.ridge, newx = x.train)
```

```
## [1] 9.575001
```

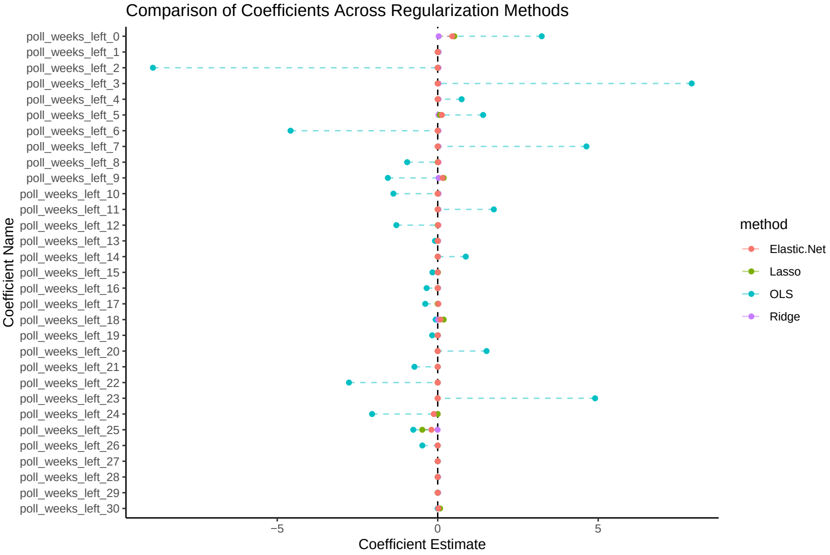
```
(mse.lasso <- mean((predict(lasso.pollsweeks, s = lambda.min.lasso, newx = x.train)
```

```
## [1] 3.663094
```

```
(mse.enet <- mean((predict(enet.pollsweeks, s = lambda.min.enet, newx = x.train) - y
```

```
## [1] 4.228987
```

Comparing Coefficients from OLS, Ridge, LASSO, E-net



Example: 2024 Predictions Using E-Net and Weekly Poll Averages

```r
# First check how many weeks of polling we have for 2024.
d_pollav_natl |>
  filter(year == 2024) |>
  select(weeks_left) |>
  distinct() |>
  range() # Let's take week 30 - 7 as predictors since those are the weeks we have
```

```
## [1]  7 36
```

```r
x.train <- d_poll_weeks_train |>
  ungroup() |>
  select(all_of(paste0("poll_weeks_left_", 7:30))) |>
  as.matrix()
y.train <- d_poll_weeks_train$pv2p
x.test <- d_poll_weeks_test |>
  ungroup() |>
  select(all_of(paste0("poll_weeks_left_", 7:30))) |>
  as.matrix()
```

Example: 2024 Predictions Using E-Net and Weekly Poll Averages

```
# Using elastic-net for simplicity.
set.seed(02138)
enet.poll <- cv.glmnet(x = x.train, y = y.train, alpha = 0.5)
lambda.min.enet.poll <- enet.poll$lambda.min

# Predict 2024 national pv2p share using elastic-net.
(polls.pred <- predict(enet.poll, s = lambda.min.enet.poll, newx =
```

```
##              s1
## [1,] 51.79268
## [2,] 50.65879
```

Section 4

Ensemble Learning, Model Ensembling, and Combining Predictions

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    - The most "cutting edge" methods combine fundamentals and polls using Bayesian methods (e.g., Lauderdale, Linzer (2015))

Ensembling

- Experiment with combining your predictions using vote share, economic fundamentals, and polls, either using combined models with feature selection or ensembles.
- I have a few examples at the bottom of the code and will go into greater detail next week.

Blog Extensions

1. **Incorporating Pollster Quality.** Consider 2016-2024 pollster ratings from FiveThirtyEight. (1.) How much variation is there in pollster quality? (2.) Using tools and knowledge you have gained so far, build a model (or ensemble model) that uses individual polls from 2016 (`president_polls_2016.csv`), 2020 (`...2020.csv`), and 2024 (`...2024.csv`). How does your model compare to the models this week in lab?
2. **State-Level Polls.** How do state-level polls differ from national level polls? Using careful model evaluation techniques (possibly with ensembling), build a predictive model for 2024 using state-level polls.
3. **What Do Forecasters Do?** Based on what you've learned about fundamentals and poll-based forecasts, (1.) briefly summarize Silver (2024) and Morris (2024) and (2.) compare and contrast their approaches. In your opinion, which of the two is the better approach?