Fundamentals II: Incumbency

Gov 1347: Election Analysis

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Harvard University

Today's agenda

- **Review ensemble models**
- **(Slowly) moving from prediction with linear models to prediction with probabilistic models**
  -Discuss Blog 03, Extension #1: differences between FiveThirtyEight and The Economist forecasting models -Build out toy preliminary versions of FiveThirtyEight, The Economist and Klarner et al. (2006) models
- **(Slowly) moving from predicting voteshare and seatshare to predicting outcomes for individual seats**
  -Case 1: A district with good polling data -Case 2: A district with bad polling data -Aggregating individual seat predictions
- **Incumbency advantage and expert predictions** -Relationship between incumbent voteshare (seatshare) and different expert predictions
- **Preview of next week: Probabilistic models**

Ensemble models

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- Review: **weighted ensembles** are combinations of models (any kind) where you pick the weights (in some meaningful way)!
    - a model could be the raw poll
    - a multivariate regression is not an ensemble of *models*, though you can interpret coefficients as weights
    - **sensitivity analyses** are important: is your prediction heavily reliant on one model or a particular set of weights?

Previously on Gov 1347...

Extension 2/3: 4 options for a "weighted ensemble" of individual polls (with X weeks left)

1 (2022 polls adjusted by recent expert grades):

$PV^{(inc)}_{2022} = \left(\sum_{i=1}^{n} w_i \times Poll^{(inc)}_{2022,i} / \sum_{i=1} w_i \right)$ where

$$w_i = \begin{cases} 0.75 & \text{if } Grade2018_i = A \\ 0.2 & \text{if } Grade2018_i = B \\ 0.05 & \text{if } Grade2018_i \leq C \end{cases}$$

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4 (2022 polls adjusted by two most recent grades):

$$PV^{(inc)}_{2022} = 0.75 \times \Big(\sum_{i=1}^{n} w_i^{(2018)} Poll^{(inc)}_{2020,i} / \sum_{i=1} w_i^{(2018)} \Big) + \quad 0.25 \times \Big(\sum_{i=1}^{n} w_i^{(2014)} Poll^{(inc)}_{2016,i} / \sum_{i=1} w_i^{(2014)} \Big)$$

Discussion (15 minutes)

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In pairs...

1. Between the FiveThirtyEight and The Economist election forecasts, which one seemed better to you? Any better ones out there?
2. Share something you found (a) interesting and something you found (b) confusing while updating your blogs last week.
3. Review Klarner and Buchanan (2006) from discussion this week (in Lab sessions folder).

How does FiveThirtyEight's model take polling and incumbency into account?

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Polling

-Step 1: Collect, weight and average polls. -weight based on sample size -weight based on recency -pollster rating

-Step 2: Adjust polls.

-Step 3: Combine polls with demographic and (in the case of polls-plus) economic data.

-Step 4: Account for uncertainty and simulate the election thousands of times.

"Borrowing polls" - partisan lean metric + adjustment with district similarity score (we'll see this in a few slides)

Incumbency

-Factors into "fundamentals"

-Incumbent's lagged margin of victory

-Congressional approval ratings (attitudes toward incumbent)

-Scandals

-Roll call voting record (in-line voting w/ party)

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Polling

Step 1: Estimate national and district-level trends in support for candidates (1) Congressional generic ballot (2) Weighting! By proximity to election day, changes in national political environment (party generic ballot), pollster quality (record of over/underestimating)

Incumbency

???

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Two approaches outlined:

(1) District-level approach: Polls

(2) Aggregate approach: "National partisan tide" (similar to a fundamentals-only model) -health of the economy, presidential approval, quality of candidates, voting intentions

Their approach: combine both (similar to what we did last week!) -DV: Democrat two-party voteshare -IVs: (a) district partisan composition (i) past House vote: Democrat two-party voteshare from most recent House election (ii) past presidential vote: district presidential voteshare - national Democratic two-party voteshare

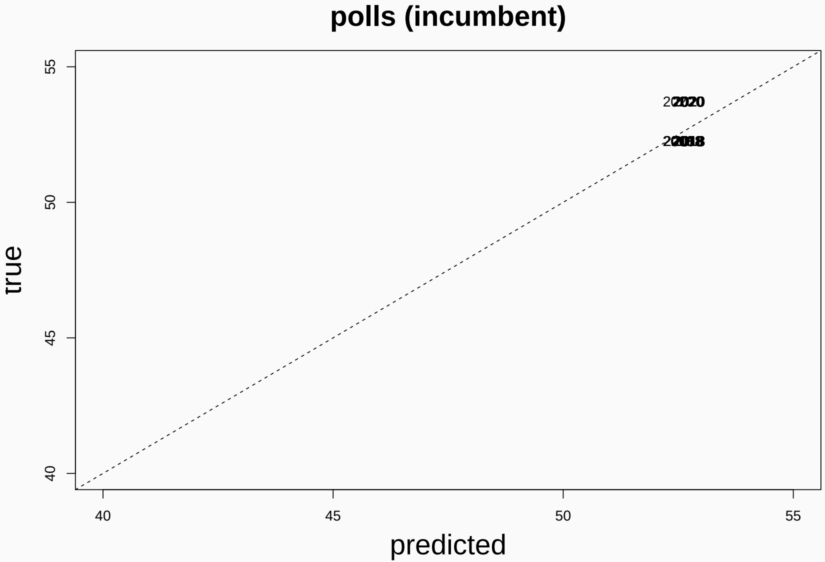
(b) candidate attributes (i) Incumbency (ii) quality candidate, closed: candidate facing an incumbent (iii) quality candidate, open: two non-incumbents (iv) past House member, closed (v) past House member, open

(c) national partisan tides (i) Democratic vote intention: % of respondents who expressed intention to vote for Democratic House candidate (Gallup poll ~March 10) (ii) Presidential approval: coded towards Democrats and conditional on party of sitting president (if Dem president, approval rate; if Rep president, disapproval rate) (Gallup poll ~March 10) (iii) change in RDI: percent change per capita RDI, February of year before election year - February of election year (iv) Midterm penalty: president's party should lose votes

Individual seat prediction: A district with (pretty) good polling data

Example: Ohio District 01 (3901)

```
## [1] 0.6135967
```



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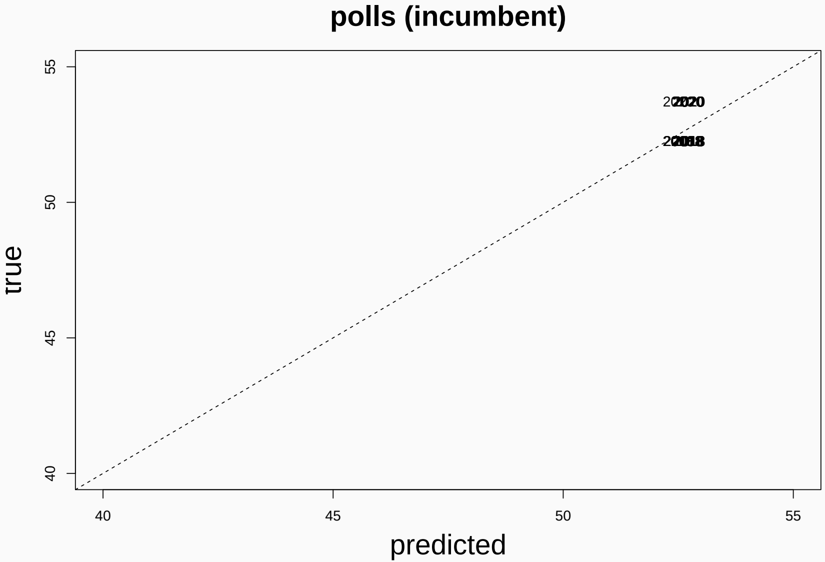

Individual seat prediction: A district with bad polling data

Example: Florida District 18 (something with similar demographics or likely R)

We will "borrow" data from a district that is comparable on relevant variables to OH01. Q: What do you consider relevant variables? What is a reasonable margin for comparison?

General process: (1) Choose a district that is comparable on relevant demographic and electoral characteristics (2) Append polls (3) Consider weighting here: we probably want to attach smaller weights to the borrowed polls or account in some other way for the fact that they are borrowed. (4) Model (5) Predict

Description: df [9 × 4]

demogs_OH <chr>	var <chr>	demogs_FL <chr>	var.1 <chr>
CPVI	R+5	CPVI	R+5
VAP	551000	VAP	556783
black_vap	115710	black_vap	70711.441
white_vap	407740	white_vap	380839.572
foreignborn_vap	22040	foreignborn_vap	86858.148
median_income_all	$64000	median_income_all	$68744
bachelors_degree_all	187340	bachelors_degree_all	189306.22
urban	92.5%	urban	96.37%
rural	7.5%	rural	3.63%

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```
# compare
```

Aggregating seat predictions

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As we just saw, predicting individual seats involves a lot of discrete work.

See Yao's code in the Class dropbox for starter code on how to do aggregate our seat-level predictions.

The incumbency advantage

The incumbency advantage: descriptive statistics

How many post-war elections where incumbent candidate won?

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```
# in how many elections did the incumbent candidate win
incumb_df %>%
  select(year, winner_party, winner_candidate, winner_candidate_inc) %>%
  mutate(winparty_last = lag(winner_party, order_by = year),
         wincand_last  = lag(winner_candidate,  order_by = year),
         wincand_last_inc  = lag(winner_candidate_inc,  order_by = year)) %>%
  mutate(reelect.cand = wincand_last_inc == winner_candidate_inc) %>%
  filter(year > 1948) %>%
  group_by(reelect.cand) %>%
  summarise(n = n()) %>%
  as.data.frame() %>%
  kable(format = "latex")
```

reelect.cand	n
FALSE	4460
TRUE	11174

The incumbency advantage: descriptive statistics

How many post-war elections where the president's party won?

```
incumb_df %>%
  select(year, winner_party, winner_candidate, winner_candidate_inc, president_
  mutate(winparty_last = lag(winner_party, order_by = year),
         wincand_last  = lag(winner_candidate,  order_by = year)) %>%
  mutate(reelect.party = winparty_last == president_party) %>%
  filter(year > 1948) %>%
  group_by(reelect.party) %>%
  summarise(n = n()) %>%
  as.data.frame() %>%
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```

reelect.party	n
FALSE	7948
TRUE	7686

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- Campaign finance access
- **In the presidential context, "Pork"** $\rightsquigarrow$ short-term economic gains (Bartels 2008), credit-claiming (Kriner and Reeves 2012)

Some incumbency (dis/non-)advantages:

- Polarized electorate $\rightsquigarrow$ partisanship, not incumbency matters (Donovan et al. 2019)
- Recessions, disasters $\rightsquigarrow$ blame attribution (Achen and Bartels 2016)
- Incumbency fatigue

(2) Credit and blame: the time-for-change model

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Alan Abramowitz's **time-for-change** model is a classic model of incumbency and, since 1992, has a <u>true</u> out-of-sample PV prediction error of 1.7% (Typically used in the presidential forecasting context, but if we consider the fact that midterm elections are often referenda on the president, it may be relevant).

$$\underbrace{\texttt{pv2p}}_{incumbent\ \ party} = A + B_1 \underbrace{\texttt{G2GDP}}_{Q2\ \ GDP\ \ growth} + B_2 \underbrace{\texttt{NETAPP}}_{Gallup\ \ job\ \ approval} + B_3 \underbrace{\texttt{TERM1INC}}_{sitting\ \ pres}$$

(pollyvote.com model repo)

Preview of next week: Probabilistic models

One major problem with linear regression

- When we fit a linear regression model $Y = \alpha + \beta X$, there are no restrictions on Y. What's wrong with that?

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- $\rightsquigarrow$ It is possible to have a prediction interval lower bound < 0 (**out of support**).
- **This often occurs when we are extrapolating but also when there is sparse data (e.g. district-level polls).**

Solution: probabilistic models

- In a linear regression,

$$DemPV_{state} = \alpha + \beta_1 x_1 + \ldots + \beta_k x_k,$$

  our probabilistic assumption is that errors in predicted PV follow a bell curve, $DemPV_{state} - \widehat{DemPV}_{state} \sim Normal()$

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- In reality, the process of elections is some "draw" of voters from the voter-eligible population (VEP) turning out to vote for a party:

$$\Pr\left(DemPV_{district} = 2 \texttt{ million} \mid VEP_{district} = 5 \texttt{ million}\right) = f(\alpha + \beta_1 x_1 + \ldots + \beta_k x$$

  with some other probabilistic assumption, $DemPV_{district} \sim ?$.

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  with some other probabilistic assumption, $DemPV_{district} \sim ?$.
- A model that allows the DV or error to have a non-normal distribution (specified by a particular choice of function $f(\cdot)$) is called a **generalized linear model** $\rightsquigarrow$ more on this and how to apply them in R next time!

Blog Extensions

1. **How accurate are expert predictions? pt.1** Visualize actual voteshare (seatshare) in 2018 and compare that to various expert predictions for that election cycle. How do they compare?
2. **How accurate are expert predictions? pt.2** Visualize actual voteshare (seatshare) in 2018 and compare that to various expert predictions for that election cycle. How do they compare? Create 3 maps: (1) a map that visualizes voteshare (seatshare) at the district-level; (2) a map that visualizes expert predictions at the district-level; (3) a map that visualizes the difference between actual voteshare and expert prediction at the district-level.

This is going to require you to use your own discretion in coding up variables.

On (2): these expert predictions are in the form of "lean D/R," "likely D/R," etc. Transform these variables into a continuous numeric variable, i.e. "Likely R" ~ -2, "Lean R" ~ -1, "Tossup" ~ 0, "Lean D" ~ 1, "Likely D" ~ 2, and so on. Visualize the results.

On (3): you will need to figure out how to compare voteshare and expert predictions. One possibility: transform one of the variables to be on the same scale as the other variable. Ex: voteshare of 54% for Democrats ~ "Safe D," voteshare of 52% for Democrats ~ "Likely D," etc. or vice versa, "Safe D" district ~ "54% voteshare" . . .