CS 109A

Final Project

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GitHub Sites link

Predicting the 2018 Election

Research Question: Which candidates will be elected to the U.S. House of Representatives in 2018?

Motivation:

Figure 1: Successful President-Elect Harry Truman Holding "Dewey Defeats Truman" (1948)

Ever since competitive elections have existed, people have tried to predict them. And with good reason -- elections determine the people who will run a town, state, or country for a significant amount of time, and gives those elected the reins of the state to use as they wish.

Knowing what's at stake, the general public, including heads of households and business leaders look to plan for proposed tax hikes, safety regulations, etc. Having an idea of what the new government will look like before it's set in stone thus allows for a calmer transition between governments. When parties were less ideological (such as in Figure 1 above, where president-elect Harry Truman holds up the *Chicago Tribune* [inaccurately] announcing his defeat), predicting elections was interesting but perhaps not extremely consequential, since either party was expected to promote the same kinds of policies. In the increasingly divided and polarized U.S., such questions of government composition become essential.

Newspapers and universities took up the task of polling voters in both in their communities and across the country. While these polls have played an essential role in drawing up predictions, some polls may be biased due to their participant selection mechanism or question wording.

When a survey firm uses random-digit dialing, potentially-valid phone numbers are generated by the survey firm at random and called to recruit potential participants. While this method worked well in the past, when everyone had a phone and answered nearly every time, the advent of caller ID meant that fewer people picked up a phone call from a number they did not recognize, and those who did likely constituted a non-random, biased sample of all voters (Green & Gerber 2002). This non-random sampling makes the poll less reliable as a signal for the actual outcome of the election.

Similarly, different polls may ask what is essentially the same question in different manners. Research has shown that the way in which a question is posed to the survey participant affects the respondent's answer. For example, a registered Republican voter, when asked whether she supports John Doe (Dem.) in the governor's race, may answer yes, since she supports his stance on support for young parents. That same respondent, if she is asked whether she supports the Democrat in the governor's race, may think first about her partisan affiliation and second about the actual candidate, and respond no. Thus, given multiple polls whose question wording differs are very difficult to aggregate into any coherent picture of the state of the country.

In the lead-up to the 2008 election, news media and newly-minted forecasting agencies began to use statistics to assess polls' accuracy (by predictive power and with reference to other polls). Using a Bayesian approach, the researchers used the prior election result in the district as a prior, and also included information about the survey design (participant selection, question wording, target audience, sample size etc.) to weight the trustworthiness of each poll and ultimately to aggregate them into an overall prediction for each Congressional district ($N = 435$).

However, the results of the 2016 election did not match those predicted by most analysts. Following the 2016 election, the data analytics firm 538 published a post-mortem on what went wrong in the production and mass interpretation of their and others' models.

Figure 2: New York Times' *Upshot* Election Forecasting Graphic

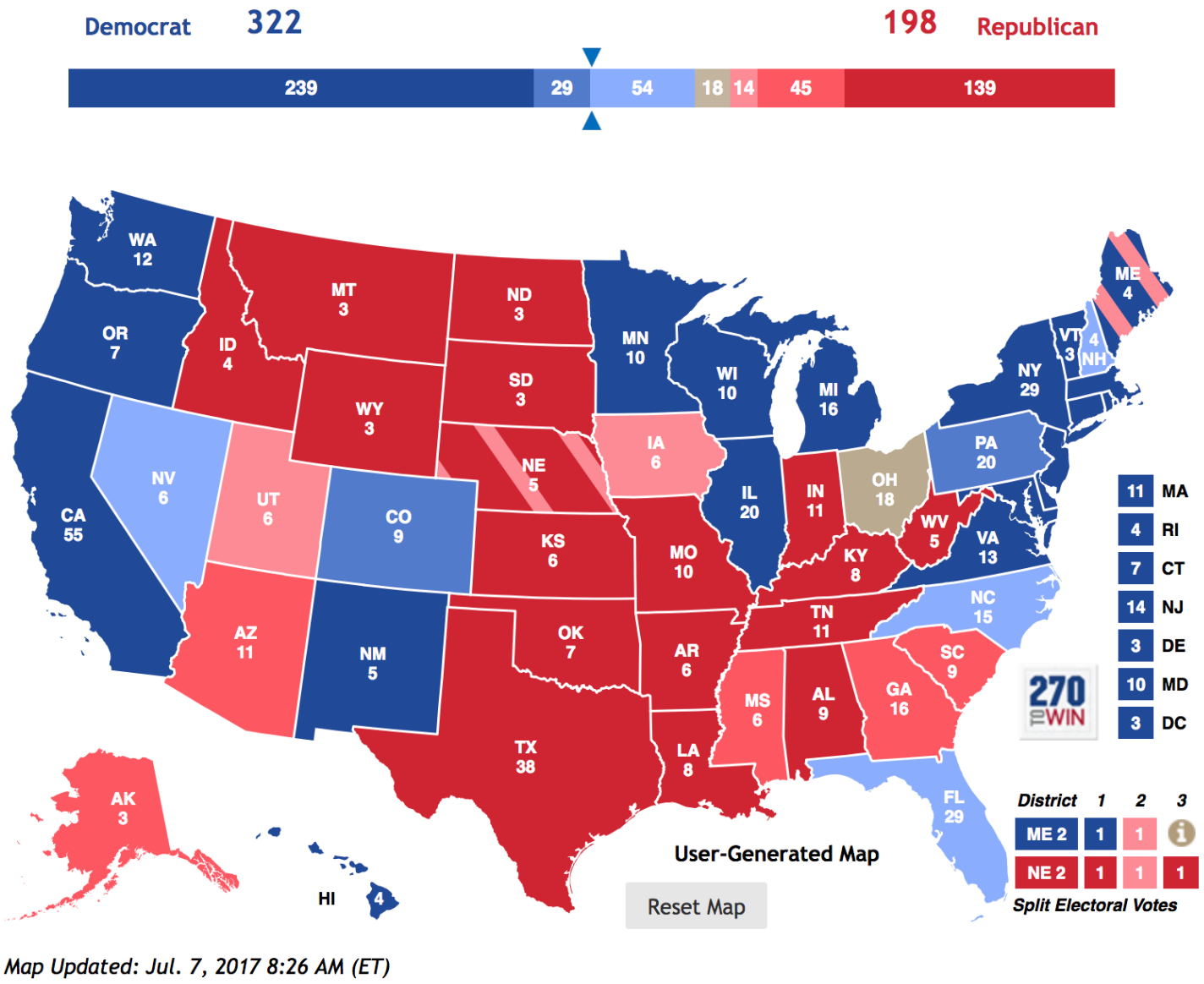


Figure 2 shows the user interface of the New York Times' election forecast visualizer as it was presented prior to the 2016 election (though not using the predictions the Times' team generated). In the map, each state is presented with its abbreviation and the number of votes it has in the electoral college, the formal body that technically elects the president. Geographically smaller states are presented in the boxes on the right, and states that are allowed to split their electoral college vote between candidates, Maine and Nebraska, are listed in the bottom right.

The *Times*, as well as several others, distinguished the degrees of partisanship here: Districts could be "Strong" Democrat/Republican, "Likely" Democrat/Republican, "Lean" Democrat/Republican, or a toss-up. While this method clearly distinguishes what's likely an uncompetitive race in New York (Strong Democrat), the underlying differences between these groups are opaque to the reader. By obscuring the underlying data and the uncertainty of the predictions that can be made using it, the map does more harm than good.

Therefore, in this project, we make it a priority to emphasize the uncertainty in our model. It is highly unlikely that we will be able to accurately predict all districts, but it is likely less costly to know that the race is uncertain, than to predict the wrong outcome entirely.

Description of Data and EDA:

Due to the nature of politics, all of our data is observational -- without fortuitous exogenous shocks, there is no way to make causal claims about what social or political factors produce an election outcome. Despite this caveat, we explore the correlations between variables and our outcome, whether, for each district, a Democrat or Republican candidate wins in the 2018 Congressional Election.

Data Selection and Justification

Political Outcomes

- As our main outcome of interest, we aim to predict which candidate will win the election for each of the 435 races for Congress. Simplifying this, without loss of generality, we model whether the *Democratic* candidate in each district will win; additionally, the two-party nature of politics allows us to operationalize the binary outcome as one where we predict that the Democrat candidate will win the election if her odds of winning are greater than those of the Republican candidate (that is, if the log-odds is greater than zero). In training datasets, if the Democratic proportion of the two-party vote is greater than 0.5, then the Democrat candidate wins.
- (Note: There have been a handful of independent members of the House of Representatives of 435 [no more than two per term]. However, as all of the top candidates 2018 election were either Democrats or Republicans, it is safe to ignore third parties/independent candidates in our analysis).
- **Data sources:**
    - 2018 election: At the time of writing, the results of the 2018 Midterm Elections have not yet been published in accessible formats; however, they are available via media outlets online. For this reason, we scraped *Politico*, a trusted online politics website, for the data. Results presented in this project are presented as they stood December 2, 2018, when final scraping was conducted. At this time, in at least two districts, (North Carolina's Ninth and California's 21st), voting irregularities and very close margins mean that these results have not yet been finalized. Whichever candidate was in the lead at this time is recorded as the winner.
    - 1980 - 2016 outcomes: Data collected based on official records by the Constituency-Level Elections Archive. Following the modeling plan outlined above, we calculated the Democratic share of the two-party vote for each district across 19 elections.

Code is attached in the accompanying Jupyter Notebook.

Political Explanatory Variables

- Candidate data
    - Incumbency status: Much research in political science has shown the large positive effect on a candidate's chances of being elected if she is the current holder of the seat (the incumbent). Taking this into account, we create a binary variable for whether the incumbent is running in the election. Next, we combine this binary variable with another that indicates whether the incumbent is a Democrat or Republican, forming an interaction term. When the interaction term indicates that there is a Democratic incumbent running for re-election, we expect predicted Democratic vote share to be higher. When there is a Republican incumbent running for re-election, we expect Democratic vote share to be lower.
    - Ideological position(s): Political scientists have developed techniques to estimate the ideological position of elected representatives, especially those in Congress. Poole and Rosenthal have developed DW-NOMINATE (Dynamic Weighted NOMINAl Three-step Estimation) scores, which are an aggregate measure of a Congressmember's lifetime public voting record in office over two dimensions, which broadly reflect differences in preferences on economic and social policy. We also include the Nokken-Poole score, which does not make assumptions about ideological stability in members of Congress over time, allowing for more fluctuations within the same legislator over time. Both measures provide for different understandings of the ideology of the incumbent (essentially, how long a memory constituents have); thus, we include both in our dataset.
- Contextual data
    - District prior vote share: For each district, we have a long record of voting. It is likely the case that a district's partisanship, as measured by its most recent vote results, predicts the next future results very well. However, politics is cyclical and all data is subject to random variation. Thus, we include results from multiple years prior to 2018 to train the model. A potential issue with this is the changing nature of districts over time due to redrawing of district boundaries (redistricting).

Socio-economic Data

Here, we utilize data from the American Community Survey (ACS), which collects demographic and economic information about 1% of the U.S. population each year. This information is also presented at the level of the Congressional district, making our anlaysis more straightforward. Unfortunately, however, the ACS the only started collecting data at this level in 2005, and other public datasets do not present their data at the level of the Congressional district prior to 2005. Moreover, due to the 'creative' drawing of some district boundaries, it is virtually impossible to map county-level variables to Congressional district variables.

Our variables of interest are as follows:

- **Unemployment Rate**: What percent of people *want* a job but do not have one, for each district? Measures economic stagnation/discontent in a district. When unemployment is higher, we expect the majority party to do more poorly in the next election. (Arzheimer 2009).
- **Median Household Income, Median Mortgage Cost**: Political scientists have long established the connection between income/wealth and voting (cf. Evans & Tilley 2012). Left-wing parties tend to support higher levels of income and wealth redistribution; thus, the poor/less wealthy tend to vote for the parties on the economic left, broadly, and the rich/more wealthy tend to vote for parties on the economic right. Here, median mortgage cost proxies for the median wealth in the district, since many Americans' most valuable asset is their home. Thus, we expect districts with higher median incomes and/or higher mortgage costs to favor Republicans over Democrats in elections.
- **Median Age**: We expect that voters become slightly more conservative as they age.
- **Percent White, Percent Black**: Race is a very important characteristic in American politics and the Democratic Party is seen as the defender of the interests of racial minorities, while white identity was made salient in the 2016 election by Donald Trump. For these reasons, we expect these variables to have an effect on the election outcome.
- **Highest Education, High School Diploma; Highest Education, Bachelor's Degree**: The Democratic Party tends to attract voters with higher levels of education, so we expect `Highest Education, Bachelor's Degree` to correlate with the Democratic vote share in each district.

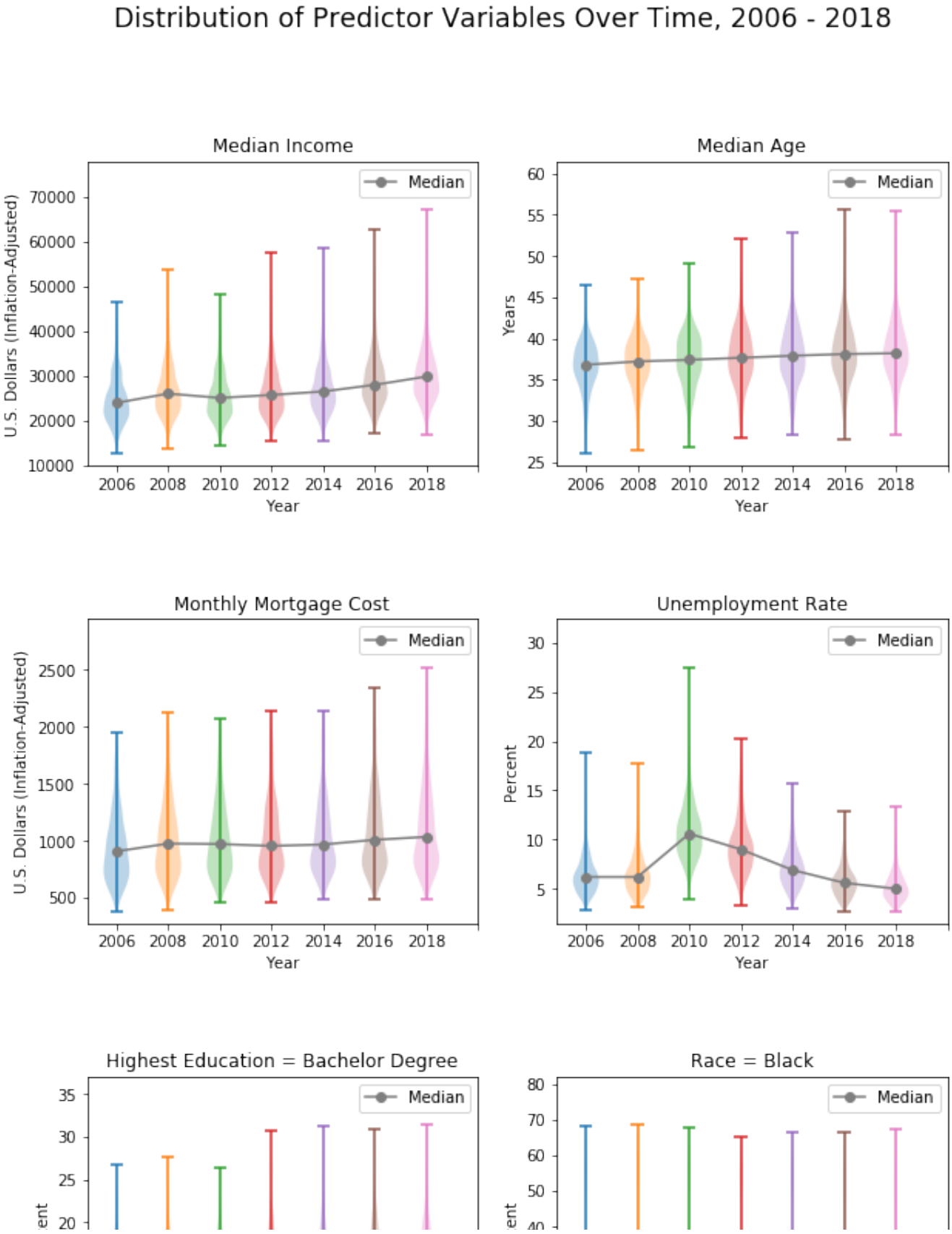
Using ACS data starting in 2005, we have 435 districts * 6 elections = 2610 election observations prior to the 2018 election. While this is a sufficiently high number of observations to train basic models on, as models become significantly more complex, we may run into issues with overfitting to the training set. We take care to limit such problems by not using very high degree polynomials and through regularization, discussed below.

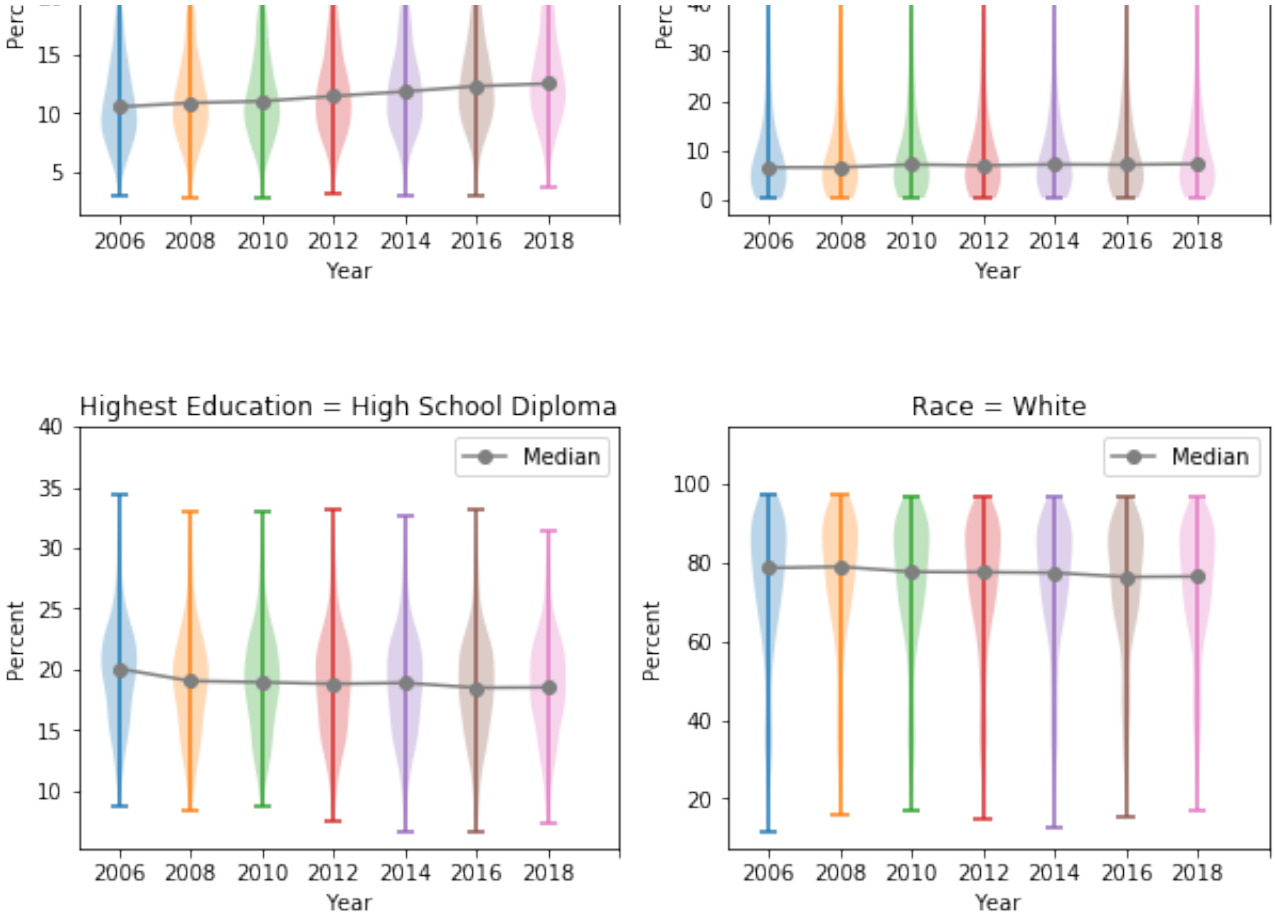
None of our data had missing values, though the estimates that the ACS makes are based at least partially on hot-deck imputation of missing values. The ACS describes hot-deck encoding as a method by which "sampled units are ordered by some frame variables and a unit's missing items are assigned from a unit – usually the nearest unit in the ordered frame list – within the subset of 'donors' defined as units sharing certain geographic, frame, and possibly demographic attributes with the unit to be imputed (Wright et al. 2015, p.7).
Essentially, the Census Bureau matches missing observations on non-missing observations using observable characteristics present in both respondents, and imputes the missing value probabalistically, given a set of potential matches. It is unclear to what extent this imputation affects our findings, but given that we are only looking at top-level variables within each district, these issues should be minimal.

Exploratory Data Analysis

District-level variables

Figure 3





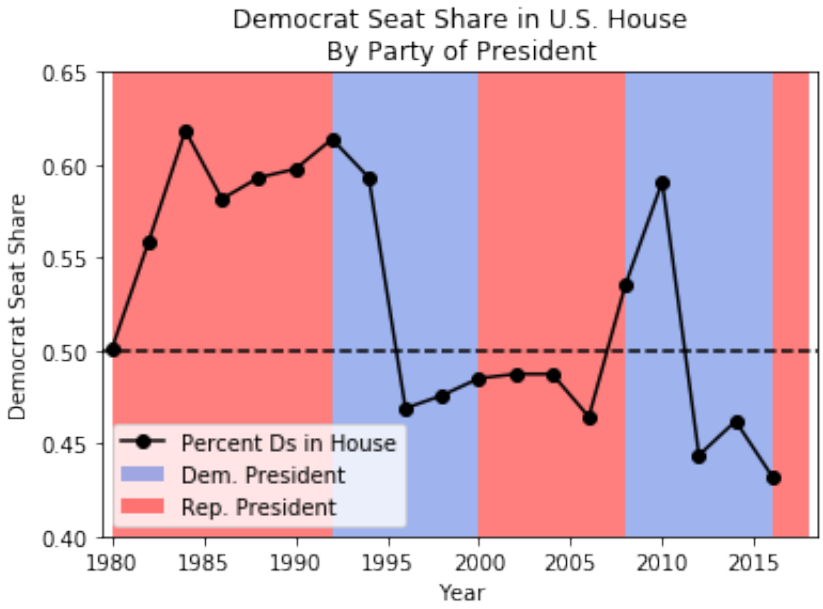
In Figure 3, we see the distribution of district-level variables over time in their original scale. The first aspect to note is the relatively high range of most of the predictors -- while the bulk of districts for each predictor/year are concentrated in one range, there are several important extreme values for each. For example, in the vast majority of districts, the percent of residents who are black lies at about 8%. However, in at least one district, that share is around 69%. These skewed distributions may lead to biased estimates if we use regression.

The second aspect to notice in the violin plots is the extent to which the distribution changes over time. We notice that some variables, such as ethnic composition, remain fairly steady over time, while others, such as the unemployment rate, are relatively volatile. Prior to the 2010 election, national unemployment was still high in the aftermath of the Great Recession, and surpassed 25% in some heavily-affected districts.

There are multiple ways to incorporate this information. If, for example, the relevant cause for a person's candidate choice is the *overall* state of the economy, then it might not make sense to create interaction terms between the unemployment rate and year -- 10% unemployment has the same effect on politics whether a country is in recession or not. If, however, there are separate effects of *absolute* economic deprivation (in the form of high district-level unemployment) and also *relative* economic deprivation (unemployment that would be high for normal years, but relatively low when compared to all other districts that year), then we should include interaction terms between unemployment and year. Ansolabehere et al (2014) suggest that the latter is the case; therefore, we include interaction terms in our model.

National-level variables

Figure 4:



Above, we see the percent seats held by Democrats in the House over time and under Presidents from different parties. This plot shows the midterm advantage enjoyed by the non-presidential party in American politics -- at midterm elections (two years after the President was [re-]elected), voters tend to support the party in opposition. This is seen in the graph above by steep drop-offs in the proportion of House seats held be Democrats 1994-1996 and 2008-2010. Additionally, Republicans lost a large share of seats 1982-1984 and 2006-2008.

In terms of modeling, this suggests that we include a dummy variable indicating whether the election was a Presidential or midterm election, which we do in the models below. Given that the 2018 election is a midterm election under a Republican President, we expect the Democratic Party (the opposition party) to gain seats this election.

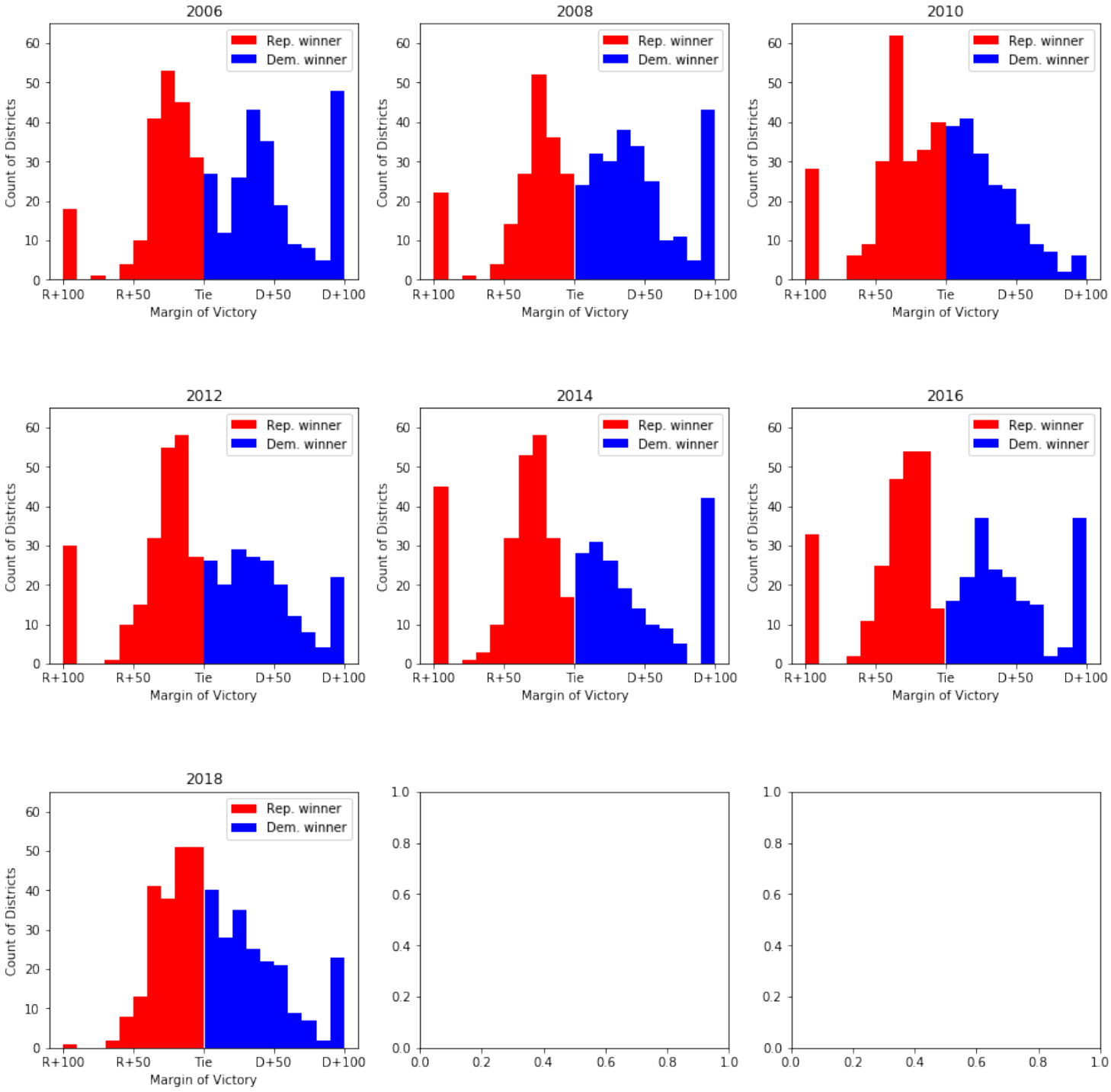
In Figure 5 below, we have histograms of district-level election results from 2006 to 2018, categorized between those that a Democrat won and those where the Republican candidate did. The *x*-axis represents the candidate's margin of victory. When the candidate runs unopposed, his or her district will appear at the extremes of the plot, since, by definition, they won all of the votes in that district. When there are many races that are very close, we see spikes in the histogram around the middle of the *x*-axis. There does not appear to be a clear pattern over time in the closeness of elections -- while there were a very high number of close elections in 2010, in 2016, very few elections were close to being a tie. Instead, it appears that many candidates won competitive races with a comfortable margin of victory (around 10-15 points).

Moving to 2018, we see a very high number of very close elections. While this may be good for democracy, indicating competitive races, it makes the statistician's job very difficult, since the margin for error decreases

significantly. When only 2 points separate the candidates, it becomes much more likely that our models will predict the 'wrong' winner.

Figure 5:

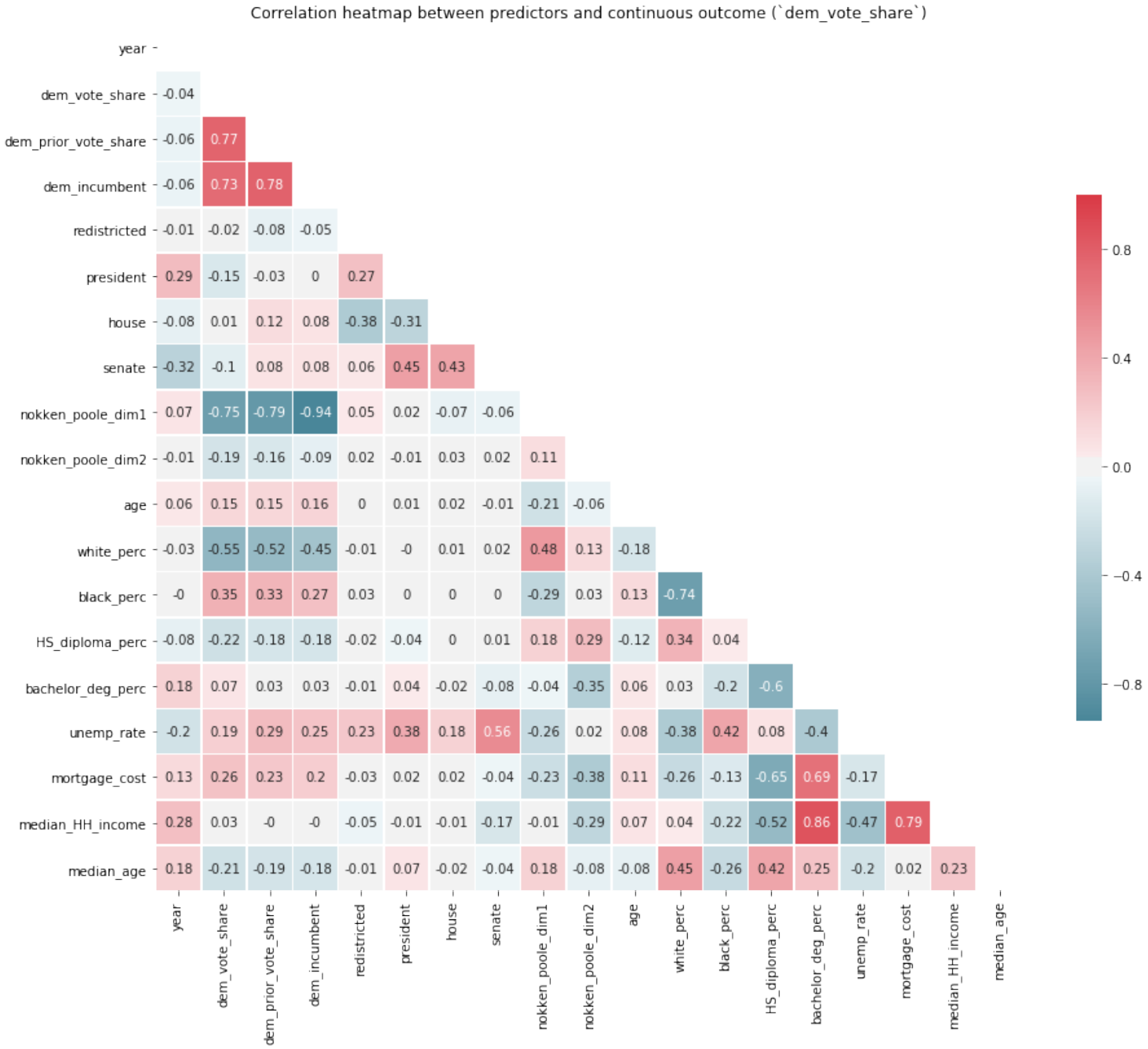
Histogram of Election Winners by Margin of Victory, 2006 - 2018



Summary of EDA

Below, we see a heatmap of correlations between all of the explanatory variables in our model. Interestingly, we only see very high correlations among variables that proxy for social class: education, income, and wealth. If we use regularization in our models, the effect of these correlations will be limited.

Figure 6:



Time effects

It is likely that the results of more recent elections predict the 2018 outcome better than do those from earlier years. This might be due to factors such as incumbency, changes in ideology, or changes in racial/ethnic makeup. For this reason, we include an interaction term between the prior vote results and the year in which

that result occurred.

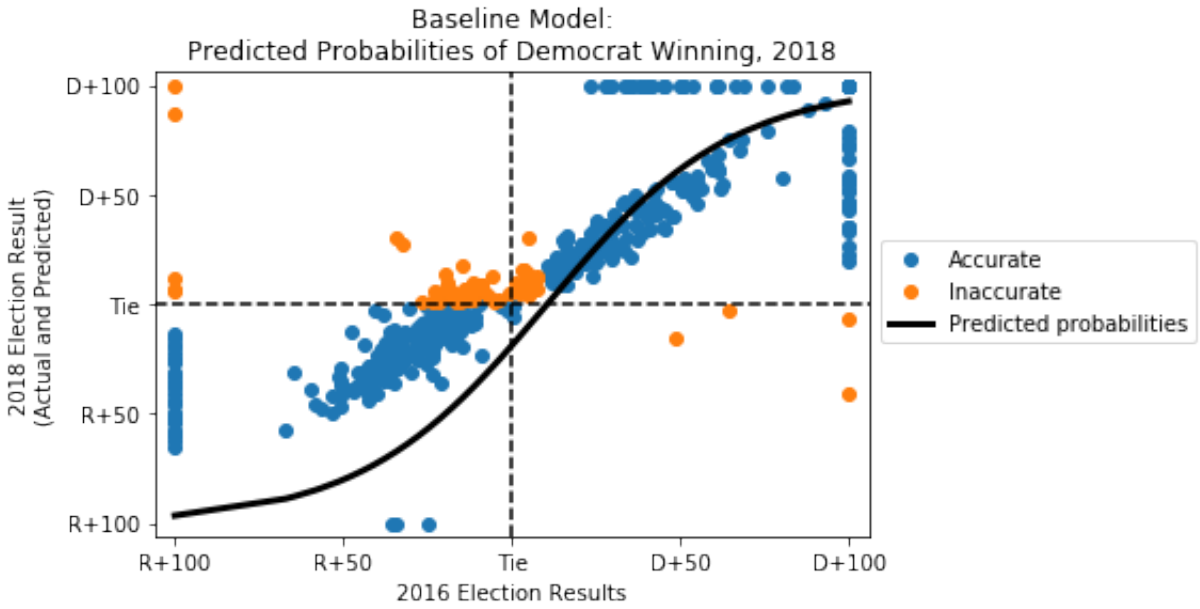
Results:

Baseline Model

Our baseline model for predicting the results of the 2018 election is a logistic model predicting whether a Democrat won, using the district's prior election results as the sole predictors. We work under the assumption that we do not know the results of the 2018 election yet, and have to make a predictive model for them. To do this, we git a baseline logistic regression model to the 2016 outcome, based on the district's prior vote share in all of the previous elections for which we have complete data.

Mathematically, this is: $P(D_{win} =1) = (1+e^{-\beta X + c})^{-1}$, where β is composed of the combined results of each election between 2004 and 2014.

Figure 7:



Using this simple model, we can predict the 2018 results with 86.9% accuracy.

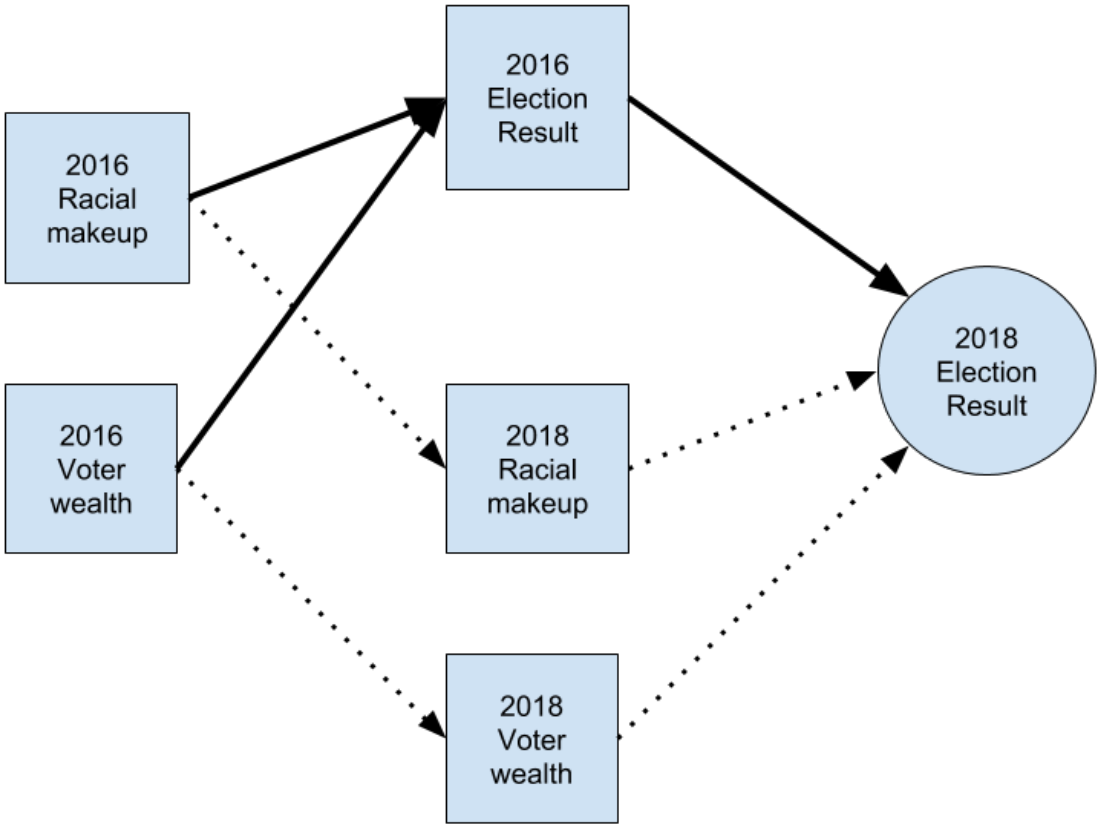
It is striking to the researchers that even with no additional covariates besides the district's past eight election results, the predictive accuracy of the model is 86.9%. Moreover, this prediction on the test set is over 5 points higher than the training set accuracy, which is 81.57%. It appears that the 2016 election may have been anomalous while 2018 was more of a 'normal' election where traditional predictors were better at predicting the outcome.

Additionally, we see in Figure 7, that the results are not a simple mapping from prior vote share to predicted

vote share -- it does not appear to be true that a district's election result can be assumed to be exactly the same as the past result. Specifically, the model only predicts the Democrat to win the election if the Democrat won the past election by at least ten points (Democrat vote share at least 55%), and predicts the winner to be Republican for the remaining cases.

Our likely theory for the success of this model is that since prior election results are themselves products of the characteristics of the districts and of the representatives who are elected from them, the effects of many of the other predictors are already present in the prior voting reuslts.

Figure 8: Directional Acyclic Graph of Model



This effect is shown graphically in Figure 8 above for a two-period case. In this example, the result of the election in 2016 is dependent on the racial makeup and voter wealth in that year. Since district wealth and racial makeup of a district are slow to change, these values in 2016 are likely to be very similar to those in 2018. Therefore, the 2016 election results are extremely good predictors for the 2018 results, since the prior results are the products of innumerable district-level variables that help predict the results of elections,

regardless of other time-sensitive predictors.

Extended Models

Model selection and implementation

Our goal of predicting the result of the midterm elections is essentially a binary classification problem with two classes (Democrat win = 1 and Republican win = 0). We have a number of choices in terms of which classification model to choose, including linear or quadratic discriminant analysis, k-nearest neighbours, decision trees or logistic regression. Given that are dataset is relatively small with 435 districts and would lead to a reasonable computational time, we decided not to use discriminant analyses. The benefit of the simplicity of k-nearest neighbours is also limited given the nature of our dataset. Therefore, we decided to use Logistic regression and its variants to model our data. In addition, we explored the performance of decision trees (bagging and random forest) for comparison.

The performance of the various models in our analysis is summarized in Table 1. The models were all trained on the data from 2005 – 2016 and then used to predict the results for 2018. The model that gave the best predictions is Logistic regression with power and interaction terms. Therefore, the results presented in this report are based on the predictions from this model.

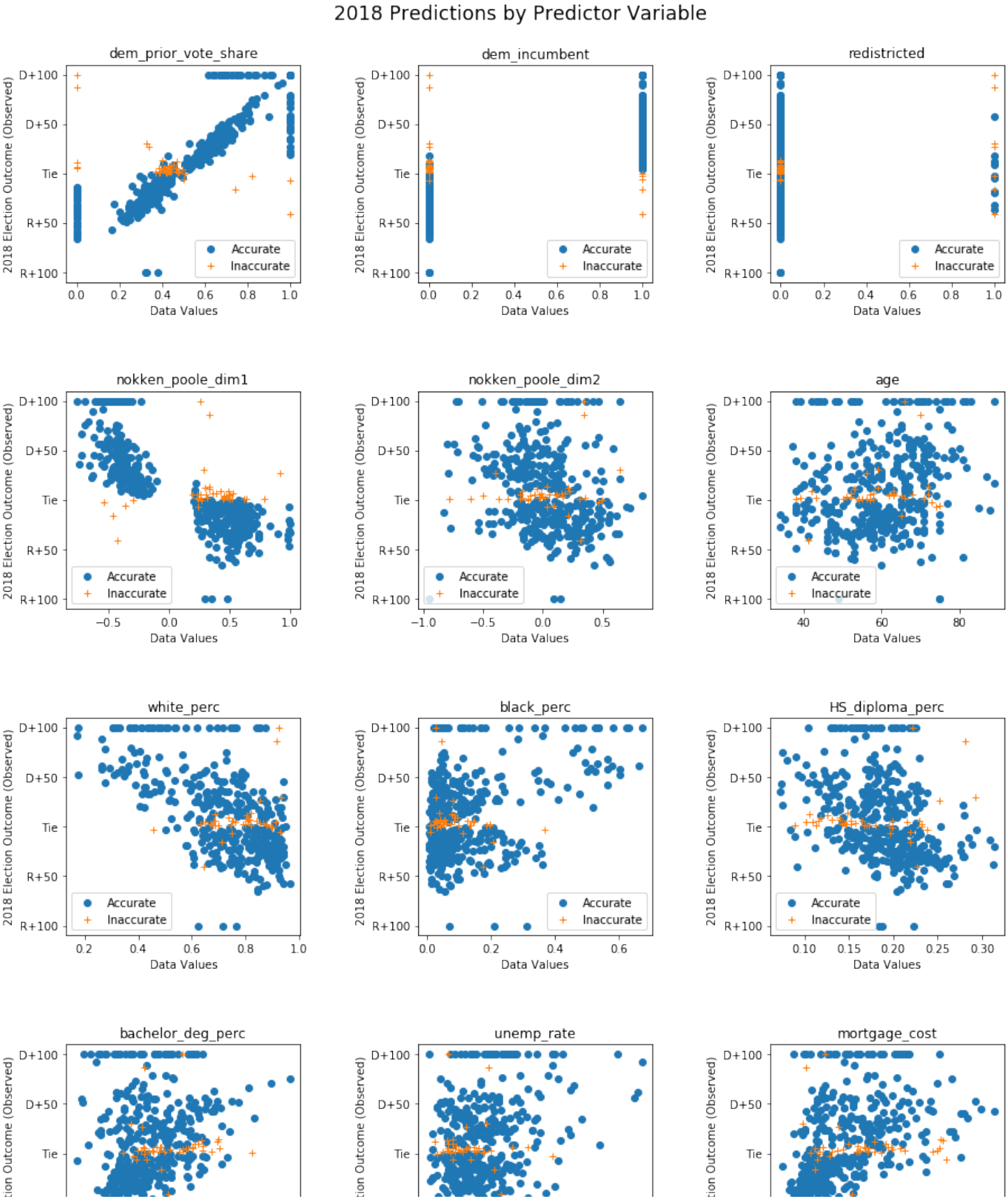
Note in Table 1 that the non-regularized models perform basically just as well as the non-regularized models. This is likely due to the fact that we have relatively few predictors to begin with, and many predictors are not highly correlated with one another (see Figure 6), so dropping variables (LASSO) or reducing the magnitude of coefficients (Ridge) does not seem necessary, especially in the degree-1 models.

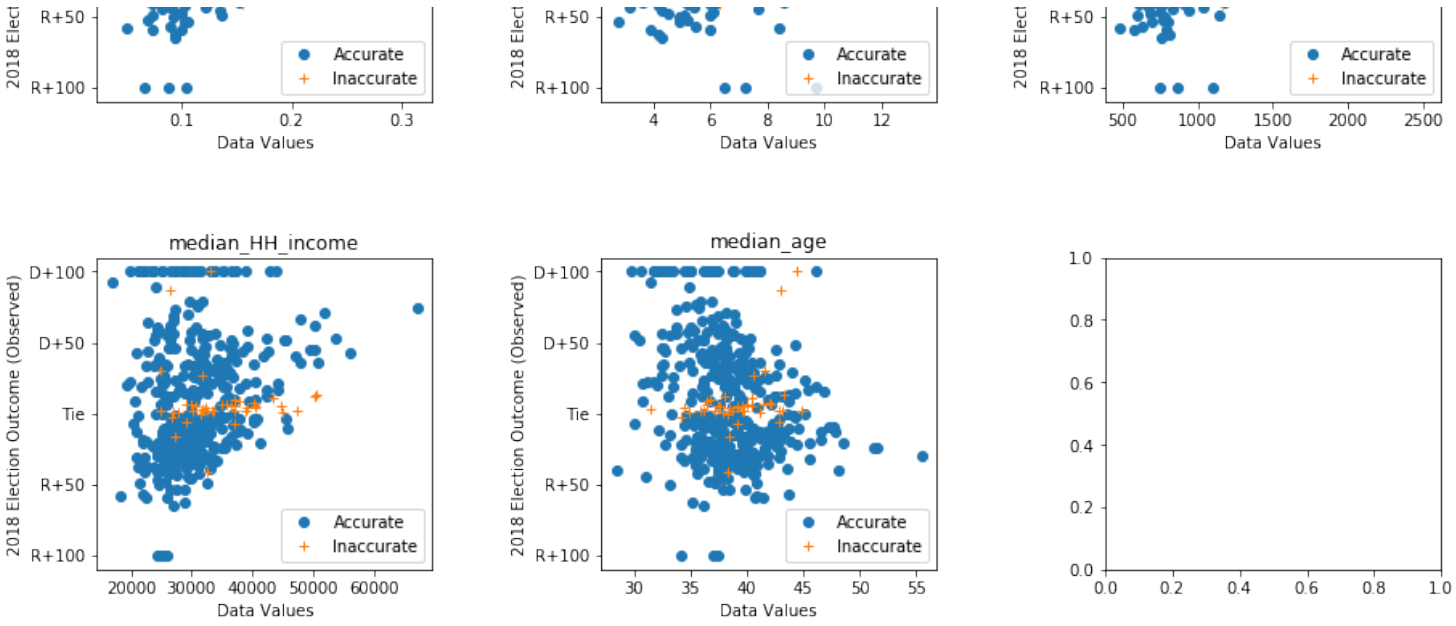
Table 1: Model Performance

classifier	training accuracy	test accuracy
Logistic Regression	0.910281	0.896552
Logistic Regression with CV (Lasso)	0.896552	0.896552
Logistic Regression with CV (Ridge)	0.907971	0.896552
Linear Regression (Ridge)	0.914132	0.905747
Bagging	0.993454	0.896552
Random Forest	0.998845	0.896552
Logistic with Power terms and Interactions	0.915671	0.905747

We further analyze this model below.

Figure 9:





To test our model performance, we use the fitted model to predict the 2018 election results, using only data from 2018. Figure 9 above shows the predicted probabilities of the Democratic candidate winning, translated to what his/her expected election margin might be. The *x*-axis for each plot is the value of the untransformed predictor set.

As we can see, there are only a few cases where 2018 predictor values were especially bad at predicting the outcome, as evidenced by clusters of inaccurate predictions in one region of the graph. We see, for the most part, the model predicted the wrong outcome only in very close races (near ties), where other factors, such as rain on election day, might have suppressed turnout in an unpredictable way.

One pattern that appears in this analysis is the relationship between economic ideology (`nokken_poole_dim1`) and prediction accuracy. It appears that the model performed especially poorly among moderate to mainstream Republican members of Congress. For districts whose members were between +0.20 and +0.40 (i.e. moderate to mainstream Republicans), the model predicted that they would win, while actually, they lost. This finding supports the observation in the media that the 2018 election would be a "blue wave" -- many moderate Republicans in the House of Representatives were voted out of office by a mobilization of Democratic voters, especially in suburban areas.

Crucially, these plots show us the importance of including uncertainty in the model. When we restrict our prediction to those districts whose predicted margin of victory was within 4 percentage points, we improve our model accuracy to 96.12%. The code snippet below shows how we created this measure.

```
confident_results_indices = [i for i in range(len(ytest.values)) if \
                             np.abs(ytest.values[i]-0.5) >0.04]

accurate_confident_mean = np.mean(y_test_predict_bool[confident_results_indices]\
                                  == y_test[confident_results_indices])

print("Our model confidently predicts the outcome with ",
      np.round(accurate_confident_mean*100,2), "% accuracy.", sep ="")
```

Finally, these plots show us the limitations of using only demographic and political information without supplementing it with polling data. These limitations are further discussed in the Conclusions and Summary.

Conclusions and Summary:

In this project, we aimed to predict the results of the U.S. Congressional Elections in 2018.

Our model was over 90 percent accurate in predicting the results of the 2018 midterm elections. Given that the highest accuracy achieved by professional election forecasters is 95 percent, we are relatively happy with the performance of our model. A closer look reveals what may have made a difference in the accuracies of our model as compared to the best available model. We find that one important predictor that was used in their model was the past years' polling data which is not easily available for us to use.

In our discussion above about the evolution of election forecasting, we emphasized the importance of getting accurate polling data and weighting it to produce a consistent measure of partisanship (and therefore predicted election outcome) across districts. If we had had extensive polling data and the resources to make it usable (538's team of full time staff, for example), it is possible we would have been able to recreate their high levels of accuracy by foreseeing the "blue wave" -- increased enthusiasm among self-identified Democrats.

Another point to note is that 538 used elastic net regularization which, in essence, is a combination of ridge and lasso regularization methods. We tried each of these regularization methods separately but did not find them to be better than our logistic model. Perhaps with several more significant predictors, we would have seen an improvement over our model using regularization methods.

Future work:

For future work, it would be interesting to see the effect of adding several more significant predictors to our data set such as past years' polling data. In terms of modeling, depending on size of the data set, we could explore discriminant analyses and elastic net regularization methods.