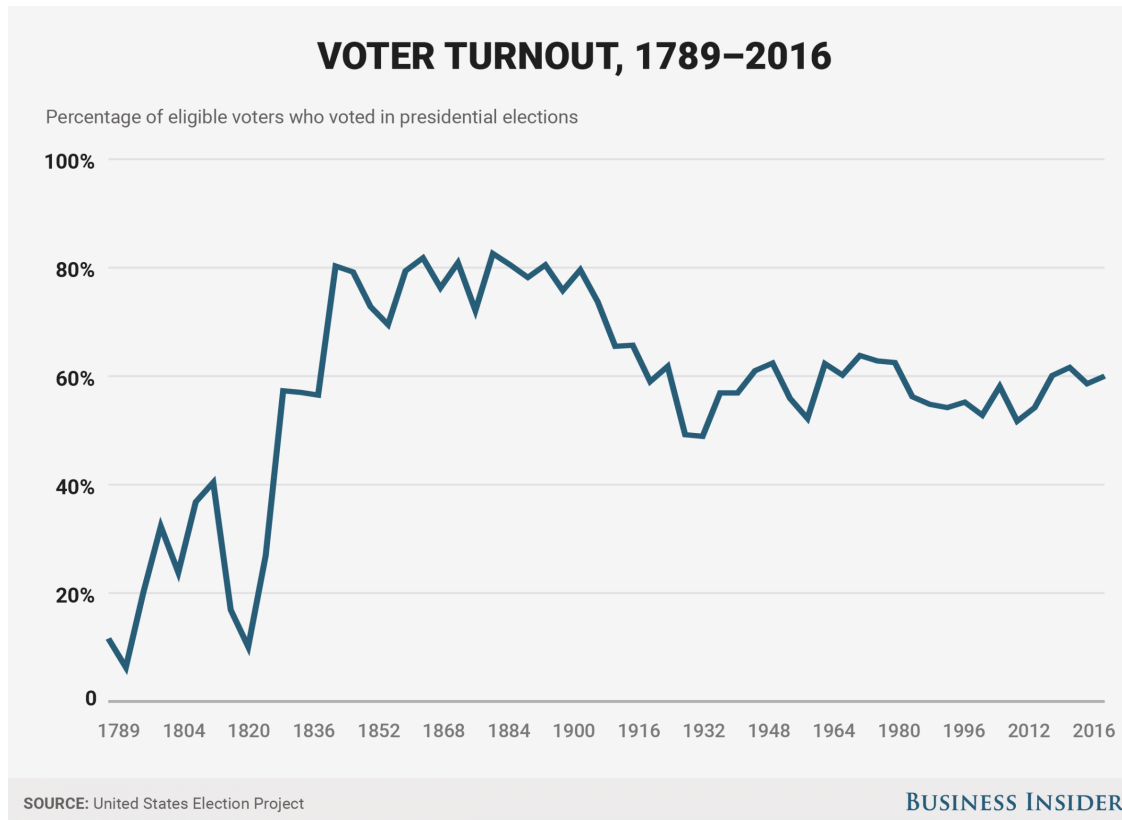


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# Improving Polling Accuracy in US Presidential Elections

A machine learning approach to developing likely voter models

# Why do we care?

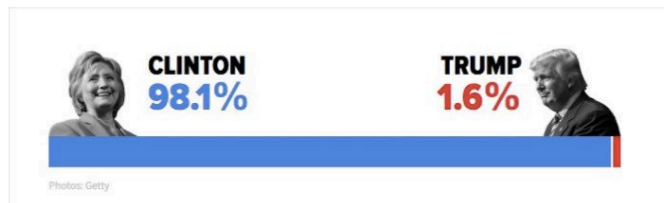


- For the past two decades, less than 60% of eligible voters participated in presidential elections
- Difficulty of determining who will vote is a primary factor in polling inaccuracy

# Garbage In, Garbage Out

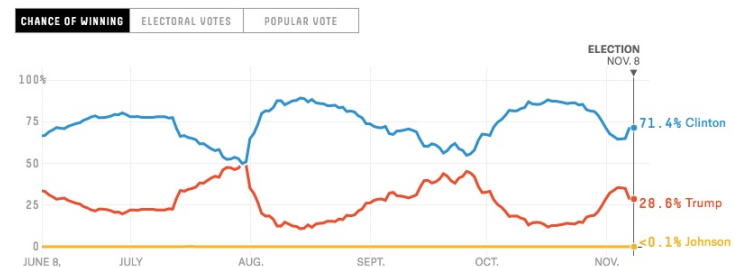
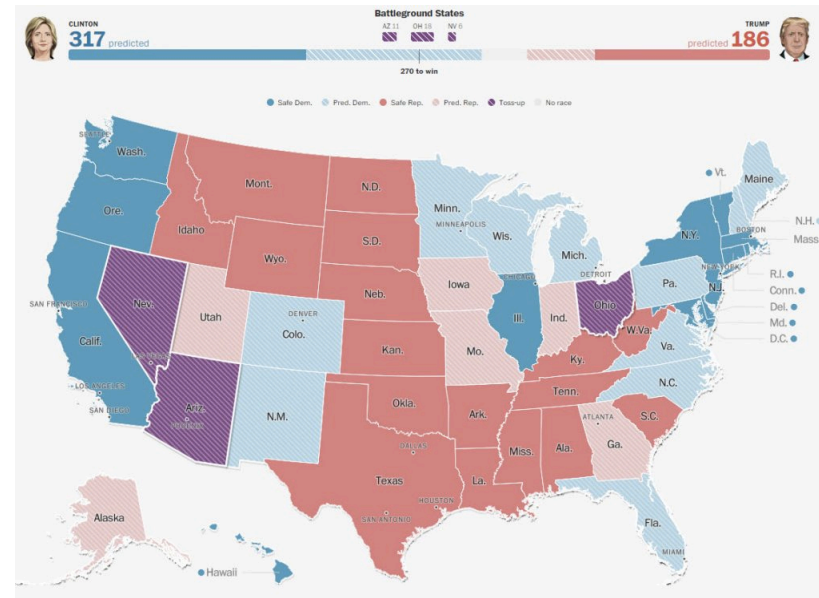


Our @pollsterpolls model gives @HillaryClinton a 98.1% chance of winning the presidency [elections.huffingtonpost.com/2016/forecast/...](http://elections.huffingtonpost.com/2016/forecast/)



2016/11/07, 11:25

4 728 RETWEETS 3 812 LIKES



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# American National Election Studies

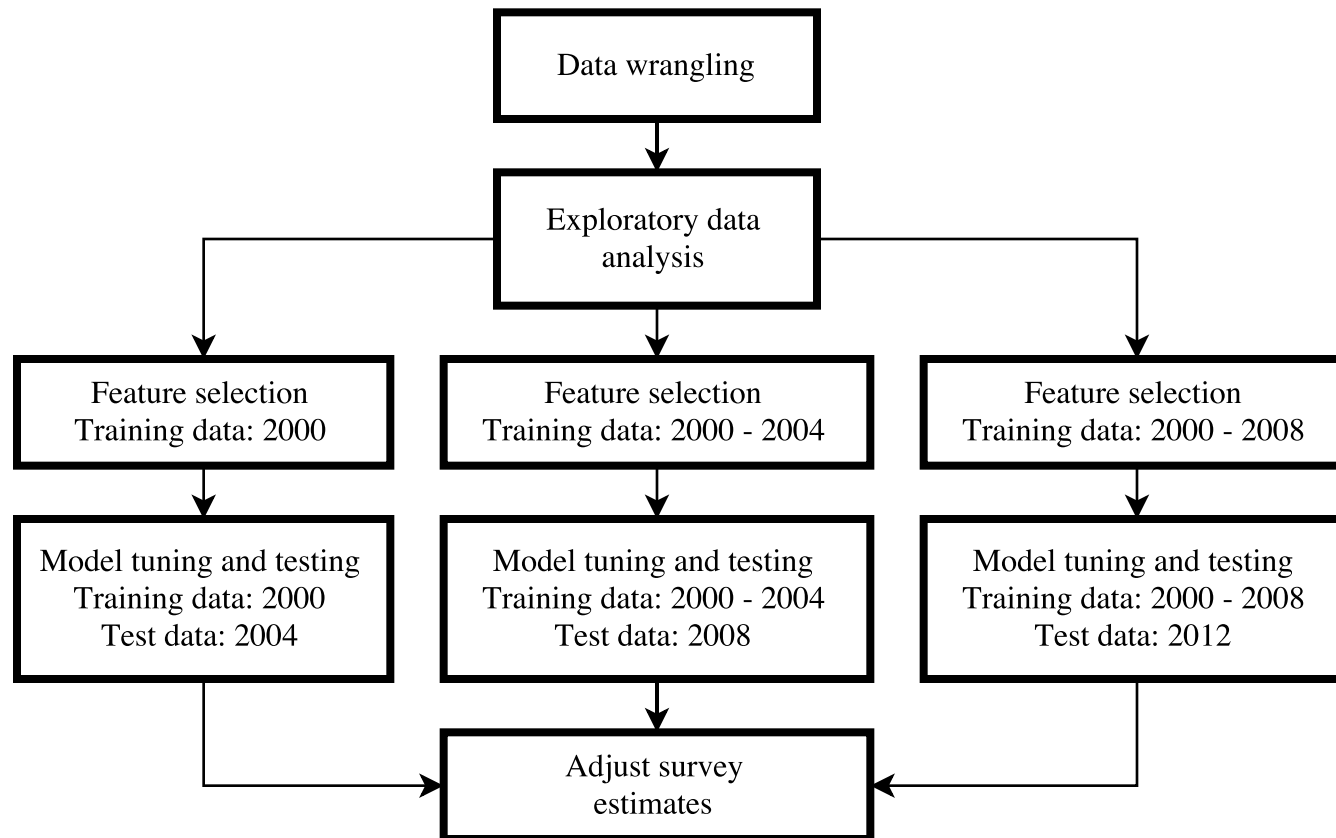
- ANES is a research organization specializing in time series studies of voting, public opinion, and political participation
  - Cumulative time series data
    - 50000+ respondents, 900+ features
    - Each respondent interviewed prior to election as well as after
    - All pre and post-election interviews from 1948 to 2012
-

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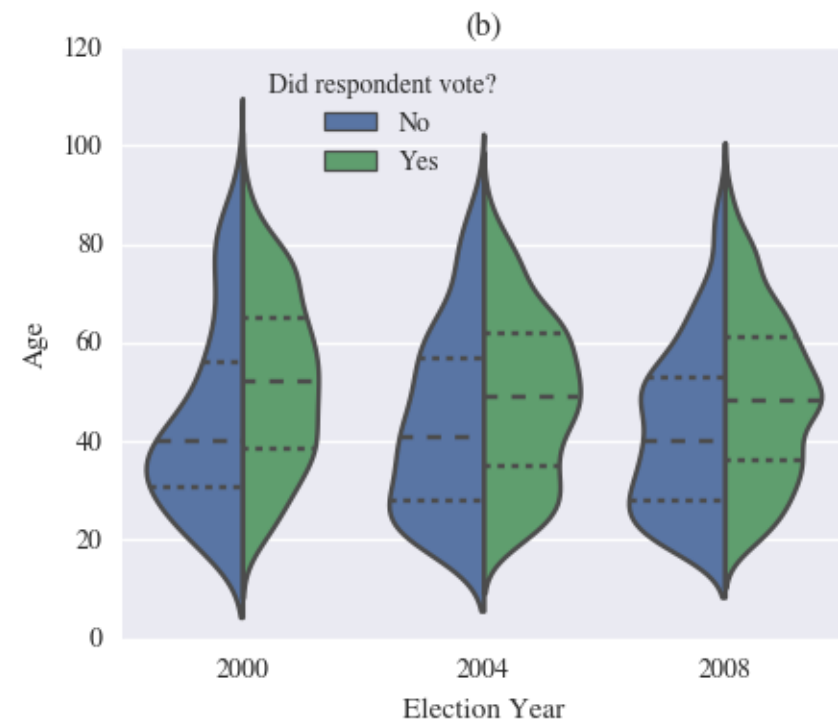
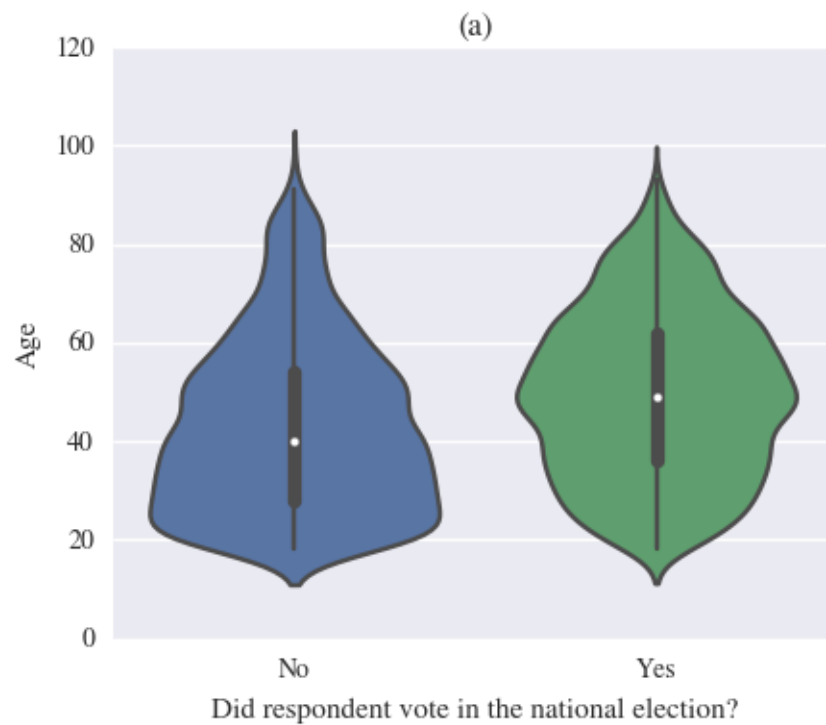
# For This Project

- Two goals:
    - Find best classification model for separating voters from non-voters
    - Determine change in polling error
  - Interested in recent elections
    - Data from 2000 to 2012
    - 9,374 respondents and 263 features
-

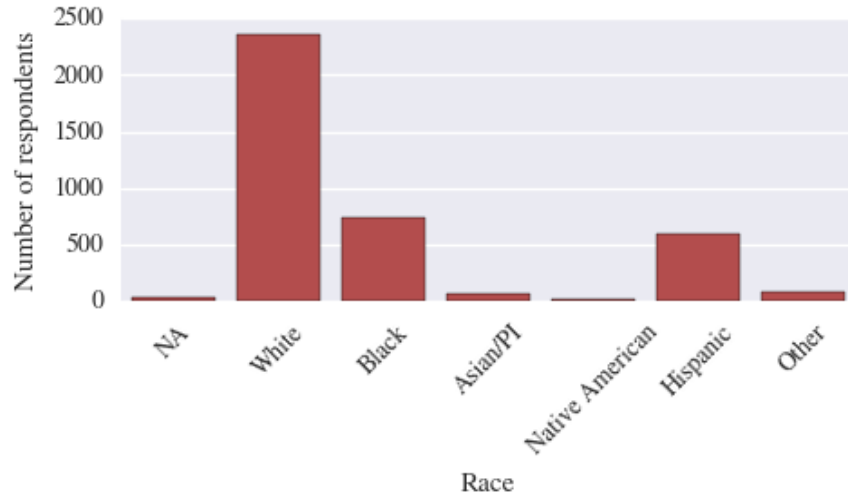
# Project Flow



# Non-Voters Skew Younger

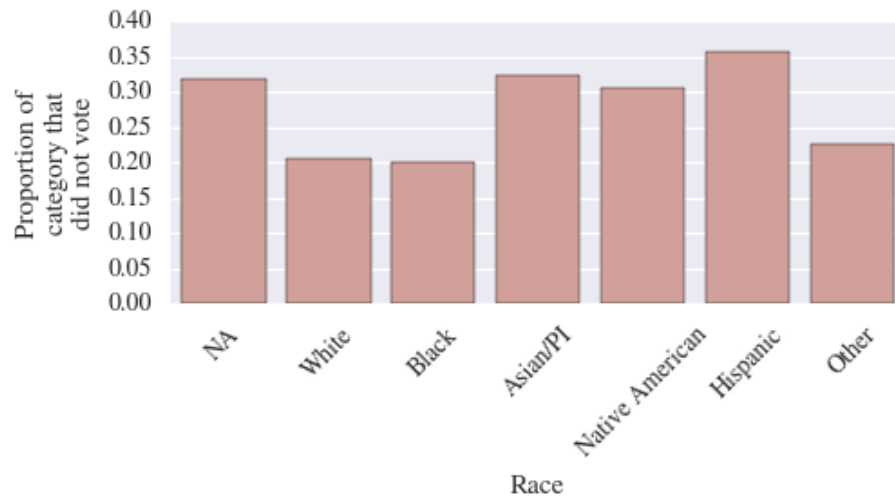


# Non-Voter Proportions by Ethnicity



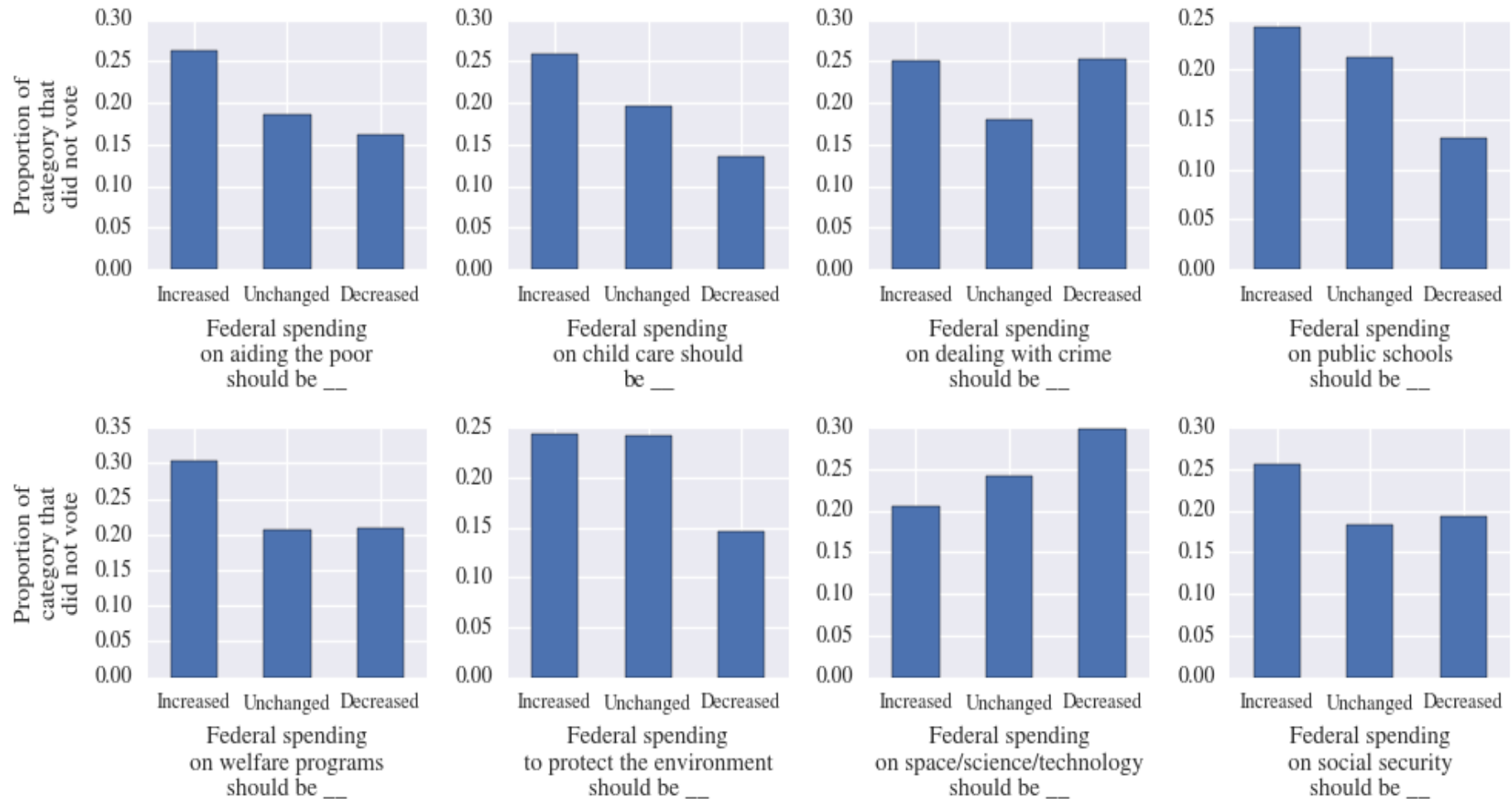
Whites and blacks have highest vote participation rates

Hispanics have the lowest despite being third largest racial group

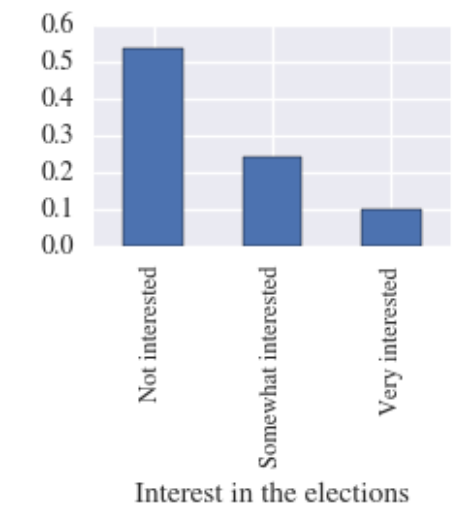
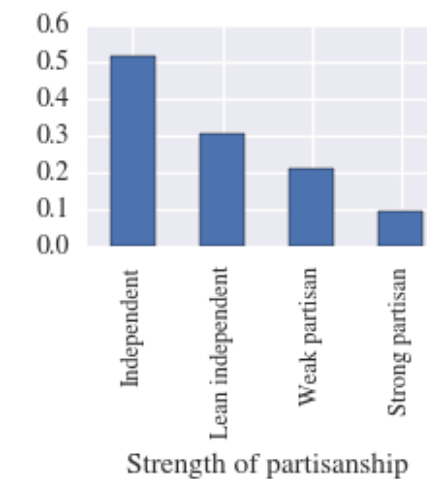
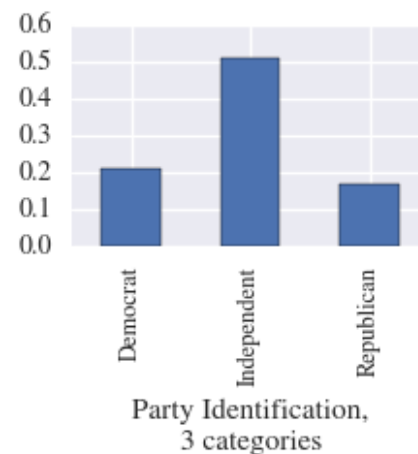
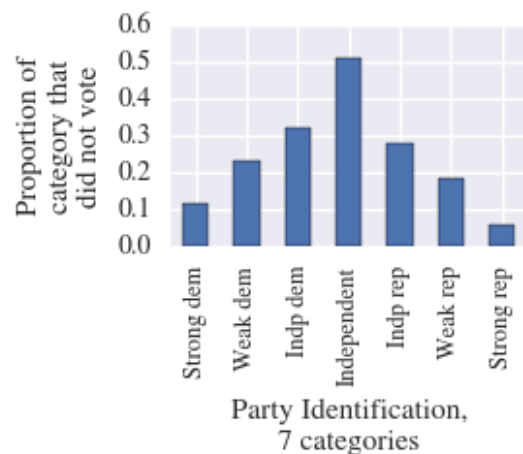
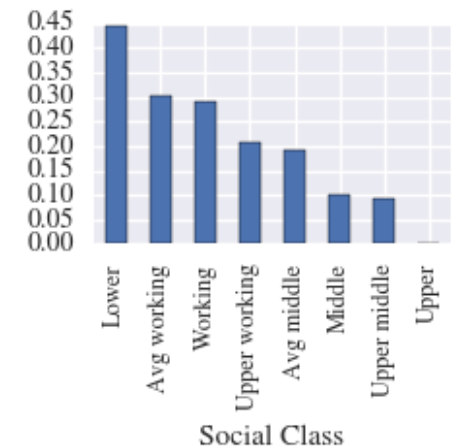
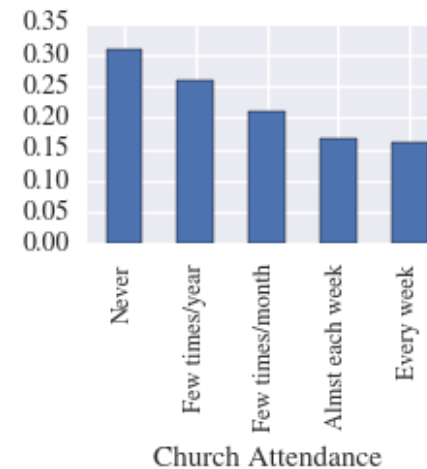
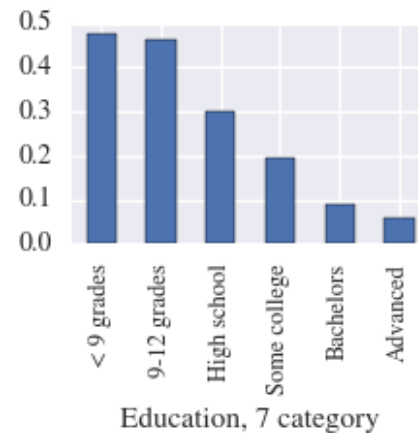
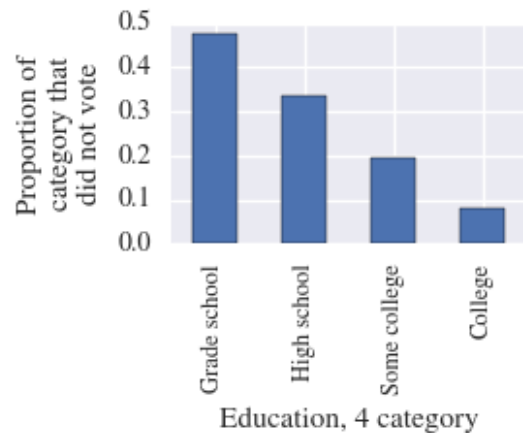




# Non-voting hurts Democratic policies



# More Patterns

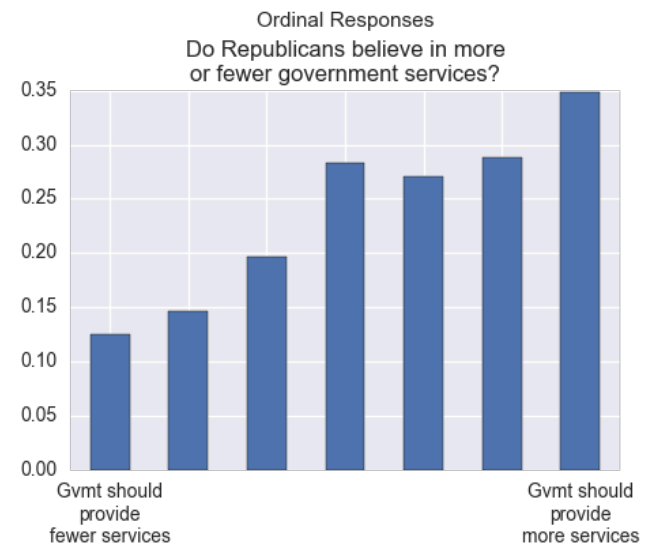
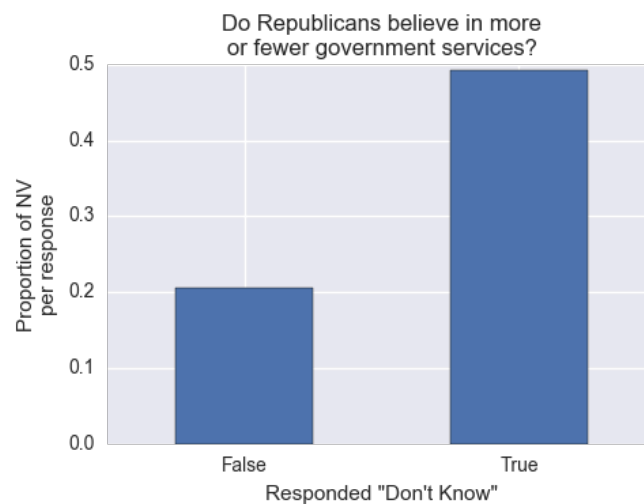
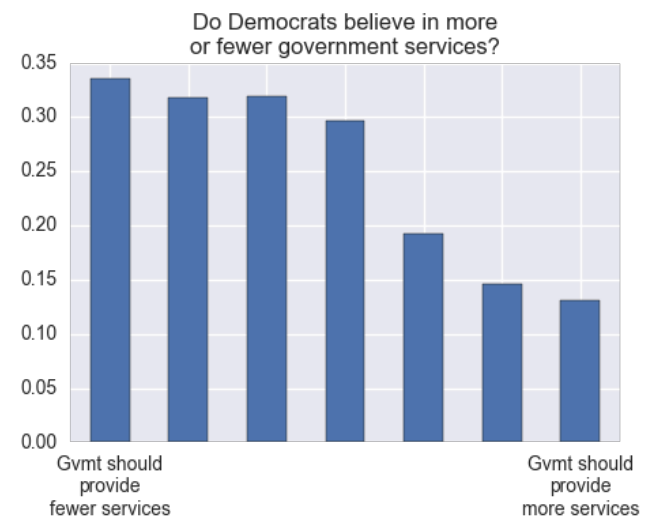
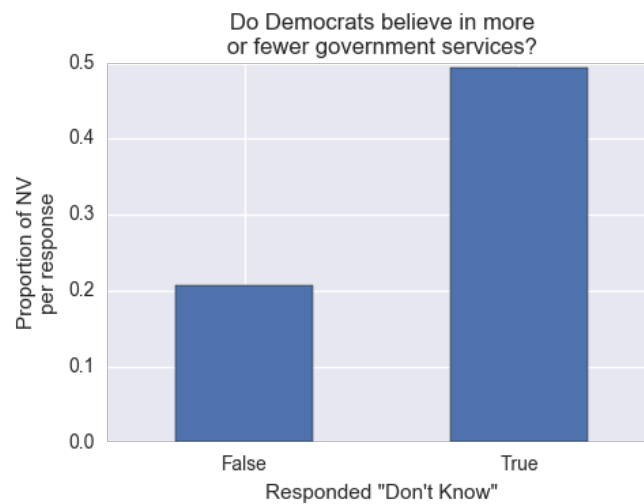


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# Non-Voters and Political Knowledge

- ANES time series survey includes a battery of questions testing political knowledge
  - Do wrong or “don’t know” responses indicate a greater likelihood of being a non-voter?
-

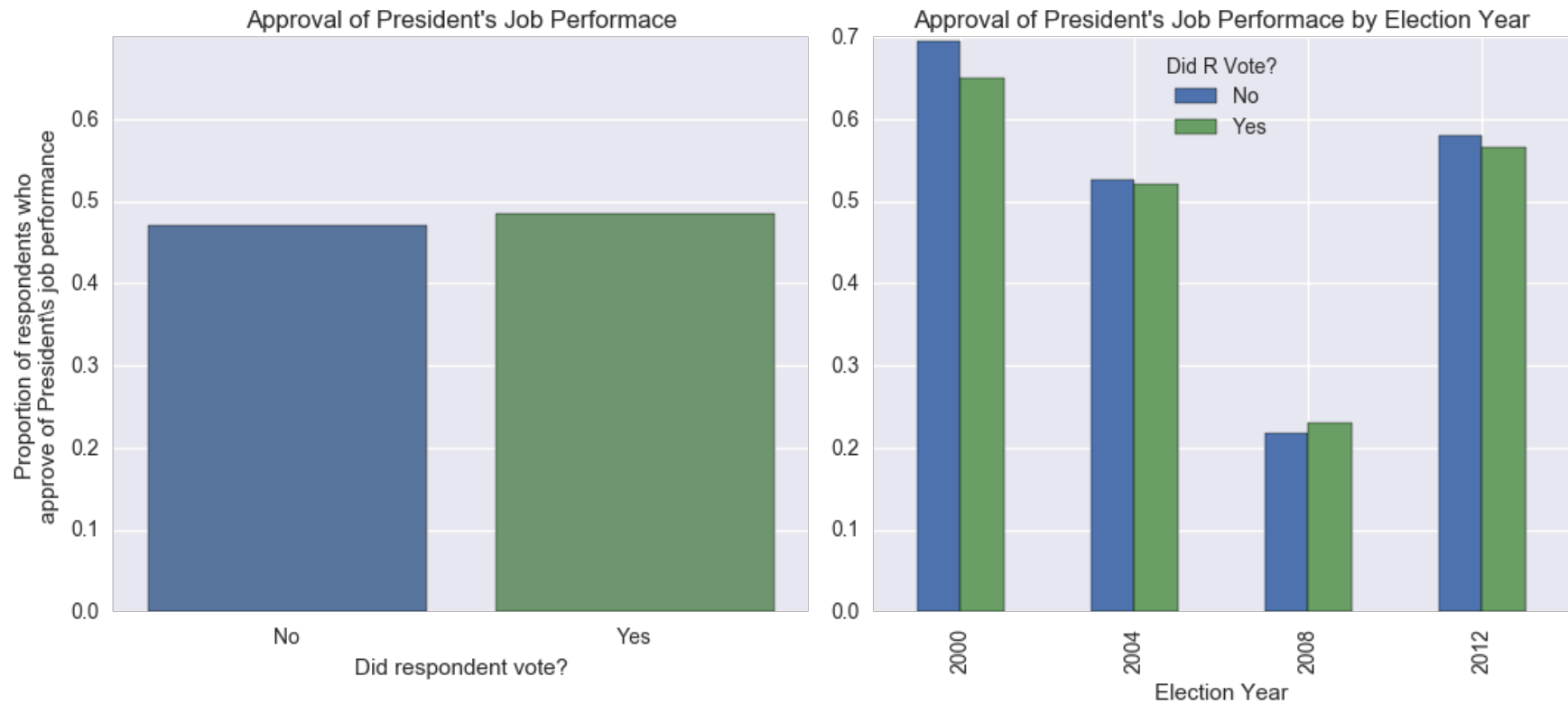
# Example



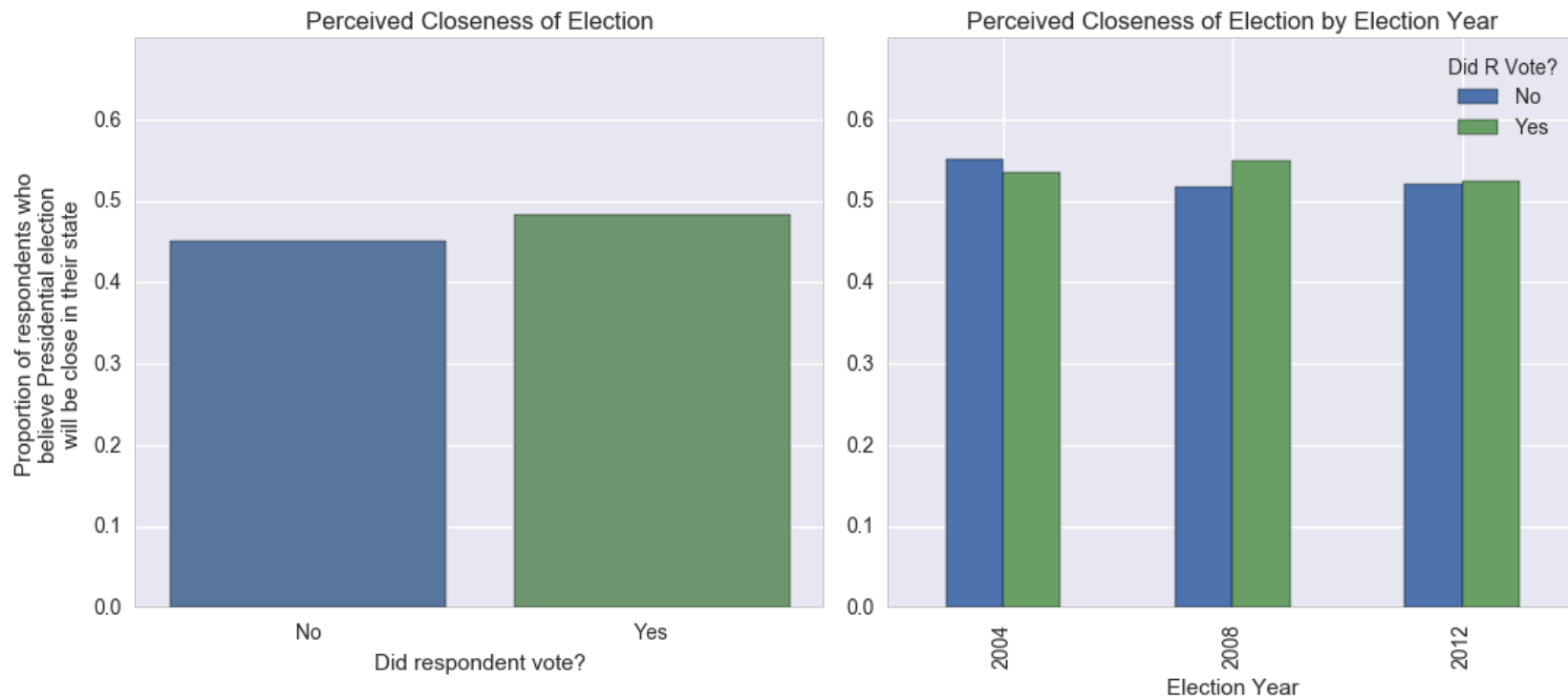
# More “Don’t Know” Responses = Probably a Non-Voter



# President's Job Performance Equal Across Voters and Non-Voters



# Closeness of Elections Do Not Matter



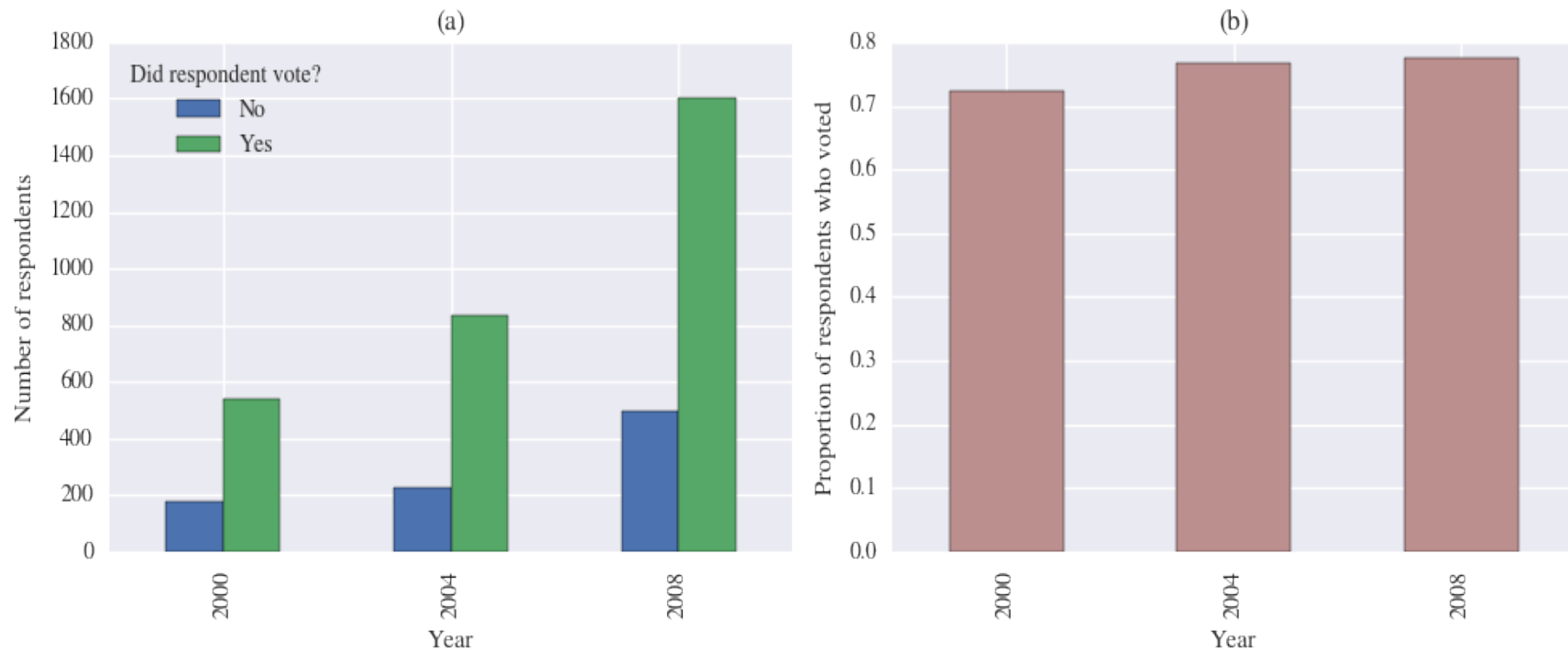
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# Non-Voters Are

Younger	More apathetic	More Hispanic	More pro-government	More culturally conservative
Less educated	Less religious	Less engaged	Less partisan	Less wealthy

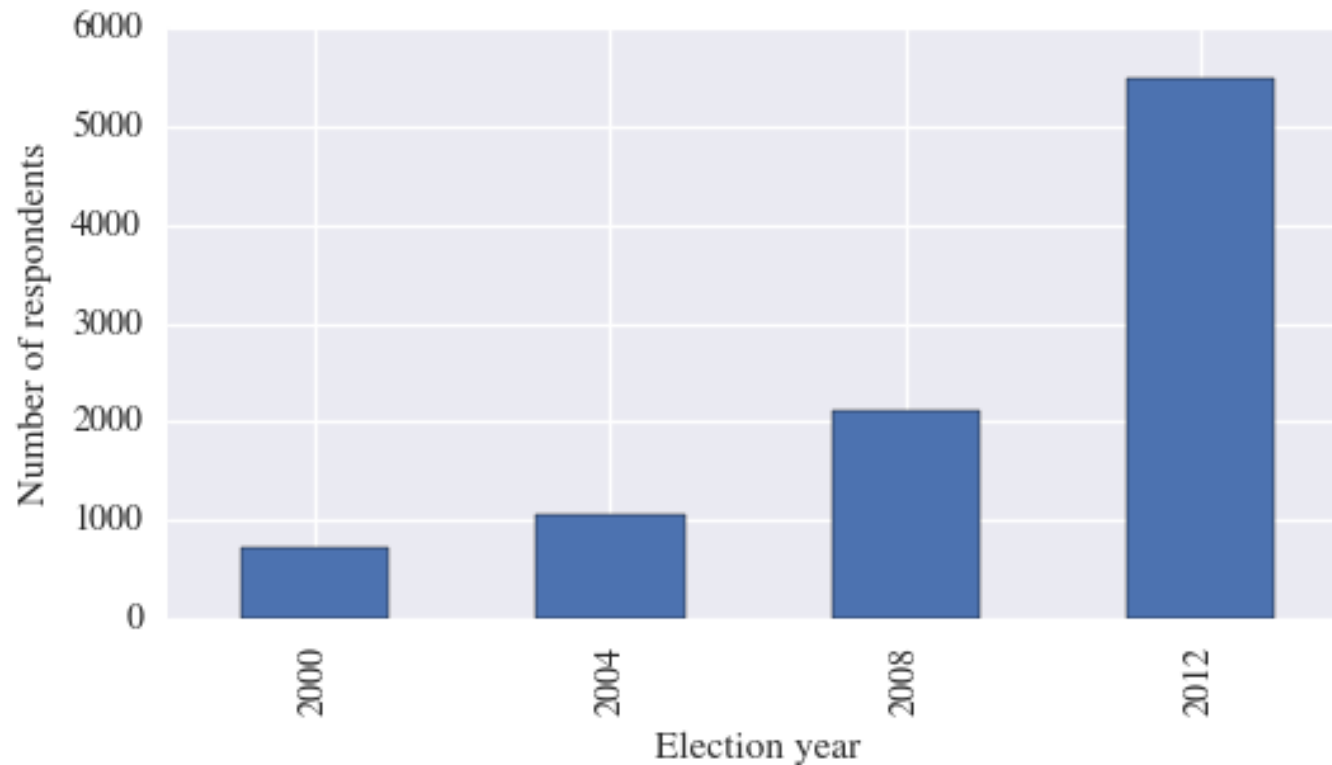


# Problem: Unbalanced Data



■ Solution: evaluate models using F1-score rather than accuracy

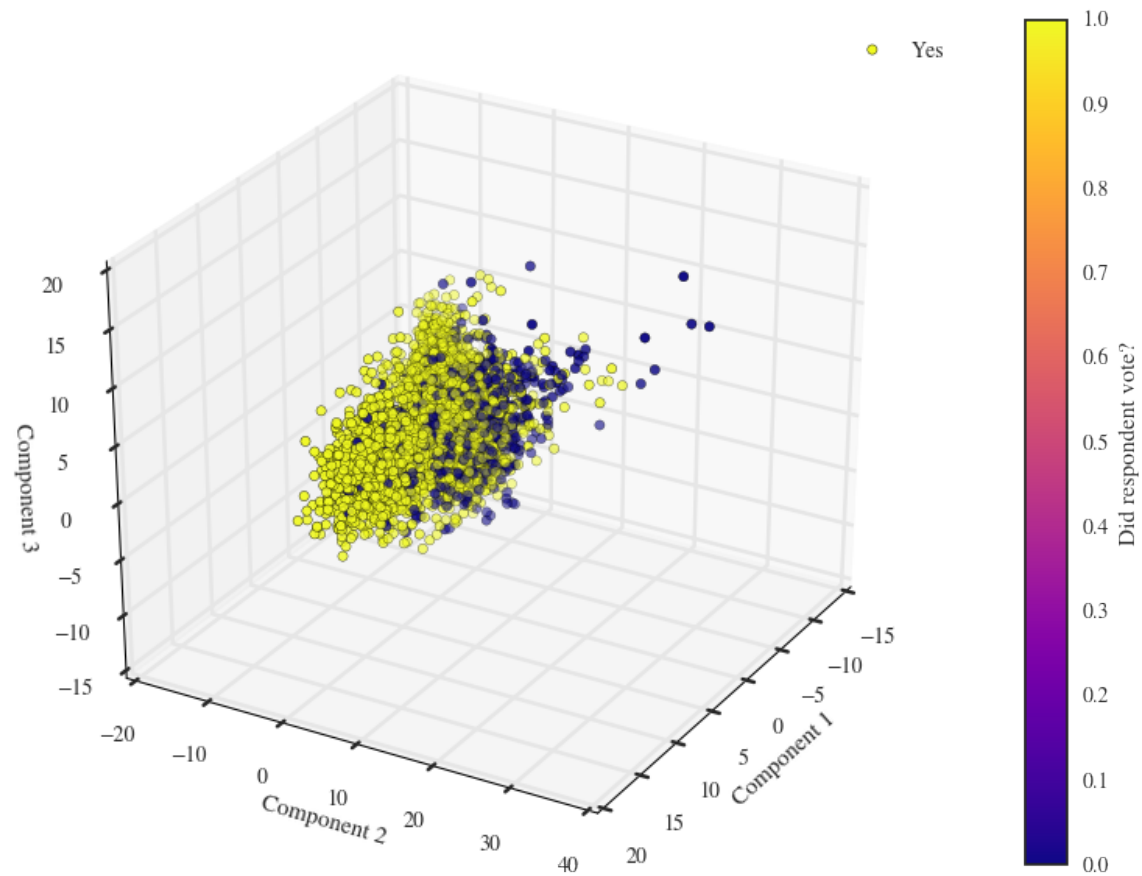
# Problem: Unbalanced Data



- Varying amounts of data available for training on different target years
- Solution: automate feature selection with recursive feature elimination

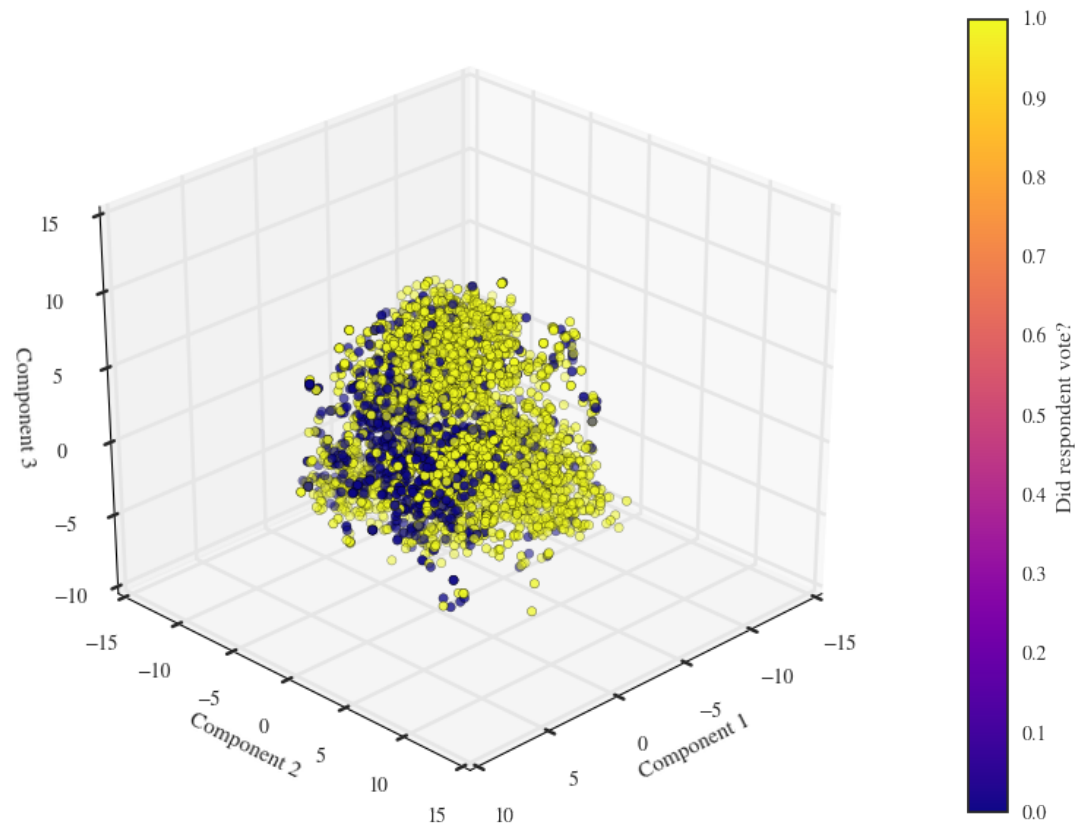
# Mixed Signals

Principal component analysis



# Mixed Signals

t-Distributed Stochastic Neighbor  
Embedding



# Training and Testing Models

	Target year of test set								
	2004			2008			2012		
	F1	Prec.	Rec.	F1	Prec.	Rec.	F1	Prec.	Rec.
Logistic Regression	0.612	0.604	0.620	0.614	0.531	0.727	0.595	0.606	0.585
Adaptive Boosting	0.611	0.694	0.546	0.617	0.522	0.699	0.584	0.532	0.565
Bernoulli Naïve Bayes	0.636	0.647	0.624	0.618	0.525	0.749	0.538	0.655	0.456
Support Vector Machine	0.659	0.703	0.620	0.618	0.518	0.764	0.542	0.448	0.687

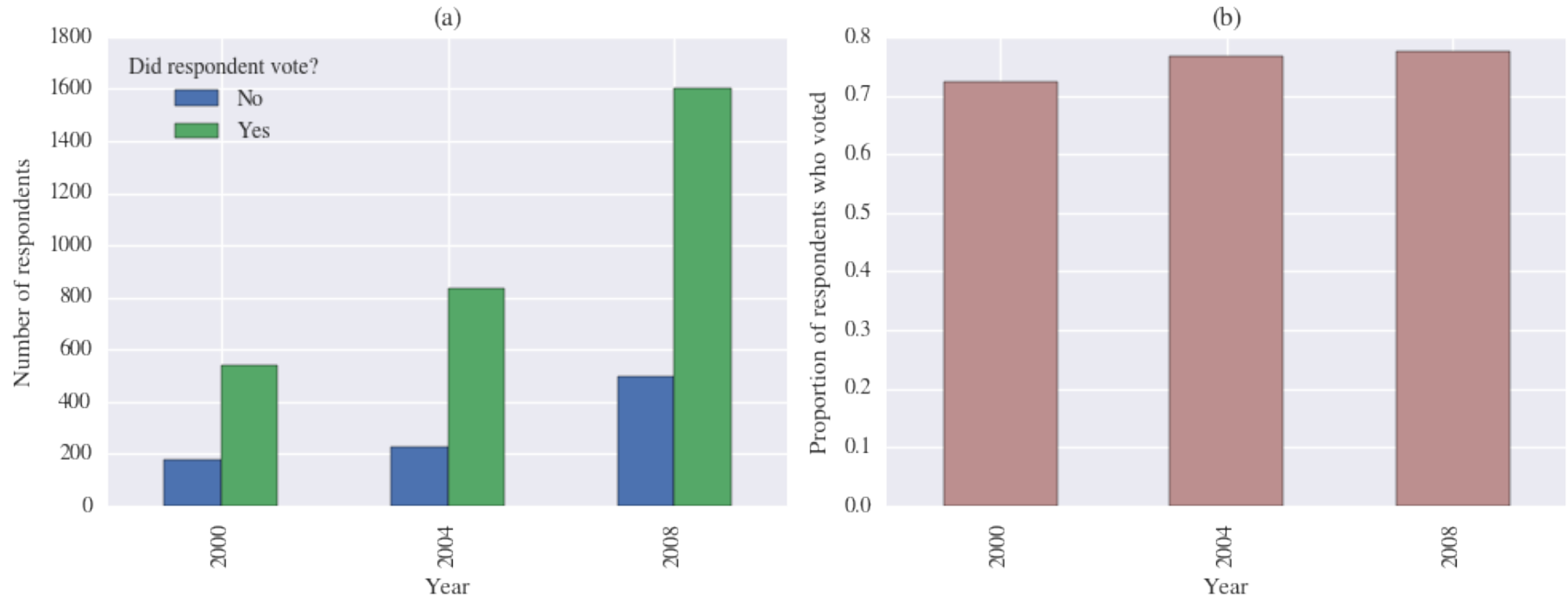
- Cross-validated training scores between 0.7 to 0.75
- No individual model appears to consistently outperform all others

# Soft Voting Classifier

	Target year		
	2004	2008	2012
Training F1	0.726	0.765	0.784
Test F1	0.619	0.647	0.611

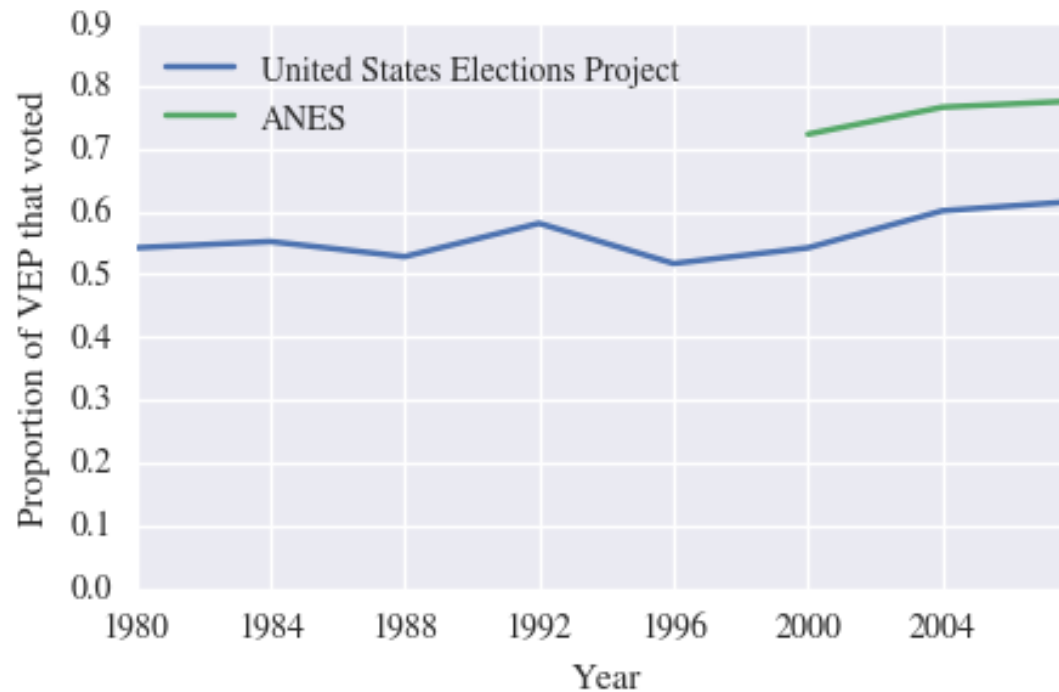
- Leverages the strength of each individual model
- Outputs prediction based on weighted averages of each model's classification probability
- Improves test F1-score for 2008 and 2012

# Problem: Social Desirability Bias



- Self-reported vote participation is un-reliable
- Many respondents claimed to have voted despite not voting

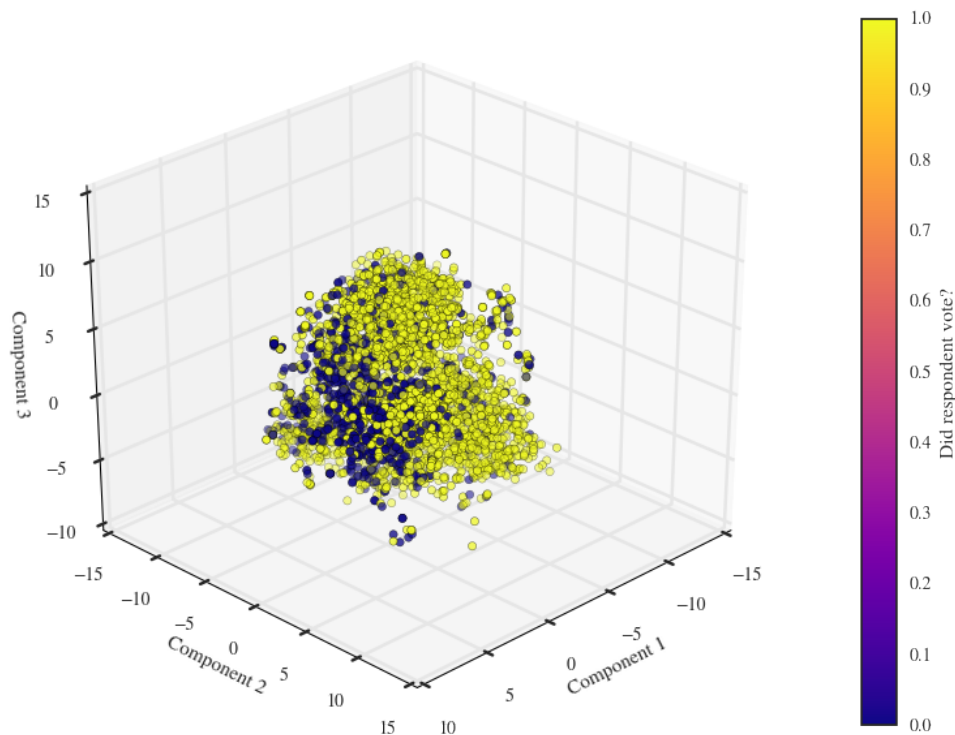
# Problem: Social Desirability Bias



- Ground truth is unreliable
- Solution: require recall above threshold



# Dealing with Unreliable Respondents



- Rig models to aggressively identify non-voters
- False positives preferred to false negatives
- After training a model, find lowest classification threshold that gives recall  $> 0.8$
- Adjust threshold on test set classification

# Calculating Polling Results

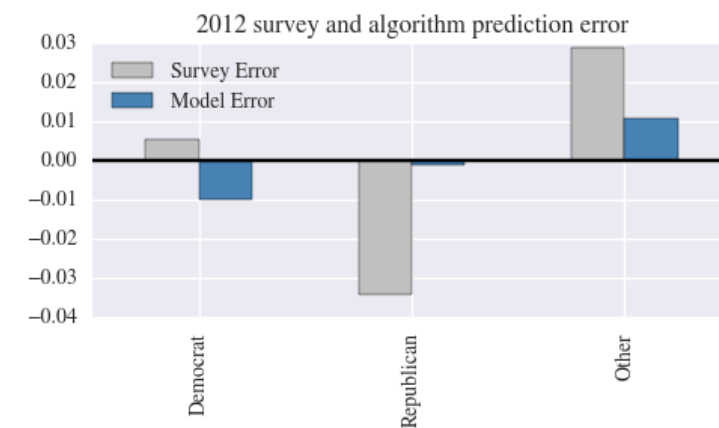
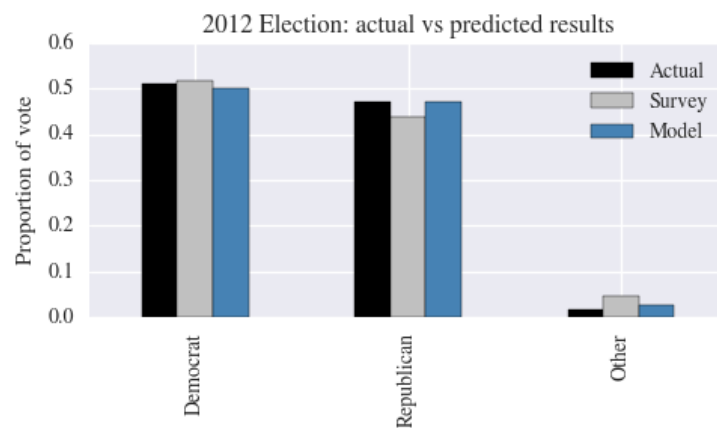
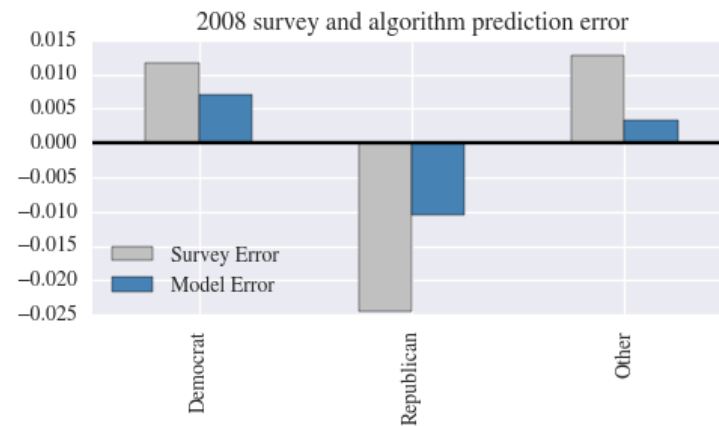
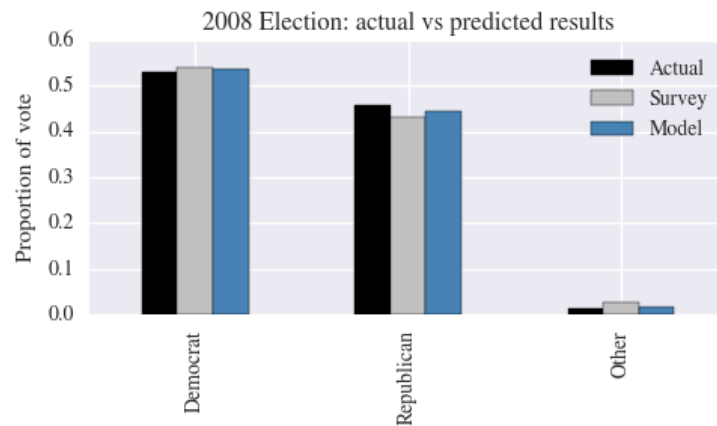
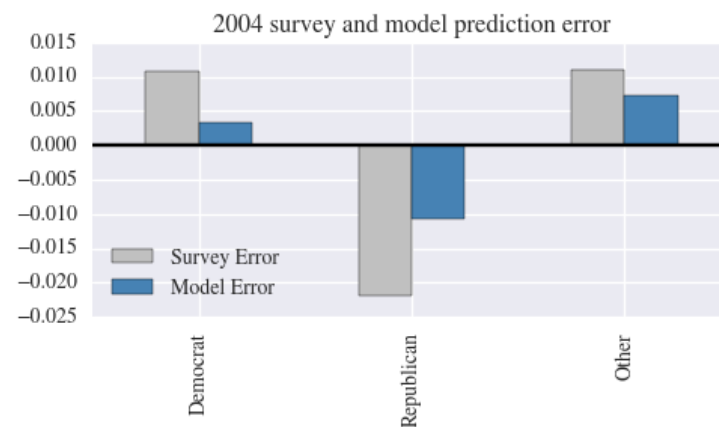
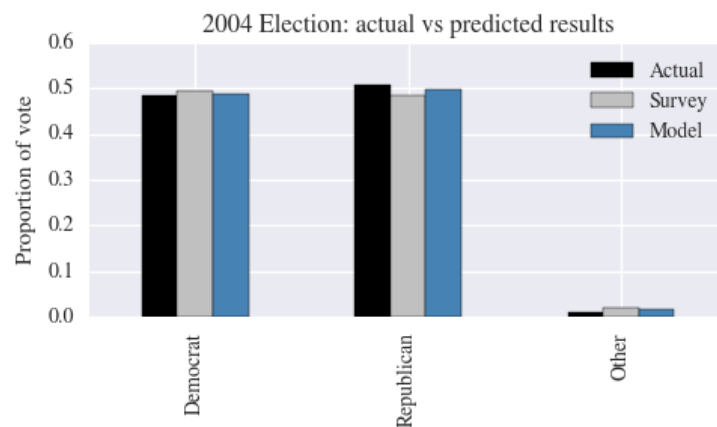
- Without non-voter filter:

$$P_j = \frac{\sum_{i=1}^m w_i \delta_{v_i j}}{\sum_{i=1}^m w_i (1 - \delta_{v_i n})}, \text{ where } \delta_{v_i j} = \begin{cases} 0, & \text{if } v_i \neq j. \\ 1, & \text{if } v_i = j. \end{cases}$$

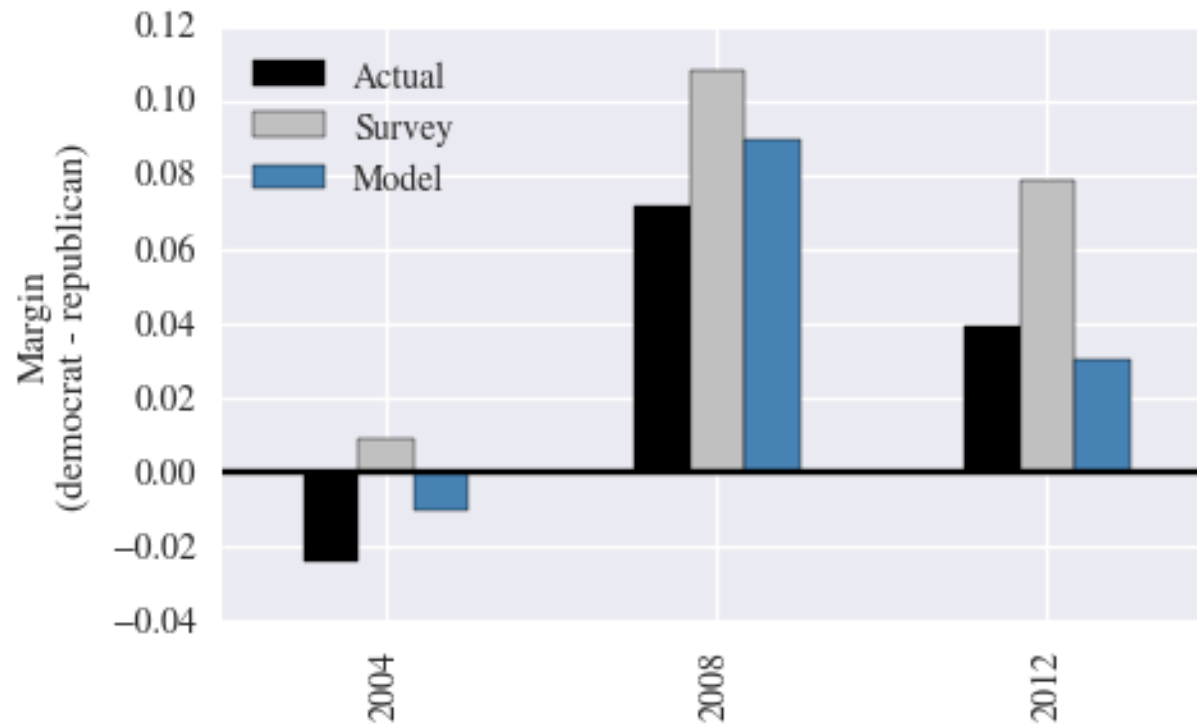
- With non-voter filter:

$$P'_j = \frac{\sum_{i=1}^m w_i \delta_{v_i j} (1 - z_i)}{\sum_{i=1}^m w_i (1 - \delta_{v_i n}) (1 - z_i)}, \text{ where } \delta_{v_i j} = \begin{cases} 0, & \text{if } v_i \neq j. \\ 1, & \text{if } v_i = j. \end{cases}$$

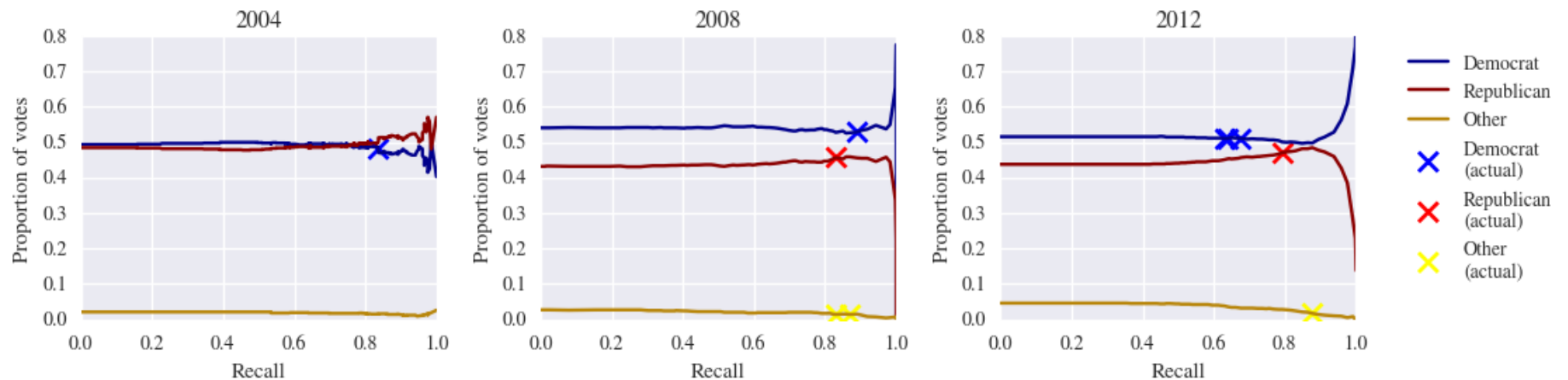
- Where  $P_j$  is the proportion of voting respondents who supported candidate  $j$ ,  $w_i$  and  $v_i$  in  $\{n, 1, 2, 3\}$  are the sampling weights and vote intentions of the  $i^{\text{th}}$  respondent,  $n$  in  $v$  denotes the intention of the respondent not to vote, and  $z_i$  in  $\{0, 1\}$  denotes the prediction as to whether the  $i^{\text{th}}$  respondent voted.



# Using a Filter Improves Predicted Margins

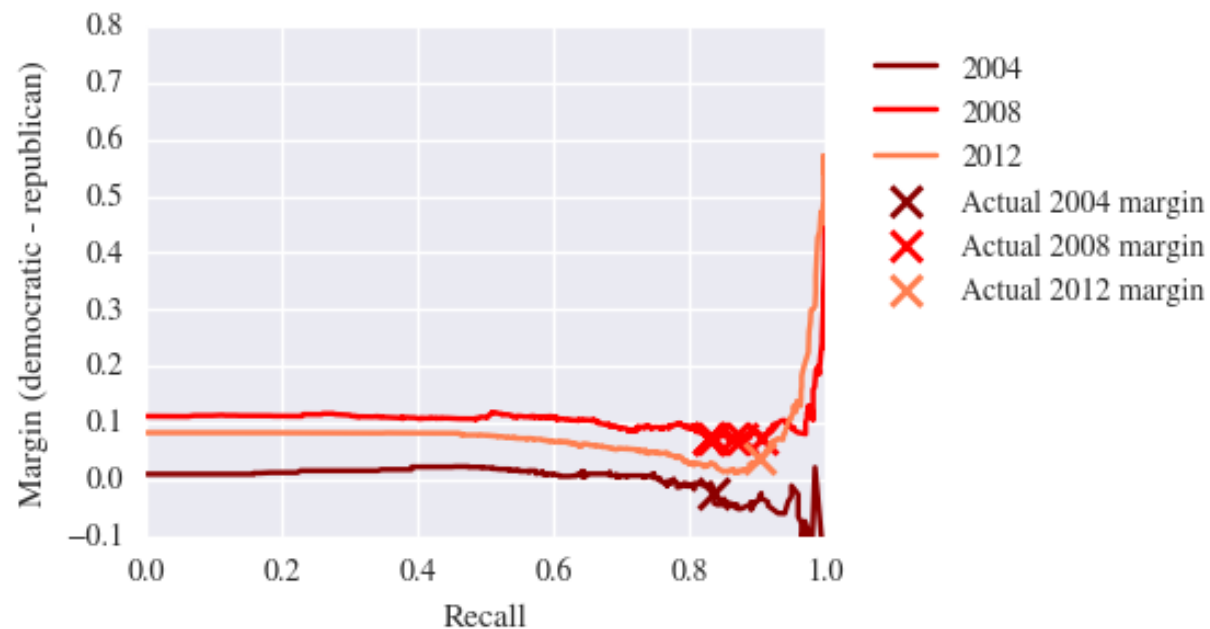


# Recall Analysis



- A recall of 0 is equivalent to not using the non-voting filter
- 0.8 appears to be a good recall requirement, but other values within 0.6-0.9 would also adjust polls in correct direction

# Recall Analysis



- Vote margin predictions are also robust against different recall requirements

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# Conclusion

- A soft voting classifier appears to perform best for classifying voters and non-voters from a survey
  - Using soft voting classifiers to serve as a non-voting filter improves the accuracy of national polls
  - Machine learning may be a viable model for developing likely voter models
-

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## Further Study

- Compare performance of machine-learning based models against current heuristic models (i.e. Perry-Gallup Index)
  - Apply the same technique to recently released 2016 ANES data
  - Explore whether this method works on data for which ground truth is reliable (i.e. extending data with state voter registries)
  - Perform similar studies for state and local level polling
-



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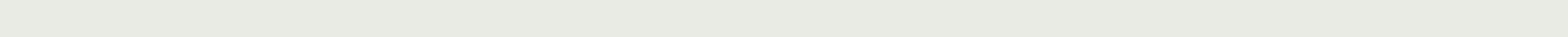
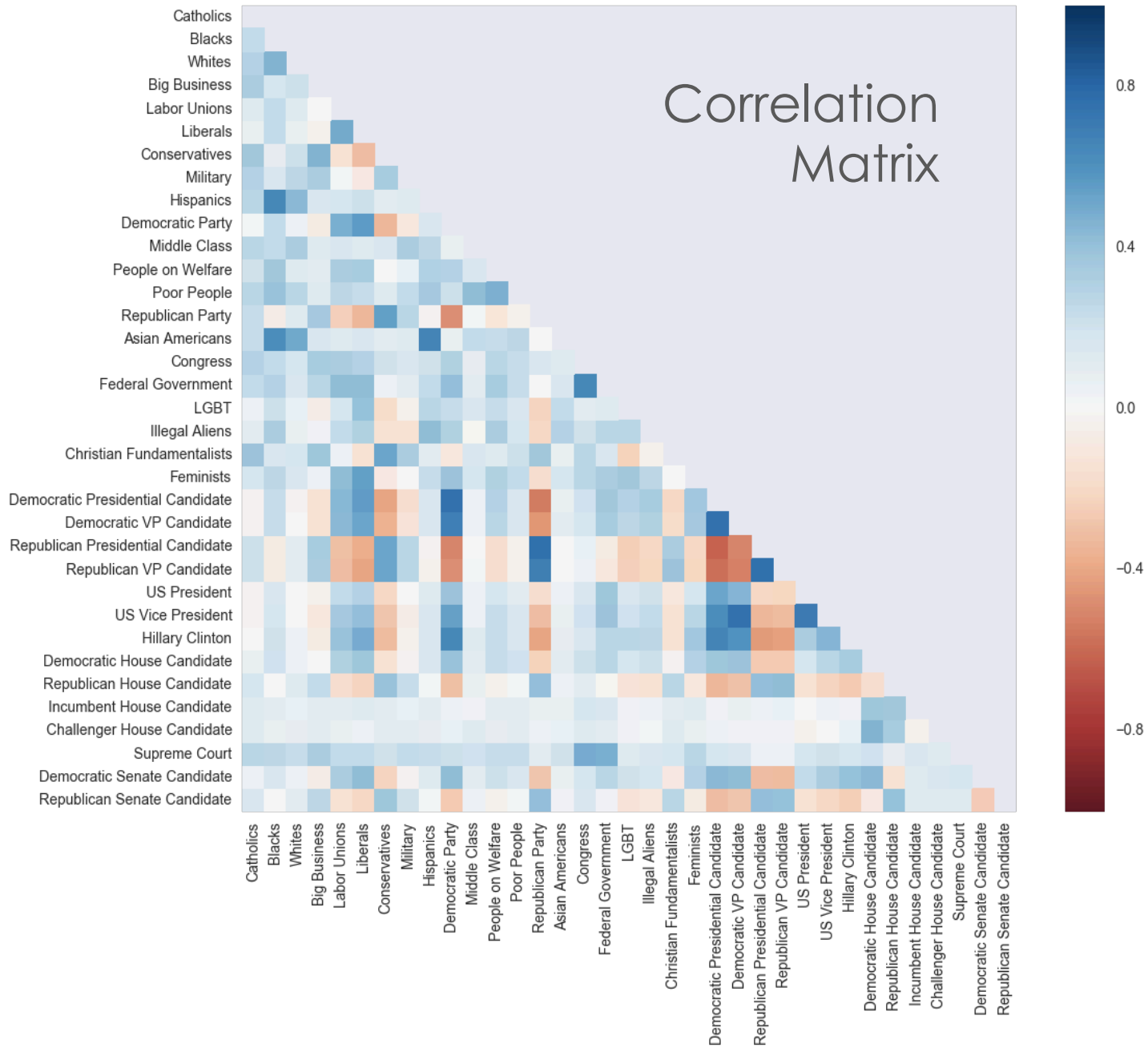
# A Detour: Partisanship in America

How divided are we?

---

# Thermometer features

- ANES surveys contain a set of “thermometer” questions
  - Measure negative/positive sentiment
  - Response is an integer value
    - 0 = negative sentiment
    - 100 = positive sentiment
- Remaining analyses incorporates sampling weights for population inference



# Identity vs. Ideology

Thermometer Pair	Correlation Coefficient
Democratic vs. Republican Presidential Candidate	-0.61752
Democratic vs. Republican VP Candidate	-0.530565
Democratic vs. Republican Party	-0.469287
Liberals vs. Conservatives	-0.306816
Democratic vs. Republican Senate Candidate	-0.254292
LGBT vs. Christian Fundamentalists	-0.230465
Democratic vs. Republican House Candidate	-0.159287
Big Business vs. Labor Unions	0.015196

- Expected anti-correlated pairs only moderately correlated at best
- Correlation weaker for parties and weaker still for ideology
- Down ballot races far less divisive
- Temporary polarization
- Politics is tribalism, not ideology