# Classification and Clustering Methods to Predict Pollster Accuracy in US Elections

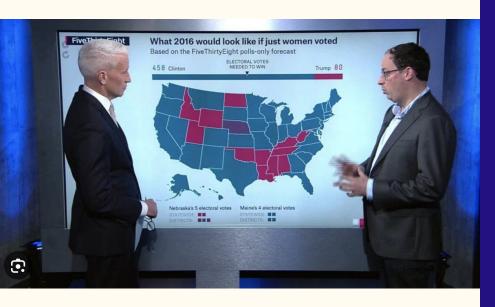
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# Problem Statement

We will investigate polling accuracy across different methodologies, partisan status, and type of race. Our goal is to predict if a poll will make the right call based on polling features or discover similar trends in accurate or inaccurate polls based on clustering methods.

# The Data





- Started in 2008 as a blog
- Namesake 538 electors in US electoral college
- 2013 acquired by ESPN
- 2018 transferred to ABC
- Broad spectrum of subjects now focusing on elections, politics, and American society

Picture Source: <u>CNN</u>
Picture Source: <u>Nieman Lab</u>

# Using SpaCy Models for Comment Detail

comment			
for New York Daily No	ews   W	ABC-TV(I	New York)
for unspecified Demo	ocratic s	ponsor	
for New York Daily No	ews   W	ABC-TV (I	New York)
for Charles E. Schum	er		
for Richard Stallings			
for Richard Stallings			
sample size unavaila	ble; esti	mated at	600 as a default
for Tom Vilsack			
for Richard A. Hill			
for Robert C. Hayes			

Flags for organization, person, poll for a  $unspecified \ D/R$  sponsor

Regex to flag: among registered voters, average of multiple versions/turnout models listed, and imputed sample size

#### EN\_CORE\_WEB\_TRF



Sources: TRF image

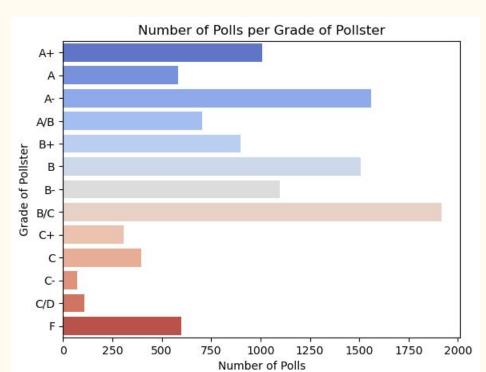
**SpaCy** 

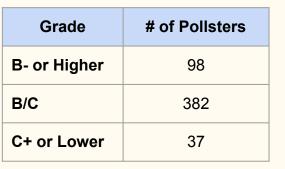
for CNN | Time

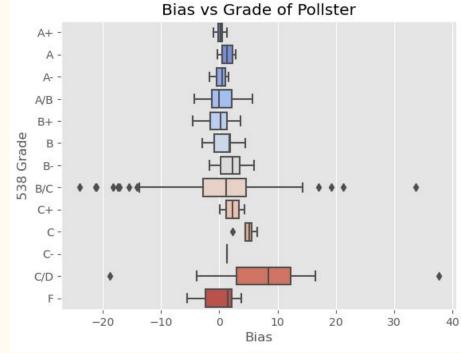
# Exploratory Data Analysis

#### EDA on Pollster Grades

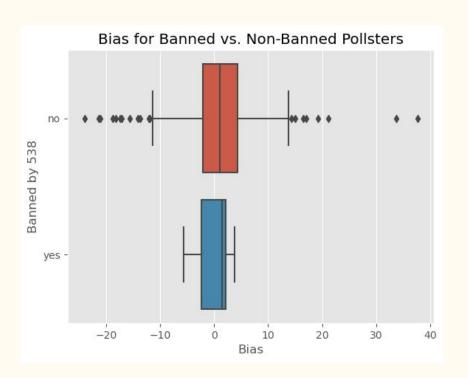
Context on 538 Grading: 538

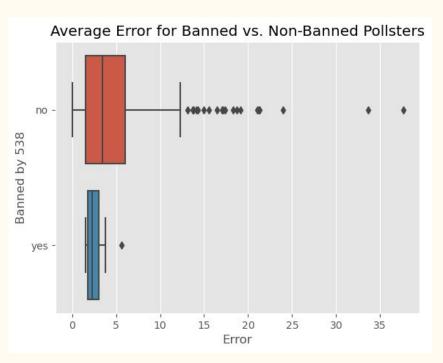




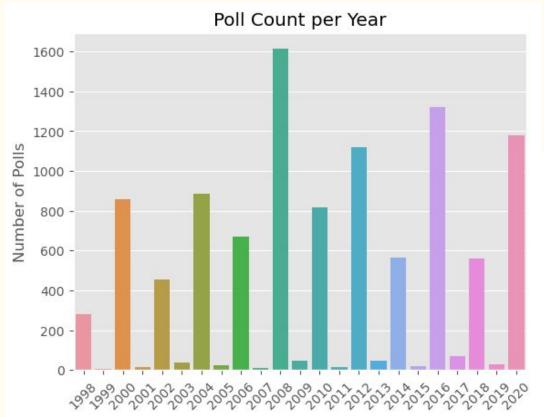


#### EDA on Pollster Grades





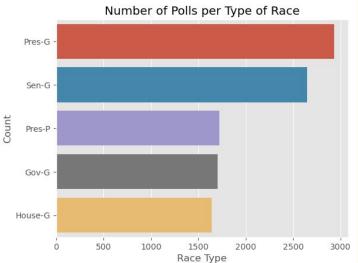
# Number of Polls - Spike in Polls in 2008



Increase in polls in 1998-2008

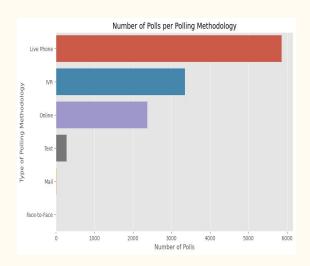
Access to online and text capabilities

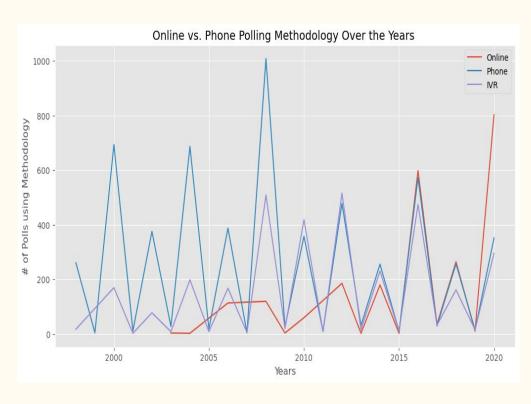
Most polling done on **Presidential Election** 



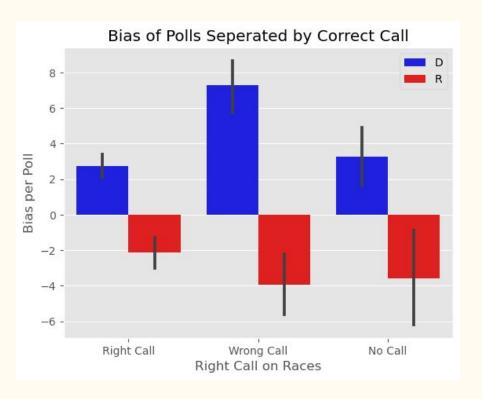
# Types of Methodologies

Live Phone, IVR, and Online polls were by far the most common methodologies.





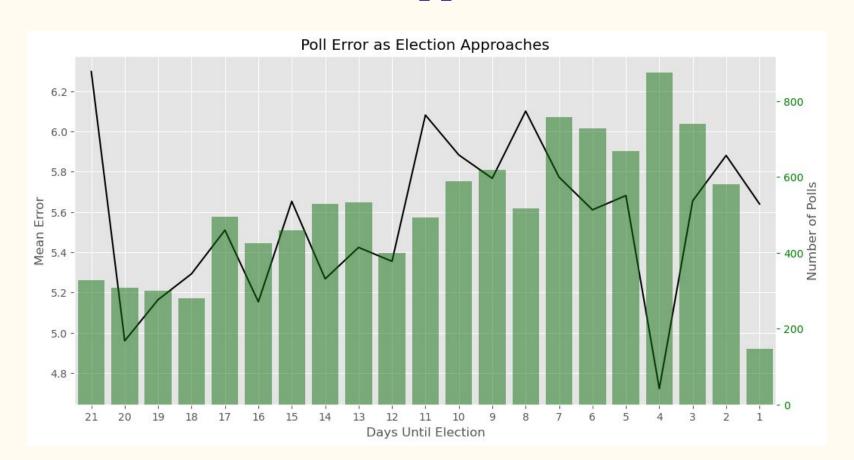
# Understanding Bias vs. Error



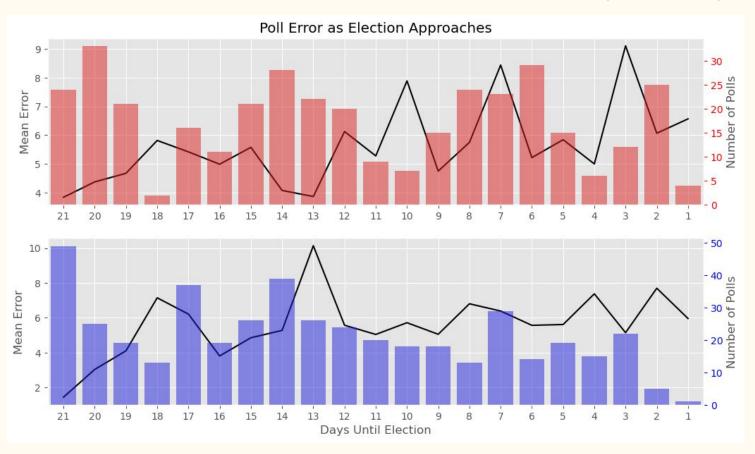
- Positive Bias Score favorable to a Democratic candidate compared to actual score
- Negative Bias Score favorable to Republican
  candidate compared to actual
  score
- Error Absolute Value of Bias

	Wrong Call	No Call	Right Call
Democratic (D)	121	36	294
Republican ( R )	98	19	244

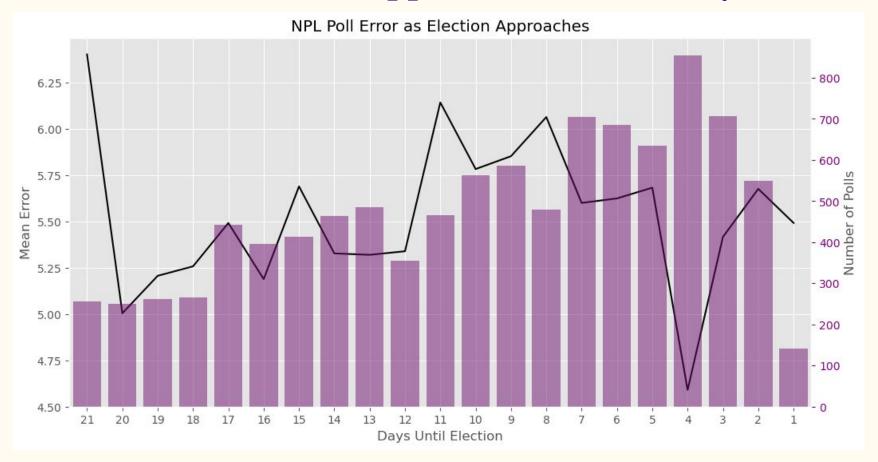
# Poll Error as Election Approaches



# Poll Error as Election Approaches by Party



## Poll Error as Election Approaches - No Party Label



# Prediction Methods

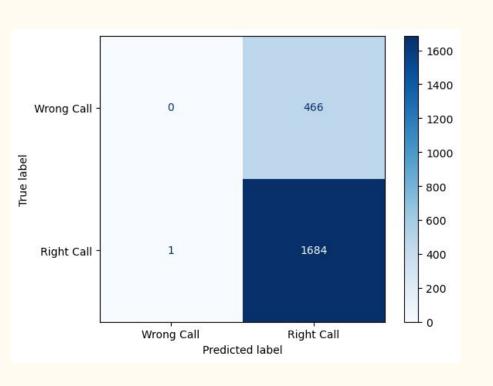
# Modeling and Analysis:

#### Target - if a Poll made the Right call

- 1. Logistic Regression with Numeric Features (using StandardScaler and MinMaxScaler)
- 2. Logistic Regression + Categorical Features (using StandardScaler)
- 3. Simple Decision Tree (Cat + Num features)(using StandardScaler and MinMaxScaler) Best Model
- 4. Grid Search Decision Tree (Numeric and Categorical) (StandardScaler)
- 5. Random Forest Model (Numeric and Categorical) (StandardScaler)
- 6. Random Forest with Interaction Features using PolynomialFeatures
- 7. Analyzing our best model (RF) Performance by Partisan group

### Logistic Regression - Numeric Features

With StandardScaler

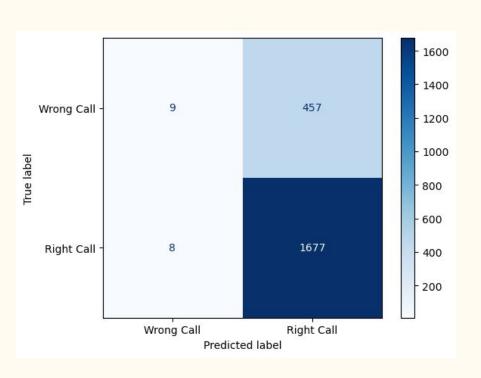


- Numeric features 'year', 'samplesize', 'cand1\_pct', 'cand2\_pct', 'days\_bt\_polldate\_election'
- **Target Mapped Right Call** 0 or 1 0.5 (dead heat imputed to 0)

Baseline	0.7835
Train Score	0.7827
Test Score	0.7829
Recall	0.9994
Precision	0.7833
f1 score	0.8782

## Logistic Regression - Numeric and Categorical **Features**

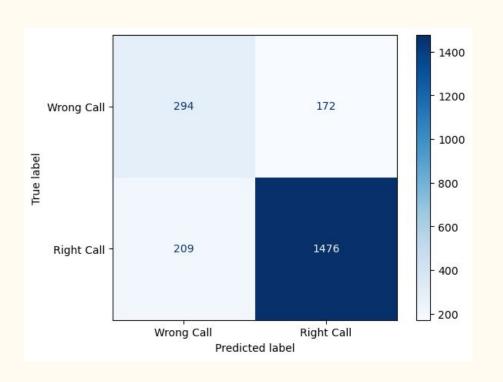
With StandardScaler



- Numeric features
- Categorical features 'org', 'person', 'anon', 'registered\_voters', 'averaged', 'imputed 600', 'Text', 'Live Phone', 'Mail',' Face-to-Face', 'IVR', 'Online', '538 Grade'
- Target Mapped Right Call 0 or 1 0.5 (dead heat imputed to 0)

Baseline	0.7835
Train Score	0.7810
Test Score	0.7838
Recall	0.9953
Precision	0.7858
f1 score	0.8782

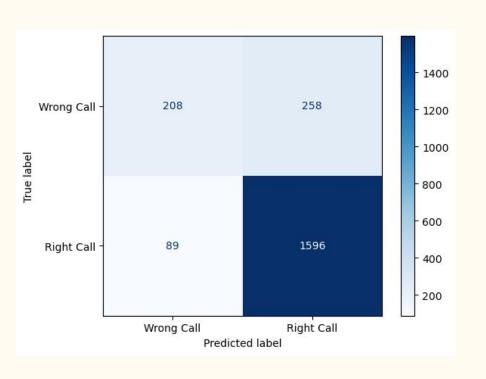
#### **Decision Trees**



- StandardScaler preformed pretty much the same MinMaxScaler
- Grid Search did not make much improvement compared to default

Baseline	0.7835
Train Score	0.8133
Test Score	0.8229
Recall	0.8760
Precision	0.8956
f1 score	0.8857

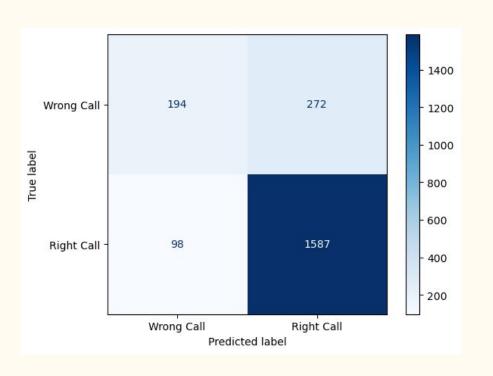
#### Random Forest Model



- Numeric and Categorical features
- **Target Mapped Right Call** 0 or 1 0.5 (dead heat imputed to 0)

Baseline	0.7835
Train Score	0.8332
Test Score	0.8387
Recall	0.9472
Precision	0.8608
f1 score	0.9019

#### Random Forest with Interaction Features

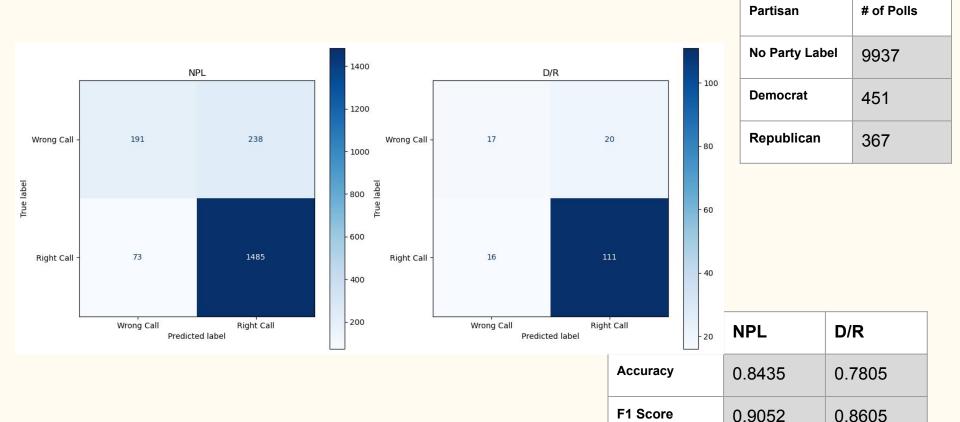


#### Used **PolynomialFeatures** on

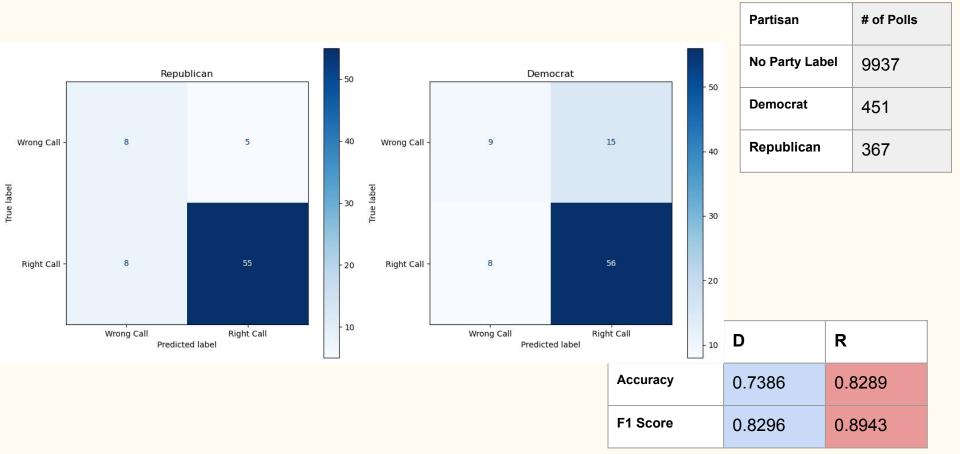
- Three most popular methodologies (Live Phone, IVR, Online)
- Imputed 600 and sample size

Baseline	0.7835
Train Score	0.8269
Test Score	0.8280
Recall	0.9418
Precision	0.8537
f1 score	0.8956

## Analyzing our Best Model by Party - Random Forest



### Analyzing our Best Model by Party - Random Forest



# Clustering Methods

#### Process

- Three clustering algorithms attempted:
  - o K-Means
  - DBSCAN
  - Hierarchical DBSCAN
- Compared results between Standard Scaler and Min-Max Scaler
  - Min-Max Scaler separates categorical features much more than Standard Scaler
  - Which scaling method was better depended on the clustering algorithm
- Applied Principle Component Analysis (PCA)
  - Used 85% of the variance as our cutoff
  - Did not change the results by much but did improve our clustering slightly
- Used Silhouette Score as our performance metric
  - Compares within cluster similarity with outside of cluster similarity(range: [-1,1], higher is better)
  - Not an appropriate measure for density-based clustering!

#### K-Means

- Min-Max Models:
  - Separated primarily on methodology
  - 2-means model split Live Phone polls into a cluster and the rest into the second
  - 3-mean model made separate clusters for Live Phone, Online, and IVR
- Standard Scaled Model:
  - □ Isolated some partisan polls that were a bit less accurate on average (~10% lower)
- Generally, K-Means did not show particularly interesting clusters

K	Scaler	Score
2	Min-Max	0.634
3	Min-Max	0.598
2	Standard	0.675

#### DBSCAN

- Standard Scaler gave very poor results
  - Standard Scaler best silhouette score: 0.095
    - Unable to find any meaning in the clusters
- Min-Max gave mixed but very interesting results
  - Best silhouette score: 0.423
  - Only created 1 cluster and identified 28 outliers
- The Outliers:
  - Very inaccurate polls (26.79% accuracy)
  - All partisan (15 Democratic, 13 Republican)
  - Ranged from 2012-2020
  - Almost all were done for unspecified donors

## Hierarchical DBSCAN (HDBSCAN)

- Extension of DBSCAN that can detect clusters of varying densities
  - No more tuning epsilon!
- Identical best silhouette score for Min-Max and Standard scaler (0.383)
  - Completely different clusters however
  - Standard Scaler found clusters that did not seem meaningful
- Min-Max Scaler on the other hand:
  - Found 24 clusters + outliers
  - 8 of those clusters had 0 correct calls between them
    - 1070 incorrect calls (10% of our data)
    - 4 no-calls
  - All were nonpartisan polls
  - None were online polls
    - Likely coincidental

# Conclusion

#### **Conclusions**

- Predicting poll accuracy through this approach is not easy
  - We were only able to improve our baseline by 5%
  - Polls are generally accurate and what causes them to be wrong is not easy to measure
    - Polls are trying to predict the future so there will always be some meaningful error present
- Clustering has some merit
  - Saw some interesting and meaningful clusters from all 3 approaches
  - Hard to tell whether clusters are valuable until we look at them very closely
- We did not find strong evidence of trends between partisan or methodological differences with error

# Next Steps

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- Using geopandas to create a heat map to visualize EDA by state
  - Methodology, Error, Bias, number of polls conducted
- Extend the clustering approach to find better separated clusters
  - Train a model to classify into those clusters to predict whether a poll is accurate by proxy
  - Implement a more effective measure of cluster quality
    - Density-Based Clustering Validation (DBCV)

# Any Questions?