# Money in Politics: The relationship between contributions and congressional voting

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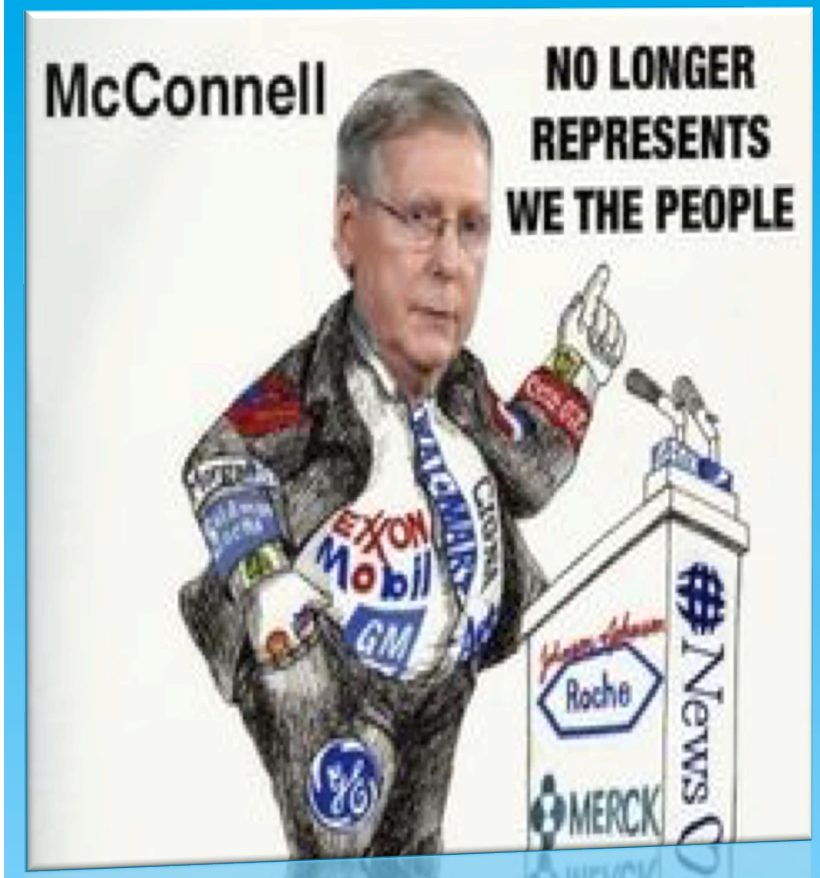



# Project Overview:

**Research Question:**

Is there a relationship between campaign contributions and congressional voting?

**Null Hypothesis:**

Using campaign contributions to predict congressional voting will not be more accurate than predicting congressional voting using the baseline metric (i.e. defined susequently).

# Data Set

Collection:

- All bill from the 101st to the 114th congress - 1989 to present (subset for project, Armed Forces and Nation Security ) (api: govtrack.us)
- How each official voted on a bill (api: govtrack.us)
  - Script for pulling data from govtracks's api (needs to be refactored)
  - get_legislation_data_script.ipynb
- Contributions to each political official since 1981 (bulk export)
  - https://sunlightlabs.github.io/datacommons/bulk_data.html
- Total rows: 51,120

# Cleaning

Cleaning:

- Create SQL database for all contributions
  - Subset database to only be congressional contributions
  - Group 400+ category codes by their 114 parent industries
  - Create CSV for each of the 114 industries
    - Because of the quantity of data, it is less expensive to open multiple CSV for industries I want, rather than all at once.

# Cleaning Cont.

Cleaning:

- Connect government id to campaign funding id (opensecrets_id)
  - Code found here:
  - Connect_government_id_to_campaign_funding_id.ipynb
- Running Tally of cumulative contributions & voting history for each vote that took place. i.e.:
  - Add columns for each campaign funding industry to show how much money each congressperson has accumulated up the date of each vote.
    - Code found here:
    - add_contribution_amount_collected_when_vote_occured.ipynb
  - Add columns to track each persons voting history
    - Code found here:
    - add_vote_history_to_voting_data_with_funding.ipynb

# Cleaning Cont.

## Running Tally visualized:

| GENERAL CONTRACTORS | LOBBYISTS | PUBLIC SECTOR UNIONS | bill_id | class_variable | date | opensecrets_id | party | prior_total | prior_yea_percent | prior_yea_total |
|---|---|---|---|---|---|---|---|---|---|---|
| 500 | | 3000 | hr2402-101 | 1 | 6/22/89 | N00000010 | R | 1 | 1 | 1 |
| 500 | 250 | 3250 | hr3012-101 | 1 | 10/26/89 | N00000010 | R | 2 | 1 | 2 |
| 800 | 250 | 8850 | hr2748-101 | 1 | 11/16/89 | N00000010 | R | 3 | 1 | 3 |
| 800 | 250 | 8850 | hr3072-101 | 1 | 11/17/89 | N00000010 | R | 4 | 1 | 4 |
| 6100 | 5300 | 14150 | hr486-101 | -1 | 10/23/90 | N00000010 | R | 5 | 1 | 5 |
| 6100 | 5300 | 18150 | hr5803-101 | -1 | 10/24/90 | N00000010 | R | 6 | 0.833333333 | 5 |
| 6100 | 5300 | 18150 | hr5313-101 | -1 | 11/5/90 | N00000010 | R | 7 | 0.714285714 | 5 |

# Initial Exploration*: 2 Mistakes

1. Holist view of the data set:

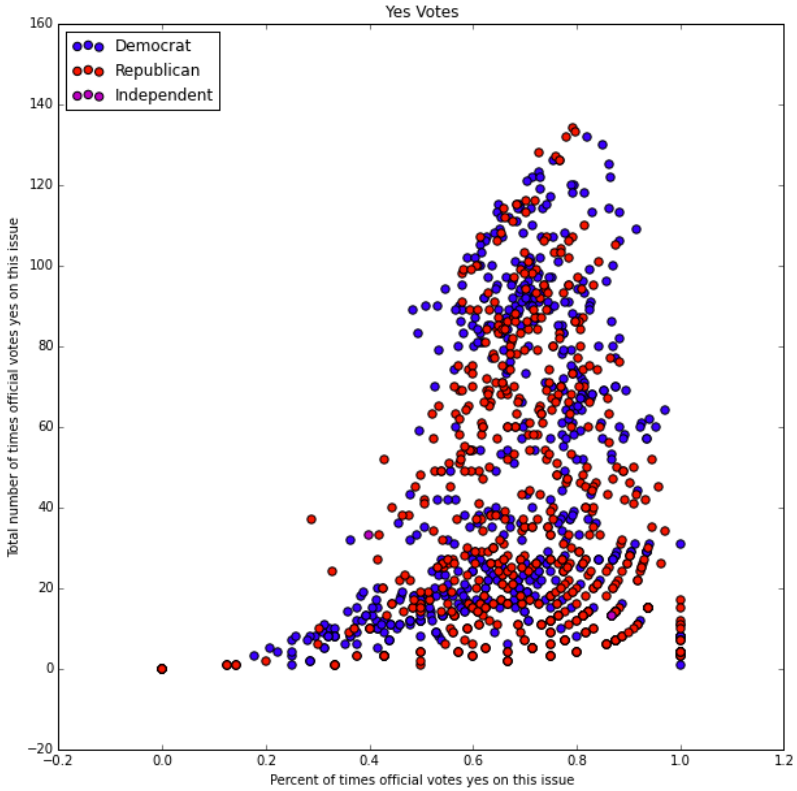
- Could not see the true relationship between contributions and votes.
- Instead, a was looking at two variables that were unlinked:
    1. Total money collected from contributions by industry.
    2. Everyone's voting record.
- How could a vote in 1990 be influence by money collected in 2007? It can't.

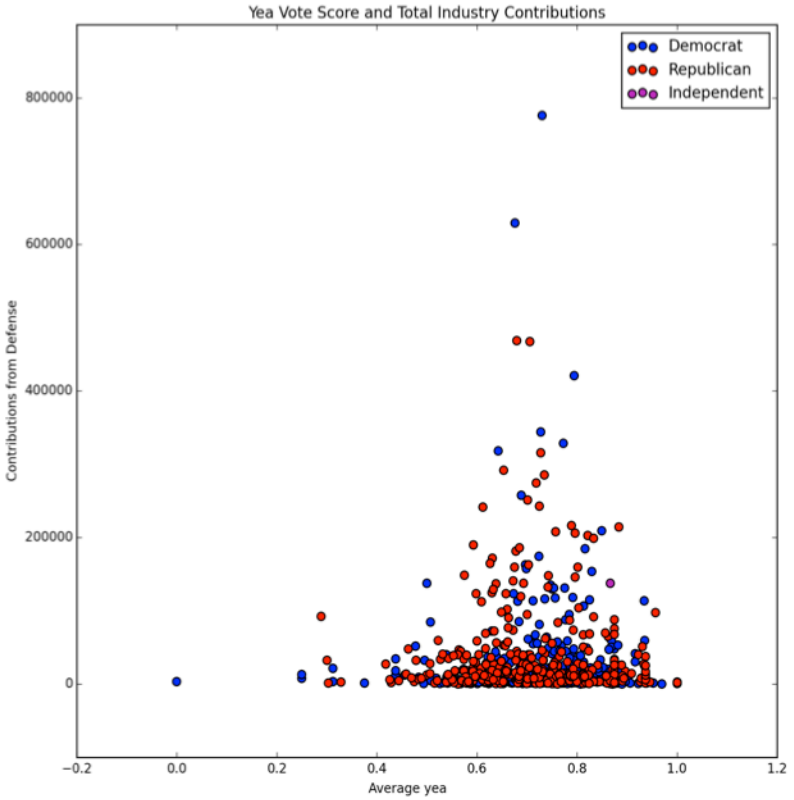
2. Looked at contributions and voting history together

- Contribution industries need to be the only predictor variables.
- This will determine if there is a relationship between money given to a campaign, and how the congressperson votes.

*Initial Exploration did not contain Running Tally

# Initial Exploration: Plots



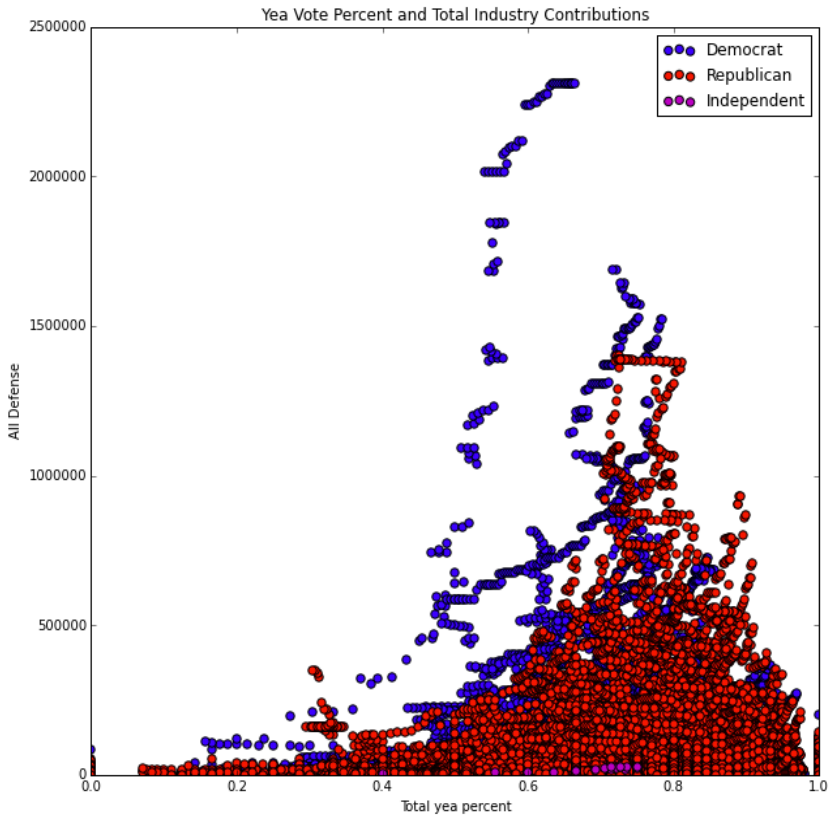



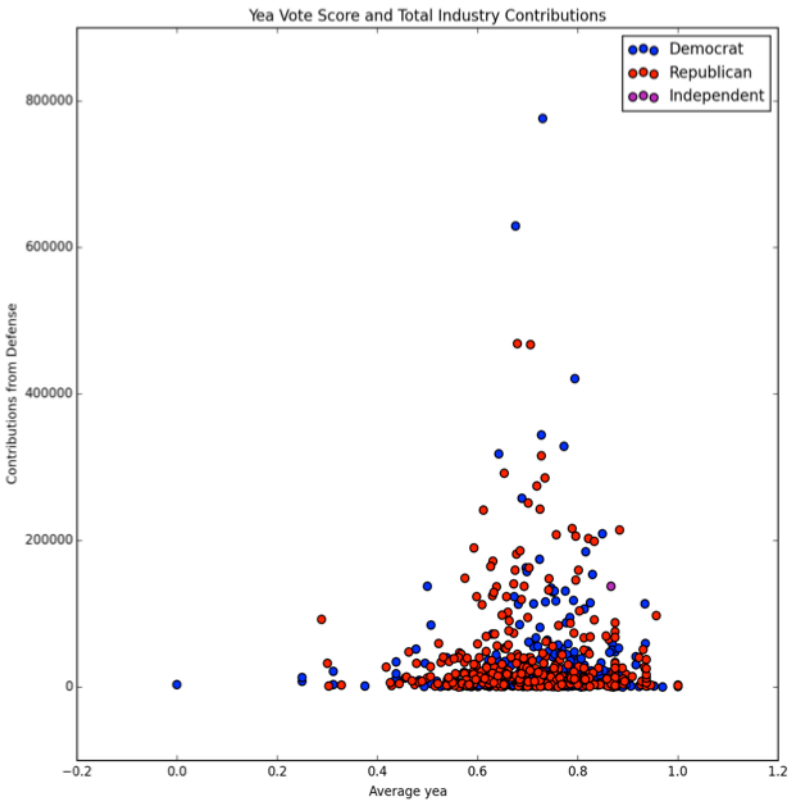
# Re-cleaning

- Re-cleaning was only performed to add Running Tally statistics.
- Data set went from being sparse to being rich.
- Data is now ready for modeling!

# Re-cleaning: Visualized

With Running Tally vs. Aggregated Contributions



# Choosing Variables

- 13 industries were used for the final analysis.
  - ‘Abortion Policy Pro-Choice', ’Accountants', 'Business Services', ’Defense Aerospace', 'Defense Electronics', 'Democratic Liberal', 'Environment', 'Foreign & Defense Policy', 'General Contractors', 'Lobbyists', ’Misc Defense', 'Public Sector Unions', 'Women’s Issues'
- Since the bills analyzed are on “armed forces and national security”, every contribution industry with the word “defense” is included.
  - Four in total.

# Choosing Variables Cont.

- The other nine industries were included by analyzing a subset of the data. Analysis was performed as follows:
  - Subset 56 congress-people who participated in the most votes.
  - Subset of 32 industries that were rich in data
  - Ran logistic regression to find coefficient scores.
  - Ran random forest to find importance scores.

# Modeling

Modeling was done examining two sets of predictor variables:

1. Running Tally of contributions by all 13 industries.
2. Running Tally of each congressperson's voting history.

Modeling was split in order to compare how contributions compared to voting history.

Class Variable:

- Voting result
- 1 = yea, 0 = present, but abstained from vote, -1 = no

# Modeling

Setting the baseline:

- The baseline accuracy will be determined by the most common class variable (‘yea’ votes).

If the model is unable to beat the baseline then the null hypothesis cannot be rejected.

- i.e. using campaign contributions is insufficient for predicting how congress people with vote.

# Modeling

Because of the size of the data set the modeling was done on a sample of the data. Additionally, a random state condition was included to ensure replicability.

To test the performance of the analysis, 2 baseline metrics were created. One for the entire data set, and on the sample:

1. Baseline for the overall data set: 70.81%
2. Baseline for the sample data set:  70.7%

# Modeling

Algorithms used:

- PCA for dimensionality reduction
- SVM to predict vote

Both models* were subset by 10,000 rows**

Other models were tried but did not beat the baseline accuracy.

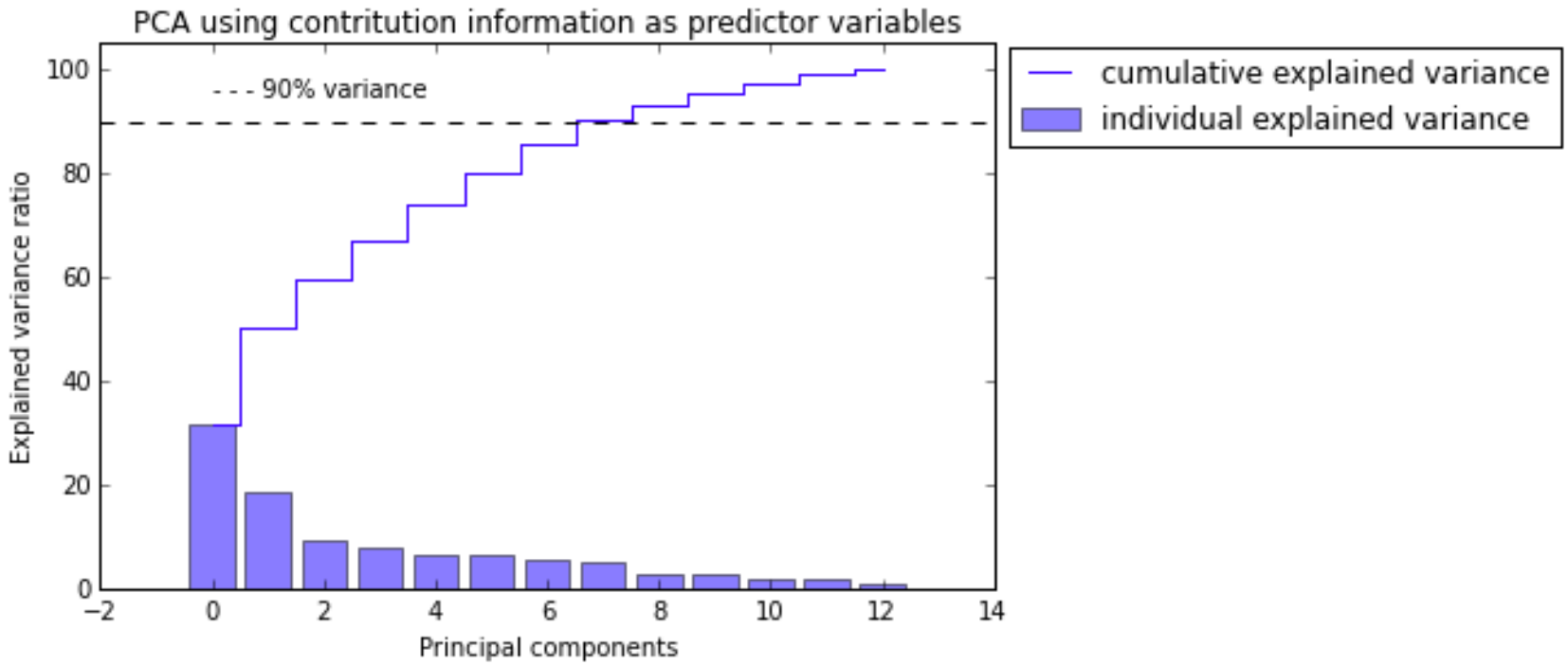
- kNN, k-means, random forest, logistic regression, naive bayes, PCA with kNN, PCA with k-means

* One for contributions, one for vote history

** The same random state was used to ensure replicability

# Model #1:
# Contributions as Predictor

Number of components used for PCA was when variance reached 90%



# Model #1:
# Contributions as Predictor

Parameters to use for SVM were determined by performing GridSearch on a subset of 500 data points.

Parameters tested:

- 'C': np.linspace(.001, 10, 10), 'kernel': ['poly', 'rbf', 'linear'], 'degree': range(1,4), 'gamma': np.linspace(.001, 10, 10)

Parameters used:

- C=0.001, degree=3, gamma=1.1119999999999999, kernel='poly'

# Model #1:
# Contributions as Predictor

Findings:

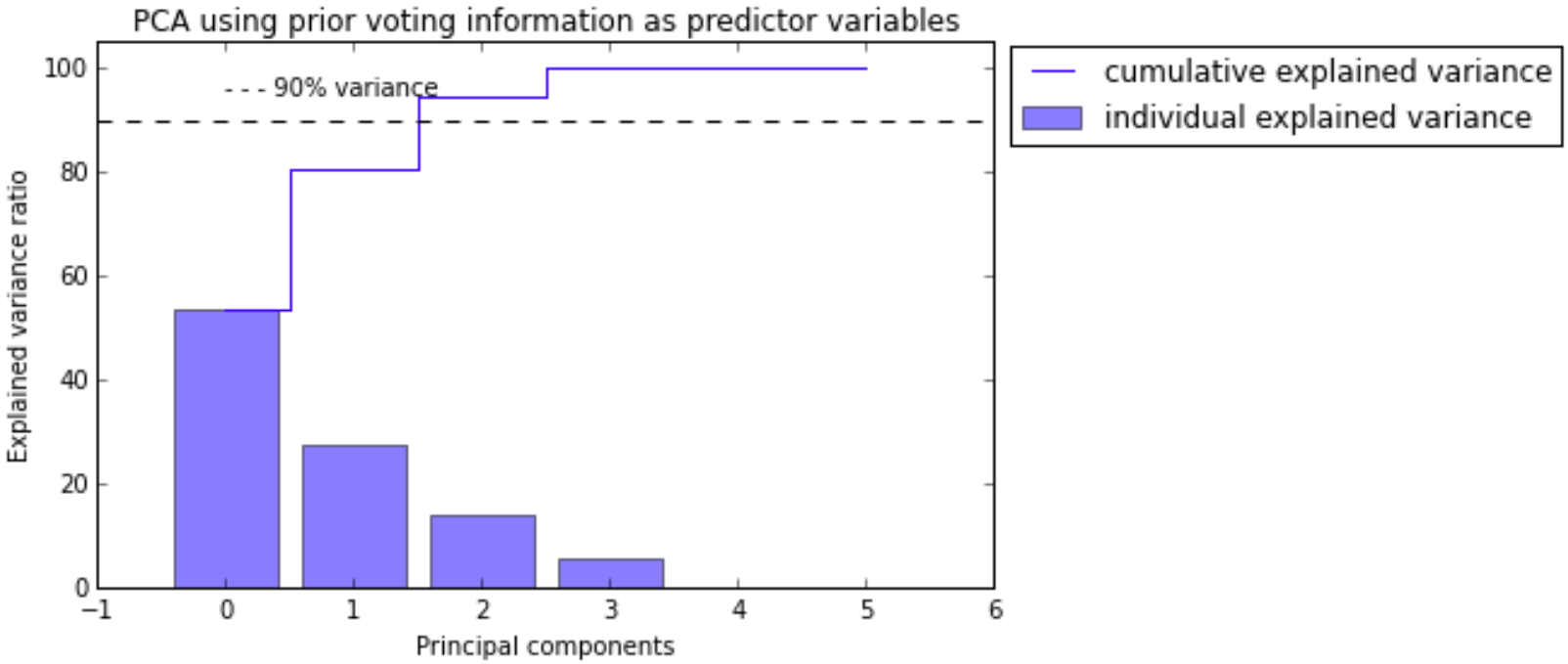
- The accuracy of the model was 82%
- This is ≈ 11% higher than the baseline
- Rejection of null hypothesis!

Below are the results of using contritution information as predictor variables:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| -1 | 0.00 | 0.50 | 0.01 | 4 |
| 0 | 0.00 | 0.00 | 0.00 | 0 |
| 1 | 1.00 | 0.70 | 0.83 | 1996 |
| avg / total | 1.00 | 0.70 | 0.82 | 2000 |

# Model #2:
# Voting History as Predictor

Number of components used for PCA was when variance reached 90%



# Model #2:
# Voting History as Predictor

Parameters to use for SVM were determined by performing GridSearch on a subset of 100 data points.

Parameters tested:

- 'C': np.linspace(.001, 10, 10), 'kernel': ['poly', 'rbf', 'linear'], 'degree': range(1,4), 'gamma': np.linspace(.001, 10, 10)

Parameters used:

- C=0.001, degree=3, gamma=3.3340000000000001, kernel='poly'

# Model #2:
# Voting History as Predictor

Findings:

- The accuracy of the model was 83%
- This is ≈ 12% higher than the baseline
- This is only 1% higher than using campaign contributions as the predictor

Below are the results of using prior voting information as predictor variables:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| -1 | 0.00 | 0.00 | 0.00 | 0 |
| 0 | 0.00 | 0.00 | 0.00 | 0 |
| 1 | 1.00 | 0.70 | 0.83 | 2000 |
| avg / total | 1.00 | 0.70 | 0.83 | 2000 |

# Key Learnings

1. Using contribution data as the predictor variables beat the baseline accuracy. In other words, there is a relationship between how much money a congressperson gets from an industry, and how they vote on armed forces and national security bills. It should be stated that it is unclear if the contribution causes the voting pattern, or if the voting pattern causes the contribution.

- Accuracy of campaign contributions: 82%
- Baseline accuracy: ≈71%

# Key Learnings

2. There was an observed relationship between voting history and votes on armed forces and national security. When using voting history as the predictor variable, and excluding campaign contributions, the model beat the baseline accuracy.

- Accuracy of voting history: 83%

# Key Learnings

3. Using contributions to predict how congressional officials vote on armed forces and national security bills is just about as accurate as using an individual congressperson's voting history.

# Challenges and Successes

Challenges:

- Quantity of data
- Multiple data sources
- Cleaning the data (time)
- Visualizing results
- Keeping work organized
- Refactoring
- Computational expense
  - gathering data, cleaning data, running models

# Challenges and Successes

Successes:

- Analysis beat the baseline accuracy.
- Rejection of null hypothesis!

# Extensions or Business Applications

Extensions:

- NLP to create feature that determines if the bill is helpful or harmful the its subject.
  - E.g. not all bills where the top_subject as "Armed forces and national security" will be helpful to armed forces and national security.
  - Some of the bills will call for budget cuts, reduction in personnel, etc.
- Perform analysis on other bill_subjects
- Fully predict congressional voting
  - Use campaign contributions as a section of the pipeline

# Extensions or Business Applications

Business applications:

- Create application to predict congressional votes.
- Reach out to companies that are attempting to predict elected officials voting patterns, looking for relationships in money and voting, etc.
- Publish an academic journal reporting my findings.