Automated Political Affiliation Ranking via Subjectivity Detection in Political Discourse

IST 664 – Natural Language Processing David Caspers

Objectives

1

Develop a model to classify statements as **objective** or **subjective**.

2

Extend the model to classify public statements from members of the **US House and Senate** as objective or subjective.

3

Implement a methodology to rank politicians on a political spectrum based on their opinion statements.

Why Is this Interesting?



REDUCE BIAS AND EFFORT



IMPROVE TRANSPARENCY



TRACK CHANGES OVER TIME

About the Data



Labeled Subjectivity Corpus

Source: NewsSD-ENG (English news articles).

Topics Covered: Law, civil rights, economics, and other controversial political subjects.

Labels:

- **Subjective:** Based on or influenced by personal feelings, tastes, or opinions.
- **Objective:** Factual statements, free from personal influence.

Usage: Train and evaluate sentence classifier



VoteSmart API

Source: Non-partisan organization.

Data: Public statements (Tweets, interviews, speeches) from **2022-2023** for all thenelected members of Congress

Usage: corpus of politician's publicly stated political opinions

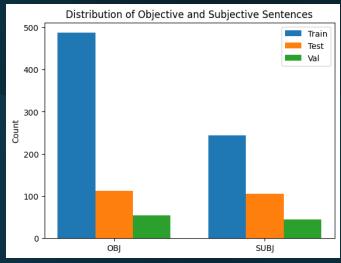


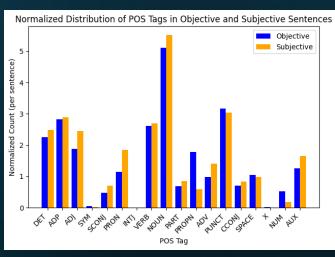
Limited Government Scorecard, Institute for Legislative Analysis

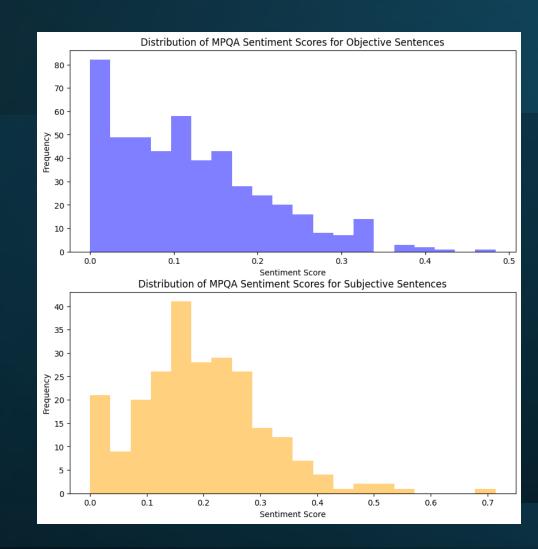
Purpose: Ranks politicians based on their voting records reflecting commitment to **limited government principles**.

Usage: Benchmark to compare my methodology's rankings with expert opinions.

Exploratory Analysis







Results

Model *all Naïve Bayes models use TFIDF*	Accuracy	Precision	Recall	F-1
	BNB / MNB	BNB / MNB	BNB / MNB	BNB / MNB
Bag of Words (Unigram)	53.42%	62.83%	53.42%	44.95%
	49.31%	75.24%	49.32%	33.56%
Bigrams + Trigrams	47.95%	43.94%	47.95%	32.90%
	47.95%	46.21%	47.94%	34.32%
Unigram + Bigram + Trigram	65.66%	64.98%	65.66%	65.81%
	67.44%	64.14%	67.44%	62.72%
Part of Speech Appended to Words,	50.22%	54.32%	50.22%	40.93%
Unigram, Bigram, Trigram	49.77%	75.35%	49.77%	34.53%
Unigram, Bigram, Trigram, and POS Counts	64.84%	69.45%	64.84%	63.12%
	48.86%	57.92%	48.86%	33.35%
Unigrams + Bigrams + Trigrams + MPQA	65.30%	69.81%	65.30%	63.68%
Sentiment Score	49.32%	62.34%	49.32%	34.31%
Tuned "distilbert-base-uncased"	75.80%	76.73%	75.80%	75.68%

BERT Classifier Model Applied to Political Discourse

Text: Today Rep. Ilhan Omar released the following statement to commemorate the one year anniversary of the January 6th insurrection.

Predicted Class: OBJ

Class Probabilities: [0.9988122 0.00118786]

Text: "Today marks one year since the attacks of January 6th.

Predicted Class: OBJ

Class Probabilities: [9.990722e-01 9.278190e-04]

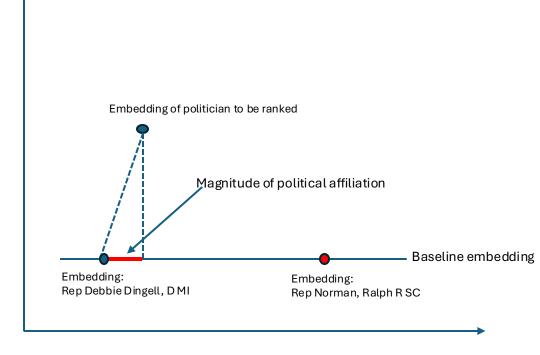
Text: I will never forget the experience of fearing for my life, my fellow members, and staff on a day designed to show the strength of our democracy.

Predicted Class: SUBJ

Class Probabilities: [0.00251374 0.99748623]

Methodology for Inferring Political Alignment

- 1. Classify each sentence of Politicians Public Statements
- 2. Only retain Subjective Sentences
- 3. Embed Sentences Using Pre-trained Bert Sentence Embedder "all-MiniLM-L6-v2"
- 4. Average each politician's embeddings to get one 'representative' embedding
- 5. Use Politicians on opposite side of political spectrum (as defined by the Limited Government Scorecard) as base case and project embeddings onto vector
- 6. Rank by Magnitude
- 7. Compare to Limited Government Scorecard



Projecting Politicians Political Spectrum

Conclusions:

- Delineation between subjective and objective content can be unclear
- Quality and quantity of available data matters
- Methodology seems promising though requires significant tuning and cleaner/higher quality data sources.

Politician	The Institute for Legal Analysis Ranking*	Predicted Ranking	Sentences Available To Draw Inferences From
Rep Chip Roy	1	45	48
Rep Andy Biggs	2	24	75
Rep Matt Rosendale	3	70	9
Rep Lauren Boebert	4	12	167
Rep Greg Steube	5	109	109

^{*} Reps with no available public statements omitted from ranking



Questions?