

The USA representatives' articles analysis



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Project overview

Our aim was to collect a comprehensive dataset of articles and statements from various U.S. Congressmen and Congresswomen to explore key political patterns and get insights into political communication trends.



Considered Classification Tasks

1

**Author
Prediction**

3

**Topic
Classification**

2

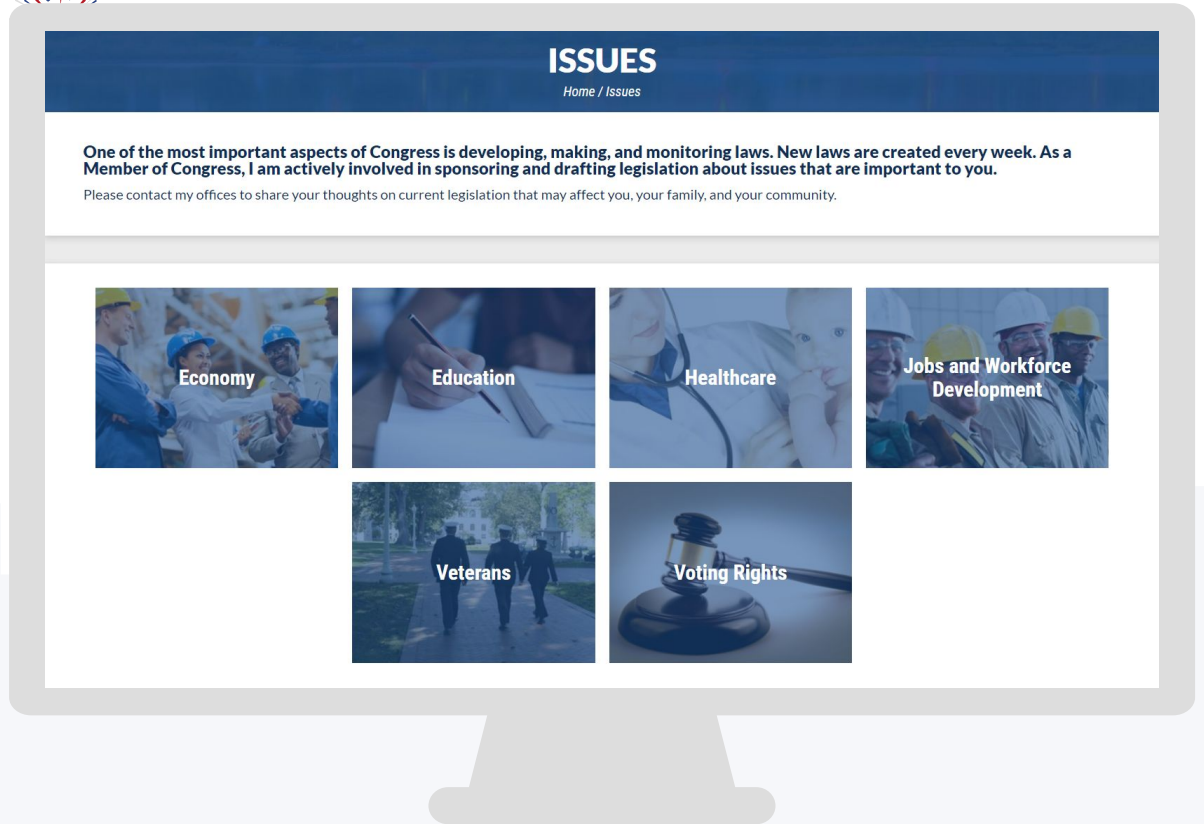
**Political
Affiliation
Prediction**



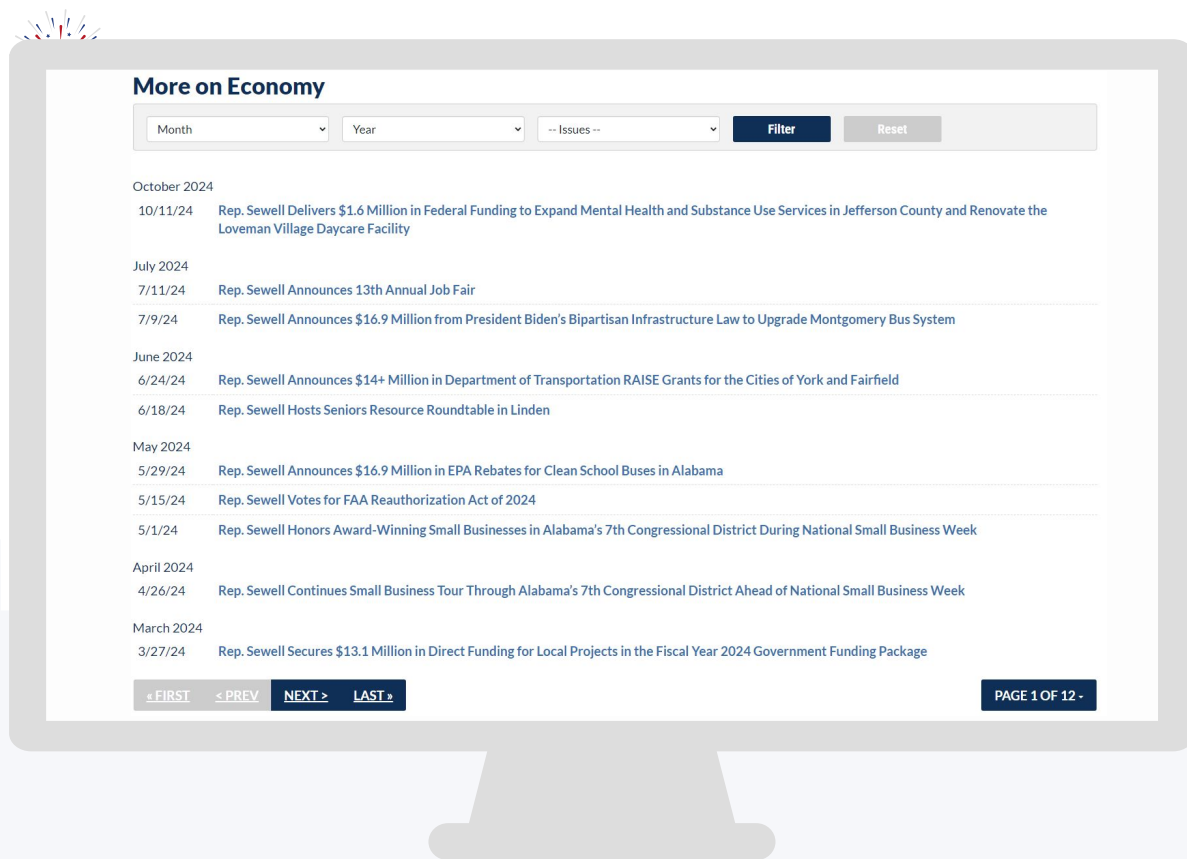
01

Data Acquisition

Rep. Terri Sewell issues page



Rep. Terri Sewell articles on economy



How to access and process 18000 pages in manageable time

Execution



Process for Representative #1

Thread per page



Thread per page



Thread per page



Thread per page



Thread per page



200 threads

Process for Representative #2

Thread per page



Thread per page



Thread per page



Thread per page



Thread per page



200 threads

This ensures that both whole processing power and whole internet bandwidth can be used.

Downloading and scrapping 5000 pages took only 6 minutes.



02

Data Preprocessing



1. Cleaning and formatting

1

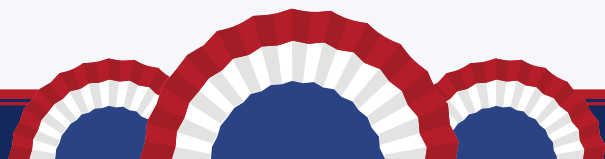
**Date format
standardization**

2

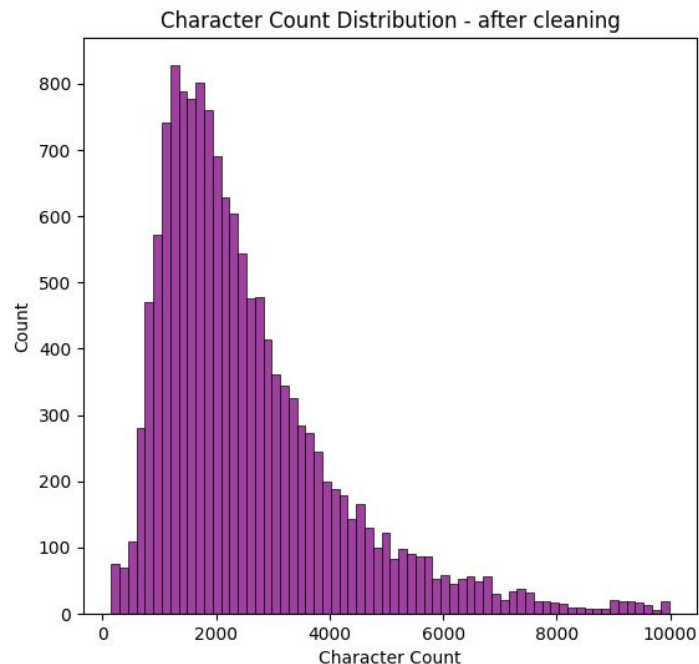
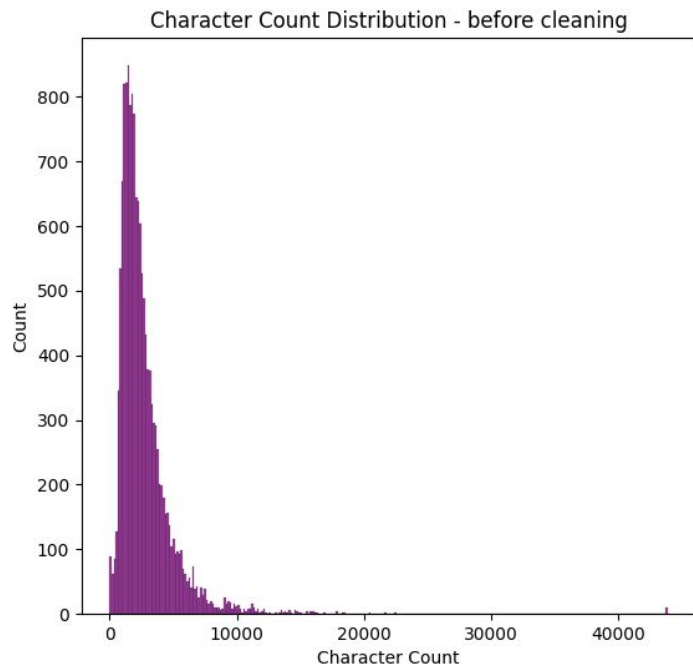
Article content cleaning

3

Removing faulty articles



2. Filtering by Character Count



in range (150; 10 000)

3. Topics standardization



Health Care and Social Security

Health; Healthcare;
Healthcare, Social Security, & Support
Programs;
Social Security and Medicare;
Improving Access to Affordable Healthcare;
Social Security; Health Care;
What Rep. Flood is doing to expand
healthcare options
...



Undefined

Back the Blue; Getting Things
Done; Program Awards &
Announcements; Crumbling
Foundations; Congressman
Larson's Committees
...

Final topics (from 358 to 19)

National Security, Defence, Foreign Affairs	3673
Health Care and Social Security	2930
Energy and Environment	2380
Jobs and the Economy	2333
Education	1411
Veterans and Military	1376
Government and Law	1015

Infrastructure and Transportation	823	2nd Amendment and Gun Violence	306
Agriculture	758	Supporting Seniors	146
Local issues	750	Pro-Life/Abortion and Family Values	141
Federal Budget and Taxes	667	Housing	115
Equality and Civil Rights	511	Disaster Relief & Preparedness	67
Science, Technology, & Telecommunications	337	Constitution	26

Articles in numbers

50 303

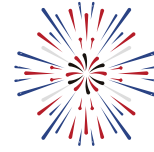
Collected articles

25 643

Cleaned up and UNIQUE articles

19 270

Articles with a single issue





03

Explorative Data Analysis

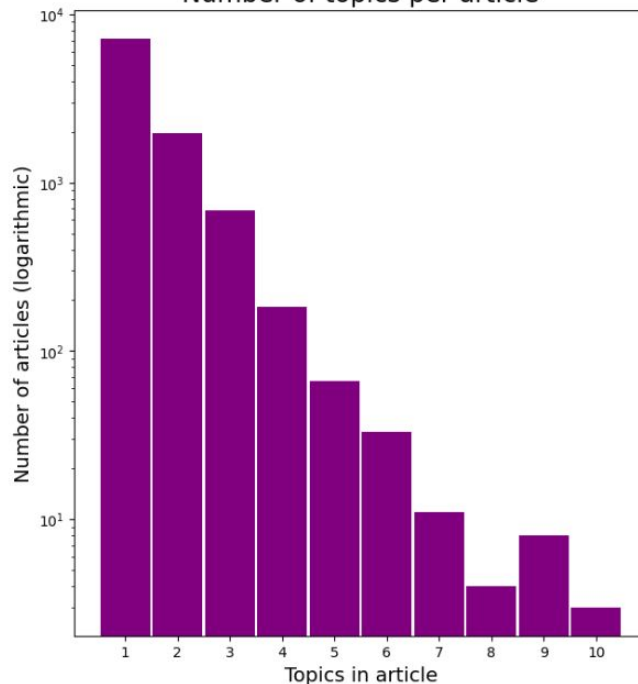
Articles are complex!

One article might regard multiple topics at once

How many topics appear only on their own?

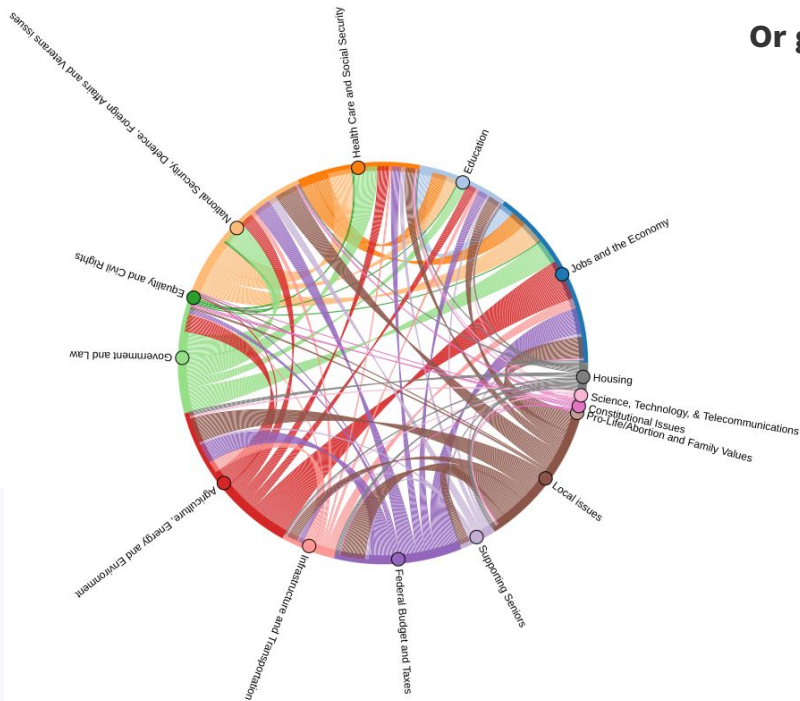
Constitutional Issues:	10.5%
Housing:	15.6%
Pro-Life/Abortion and Family Values:	16.7%
Supporting Seniors:	19.5%
Local issues:	32.0%
Federal Budget and Taxes:	39.5%
Government and Law:	40.7%
Science, Technology, & Telecommunications:	46.8%
Jobs and the Economy:	50.2%
Agriculture, Energy and Environment:	52.7%
Health Care and Social Security:	55.4%
National Security, Defence,	
Foreign Affairs and Veterans issues:	59.6%
Education:	59.9%
Infrastructure and Transportation:	60.4%
Equality and Civil Rights:	77.7%

Number of topics per article



Topics walk in pairs

Or groups, in fact



Those who support seniors also often mention healthcare, social security and veterans



Local issues are of all kinds - except law and government

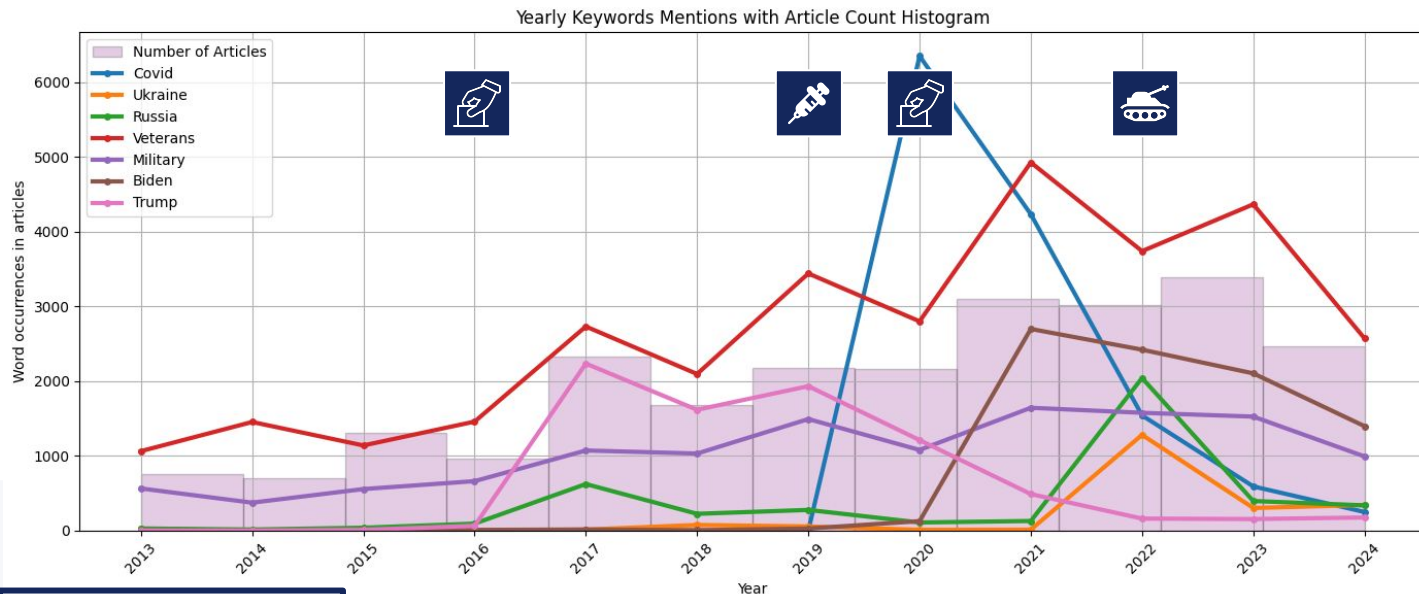


If congressman tackles education, they won't be telling of farms, nuclear plants, nor environment



Everyone needs funding from the budget, but government's financing is discussed relatively little

What's the buzz?



**No matter what,
veterans and army are
always hot topics in
the US Congress**





04

The most common phrases

Bag of words, word clouds

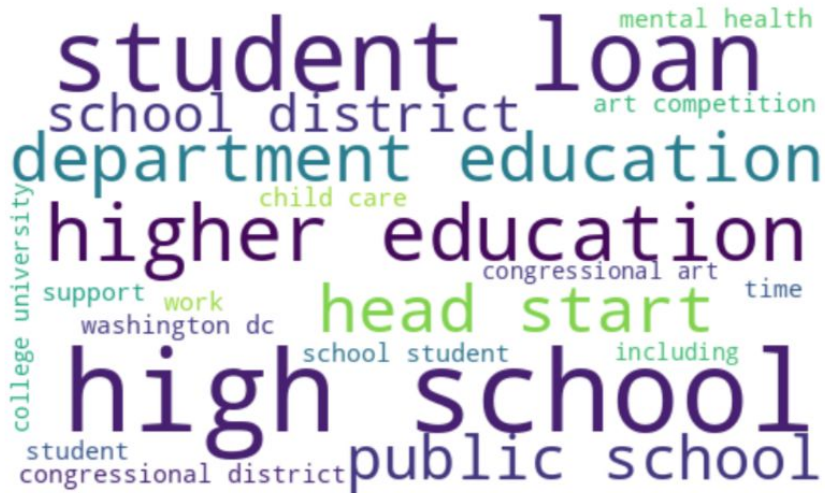
General-Purpose Words

★ act ★	★community★	year
★ state ★	★ program ★	american
today	member	house
american	rep	congressman

Extracted using BoW with
n-grams of length from 1 to 4

Topic-specific most common words

Education



A word cloud for the Education topic. The most prominent words are 'student', 'loan', 'department', 'education', 'higher', 'head', 'start', 'high', and 'school'. Other visible words include 'mental health', 'art competition', 'child care', 'congressional art', 'time', 'support', 'work', 'washington dc', 'college university', 'school district', 'public school', 'congressional district', and 'student congressional district'.

Health Care and Social Security



A word cloud for the Health Care and Social Security topic. The most prominent words are 'health', 'care', 'public health', 'mental health', 'health service', 'affordable care', 'prescription drug', 'health center', and 'health insurance'. Other visible words include 'washington today', 'congress', 'country', 'support', 'human service', 'rare disease', 'behavioral health', 'human', 'washington dc', 'department health', and 'time'.

(After removing general-purpose most common words)



05

Topic classification

Glove, Word2Vec and many more

Embedding - Part 1

Transfer Learning

Model	word2vec-googl e-news-300	fasttext-wiki-new s-subwords-300	glove-twitter-200	glove-twitter-100	glove-twitter-50
Accuracy	85.68%	84.69%	84.65%	82.28%	77.35%
Training time	225s	223s	160s	80s	49s

Classification over 6 most common classes
(Identically structured neural networks, same
train/test datasets, trained for 90 epochs)



Embedding - Part 1

Locally trained word2vec

Model	word2vec-googl e-news-300	Custom-300 Window = 5	Custom-150 Window = 5	Custom-150 Window = 7	Custom-150 Window = 9
Accuracy	85.68%	85.22%	85.71%	86.21%	86.18%
Training time	225s	228s	119s	119s	119s

Classification over 6 most common classes
(Identically structured neural networks, same
train/test datasets, trained for 90 epochs)



Embedding - Part 2

Embedding approaches



Bag of Words

Tested on various vocabulary sizes, only words with frequency above the threshold were taken into consideration

BERT Embedding

We used a sentence-transformers model: all-MiniLM-L6-v2.
It maps sentences & paragraphs to a **384** dimensional dense vector space.



BoW Embedding

accuracy 90%
f1 90%
(on imbalanced
test dataset)

3 hidden layers,
300 epochs



BERT Embedding

accuracy 91%
f1 91%
(on imbalanced test dataset)

3 hidden layers,
300 epochs



BoW Embedding

81% accuracy on test
dataset with 14
unbalanced topics





BERT Embedding

81% accuracy on test
dataset with 14
unbalanced topics





06

Key phrase extraction

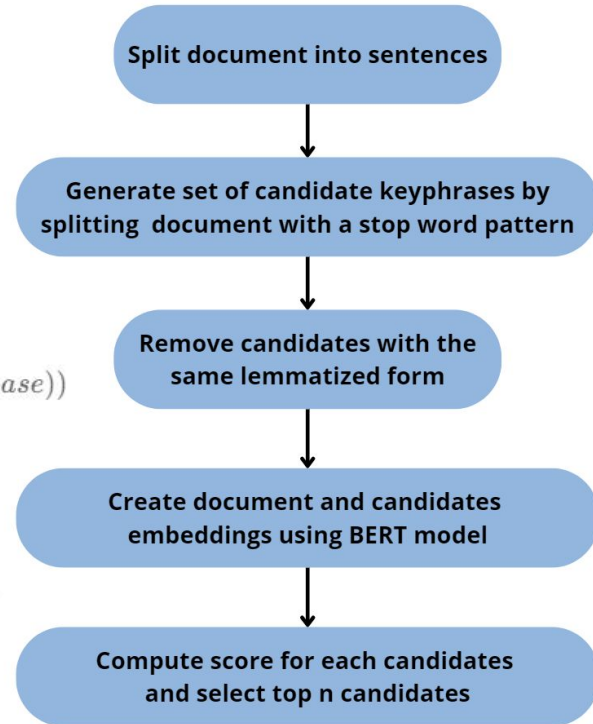
unsupervised approach

Keyphrase extraction algorithm

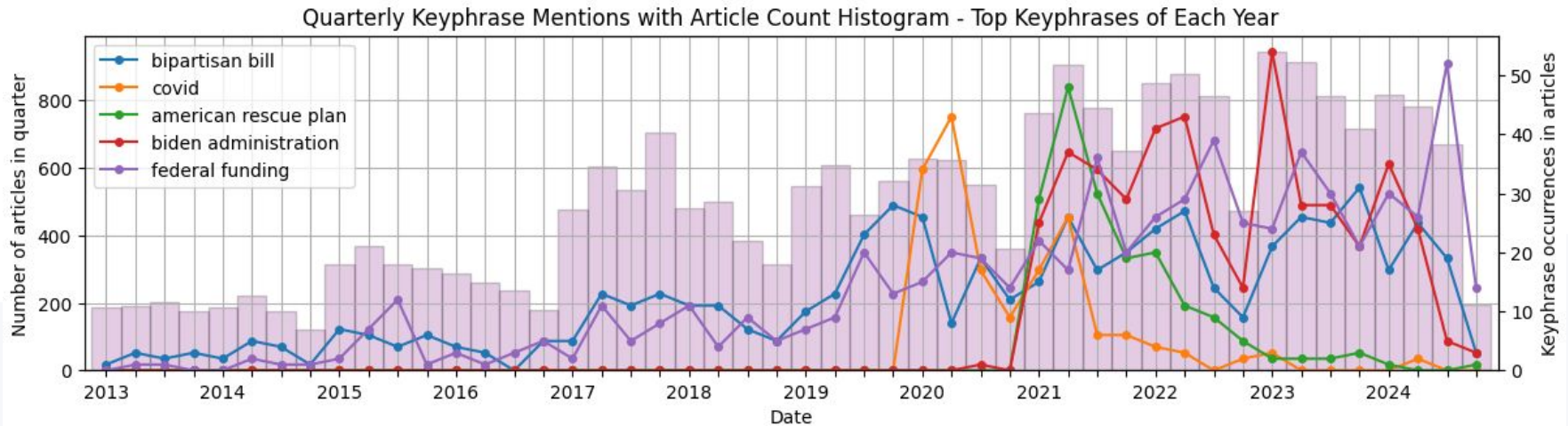
$$\text{score}(\text{phrase}) = \text{similarity}(\text{embed}(\text{phrase}), \text{embed}(\text{doc})) \times \text{prob}(\text{word_count}(\text{phrase}))$$

where:

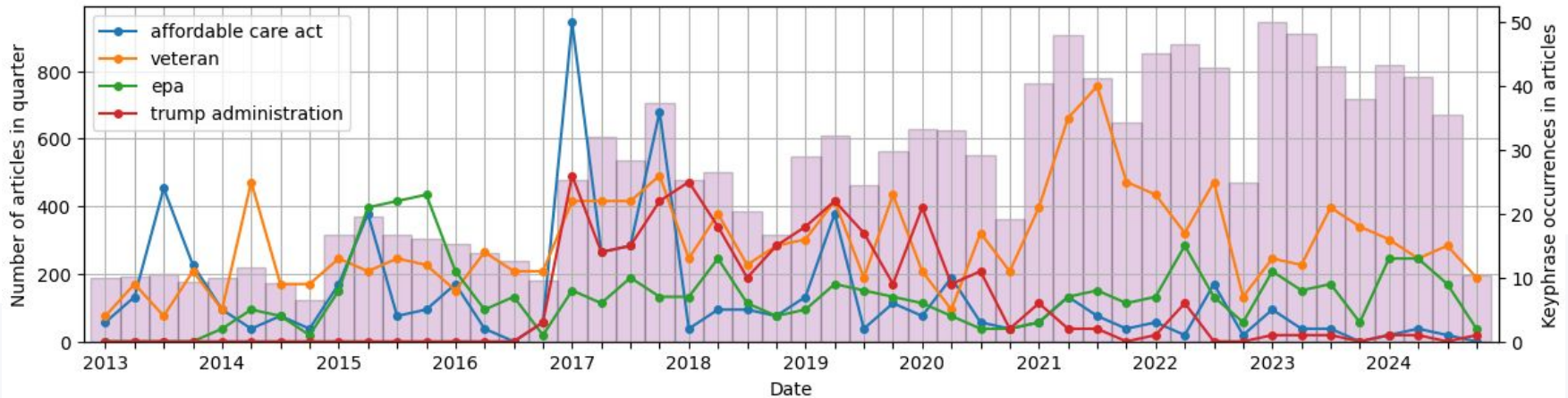
- *doc* - document text
- *phrase* - candidate keyphrase



Time-Based Distribution of Articles Containing Selected Key Phrases (1)



Time-Based Distribution of Articles Containing Selected Key Phrases (2)



10 most frequently appearing key phrases between 2013 and 2024

Key phrase	Count
veteran	747
federal funding	660
bill	622
bipartisan bill	590
funding	569
national security	453
legislation	447
biden administration	445
representative	408
bipartisan legislation	403

The top corners of the slide are decorated with stylized fireworks in red, white, and blue. There are five fireworks in the top-left area and three in the top-right area.

Bonus visualization

A light gray, stylized city skyline is positioned behind the text, spanning the width of the slide.The bottom of the slide features a decorative bunting banner with red, white, and blue segments.



Thank you!

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