

Contributors : Dylan Kakkanad , Mahika Bhartari, Rajashree Ramaprabu, Sahasra Konkala

Exploratory Data Analysis

As part of our initial EDA,

To analyze the news articles dataset, a dataset of approximately 2.7 million rows. From this extensive dataset, we employed the stratified random sampling method to derive a representative subset of approximately 27,000 rows ([1.0](#)). Followed by analyzing the data structure of our data frame and then moved to check for null, duplicate, and invalid values. Duplicate and null values present in the article column are removed. We explored the number of articles published and the average count of words used by various publishers and depicted it using bar plots([1.1](#)). We have also visualized the number of articles available in distinct sections([1.3](#)) published annually. We have created a word cloud model([1.5](#)) to showcase the most frequent words in the title, and article columns. In our further analysis and processing, we will observe how the recurring terms evolve in the word cloud.

Pre-processing

Preprocessing mainly focussed on cleaning and preparing the ‘article’ column. The new processed column is called ‘processed_article’([2.1](#)). To reach this stage we first cleaned the articles by removing hyperlinks, numbers, punctuation, and non-English characters found during EDA. Since our goal is to cluster news articles based on the subject matter in the article, numbers (not in words) would be redundant or, worst case, bias the clusters and were subsequently dropped. We also used word tokenization and filtered for stemmed English words within the nltk english corpus excluding stopwords. The number of words was thus reduced to 3,194.

Analysis Plan

Our primary objective was to cluster news articles effectively and find distinct clusters. Given the lack of a well-defined metric, we adopted an iterative approach to achieve this goal. The first step in our methodology was to reduce the dimensionality of our dataset, which initially had over 23,000 features. We employed Principal Component Analysis (PCA) for this purpose. PCA allowed us to identify and retain the top 1,000 principal components that accounted for approximately 50% of the variance in our data ([3.1](#)). This reduction was significant as it simplified our dataset while preserving its essential structure.

With a more manageable set of features, we then applied the KMeans clustering algorithm. The choice of KMeans was motivated by its efficiency and simplicity, making it a suitable choice for our initial exploration of the data. To determine the optimal number of clusters, we utilized the elbow method ([3.2](#)) and silhouette plots ([3.3](#)). Since we were not able to infer the exact number of clusters using the elbow method, we opted for a silhouette plot that provided us with the optimal number of clusters to be used. Both these techniques provided us with a quantitative means to assess the quality of our clustering. Our analysis suggested that around 10 clusters were optimal for our dataset.

Once the clusters were formed, we conducted a thorough examination of each cluster. We identified the top 30 words with the highest TF-IDF scores in each cluster. This step was crucial as it provided us with a qualitative understanding of the content of our clusters and is the only metric to assess the clusters. Similarly we have also identified top 30 words clusterwise with

n-gram scores to cross validate how the clustering model performs for different approaches. The resultant clustering was similar for both the methods when unigram technique was conducted on the data.

In conclusion, our choices of PCA for dimensionality reduction, KMeans for clustering, and the elbow method and silhouette plots for determining the optimal number of clusters were all justified based on the nature of our dataset and our objective of effectively clustering news articles. Our iterative approach allowed us to refine our methodology and achieve our goal.

Preliminary Results

The clarity of themes within each cluster was our evaluation metric. The presence of three unclear clusters suggests areas for improvement. To enhance our model, we considered removing less meaningful words and adjusting the n_grams range in TF-IDF vectorization. The first and fifth clusters, as well as the eighth, were not very well defined. The remaining clusters, however, showed distinct themes: crime news (second), federal government news (third), national politics (fourth), business finance (sixth), financial markets (seventh), sports news (ninth), and the stock market (tenth)([4.1](#)). Our evaluation metric was the clarity of the themes within each cluster. Seven out of ten clusters had distinct themes with little overlap, indicating a successful initial clustering.

Adjusting the n_grams range in TF-IDF vectorization resulted in similar clusters. Removing ineffective words('said', 'also' etc) helped find new clusters like healthcare. Despite some unclear clusters, our initial findings are promising. We have performed unigram with range(1,2) as of now. The cluster order wasn't the same as TF-IDF, however, it yielded pretty similar results([4.2](#)) with few repetitive clusters contributing to finance and politics. Two of the resultant clusters are not clearly distinguishable to figure out the genre of it. Most of the clusters provided promising results for initial clustering with minimal overlaps.

Next Steps

- N-grams: We'll include only trigrams and bigrams to discover new clusters.
- Stopwords: We'll remove additional stopwords from our dataset to enhance cluster distinctiveness.
- POS Tagging and NER: We'll use these to adjust weights for locations, organizations, and people for more semantic accuracy.
- Hierarchical clustering: Try hierarchical clustering to see if clusters are clearer using a dendrogram

Coding Contribution

All the members of the group have diligently contributed towards this phase. Rajashree & Mahika worked on cleaning the data, performing exploratory data analysis, and built a clustering model based on n-gram feature representation using KMeans. Dylan & Sahasra worked on pre-processing the data, PCA, KMeans, and hyperparameter tuning. The GitHub repository includes a 'Misc' (miscellaneous) folder with all the contributions.

A **kanban board** used for the project can be found at this [link](#).

GitHub Project [News Article Text Analysis](#)

Appendix

Fig 1.0: Data Dictionary

Name	Description	Data Type
date	Date of article publication	str
year	Year of article publication	int
month	Month of article publication	float
day	Day of article publication	int
author	Article author	str
title	Article title	str
section	Section of the publication in which the article appeared	str
article	Article text	str
url	Article URL	str
publication	Name of the article publication	str

Fig 1.1: Number of Articles by Publication

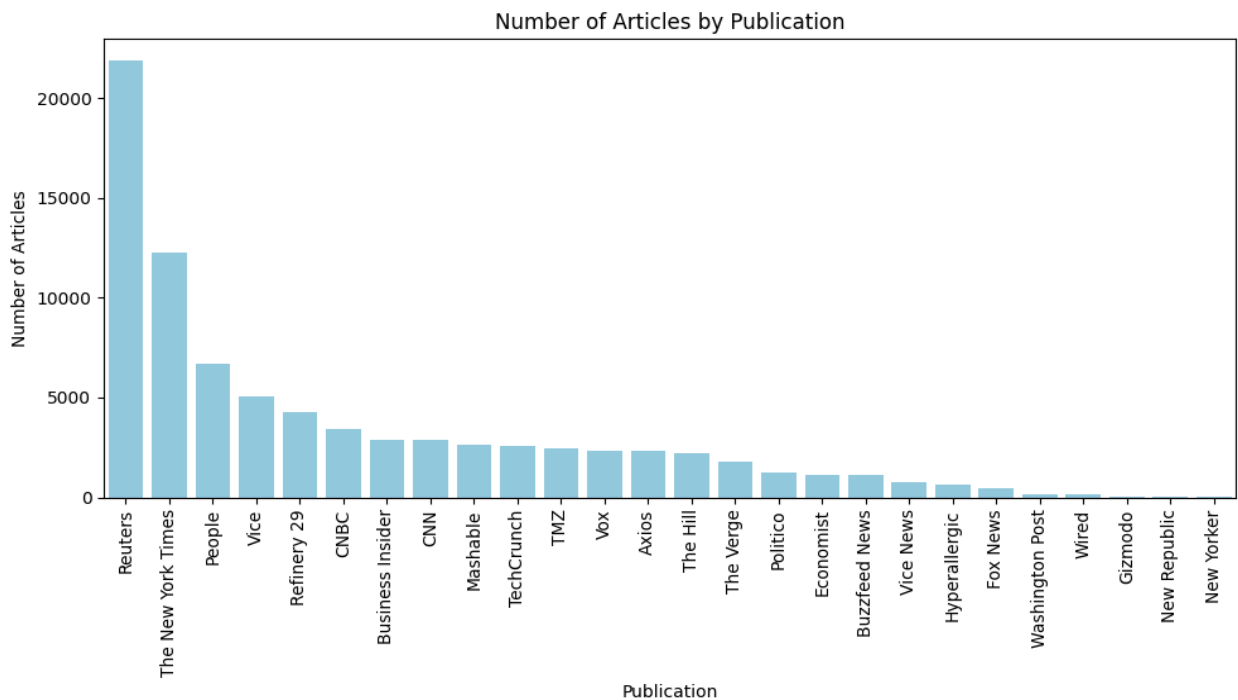
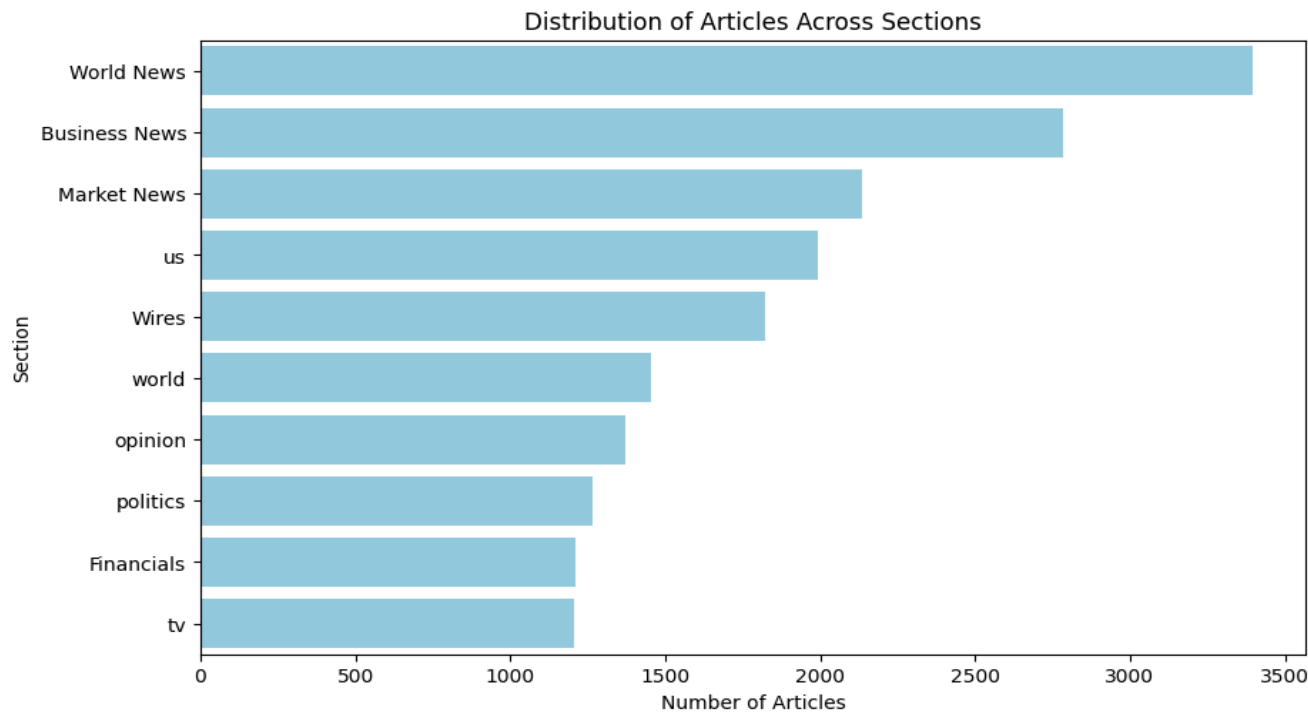


Fig 1.3: Distribution of Articles Across Sections



Word Cloud for Titles

	article	processed_article
0	the democratic party has a monopoly on a produ...	democrat parti monopoli product known primari ...
1	not long after he began contemplating running ...	long run unconstitut third term mayor new york...
2	like compulsive gamblers who react to every lo...	like compuls react everi lose streak bet strat...
3	a few days before christmas in wendell potter...	day potter offic health insur build watch prot...
4	looking at the internet can often feel like ea...	look often feel like eavesdrop slapdash youth ...

The graph shows a blue curve representing the cumulative explained variance as the number of components increases. The x-axis is labeled 'Number of Components' and ranges from 0 to 1000. The y-axis is labeled 'Cumulative Explained Variance' and ranges from 0.0 to 0.5. The curve starts at (0, 0) and rises steeply at first, then gradually levels off as it approaches 1000 components, reaching a value of approximately 0.55.

Number of Components	Cumulative Explained Variance
0	0.00
100	0.15
200	0.27
300	0.33
400	0.38
500	0.42
600	0.45
700	0.48
800	0.51
900	0.53
1000	0.55

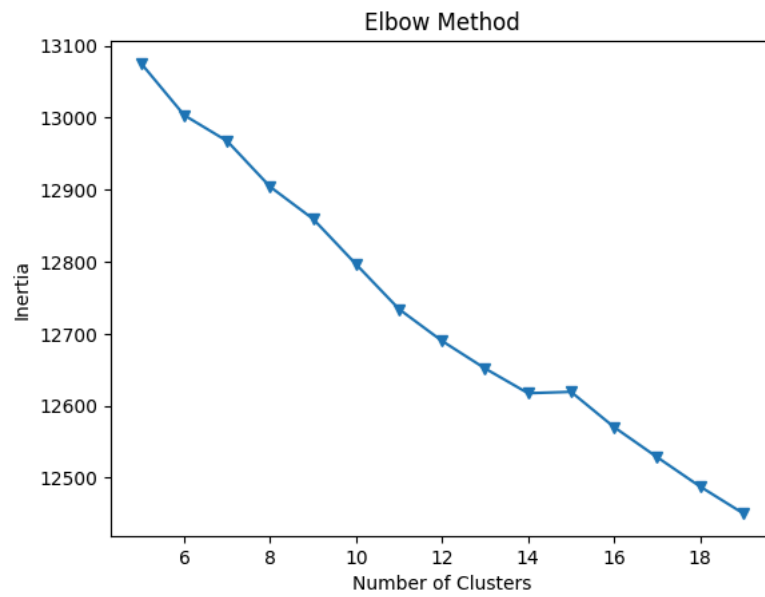
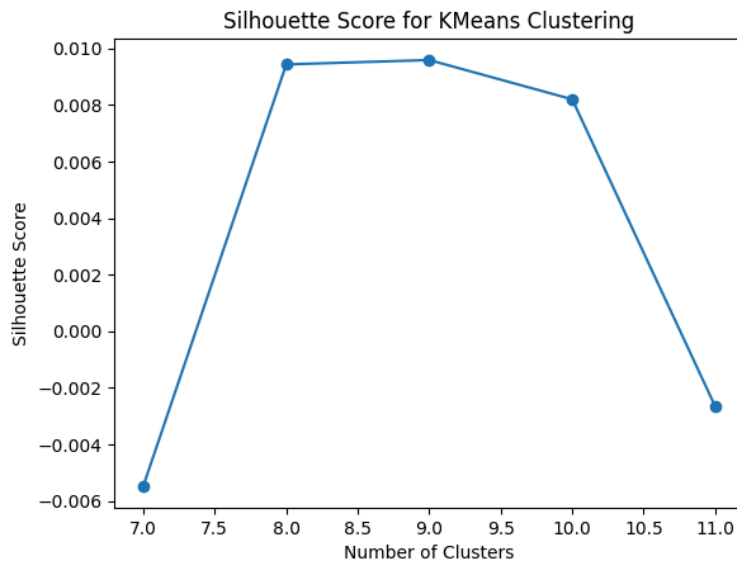
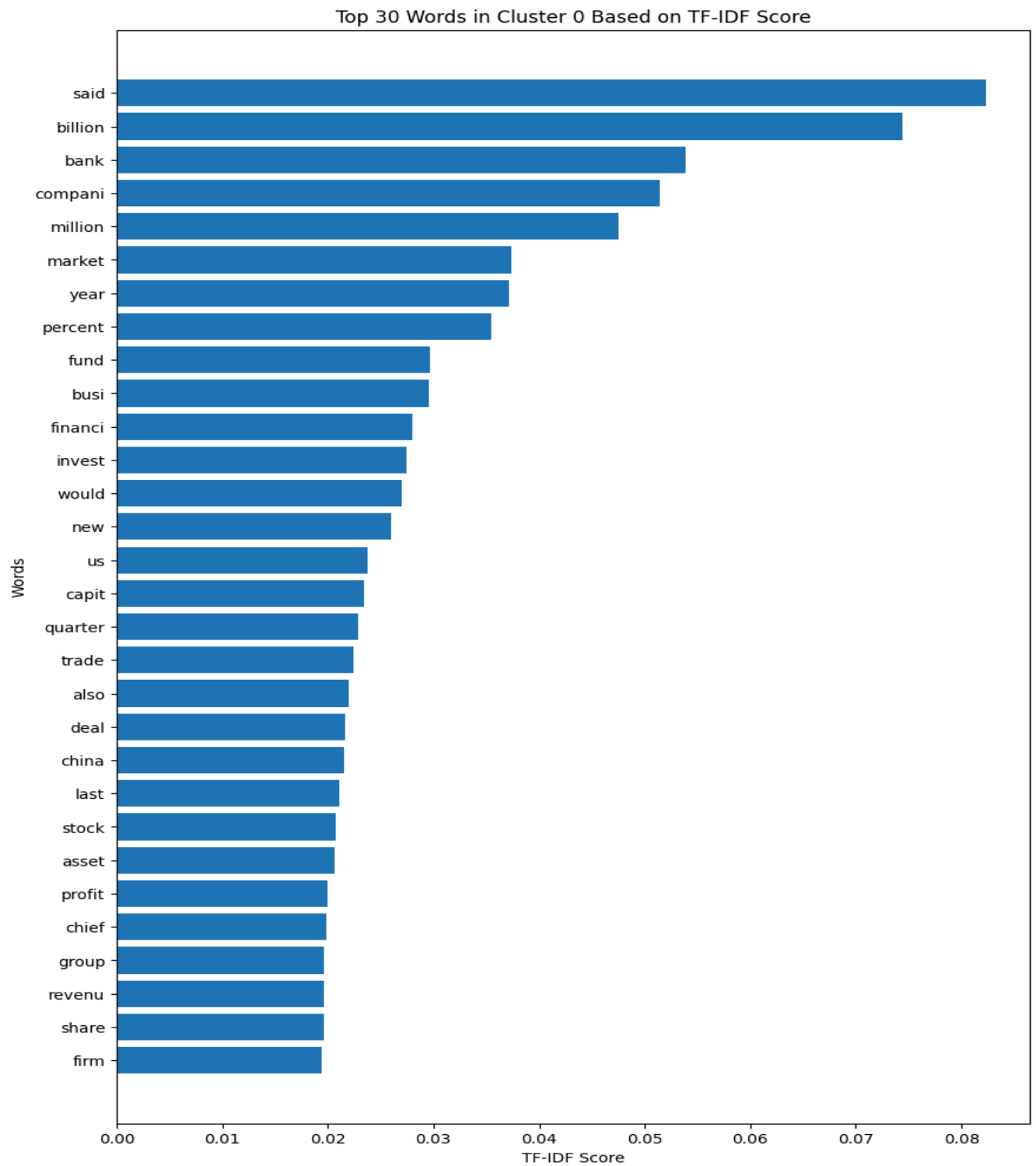
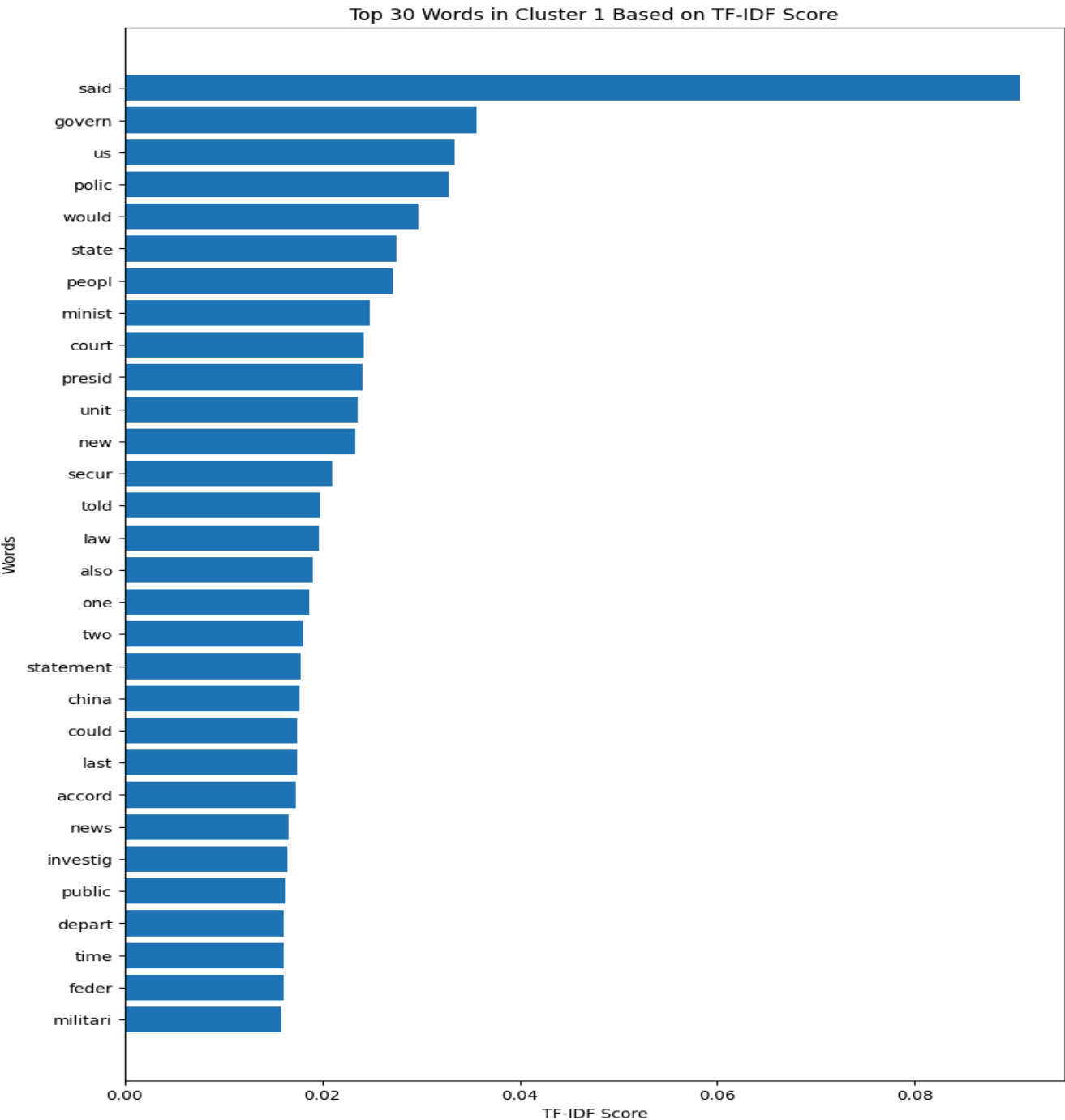
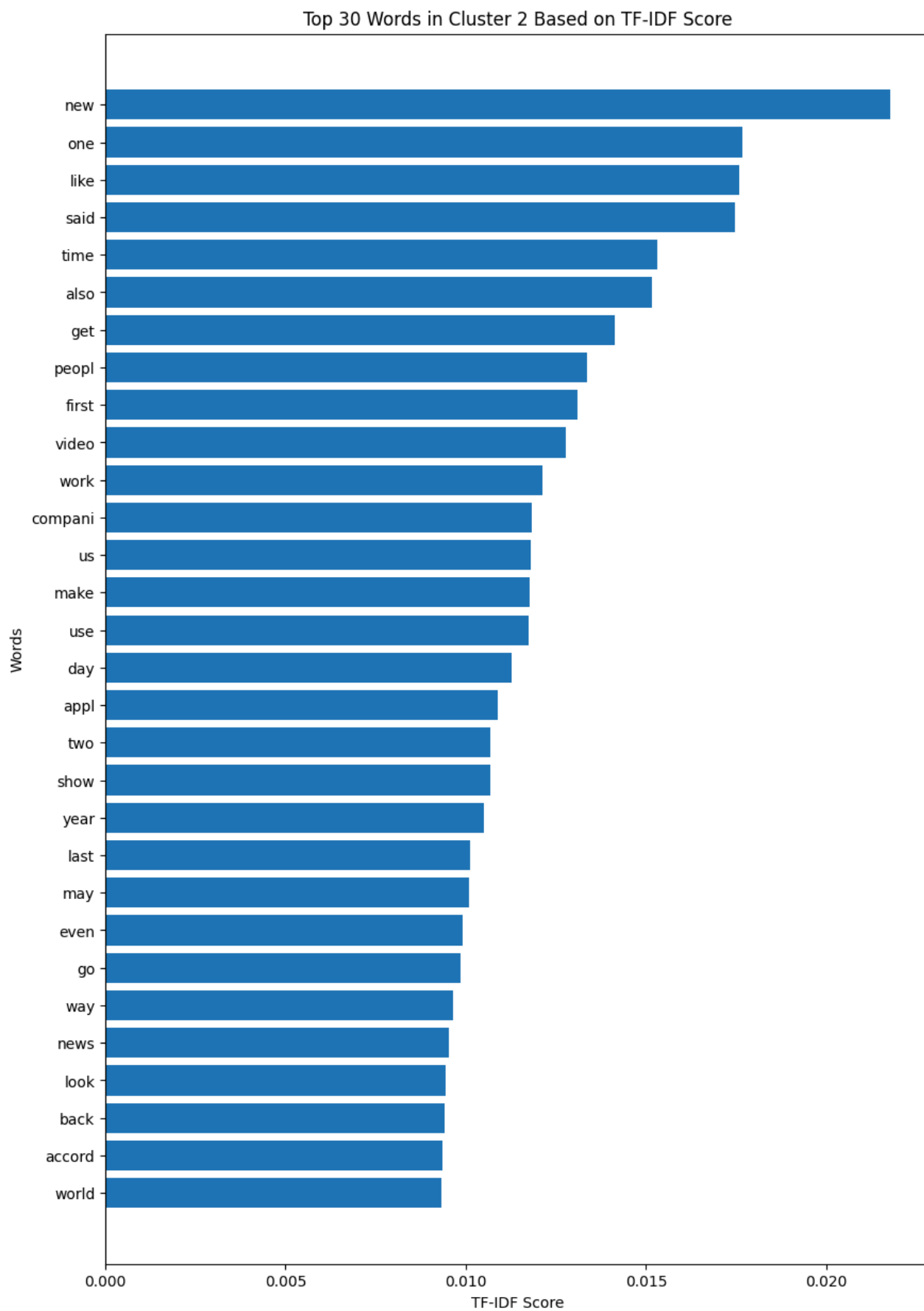
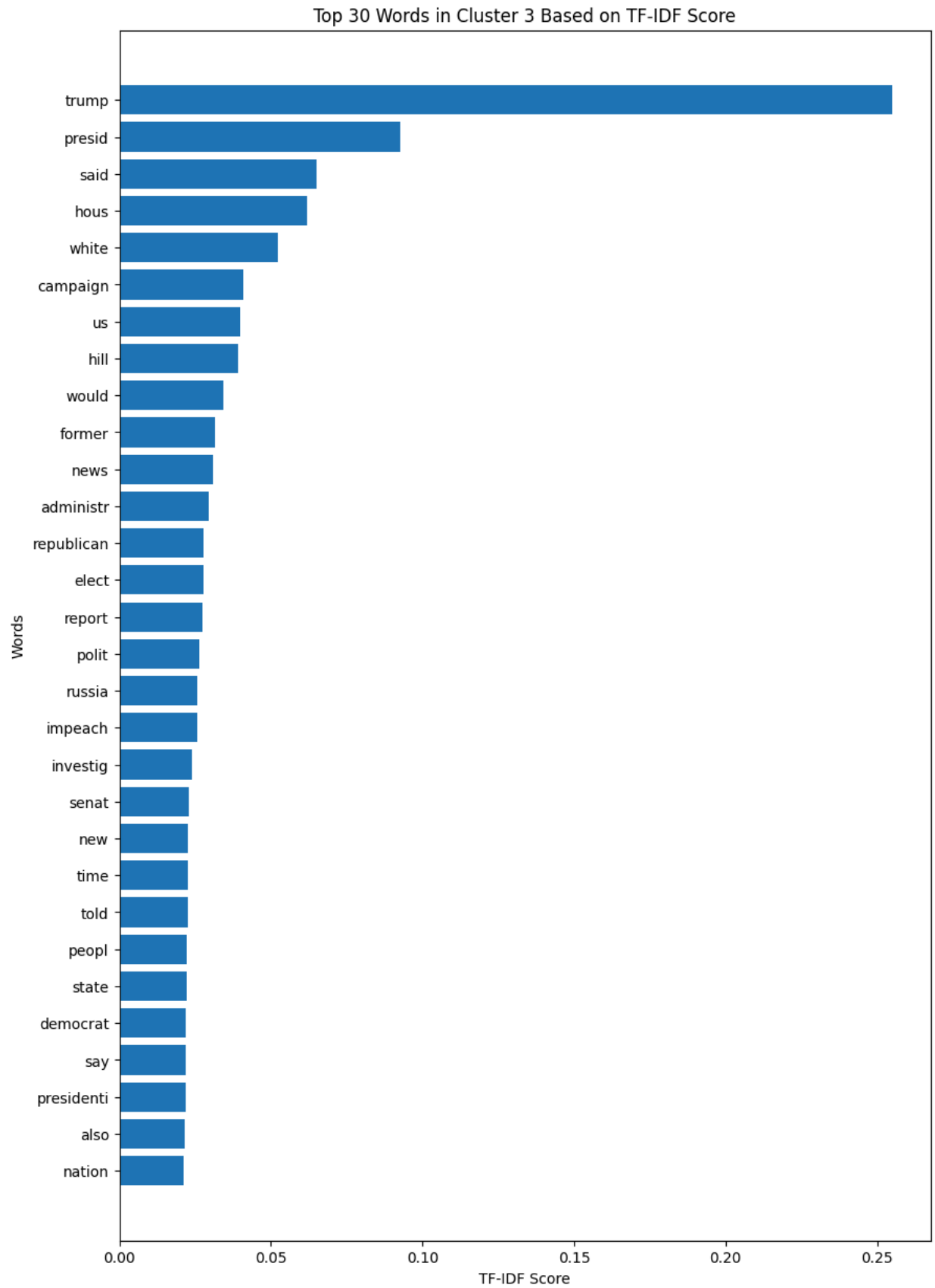
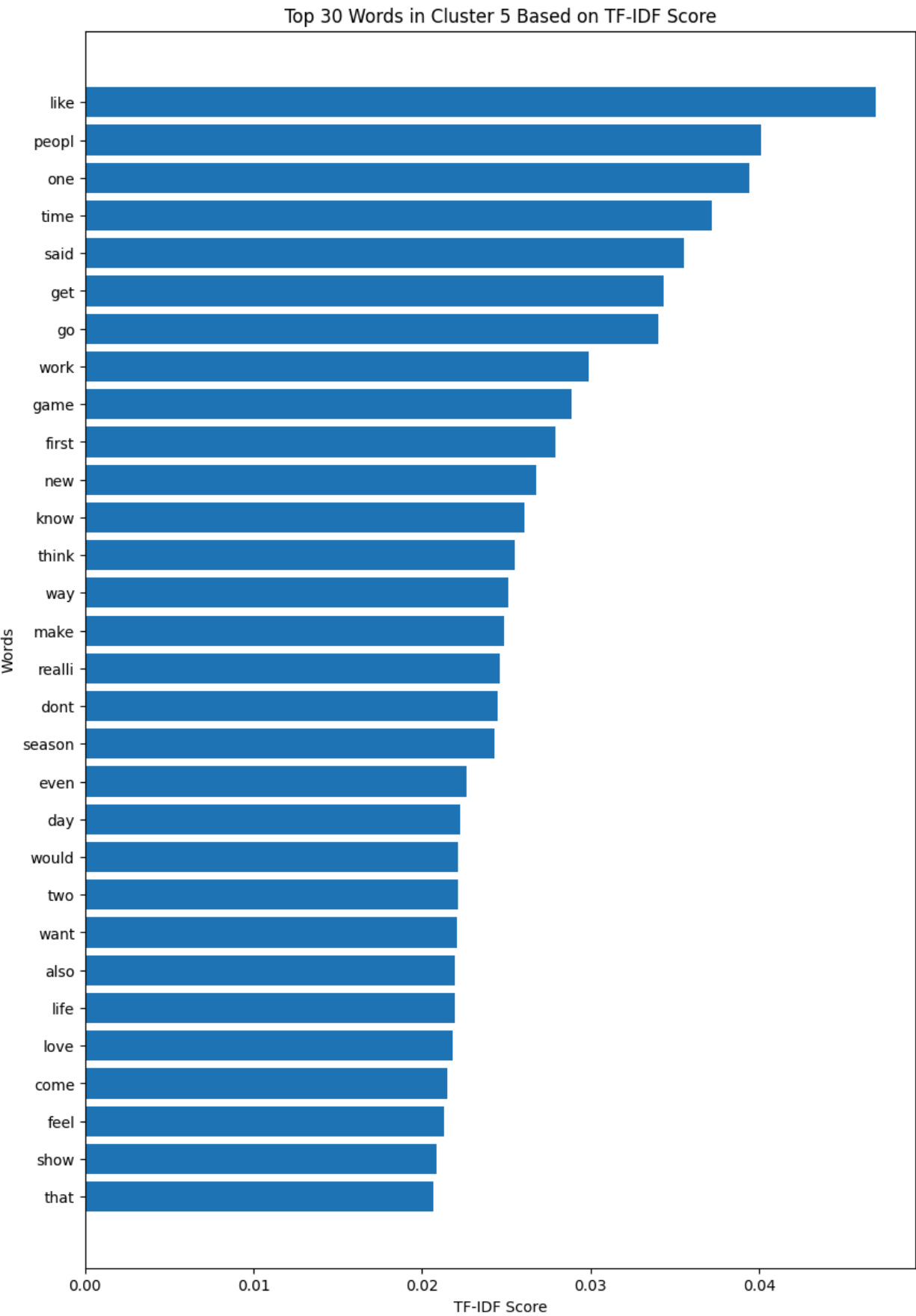
Fig 3.2 Elbow Method***Fig 3.3 Silhouette Plot:***

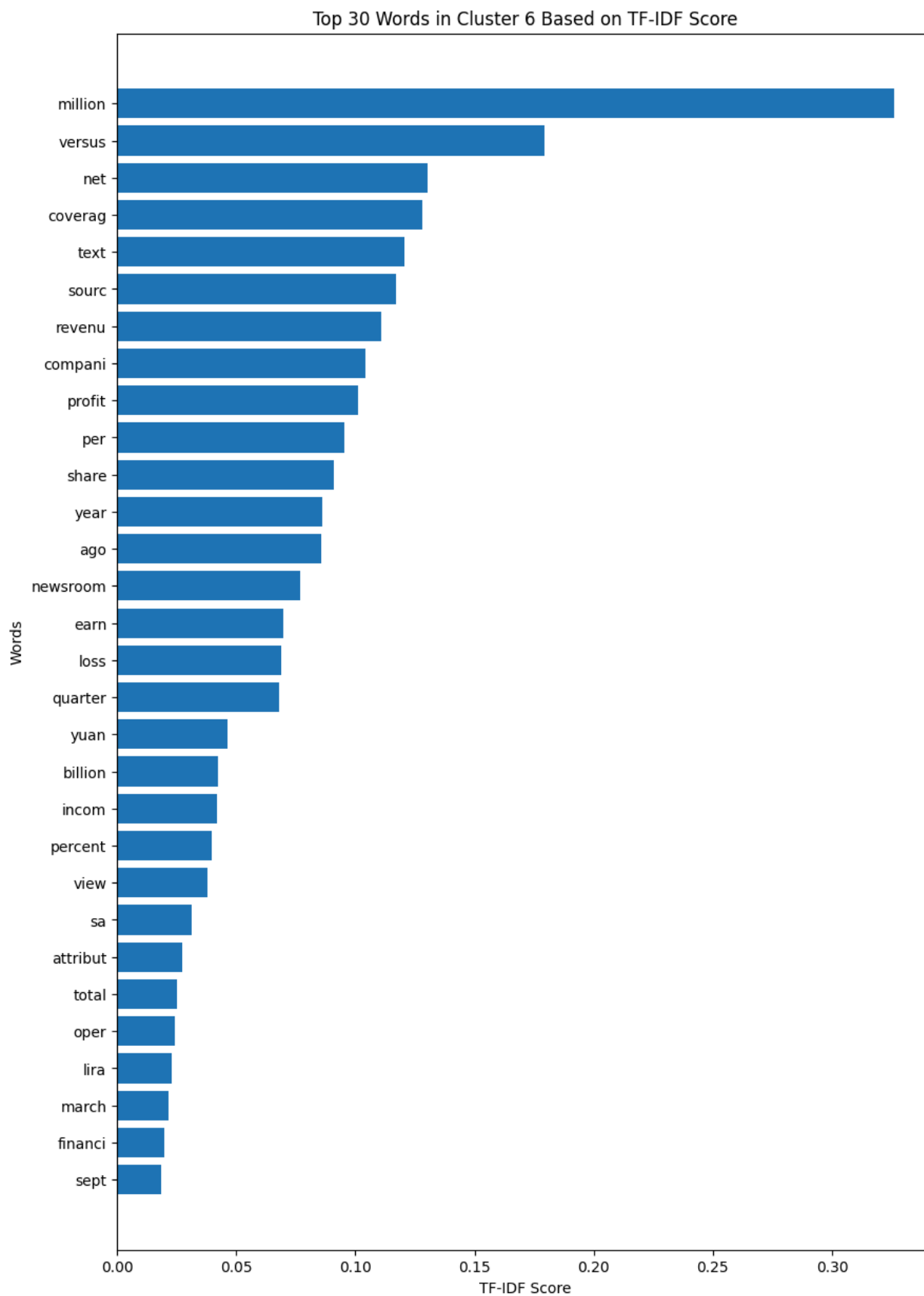
Fig 4.1 Clustering results through KMeans

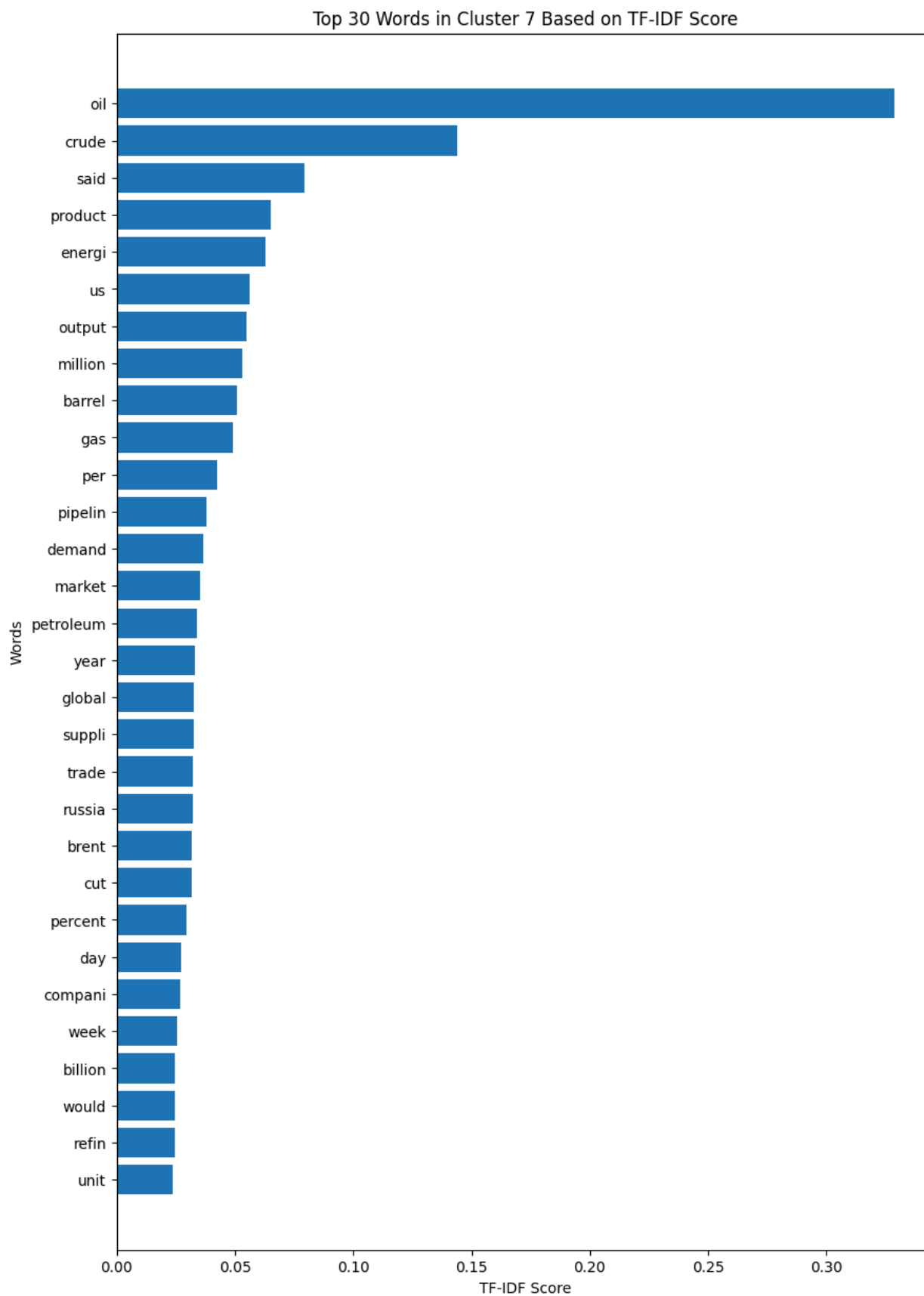


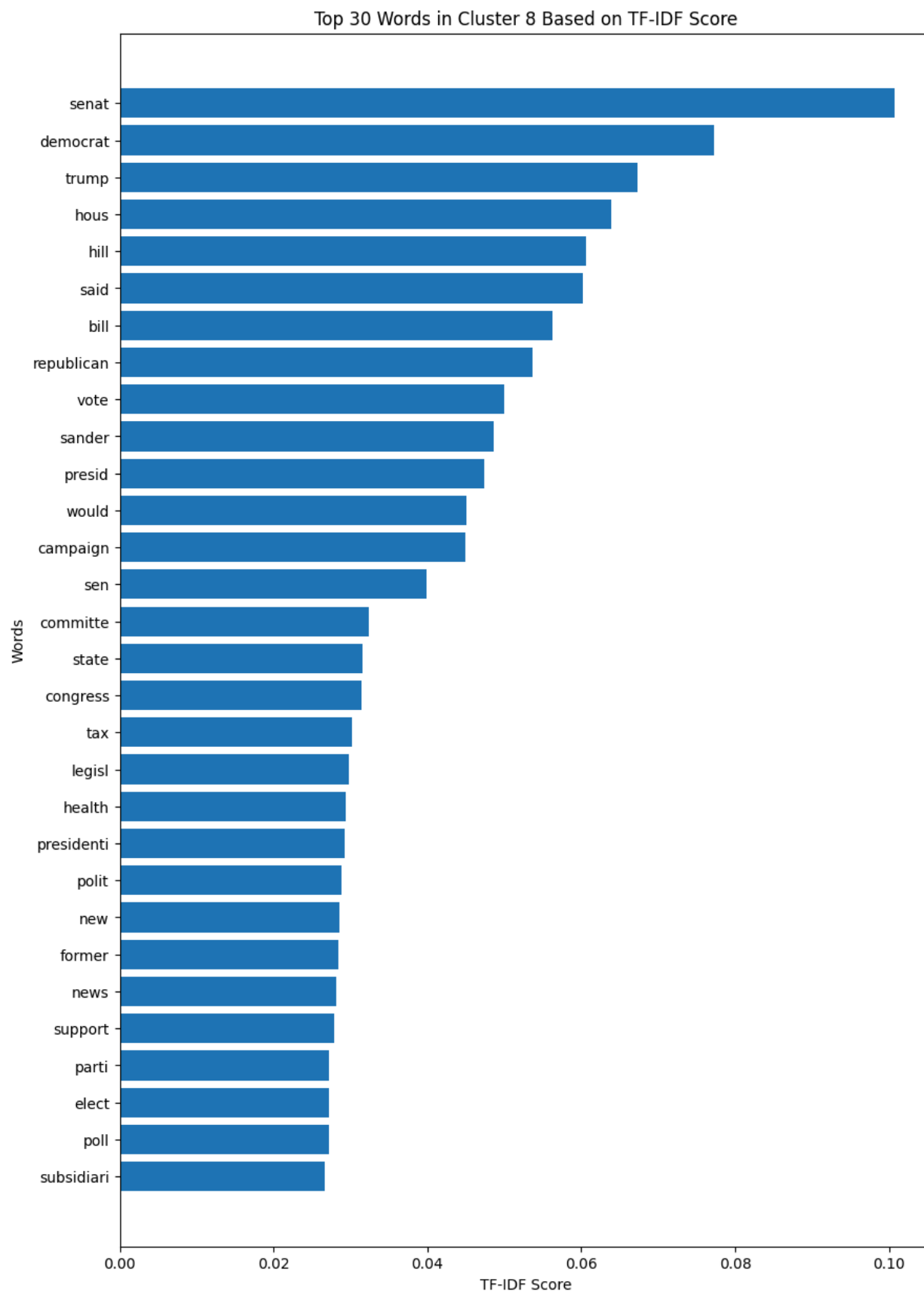












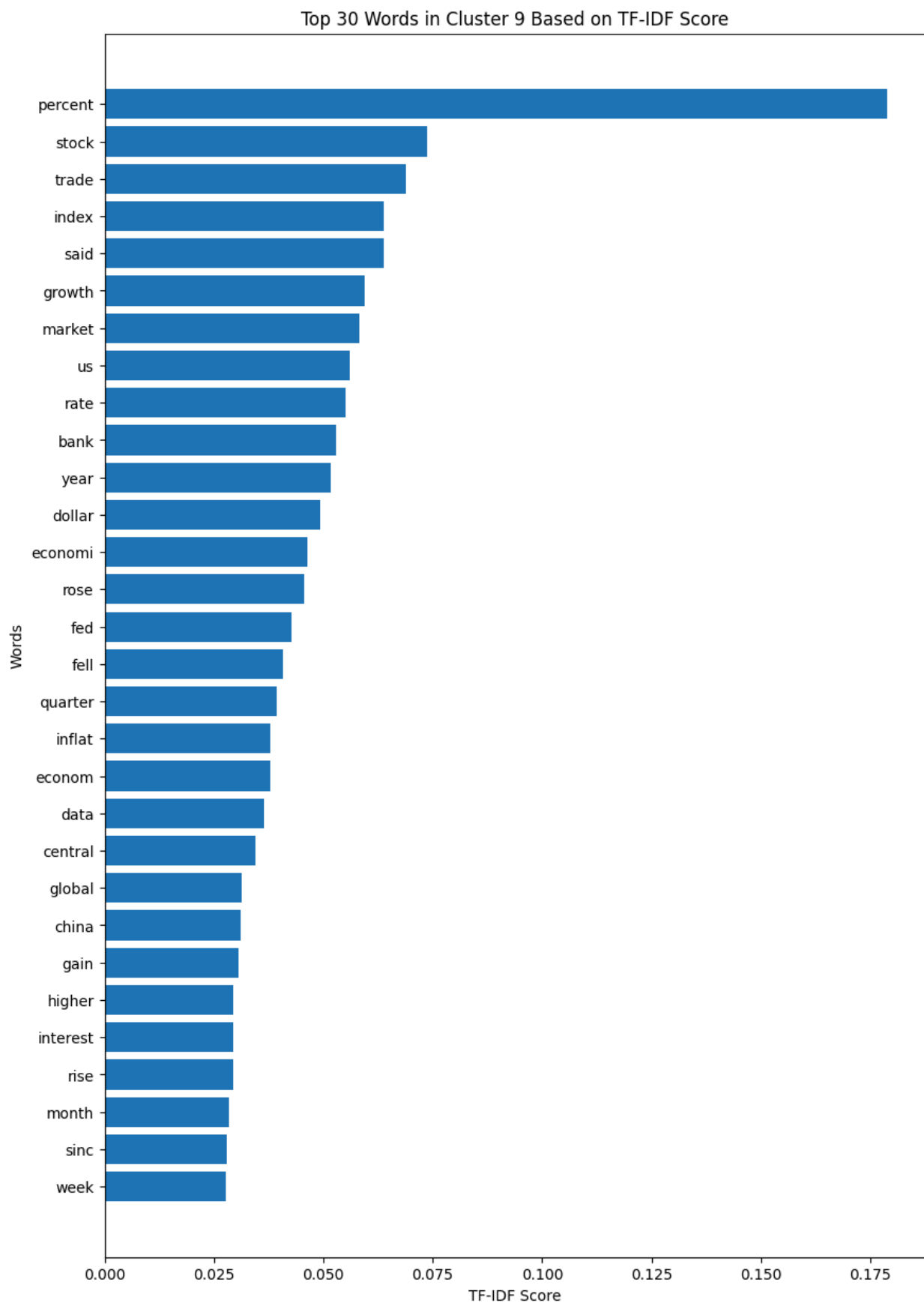


Fig 4.2 PCA ngram, Elbow Method, Silhouette Plot