Checkpoint 2: Data Exploration

InsightNews: Personalized News Sentiment Analyzer

Team Members: Avinash Amudala, Venkata Ajay Kumar Vutty, Shreya Navinchandra Patel

Introduction

This document provides a detailed exploration of the data collected for the InsightNews project. The objective of Checkpoint 2 is to demonstrate that we have collected a significant portion of the data needed for our project, describe the preprocessing steps taken, and highlight key characteristics of the data through various analyses and visualizations.

Data Collection

Source of Data

We collected news articles using the NewsAPI and MediaStack, which provide access to articles from various online sources. Our focus was on four topics: technology, politics, health, and sports.

Topics Covered

- Technology
- Politics
- Health
- Sports

Data Collection Process

We used the NewsAPI and MediaStack to fetch articles for each topic within a specified date range. The data collection process involved querying the API for each topic and saving the articles in CSV files.

Limitations

The APIs' free plans limit the number of articles that can be fetched. To manage this limitation, we collected articles in batches for each topic. Additionally, our current dataset spans from June 1, 2024, to June 30, 2024.

While this provides a good starting point, it is important to note that this limitation may affect the comprehensiveness of our sentiment analysis and trends. We can expand our dataset if needed by upgrading our API plans or integrating additional data sources to capture more articles and cover a broader date range.

Data Preprocessing

Steps Involved

- 1. Loading Data: We loaded the raw data from CSV files into a DataFrame.
- 2. **Removing Duplicates**: Duplicate articles based on the URL were removed.
- 3. Handling Missing Content and Titles: Articles with missing content and titles were addressed by either filling missing content with titles or dropping rows.
- Cleaning Content: Tokenization and removal of stop words were performed.
- 5. Calculating Content Length: The length of the content for each article was calculated in terms of the number of words.

Code for Data Preprocessing

```
import pandas as pd
import os
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
import string
def load_data(directory):
    files = [os.path.join(directory, f) for f in os.listdir(directory) if f.endswith('.csv')
    print(f"Found {len(files)} files to process.")
    dfs = [pd.read_csv(f) for f in files]
    return pd.concat(dfs, ignore_index=True) if dfs else pd.DataFrame()
def preprocess_data(df):
    if df.empty:
        print("No data to preprocess.")
        return df
    initial_count = len(df)
    print(f"Initial record count: {initial count}")
    # Remove duplicates based on URL
    df.drop_duplicates(subset='url', keep='first', inplace=True)
    after_dedup_count = len(df)
    print(f"Records after removing duplicates: {after_dedup_count} (Removed {initial_count }
    # Keep rows with either title or content
    df = df.dropna(subset=['title', 'content'], how='all')
    after_dropna_count = len(df)
    print(f"Records after removing rows with missing title and content: {after_dropna_count
```

```
# Fill missing content with title if content is missing
    df['content'] = df['content'].fillna(df['title'])
    df['title'] = df['title'].fillna(df['content'])
    # Initialize stop words
    stop_words = set(stopwords.words('english'))
    # Function to clean and tokenize content
    def clean content(content):
        tokens = word_tokenize(content.lower())
        tokens = [word for word in tokens if word.isalpha() and word not in stop_words]
        return ' '.join(tokens) # Join tokens back into a string for easier handling later
    # Apply the cleaning function to the content
    df['cleaned_content'] = df['content'].apply(clean_content)
    df['content_length'] = df['cleaned_content'].apply(lambda x: len(x.split()))
    # Keep rows with at least 3 tokens in cleaned content
    df = df[df['content_length'] > 3]
    after_cleaning_count = len(df)
    print(f"Records after cleaning content: {after_cleaning_count} (Removed {after_dropna_count})
    final_count = len(df)
    print(f"Preprocessed data from {initial_count} to {final_count} records.")
   return df
def save_data(df, filename):
    if df.empty:
        print(f"No data to save for {filename}")
    abs_path = os.path.abspath(filename)
    os.makedirs(os.path.dirname(abs_path), exist_ok=True)
    df.to_csv(abs_path, index=False)
    print(f"Data saved to {abs_path}")
if __name__ == "__main__":
    raw_data_directory = 'data/raw/'
    processed_data_filename = 'data/processed/articles_cleaned.csv'
    print("Loading raw data...")
   df = load_data(raw_data_directory)
    if not df.empty:
        print("Preprocessing data...")
        df = preprocess_data(df)
        print("Saving cleaned data...")
```

```
save_data(df, processed_data_filename)
else:
   print("No data loaded. Skipping preprocessing and saving steps.")
print("Data preprocessing complete.")
```

Data Characteristics and Analysis

Summary Statistics

The table below provides summary statistics for the dataset, including the number of articles, mean content length, and other relevant metrics.

Statistic	Value
Total Articles	32590
Mean Content Length	9.27 words
Min Content Length	4 words
Max Content Length	30 words
Std Dev Content Length	3.57 words

Visualizations

Distribution of Article Lengths The histogram below visualizes the distribution of article lengths, showing the number of words in each article.

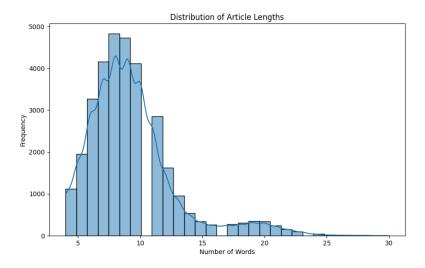


Figure 1: Article Length Distribution

Explanation: This histogram illustrates the frequency of articles based on their length, defined by the number of words they contain. From the distribution, we observe that the majority of articles fall within the 7 to 12-word range. There are very few articles with less than 4 words or more than 30 words. The distribution shows a peak around 9 words, indicating that most articles in our dataset are concise, likely consisting of brief news summaries or highlights.

This visualization is essential as it helps us understand the typical length of articles we are dealing with, which can be crucial for tasks such as sentiment analysis, where the length of the text can influence the sentiment scores and the performance of the models we use.

Number of Articles per Topic The bar chart below shows the number of articles collected for each topic.

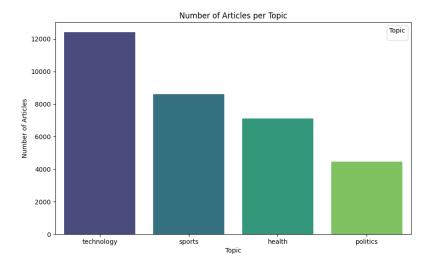


Figure 2: Articles per Topic

Explanation: This bar chart illustrates the distribution of articles across the four topics: technology, politics, health, and sports. Each bar represents the number of articles collected for a specific topic.

From the visualization, we observe that:

- The topic 'technology' has the highest number of articles.
- The topics 'health,' 'politics,' and 'sports' each have a significant number of articles, providing a balanced dataset across these topics.

Content Length Distribution by Topic The box plot below shows the distribution of content lengths across different topics.

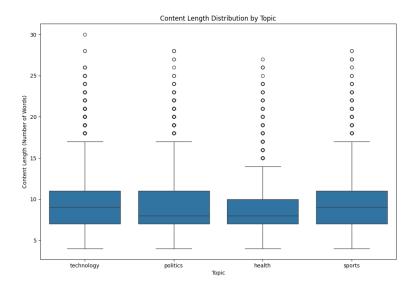


Figure 3: Content Length Distribution by Topic

Explanation: This box plot visualizes the distribution of content lengths (number of words) for articles in each of the four topics: technology, health, politics, and sports.

Key observations include:

- The median content length is fairly consistent across all topics, with most articles containing between 7 to 12 words.
- The interquartile range (IQR), which represents the middle 50% of the data, is also similar for each topic, indicating that the spread of content length is uniform across topics.
- There are several outliers, particularly on the lower end of the content length spectrum. These outliers represent articles with significantly fewer words than the majority.

Top Sources for Each Topic The bar chart below shows the top sources for each topic.

Explanation: This bar chart presents the most prolific sources for each topic in our dataset. The sources are listed on the y-axis, and the number of arti-

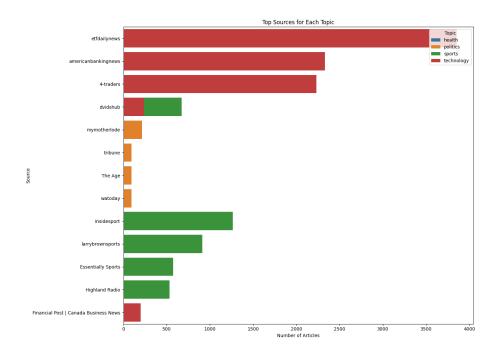


Figure 4: Top Sources for Each Topic

cles provided by each source is shown on the x-axis. Different colors represent different topics.

Key observations include:

- For the technology topic, 'Biztoc.com' is a major source, contributing significantly more articles compared to other sources.
- The health topic is covered by a diverse set of sources, including 'FDA.gov' and 'Newsweek'.
- Politics articles are predominantly sourced from 'Freerepublic.com', with other sources like 'Politicalwire.com' also contributing.
- The sports topic is well-represented by sources such as 'Bleacher Report' and 'USA Today'.

Term Analysis and Word Clouds

Most Frequently Occurring Terms

To gain insights into the common terms used across different topics, we performed a term frequency analysis. The top 20 most frequently occurring terms for each topic are presented below:

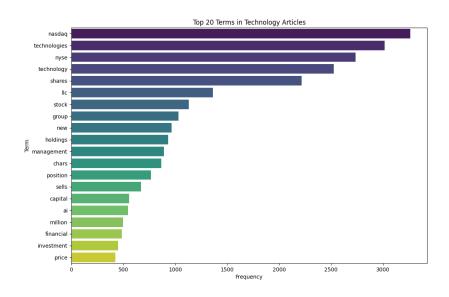


Figure 5: Top 20 Terms - Technology

Technology

Politics

Health

Sports

Word Clouds

Word clouds provide a visual representation of the most frequently occurring terms, with the size of each term indicating its frequency. The word clouds for each topic are shown below: #### Technology

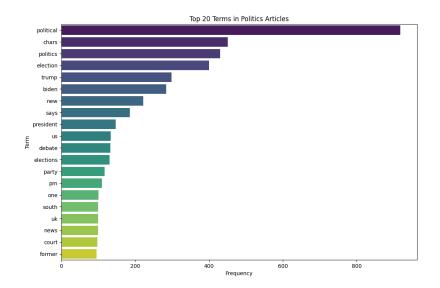


Figure 6: Top 20 Terms - Politics

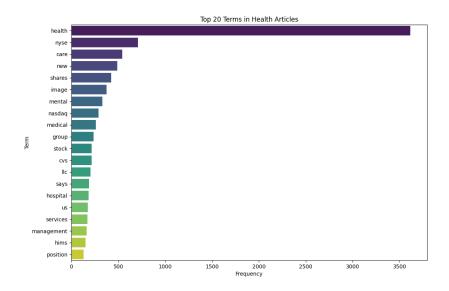


Figure 7: Top 20 Terms - Health

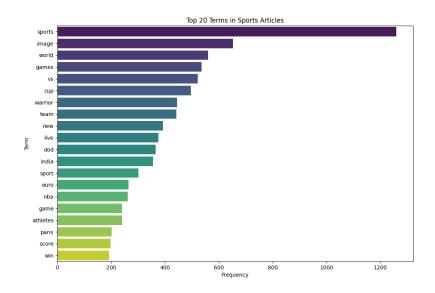


Figure 8: Top 20 Terms - Sports



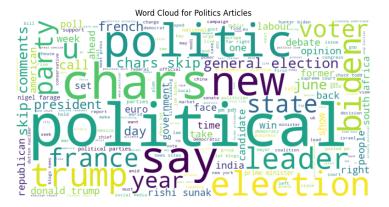


Figure 9: Word Cloud - Politics

Politics

Health

Sports

Conclusion

Through the data collection and preprocessing steps, we have ensured that the data is clean and ready for the next phases of our project. The visualizations and summary statistics provided above demonstrate that we have a solid grasp on manipulating and understanding our dataset. This sets a strong foundation for implementing the sentiment analysis and developing the interactive dashboard in the subsequent stages of the project.

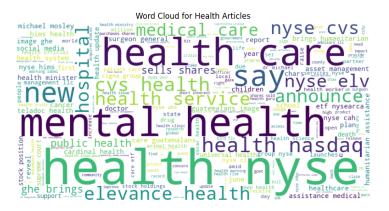


Figure 10: Word Cloud - Health

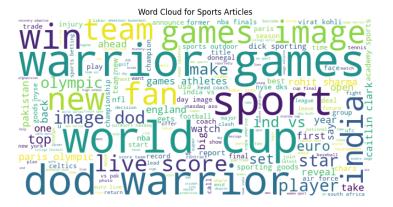


Figure 11: Word Cloud - Sports