# Methodology:

We begin by loading the dataset, which is divided into two parts: Fake News and Real News. Initially, we explored both datasets separately to understand their structure — including column names, number of rows, and more.

### Data Preprocessing:

- Before merging, a new column Label was added:
  - 0 for Fake news
  - 1 for Real news
- Both datasets were merged and shuffled to remove any ordering bias.
- We analyzed the merged dataset using .info(), .shape, etc.
- The column names were converted to uppercase for consistency.
- Duplicate rows were checked and removed.
- Unimportant columns such as DATE and SUBJECT were dropped.

### Text Cleaning:

We focused on the TEXT column:

- Removed leading/trailing spaces.
- Converted all text to lowercase.
- Removed punctuation and special characters.

### Tokenization and Lemmatization:

- The cleaned text was tokenized using TF-IDF Vectorizer and stored in a new column tokens.
- Applied simple lemmatization to reduce words to their base forms (e.g., “cats” → “cat”).

- Then applied POS-based lemmatization for more accurate word normalization (e.g., “running” → “run” depending on its part of speech).

At this point, Data Preprocessing was complete.

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### Exploratory Data Analysis (EDA)

- Visualized the distribution of Fake vs Real News using a bar plot.
- Generated Word Clouds for both fake and real articles to identify most frequent terms.
- Used a histogram to analyze word counts in fake vs real news.
- Conducted sentiment analysis:
    - Fake news tends to show lower polarity compared to real news, indicating less neutral tone and more emotionally charged language.

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### Feature Extraction

- Combined lemmatized text into strings.
- Applied TF-IDF vectorization to convert text to numerical features.
- Added extra numerical features:
    - Length of text
    - Sentiment score

Final feature set: TF-IDF + text length + sentiment score

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### Model Training

- Feature matrix: X = [TF-IDF, length, sentiment]
- Labels: y = Label

- Performed train-test split
- Applied and evaluated two models:
    - Logistic Regression
    - Multinomial Naive Bayes

**Evaluation Metrics:**

**Used:**

- Accuracy Score
- F1 Score
- Precision
- Confusion Matrix
- Classification Report

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### Design Choices

- Logistic Regression: Chosen for binary classification (0 = Fake, 1 = Real), especially effective with linearly separable data.
- Multinomial Naive Bayes: Best suited for text classification when using Bag-of-Words or TF-IDF features.

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## Evaluation Results:

### Logistic Regression

- **Training Accuracy: 0.9923**
- **Test Accuracy: 0.9866**

**Classification Report:**

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Fake (0) | 0.99 | 0.98 | 0.99 | 4652 |
| Real (1) | 0.98 | 0.99 | 0.99 | 4286 |
| Accuracy: | | | 0.99 (8938 samples) | |

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**MultinomialNB**

- **Training Accuracy: 0.9486**
- **Test Accuracy: 0.9404**

**Classification Report:**

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Fake (0) | 0.95 | 0.93 | 0.94 | 4652 |
| Real (1) | 0.93 | 0.95 | 0.94 | 4286 |
| Accuracy: | | | 0.94 (8938 samples) | |

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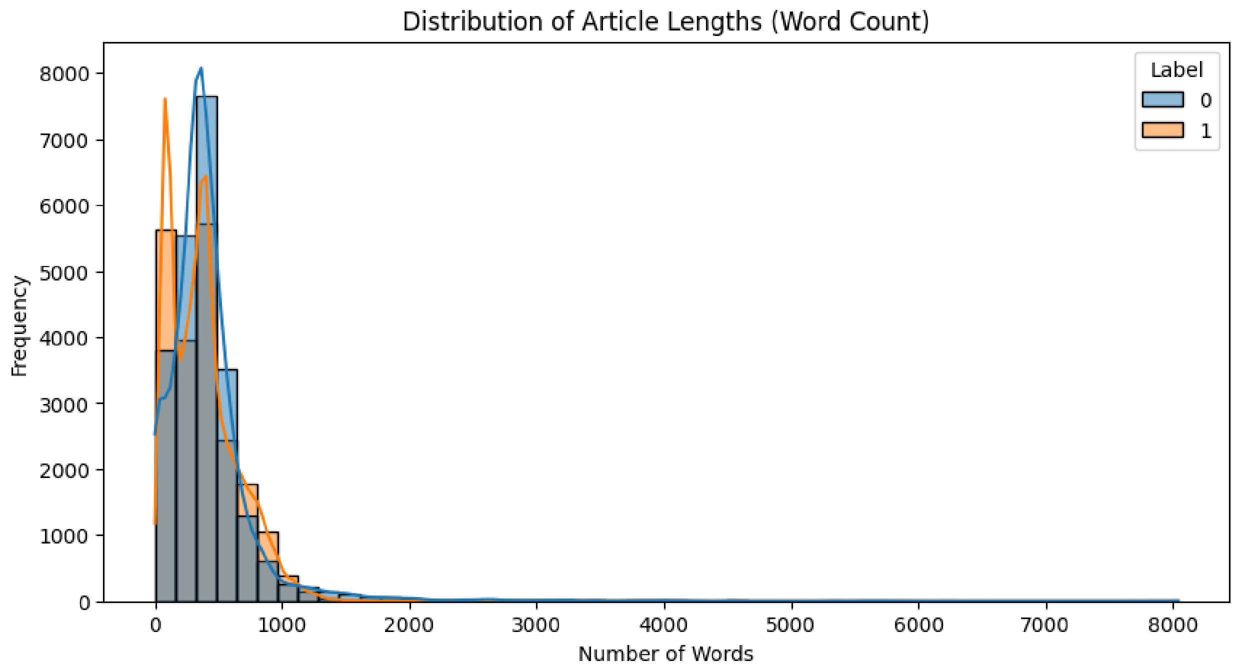
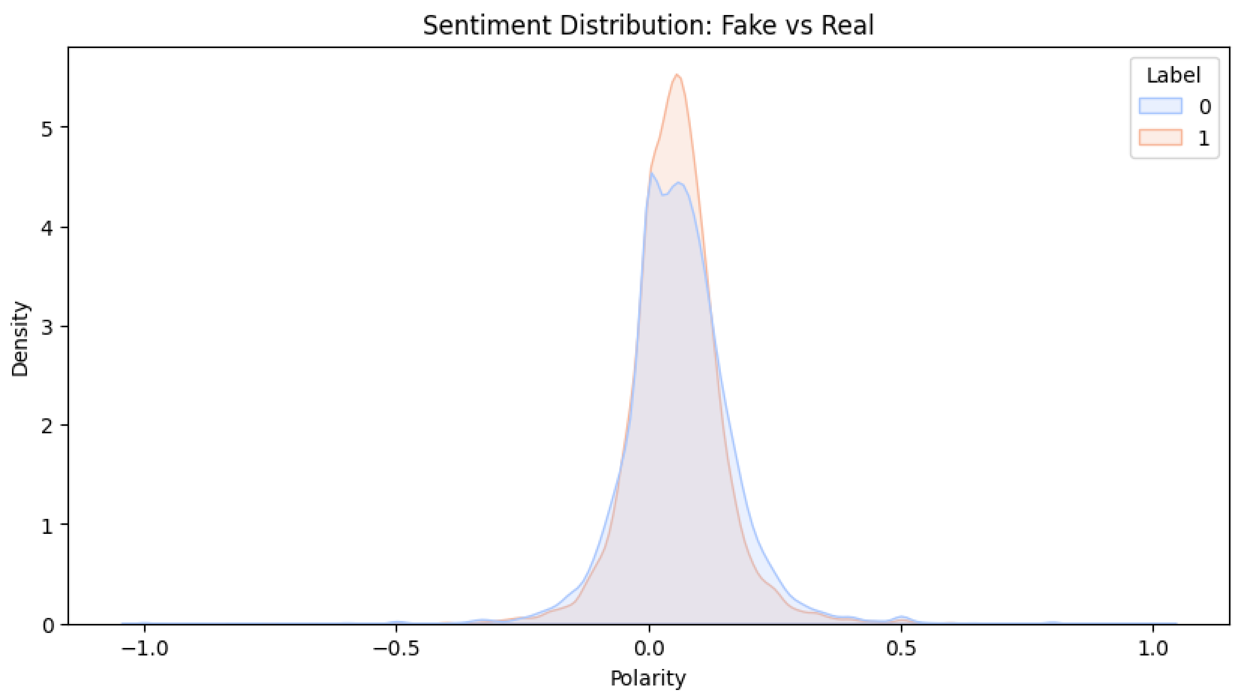
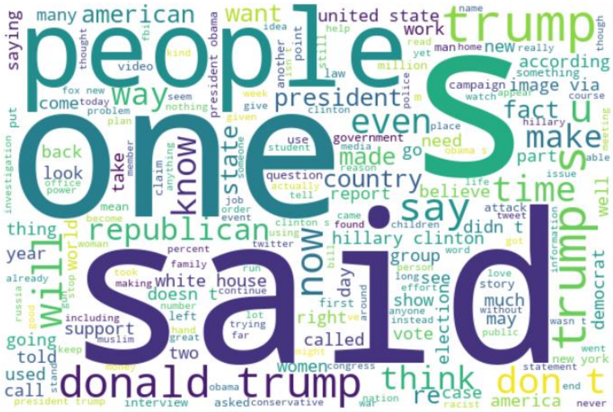
## Key Insights

- Fake news tends to have more emotional or opinionated language, as revealed by higher polarity values from sentiment analysis.
- Real news is more balanced and neutral, indicating more objective reporting.


Distribution of Article Lengths (Word Count)
Label
0
1
Frequency
Number of Words
0
1000
2000
3000
4000
5000
6000
7000
8000


Sentiment Distribution: Fake vs Real
Label
0
1
Density
Polarity
−1.0
−0.5
0.0
0.5
1.0

Most Common Words in Fake News




Most Common Words in Real News