Case Study: A Multi-faceted Approach to Detecting Fake News on Websites and Social Media

In our interconnected world, information, including fake news, spreads rapidly. While the motivation behind fake news can be elusive, its identification is possible through the analysis of both content and metadata.

1. Project Goal: Enhanced Analysis and Classification of Fake News using the BuzzFeed Dataset

This project aims to conduct a comprehensive analysis of the BuzzFeed subset within the FakeNewsNet dataset. The core objective is to develop a robust machine learning model capable of accurately distinguishing between real and fake news articles. This will be achieved through a multi-faceted approach encompassing Exploratory Data Analysis (EDA), feature engineering, and the implementation and evaluation of machine learning classifiers, with a primary focus on the Random Forest algorithm.

2. Data Loading and Initial Preparation

The project analyzed the BuzzFeed portion of the FakeNewsNet dataset. This involved loading content (title,news content, URL, etc. with a real/fake label), mapping (string IDs to numerical IDs for news and users), and interaction files (news-user spread, user-user following). Preparation included combining real and fake content, standardizing news IDs, parsing publish dates, cleaning sources to extract domains, and extracting metadata like publisher and keywords from JSON strings.

3. Exploratory Data Analysis (EDA) Key Insights

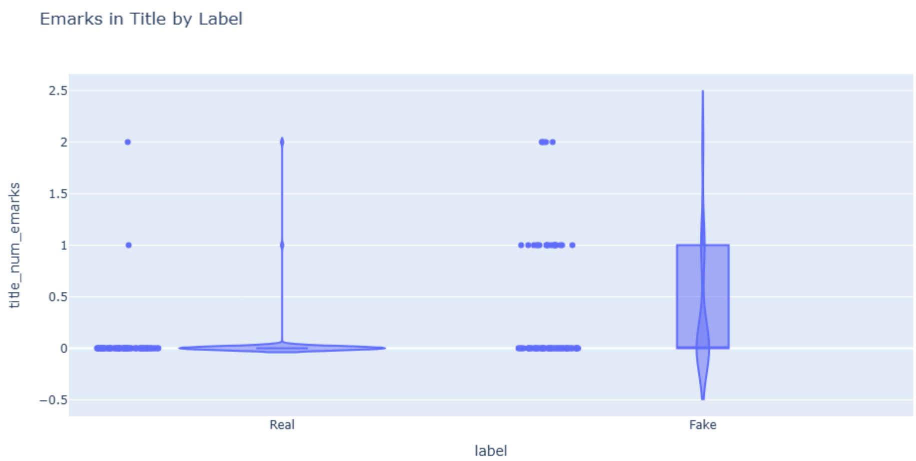

Figure 1

Fake news headlines often employ exclamation marks more frequently, possibly as a stylistic technique to create sensationalism or grab attention.

In fact, we also observed Fake News contains relatively more negative sentiments, trying to engage people emotionally.

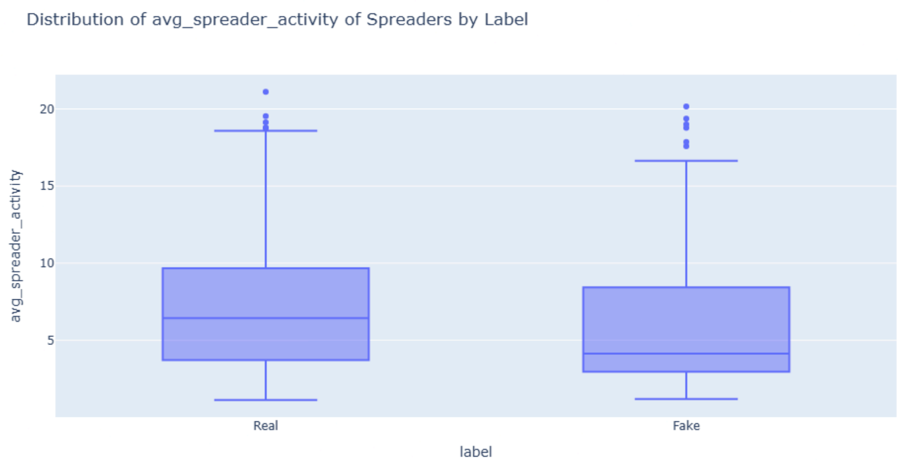

Figure 2

Figure 2 shows that users spreading real news typically share a wider variety of articles (median activity of 6-7 other articles) compared to those spreading fake news (median activity around 4 articles). This suggests spreaders of real news are, on average, more broadly active news sharers.

Furthermore, our investigation indicated that fake news articles consistently lacked keywords in their metadata.

4. Feature Engineering for Modeling

Two primary feature sets were developed to train the classification models:

- **Content-Only Features:**
  - Article titles and main text were combined and textually processed (e.g., lowercasing, removing common words, standardizing word forms).
  - These processed texts were then converted into numerical features representing word importance (TF-IDF).
- **Content + Selected Metadata Features:**
  - Numerical metadata features identified during EDA (e.g., text lengths, readability scores, sentiment scores, website meta-information, user engagement statistics) were compiled.
  - A feature importance analysis using a Random Forest model helped identify the most influential metadata features.
  - These top-performing metadata features were then numerically scaled and combined with the content-only (TF-IDF) features.

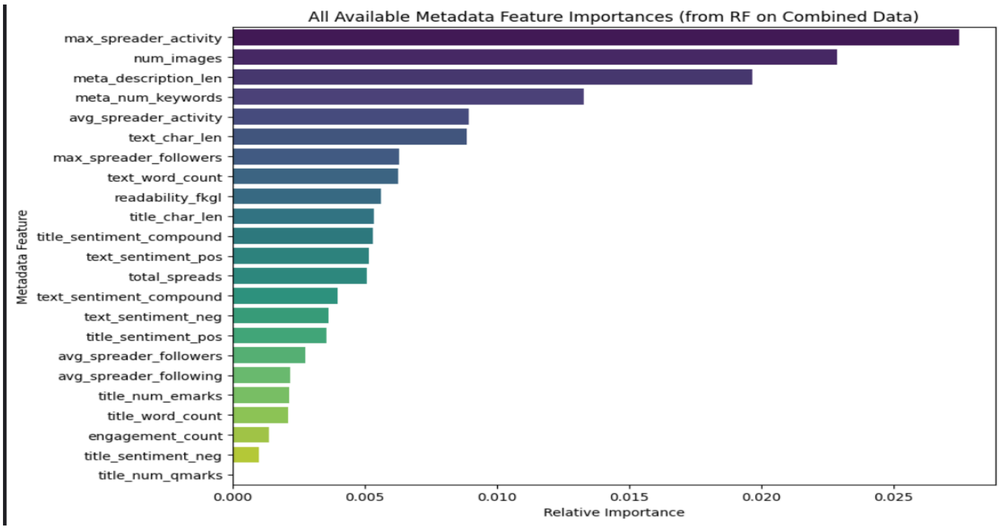

Figure 3: Feature Importance Plot

5. Modeling Approach: Random Forest

- **Algorithm:** The Random Forest classification algorithm was chosen for its effectiveness in handling diverse feature sets and its robustness.
- **Comparison:** Two main model configurations were compared:
  1. A Random Forest model trained solely on the **Content-Only features**.
  2. A Random Forest model trained on the combined **Content + Selected Metadata features**.
- **Evaluation:** Models were trained on a portion of the data and tested on a separate, unseen portion to ensure fair evaluation. The primary metric for comparison was the Macro F1-Score, which balances precision and recall.

Model Details	F1-Score
RF (**Content + Selected Metadata**)	0.714
RF (**Content-Only**)	0.629

Key Observation: Incorporating a *selected set* of metadata features alongside text content improved the Random Forest model's performance.

6. Are the above things sufficient to identify fake news?

- Identifying fake news is increasingly challenging due to the proliferation of AI-generated content beyond text, including videos and images. While advanced techniques like BERT enhance contextual understanding in text, they are insufficient on their own.
- Verifying the authenticity of news requires leveraging advanced AI tools such as Perplexity or Microsoft's Claimify, which can examine individual claims by searching the web for supporting evidence.
- Fake news isn't limited to text; it also appears in images or mixed formats. For instance, outdated photos of events might be used to falsely depict current situations.
- Multi-Modal Large Language Models (LLMs) offer a promising approach to handle diverse content formats and better identify fake news across different media.