

Understanding Misinformation: A Case Study of COVID-19 Social Media Posts

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Group 2

Motivation



March 2020 - COVID-19 declared a pandemic

May 2023 - Global Public Health Emergency ended

- What happened in between? → **constant spread of misinformation**
- Nearly early half of Americans reported obtaining either 'some' (30%) or 'a lot' (18%) of news and information about COVID-19 vaccines from social media platforms (*Pew Research Center, 2021*)

Farhoudinia et. al (2024) looked into analyzing emotions relating to misinformation, but there is still **research gap in finding most important features in misinformation detection**

Research Questions

1

Which social media features are most important for distinguishing real vs misinformation posts?

2

Does the emotional tone of a social media post correlate with the likelihood that it contains misinformation?

3

How does the language used in real and fake COVID-19 posts differ?

Dataset

Fighting an Infodemic: COVID-19 Fake News Dataset (Patwa et al., 2021)

| Real | Fake | Total |
|-------|-------|--------|
| 5,600 | 5,100 | 10,700 |

- 10,700 English-language social media posts and articles collected through web scraping and the Twitter API.
- **Real news sources:** Tweets from official organizations such as WHO, CDC, and Covid India Seva.
- **Fake news sources:** Social media posts from platforms like Facebook, Twitter, and Instagram.
- **Annotation:** Human annotators manually verified posts to ensure accuracy
- **Dimensions:** 10,700 x 3

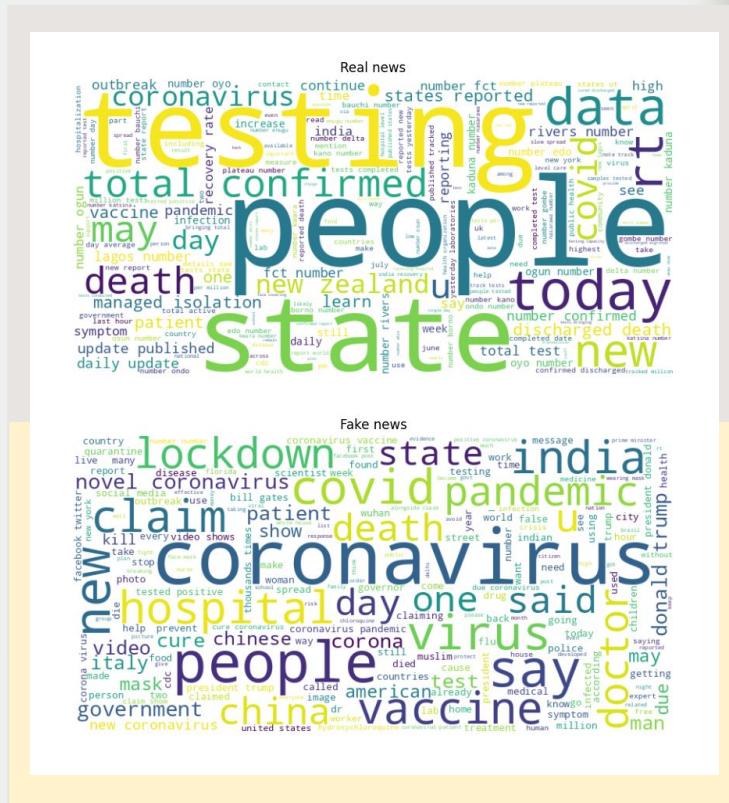
| id | posts | label |
|----|--|-------|
| 1 | Our daily update is published. States reported 734k tests 39k new cases and 532 deaths. Current hospitalizations fell below 30k for the first time since June 22. | real |
| 2 | Alfalfa is the only cure for COVID-19. | fake |
| 3 | President Trump Asked What He Would Do If He Were To Catch The Coronavirus https://t.co/3MEWhusRZI #donaldtrump #coronavirus | fake |

Data Cleaning

- Converted text to lowercase
 - Replaced:
 - a. URLs (`https://...`) → 'link'
 - b. Mentions (`@user`) → 'mention'
 - c. Numbers (e.g., 24k, 3.5M, 12,345) → 'number'
 - Applied **TweetTokenizer** to split each tweet into list of tokens
 - Removed Standard English stopwords from NLTK library
 - Removed top 20 common words

| Attribute | Fake | Real |
|--------------------|--------|--------|
| Unique words | 19728 | 22916 |
| Avg words per post | 21.65 | 31.97 |
| Avg chars per post | 143.26 | 218.37 |

(Patwa et al., 2021)

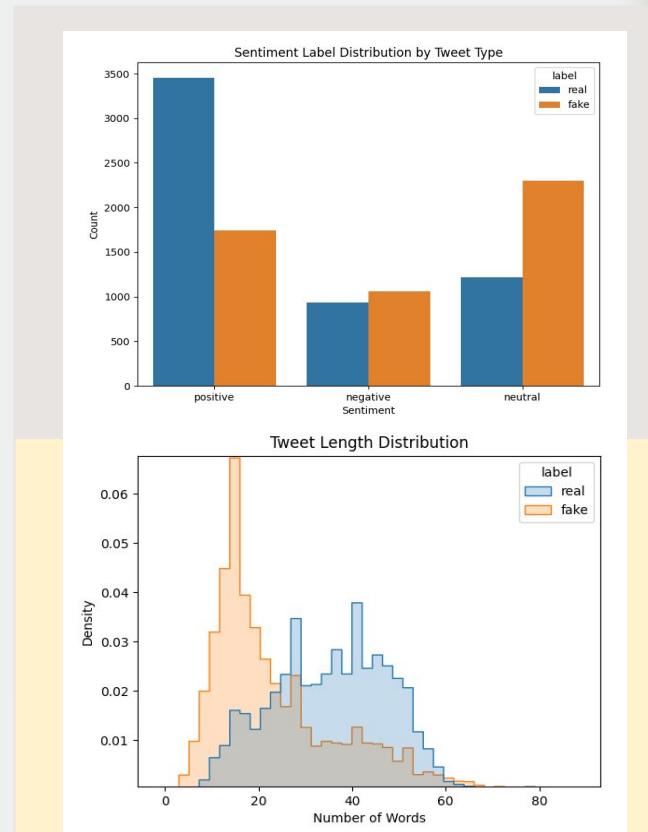


Planned Method

For each tweet, we will extract the following features:

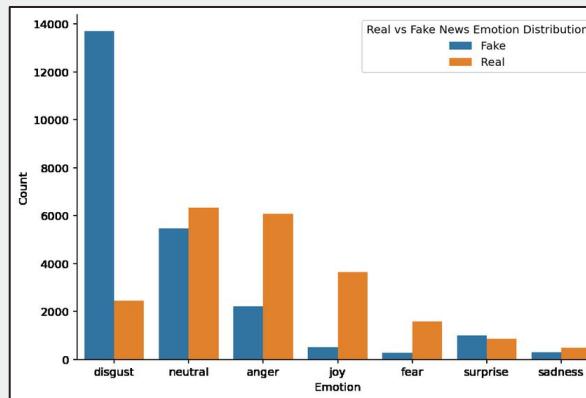
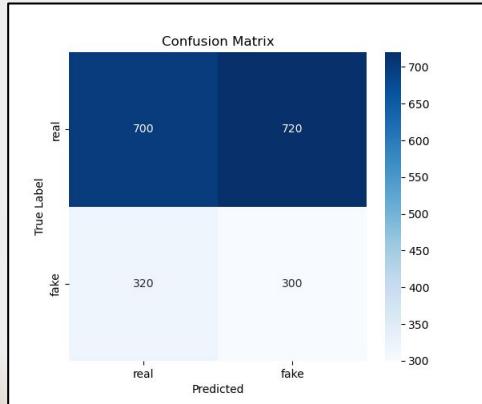
- Length
- Hashtag count
- Link presence
- Emotion (assigned by DisTilBERT)
- Sentiment polarity (positive, negative, neutral)
- Important words (identified using TF-IDF weighting)

These features will be used to train a Random Forest model to classify tweets as real or fake.

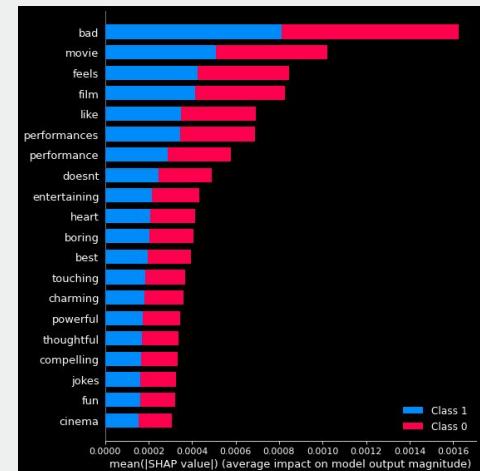


Expected Results

- Expect to show that emotional and structural features, such as sentiment polarity, emotion labels differ between real and fake posts.
- Visualize using feature importance plots from the Random Forest model, confusion matrices for classification results, and emotion distribution charts comparing real and fake posts.



(Kolev., 2022)



(Kumar., 2022)



Discussion

- Can be expanded by examining posts **over multiple years** instead of a short time frame to see if emotional and structural patterns in misinformation remain consistent over time
- Can explore how emotional content in **fake posts relates to user engagement**, such as likes, retweets, and replies, to better understand how misinformation spreads

Any Questions?



References

[https://pmc.ncbi.nlm.nih.gov/articles/PMC9114791/](https://PMC9114791)

[https://pmc.ncbi.nlm.nih.gov/articles/PMC7721433/](https://PMC7721433)