# FAKE NEWS DETECTION REPORT Gokul Narayanan Hariom Solanki

## 1. Problem Statement:

The objective of this project is to develop a machine learning model that can accurately distinguish between true and fake news articles. This includes various NLP techniques to get the accurate output

# 2. Methods Used:

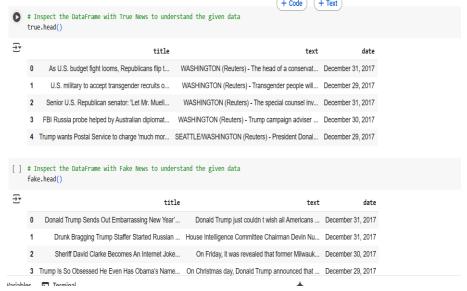
Following methods is used to get the required model

- a) Data Loading
- b) Text Preprocessing (Cleaning, tokenization, Lemmatization)
- c) EDA
- d) Feature Engineering using TF-IDF and Word2Vec
- e) Model Training and Evaluation (Logistic Regression, Random Forest and Decision Tree)

# 3. Detailed Explanation of Each Steps

#### 1) Data loading

- a) Two csv files True.csv and Fake.csv is loaded
- b) Data dictionary contains the title of the news article, text of the article and data of publication
- c) Head output of data is below



- d) Add new column news\_label to both the DataFrames and assign labels. 1 for true news and 0 for fake news
- e) True and Fake news dataframes are merged and null values are dropped

#### 2) Text Preprocessing

 a) A function was written to clean the all text and remove all unnecessary elements. This converted the text to lower case, removed the square bracket, removed punctuation and removed words with numbers

```
# Remove words with numbers
import re
import string

def clean_text(text):
    text = text.lower() #Lower case
    text = re.sub(r'\[.*?\]', '', text) # Remove text in square brackets
    text = text.translate(str.maketrans('', '', string.punctuation)) # Remove punctuation
    text = re.sub(r'\w*\d\w*', '', text) # Remove words with numbers
    return text
```

2.1.2 Apply the function to clean the news text and store the cleaned text in a new column within the new DataFrame. [1 mark]

```
[ ] # Apply the function to clean the news text and remove all unnecessary elements

# Store it in a separate column in the new DataFrame

df_clean["cleaned_text"] = merged_cleaned["news_text"].apply(clean_text)
```

b) POS tagging and Lemmatization was performed on data. This filtered stopwords and retained only NN and NNS tags

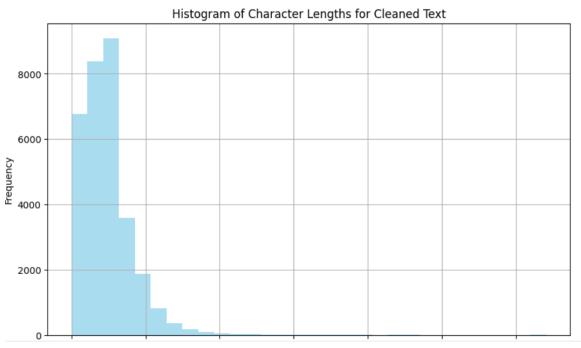
```
[ ] # Write the function for POS tagging and lemmatization, filtering stopwords and keeping only NN and NNS tags
    import spacy
     from nltk.corpus import stopwords
    from tqdm.notebook import tqdm
    # Load spacy model
    nlp = spacy.load("en_core_web_sm", disable=["ner", "parser"])
     import nltk
    nltk.download('stopwords', quiet=True)
     from nltk.corpus import stopwords
    stop_words = set(stopwords.words('english'))
    def pos_tag_lemmatize(texts):
        lemmatized_texts = []
        # Batch processing using spaCy's pipe
         for doc in tqdm(nlp.pipe(texts, batch_size=50, n_process=1), total=len(texts)):
            tokens = []
            for token in doc:
                if (token.tag_ in ['NN', 'NNS']) and (token.text.lower() not in stop_words) and (token.is_alpha):
                    tokens.append(token.lemma_.lower())
            lemmatized_texts.append(" ".join(tokens))
        return lemmatized texts
```

- c) Applied the POS tagging and lemmatization function to cleaned text and store it in a new column within the new dataFrame.
- d) Saved the new dataframe as csv file for easy usage in future.

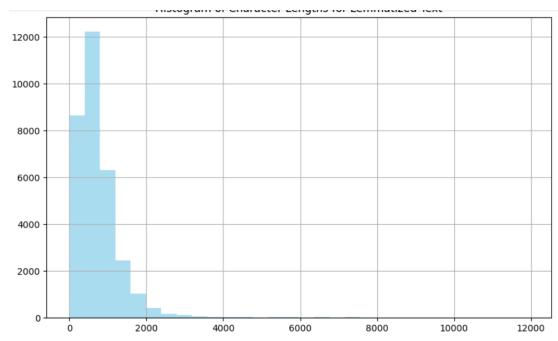


# 3) Exploratory Data Analysis (EDA)

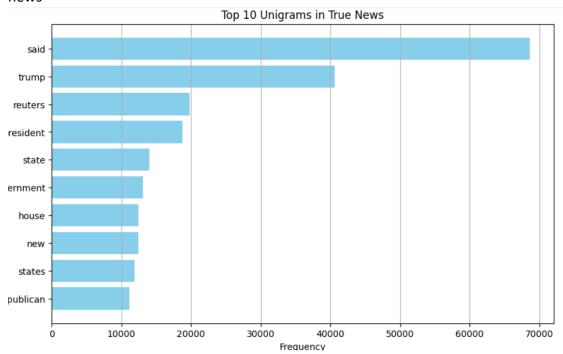
a) Histogram of cleaned text is plotted

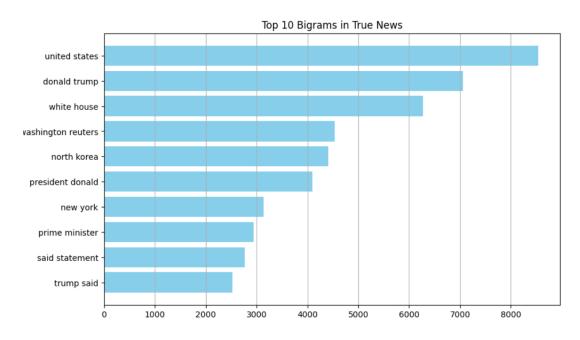


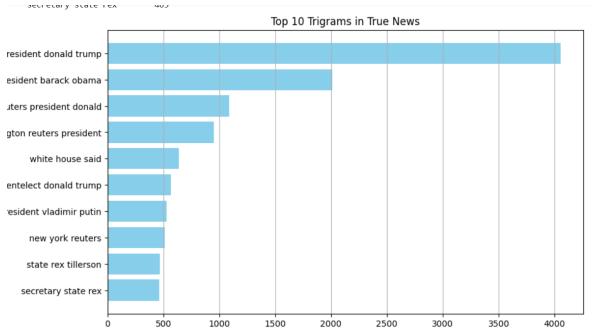
b) Histogram of lemmatized texts is plotted

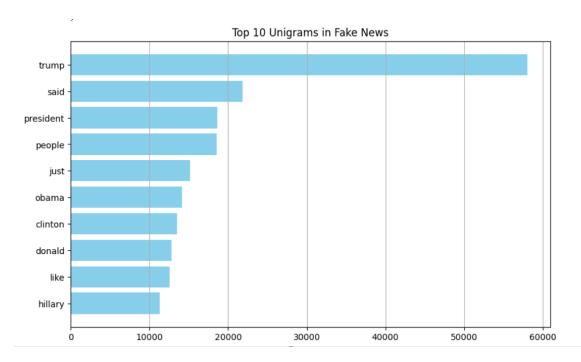


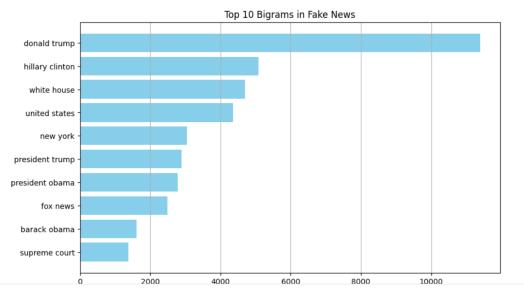
c) Displayed Top 10 unigrams, bigrams and trigrams in both True news and Fake news

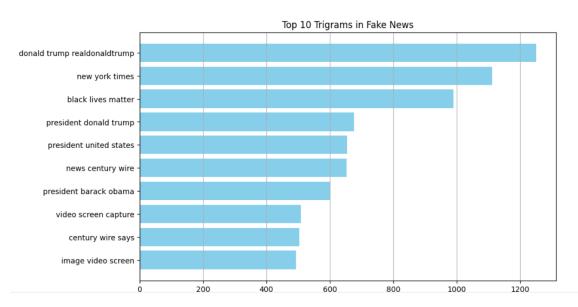












#### 4) Feature Engineering

a) Initialized the word2vec model

b) Extracted vectors for cleaned Data

#### 5) Model Training and Evaluation

a) Initially the model training and evaluation is performed for Logistic regression

```
[ ] ## Initialise Logistic Regression model
    log_reg = LogisticRegression(max_iter=1000, random_state=42)
    ## Train Logistic Regression model on training data
    log_reg.fit(X_train_vectors, y_train)
    ## Predict on validation data
    y_pred = log_reg.predict(X_val_vectors)
```

The Evaluation Data for Logistic Regression is as below

```
print("\n Logistic Regression Metrics for Val Data ---")
print(f"Accuracy: {accuracy_log_reg:.4f}")
print(f"Precision: {precision_log_reg:.4f}")
print(f"Recall: {recall_log_reg:.4f}")
print(f"F1-Score: {f1_log_reg:.4f}")
```

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Logistic Regression Metrics for Val Data ---

Accuracy: 0.9584 Precision: 0.9504 Recall: 0.9641 F1-Score: 0.9572

#### Classification report for Logistic Regression is as below

```
[ ] # Classification Report
print("\nClassification Report for Logistic Regression:\n")
print(classification_report(y_val, y_pred))
```



Classification Report for Logistic Regression:

	precision	recall	f1-score	support
0	0.97	0.95	0.96	6978
1	0.95	0.96	0.96	6498
26611112614			0.06	12476
accuracy			0.96	13476
macro avg	0.96	0.96	0.96	13476
weighted avg	0.96	0.96	0.96	13476

#### b) Secondly the model evaluation is performed on Decision Tree

```
[ ] ## Initialise Decision Tree model
   dt_model = DecisionTreeClassifier(random_state=42)
   ## Train Decision Tree model on training data
   dt_model.fit(X_train_vectors, y_train)
   ## Predict on validation data
   dt_preds = dt_model.predict(X_val_vectors)
```

Evaluation Data and Classification Report snapshot for Decision Tree is as below

```
print("\n Decision Tree Performance")
print(f"Accuracy: {accuracy_dt:.4f}")
print(f"Precision: {precision_dt:.4f}")
print(f"Recall: {recall_dt:.4f}")
print(f"F1 Score: {f1_dt:.4f}")
```

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Decision Tree Performance

Accuracy: 0.8983 Precision: 0.8985 Recall: 0.8983 F1 Score: 0.8983

₹ Classification Report for Decision Tree: precision recall f1-score support 0 0.89 0.92 0.90 6978 1 0.91 0.88 0.89 6498 accuracy 0.90 13476 macro avg 0.90 weighted avg 0.90 13476 0.90 0.90 0.90 0.90 13476

c) Finally, the model is trained using Random Forest

```
[ ] ## Initialise Random Forest model
    rf_model = RandomForestClassifier(random_state=42)
    ## Train Random Forest model on training data
    rf_model.fit(X_train_vectors, y_train)
    ## Predict on validation data
    rf_preds = rf_model.predict(X_val_vectors)
```

The evaluation result and classification report for Random Forest is as below

```
print("\n Random Forest Performance")
print(f"Accuracy: {accuracy_rf:.4f}")
print(f"Precision: {precision_rf:.4f}")
print(f"Recall: {recall_rf:.4f}")
print(f"F1 Score: {f1_rf:.4f}")
```

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Random Forest Performance

Accuracy: 0.9576 Precision: 0.9576 Recall: 0.9576 F1 Score: 0.9576



Classification Report for Random Forest

support	f1-score	recall	precision	
6978	0.96	0.96	0.96	0
6498	0.96	0.95	0.96	1
13476	0.96			accuracy
13476	0.96	0.96	0.96	macro avg
13476	0.96	0.96	0.96	weighted avg

#### 6) **CONCLUSION**

- a) Semantic Analysis helped to better grasp the inner meaning and patterns beyond just keyword detection
- b) Multiple Models like Random Forest, Logistic Regression, Decision Tree was used for this activity
- c) Random Forest and Logistic regression could give accuracy around 96 percent. But the accuracy for Decision Tree was on lower side
- d) However Random Forest was chosen as the best model. Random Forest was preferred for its flexibility and slightly better consistency across all classes

#### e) Assessment Conclusion

- 1) The Approach achieved 96 percent accuracy in Detecting Fake news which is a good number
- 2) Random Forest helped minimized the risk of overfitting
- 3) F1-score ensured model is not biased towards one class
- 4) Implementation of this model helped in detecting Fake news early