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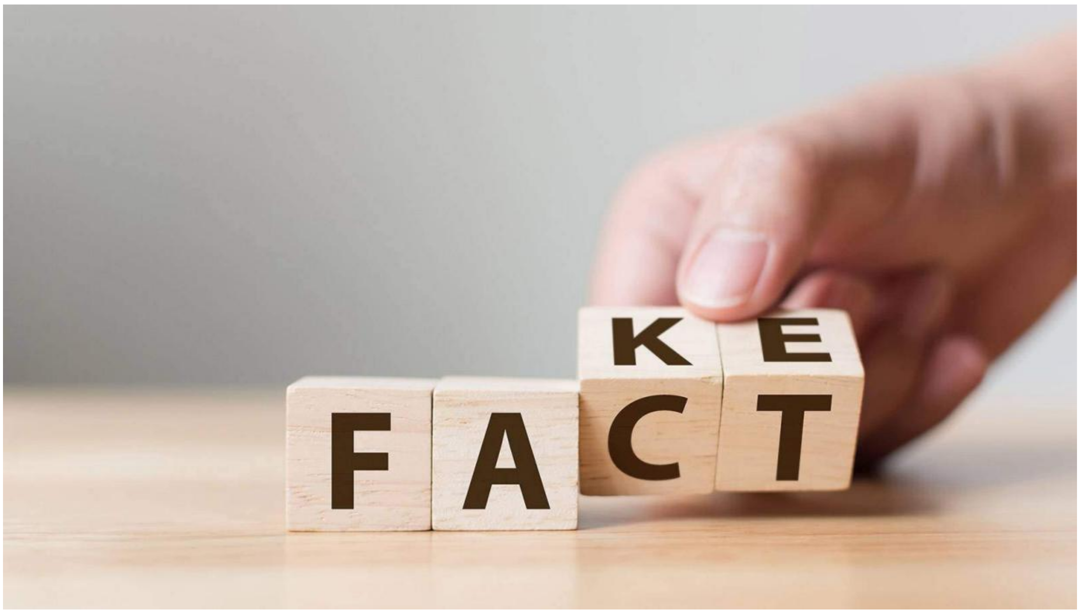
TEAM - 07

Fake News Detection Using NLP

Fake news detection using Natural Language Processing (NLP) is a crucial application of AI and NLP techniques to combat the spread of misinformation. In this example, I'll provide a simplified Python program that uses NLP and machine learning to classify news articles as either real or fake. Note that real-world applications of fake news detection are more complex and require large datasets and more sophisticated models.

Here's a step-by-step guide and a basic Python program:



Step 1: Import

```
import pandas as pd

import re

from nltk.corpus import stopwords

from nltk.tokenize import word_tokenize

from wordcloud import WordCloud

import matplotlib.pyplot as plt
```

```
from sklearn.model_selection import train_test_split
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, SimpleRNN, Dense
from sklearn.metrics import log_loss, roc_auc_score, confusion_matrix
import seaborn as sns
```

Step 2 : Import Dataset

```
true_data = pd.read_csv('/kaggle/input/fake-and-real-news-dataset/True.csv')
fake_data = pd.read_csv('/kaggle/input/fake-and-real-news-dataset/Fake.csv')
```

Step 3 : Adding Truth Value Labels

```
# Add labels and merge the data
fake_data['label'] = 'fake'
true_data['label'] = 'true'
merged_data = pd.concat([fake_data, true_data])
```

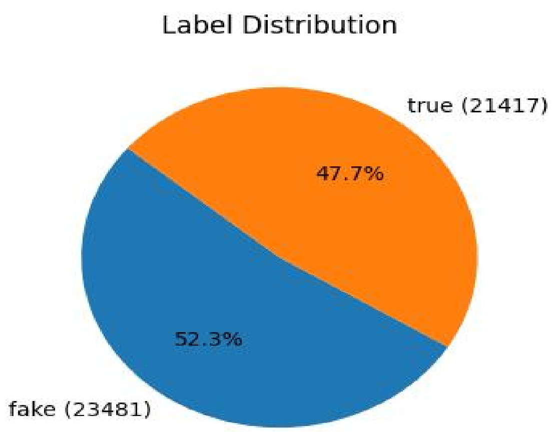
Step 4 : EDA

```
true_data.head()
fake_data.head()
merged_data =
merged_data.sample(frac=1).reset_index(drop=True)
merged_data.head()
merged_data.dtypes
# Calculate label distribution
label_distribution =
merged_data['label'].value_counts()

# Extracting labels and counts for pie chart
labels = [f"{label} ({count})" for label, count in
zip(label_distribution.index,
label_distribution.values)]

# Plotting the pie chart
```

```
plt.figure(figsize=(4, 4))
plt.pie(label_distribution, labels=labels,
autopct='%1.1f%%', startangle=140)
plt.title('Label Distribution')
plt.show()
```



Step 5 : **Preprocessing the Text**

```
def preprocess_text(text):
    # Convert text to lowercase
    text = text.lower()
```

```
    # Remove punctuations
    text = re.sub(r'[^\w\s]', '', text)
    # Tokenize the text
    words = word_tokenize(text)
    # Remove stopwords and words with length <= 2
    stop_words = set(stopwords.words('english'))
    words = [word for word in words if word not in stop_words and len(word) > 2]
    # Remove repeated words
    words = list(dict.fromkeys(words))
    # Join the words back into text
    text = ' '.join(words)
    return text
```

Distribution :

```
# Calculate label distribution
label_distribution = merged_data['label'].value_counts()
```

```
# Extracting labels and counts for pie chart
labels = [f"{label} ({count})" for label, count in zip(label_distribution.index, label_distribution.values)]

# Plotting the pie chart
plt.figure(figsize=(4, 4))
plt.pie(label_distribution, labels=labels, autopct='%1.1f%%', startangle=140)
plt.title('Label Distribution')
plt.show()
```

Step 6 :Checking Fake Political News and Fake News Buzzwords

```
fake_politics_data = ' '.join(merged_data[(merged_data['subject'] == 'politics') & (merged_data['label'] == 'fake')]['clean_text'])
total_fake_news = ' '.join(merged_data[merged_data['label'] == 'fake']['clean_text'])
```

```
fake_politics_data[0:500]
total_fake_news[0:500]
```

```
wordcloud = WordCloud(width=800,
height=400).generate(fake_politics_data)
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Fake Politics News')
plt.show()
```

```
wordcloud = WordCloud(width=800,
height=400).generate(total_fake_news)
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Fake News')
plt.show()
```

Step 7 : Splitting the Dataset

```
X = merged_data['clean_text']
y = merged_data['label']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

Step 8: Performing Tokenization

```
# Tokenize text

tokenizer = Tokenizer()

tokenizer.fit_on_texts(X_train)

X_train_tokens = tokenizer.texts_to_sequences(X_train)

X_test_tokens = tokenizer.texts_to_sequences(X_test)

# print(f"Total tokens: {len(tokenizer.word_index)}")

# Calculate total tokens

total_tokens = sum([len(tokens) for tokens in
X_train_tokens])

print("Total Tokens:", total_tokens)

maxlen = 20

X_train_pad = pad_sequences(X_train_tokens,
maxlen=maxlen, padding='post')

X_test_pad = pad_sequences(X_test_tokens,
maxlen=maxlen, padding='post')
```

Step 9 : RNN Model

```
# Build the RNN model
model = Sequential()
model.add(Embedding(input_dim=len(tokenizer.word_index) + 1, output_dim=4, input_length=maxlen))
model.add(SimpleRNN(units=128, return_sequences=True))
model.add(SimpleRNN(units=64, return_sequences=True))
model.add(SimpleRNN(units=32))
model.add(Dense(units=1, activation='sigmoid'))

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy', 'AUC'])
model.summary()
```