FAKE NEWS DETECTION USING NLP

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Phase-5 Documentation Submission

Project: Fake News Detection

Introduction:

- Fake news detection with NLP is like teaching a computer to spot lies. NLP helps the computer understand language and find strange things in news articles that might mean they're fake. It checks how words are used and the feeling of the text.

- Computers use what they learn to tell us if a news story is real or not. This is really important in today's world where wrong information spreads fast. NLP, along with smart machines, like GPT-3 and BERT, can help stop fake news by looking at the words and how they fit together.

- Using NLP to fight fake news helps make sure we get true information, making us smarter news readers.

Content:

- Phase 5 involves clearly outlining the problem statement, design thinking process, and the phases of development
- Describing the dataset used, data preprocessing steps, and feature extraction techniques.
- Explain the choice of classification algorithm and model training process

Problem Statement:

- The problem is to develop a fake news detection model using a Kaggle dataset.
- The goal is to distinguish between genuine and fake news articles based on their titles and text.
- This project involves using natural language processing (NLP) techniques to preprocess the text data, building a machine learning model for classification, and evaluating the model's performance

Design Thinking:

- Data Source: Choose the fake news dataset available on Kaggle, containing articles titles and text, along with their labels (genuine or fake).
- Data Preprocessing: Clean and preprocess the textual data to prepare it for analysis.
- Feature Extraction: Utilize techniques like TF-IDF (Term Frequency-Inverse Document Frequency) or word embeddings to convert text into numerical features.
- Model Selection: Select a suitable algorithm (e.g., Logistic Regression, Random Forest, or Neural Networks like BERT, LSTM, RNN) for the fake news detection task.
- Model Training: Train the selected model using the pre-processed data.
- Evaluation: Evaluate the model's performance using metrics like accuracy, precision, recall, F1-score, and ROC-AUC

Phases of Development:

Phase 3(Development Part 1):

- Begin building the fake news detection model by loading and preprocessing the dataset.
- Load the fake news dataset and preprocess the textual data

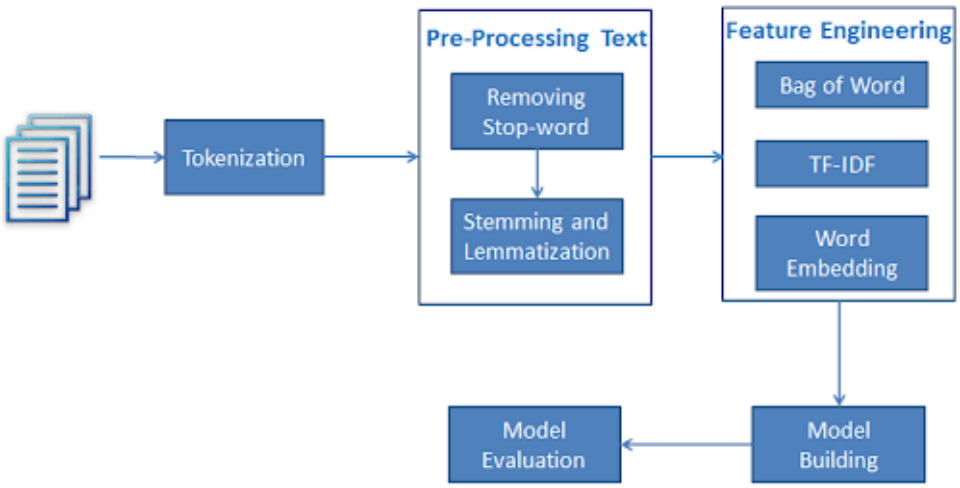
Phase 4(Development Part 2):

- In this part, continue building the project.
- Continue building the fake news detection model by applying NLP techniques and training a classification model.
    - Text Preprocessing and Feature Extraction
    - Model training and evaluation

Data Description:

- The dataset used in the project is obtained from Kaggle
- Dataset link: **https://www.kaggle.com/datasets/clmentbisaillon/fake-and-real-news-dataset**
- It contains news articles along with their labels indicating whether they are genuine or fake

Overview:



Preprocessing:

- In any machine learning task, getting the data ready (cleaning and organizing) is just as important, if not more so, than creating the actual model. This is especially critical when working with messy, unstructured text data.

Preprocessing Steps:

- Lower casing
- Tokenization
- Removal of Punctuations
- Removal of Stopwords
- HTML Tag Removal
- Stemming
- Removing Non-Alphanumeric Characters
- Vectorization
- Splitting the Dataset

Program:

#Import necessary Libraries:

```
import pandas as pd
import nltk
import re
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from sklearn.feature_extraction.text import TfidfVectorizer
```

Download NLTK resources

```
nltk.download('punkt')
nltk.download('stopwords')
```

Load the 'Fake.csv' and 'True.csv' datasets

```
fake_df = pd.read_csv('Fake.csv')
real_df = pd.read_csv('True.csv')
```

Text Processing

1. Lowercasing

```
fake_df['text'] = fake_df['text'].str.lower()
real_df['text'] = real_df['text'].str.lower()
```

2. Tokenization

```
fake_df['text'] = fake_df['text'].apply(nltk.word_tokenize)
real_df['text'] = real_df['text'].apply(nltk.word_tokenize)
```

3. Stop Word Removal

```
stop_words = set(stopwords.words('english'))
fake_df['text'] = fake_df['text'].apply(lambda tokens: [word for word in tokens if word not in stop_words])
real_df['text'] = real_df['text'].apply(lambda tokens: [word for word in tokens if word not in stop_words])
```

4. Punctuation Removal

```
fake_df['text'] = fake_df['text'].apply(lambda tokens: [re.sub(r'[^\w\s]', '', word) for word in tokens])
real_df['text'] = real_df['text'].apply(lambda tokens: [re.sub(r'[^\w\s]', '', word) for word in tokens])
```

5. HTML Tag Removal (if applicable)

```
fake_df['text'] = fake_df['text'].apply(lambda tokens: [re.sub(r'<[^>]+>', '', word) for word in tokens])
real_df['text'] = real_df['text'].apply(lambda tokens: [re.sub(r'<[^>]+>', '', word) for word in tokens])
```

6. Numbers Removal

```
fake_df['text'] = fake_df['text'].apply(lambda tokens: [re.sub(r'\d+', '', word) for word in tokens])
real_df['text'] = real_df['text'].apply(lambda tokens: [re.sub(r'\d+', '', word) for word in tokens])
```

7. Stemming or Lemmatization

```
stemmer = PorterStemmer()
fake_df['text'] = fake_df['text'].apply(lambda tokens: [stemmer.stem(word) for word in tokens])
real_df['text'] = real_df['text'].apply(lambda tokens: [stemmer.stem(word) for word in tokens])
```

8. Removing Non-Alphanumeric Characters

```
fake_df['text'] = fake_df['text'].apply(lambda tokens: [re.sub(r'[^a-zA-Z0-9]', '', word) for word in tokens])
real_df['text'] = real_df['text'].apply(lambda tokens: [re.sub(r'[^a-zA-Z0-9]', '', word) for word in tokens])
```

9. Feature Engineering (TF-IDF vectorization as an example)

```
tfidf_vectorizer = TfidfVectorizer()
fake_df['text'] = fake_df['text'].apply(lambda tokens: ' '.join(tokens))
real_df['text'] = real_df['text'].apply(lambda tokens: ' '.join(tokens))
fake_tfidf = tfidf_vectorizer.fit_transform(fake_df['text'])
real_tfidf = tfidf_vectorizer.fit_transform(real_df['text'])
```

Dataset After Preprocessing:

```
print(fake_df.head(2))
print(real_df.head(2))
```

```
                                               title  \
0   Donald Trump Sends Out Embarrassing New Year'...
1   Drunk Bragging Trump Staffer Started Russian ...

                                                text subject  \
0  donald trump wish american happi new year leav...    News
1  hous intellig committe chairman devin nune go ...    News

               date
0  December 31, 2017
1  December 31, 2017
                                               title  \
0  As U.S. budget fight looms, Republicans flip t...
1  U.S. military to accept transgender recruits o...

                                                text       subject  \
0  washington  reuter   head conserv republican f...  politicsNews
1  washington  reuter   transgend peopl allow fir...  politicsNews

                date
0  December 31, 2017
1  December 29, 2017
```

Combine the datasets:

```
combined_df = pd.concat([fake_df, real_df], ignore_index=True)
```

Create a new 'label' column and assign values:

```
combined_df['label'] = 1  # 1 represents real news
combined_df.loc[fake_df.index, 'label'] = 0  # 0 represents fake news
```

Split the dataset into train, validation, and test sets:

```
X = combined_df['text'].values
y = combined_df['label'].values

X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.2,
random_state=42)
X_valid, X_test, y_valid, y_test = train_test_split(X_temp, y_temp,
test_size=0.5, random_state=42)
max_sequencelength = 128  # Adjust as needed
tokenizer = Tokenizer()
tokenizer.fit_on_texts(combined_df['text'])
X = tokenizer.texts_to_sequences(combined_df['text'])
X = pad_sequences(X, maxlen=max_sequence_length, padding='post',
truncating='post')
y = combined_df['label'].values
```

Feature Extraction Technique:

Feature extraction is a data transformation technique used in machine learning and other fields to convert raw data into a more manageable and informative representation, referred to as "features.

Initialize the tokenizer

```
bert_name = "bert-base-uncased"
tokenizer = AutoTokenizer.from_pretrained(
    bert_name,
    padding="max_length",
    do_lower_case=True,
    add_special_tokens=True,
)
```

Encode the data

```
X_train_encoded = tokenizer(
    X_train.tolist(),
    padding=True,
```

```
    truncation=True,
    return_tensors="tf",
    max_length=128,  # Adjust the max sequence length as needed
    return_token_type_ids=False,
    return_attention_mask=True,
).input_ids

X_valid_encoded = tokenizer(
    X_valid.tolist(),
    padding=True,
    truncation=True,
    return_tensors="tf",
    max_length=128,
    return_token_type_ids=False,
    return_attention_mask=True,
).input_ids

X_test_encoded = tokenizer(
    X_test.tolist(),
    padding=True,
    truncation=True,
    return_tensors="tf",
    max_length=128,
    return_token_type_ids=False,
    return_attention_mask=True,
).input_ids
```

Create TensorFlow Datasets :

```
train_ds = tf.data.Dataset.from_tensor_slices((X_train_encoded,
y_train)).shuffle(len(X_train)).batch(100).prefetch(tf.data.AUTOTUNE)
valid_ds = tf.data.Dataset.from_tensor_slices((X_valid_encoded,
y_valid)).shuffle(len(X_valid)).batch(100).prefetch(tf.data.AUTOTUNE)
test_ds = tf.data.Dataset.from_tensor_slices((X_test_encoded,
y_test)).shuffle(len(X_test)).batch(100).prefetch(tf.data.AUTOTUNE)
```

BERT:

BERT, or **Bidirectional Encoder Representations from Transformers**, is a **cutting-edge natural language processing (NLP) model** developed by **Google**. What sets **BERT** apart is its ability to **understand the context of words** in a sentence by considering both the words that come **before and after** them, allowing it to **grasp nuances**, **context**, and **meaning in language more effectively. BERT** has achieved **remarkable success** in various **NLP tasks**, including **text classification**, **sentiment analysis**, and **machine translation**, and it has become a **cornerstone** in the field of **AI** for **understanding and generating human language**.

Initialize the BERT model for binary classification:

```
bert_model = TFAutoModelForSequenceClassification.from_pretrained(bert_name, num_labels=1)  # Binary classification

# Compile the model
bert_model.compile(
    optimizer=Adam(learning_rate=1e-5),
    loss='binary_crossentropy',  # Use binary cross-entropy
    metrics=[
        tf.keras.metrics.BinaryAccuracy(name="Accuracy"),
        tf.keras.metrics.Precision(name="Precision"),
        tf.keras.metrics.Recall(name="Recall"),
    ]
)
```

Model Training:

```
num_epochs = 5  # Adjust as needed
MODEL_CALLBACKS = []  # Add any callbacks you need
batch_per_epoch=100

model_history = bert_model.fit(
    train_ds,
    validation_data=valid_ds,
    epochs=num_epochs,
    steps_per_epoch=batch_per_epoch,
    batch_size=16,
    callbacks=MODEL_CALLBACKS
)
```

```
Epoch 1/5
100/100 [==============================] - 1882s 19s/step - loss: 0.5402 - Accuracy: 0.7468 - Precision: 0.7809 - Recall: 0.6658 - val_loss: 0.3871 - val
_Accuracy: 0.8094 - val_Precision: 1.0000 - val_Recall: 0.6004
Epoch 2/5
100/100 [==============================] - 1770s 18s/step - loss: 0.1387 - Accuracy: 0.9548 - Precision: 0.9866 - Recall: 0.9183 - val_loss: 0.0302 - val
_Accuracy: 0.9947 - val_Precision: 0.9894 - val_Recall: 0.9995
Epoch 3/5
100/100 [==============================] - 1767s 18s/step - loss: 0.0326 - Accuracy: 0.9964 - Precision: 0.9983 - Recall: 0.9941 - val_loss: 0.0314 - val
_Accuracy: 0.9958 - val_Precision: 0.9912 - val_Recall: 1.0000
Epoch 4/5
100/100 [==============================] - 1765s 18s/step - loss: 0.0178 - Accuracy: 0.9972 - Precision: 0.9966 - Recall: 0.9974 - val_loss: 0.0200 - val
_Accuracy: 0.9978 - val_Precision: 0.9954 - val_Recall: 1.0000
Epoch 5/5
100/100 [==============================] - 1818s 18s/step - loss: 0.0228 - Accuracy: 0.9976 - Precision: 0.9976 - Recall: 0.9976 - val_loss: 0.0144 - val
_Accuracy: 0.9982 - val_Precision: 0.9967 - val_Recall: 0.9995
```

Evaluate on the test set:

```
test_loss, test_acc, test_precision, test_recall = bert_model.evaluate(test_ds, verbose=0)

print(f"Test Loss      : {test_loss}")
print(f"Test Accuracy  : {test_acc}")
print(f"Test Precision : {test_precision}")
print(f"Test Recall    : {test_recall}")
```

```
Test Loss      : 0.024917991831898 69
Test Accuracy  : 0.9968819618225098
Test Precision : 0.9947941303253174
Test Recall    : 0.9985747933387756
```

Model training process:

- The model is compiled with settings:
  - Optimizer: Adam with a learning rate of 1e-5 (0.00001).
  - Loss function: Binary cross-entropy, suitable for binary classification.
  - Metrics: Binary accuracy, precision, and recall are monitored during training
- The training loop runs for a specified number of epochs (controlled by the num_epochs variable, which is set to 5).
- Training data is fed to the model in batches.
- The model updates its weights and biases based on the loss calculated for each batch.
- The training process also uses callbacks for various purposes
- After training, the model is evaluated on a separate test dataset (test_ds).
- Metrics such as test loss, test accuracy, test precision, and test recall are calculated and displayed.

The Model's training history:

```
model_history = pd.DataFrame(model_history.history)
print(model_history)
```

```
       loss  Accuracy  Precision    Recall  val_loss  val_Accuracy  \
0  0.540212    0.7468   0.780888  0.665844  0.387105      0.809354
1  0.138698    0.9548   0.986559  0.918265  0.030188      0.994655
2  0.032578    0.9964   0.998312  0.994118  0.031439      0.995768
3  0.017791    0.9972   0.996567  0.997423  0.019986      0.997773
4  0.022822    0.9976   0.997565  0.997565  0.014443      0.998218

   val_Precision  val_Recall
0       1.000000    0.600374
1       0.989372    0.999533
2       0.991208    1.000000
3       0.995353    1.000000
4       0.996741    0.999533
```

Extract training history data

```
train_loss = model_history['loss']
val_loss = model_history['val_loss']
train_accuracy = model_history['Accuracy']
val_accuracy = model_history['val_Accuracy']
train_precision = model_history['Precision']
val_precision = model_history['val_Precision']
train_recall = model_history['Recall']
val_recall = model_history['val_Recall']
```

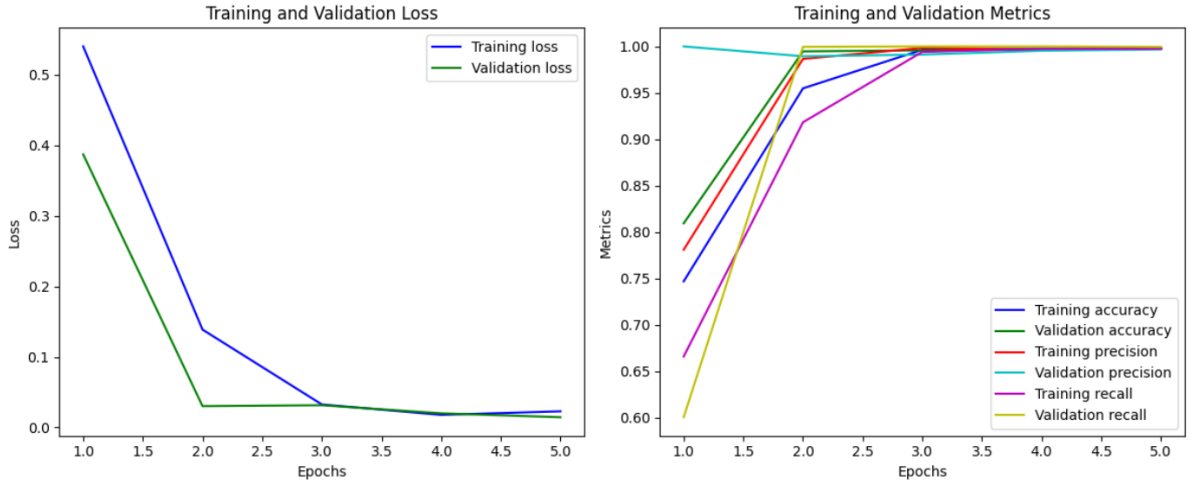
Plot training history

```
epochs = range(1, len(train_loss) + 1)

# Loss plot
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(epochs, train_loss, 'b', label='Training loss')
plt.plot(epochs, val_loss, 'g', label='Validation loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
```

Metrics plots

```
plt.subplot(1, 2, 2)
plt.plot(epochs, train_accuracy, 'b', label='Training accuracy')
plt.plot(epochs, val_accuracy, 'g', label='Validation accuracy')
plt.plot(epochs, train_precision, 'r', label='Training precision')
plt.plot(epochs, val_precision, 'c', label='Validation precision')
plt.plot(epochs, train_recall, 'm', label='Training recall')
```

```
plt.plot(epochs, val_recall, 'y', label='Validation recall')
plt.title('Training and Validation Metrics')
plt.xlabel('Epochs')
plt.ylabel('Metrics')
plt.legend()

plt.tight_layout()
plt.show()
```



Conclusion:

- The documentation covers the key steps involved in building a fake news detection model using NLP and BERT for classification. The document also mentions further evaluation using a classification report.

- BERT's understanding of contextual language and its fine-tuning capability make it a suitable candidate for fake news detection. The model has been optimized with specific settings for the task

- The project demonstrates a well-structured approach to model training, including batch processing and callbacks. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess the model's performance on a test dataset

- As fake news detection involves potentially sensitive information and content, it's crucial to address ethical concerns, including data privacy, bias, and responsible use of the technology