Google Colab Lab Assignment -NLP

Course Name: Deep Learning (PEC)

Lab Title: NLP Techniques for Text Classification

Student Name: Nabil Ansari

Student ID: 202302040004

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Group Members: 1) Arya Sadalage
2) Gourav Sable
3) Nabil Ansari

Dataset Link : https://www.kaggle.com/datasets/lakshmi25npathi/imdb-dataset-of-50k-movie-reviews

Github Link : https://github.com/nabil-repo/DL/tree/main/Assignment-4

Objective The objective of this assignment is to implement NLP preprocessing techniques and build a text classification model using machine learning techniques.

Learning Outcomes:

1. Understand and apply NLP preprocessing techniques such as tokenization, stopword removal, stemming, and lemmatization.
2. Implement text vectorization techniques such as TF-IDF and CountVectorizer.
3. Develop a text classification model using a machine learning algorithm.
4. Evaluate the performance of the model using suitable metrics.

Assignment Instructions:

Part 1: NLP Preprocessing

Dataset Selection:

Choose any text dataset from **Best Datasets for Text** https://en.innovatiana.com/post/best-datasets-for-text-classification Classification, such as SMS Spam Collection, IMDb Reviews, or any other relevant dataset.

Download the dataset and upload it to Google Colab.

Load the dataset into a Pandas DataFrame and explore its structure (e.g., check missing values, data types, and label distribution).

Text Preprocessing:

Convert text to lowercase.

Perform tokenization using NLTK or spaCy.

Remove stopwords using NLTK or spaCy.

Apply stemming using PorterStemmer or SnowballStemmer.

Apply lemmatization using WordNetLemmatizer.

Vectorization Techniques:

Convert text data into numerical format using TF-IDF and CountVectorizer.

```
#Code for Part 1
# Import required libraries
import pandas as pd
import numpy as np
import re
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from tqdm import tqdm

# Download NLTK resources
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('omw-1.4')

# Load IMDB dataset
try:
    df = pd.read_csv('IMDB Dataset.csv')
    print("Dataset loaded successfully!")
    print(f"Shape: {df.shape}")
    print("\nLabel distribution:")
    print(df['sentiment'].value_counts())
except FileNotFoundError:
    print("Error: IMDB Dataset.csv not found. Please upload the file to Colab.")
    raise

# Clean HTML tags and special characters
def clean_text(text):
    text = re.sub(r'<[^>]+>', '', text)  # Remove HTML tags
    text = re.sub(r'[^\w\s]', '', text)  # Remove punctuation
```

```
    text = re.sub(r'\d+', '', text)      # Remove numbers
    text = re.sub(r'\s+', ' ', text).strip()  # Remove extra whitespace
    return text.lower()

# Initialize lemmatizer
lemmatizer = WordNetLemmatizer()

# Get English stopwords
stop_words = set(stopwords.words('english'))

# Enhanced preprocessing function
def preprocess_text(text):
    try:
        # Clean text
        text = clean_text(text)

        # Tokenization
        tokens = text.split()

        # Remove stopwords and short words
        tokens = [word for word in tokens if word not in stop_words and len(word) > 2]

        # Lemmatization
        tokens = [lemmatizer.lemmatize(word) for word in tokens]

        return ' '.join(tokens)
    except Exception as e:
        print(f"Error processing text: {str(e)[:100]}...")
        return ""

# Apply preprocessing with progress bar
print("\nPreprocessing reviews...")
tqdm.pandas()
df['processed_review'] = df['review'].progress_apply(preprocess_text)

# Remove empty processed reviews
initial_count = len(df)
df = df[df['processed_review'].str.strip() != '']
print(f"\nRemoved {initial_count - len(df)} empty reviews after preprocessing")

# Vectorization
print("\nApplying vectorization techniques...")

# TF-IDF Vectorizer
tfidf_vectorizer = TfidfVectorizer(
    max_features=5000,
    stop_words=list(stop_words),
    ngram_range=(1, 2)  # Include unigrams and bigrams
)
X_tfidf = tfidf_vectorizer.fit_transform(df['processed_review'])

```

```
# Count Vectorizer
count_vectorizer = CountVectorizer(
    max_features=5000,
    stop_words=list(stop_words),
    ngram_range=(1, 2)
)
X_count = count_vectorizer.fit_transform(df['processed_review'])

# Prepare labels (1 for positive, 0 for negative)
y = df['sentiment'].map({'positive': 1, 'negative': 0})

print("\nPreprocessing completed!")
print("TF-IDF shape:", X_tfidf.shape)
print("CountVectorizer shape:", X_count.shape)
print("\nSample processed review:")
print(df['processed_review'].iloc[0][:200], "...")
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package omw-1.4 to /root/nltk_data...
[nltk_data]   Package omw-1.4 is already up-to-date!
Dataset loaded successfully!
Shape: (50000, 2)

Label distribution:
sentiment
positive    25000
negative    25000
Name: count, dtype: int64

Preprocessing reviews...
100%|██████████| 50000/50000 [00:29<00:00, 1692.44it/s]

Removed 0 empty reviews after preprocessing

Applying vectorization techniques...

Preprocessing completed!
TF-IDF shape: (50000, 5000)
CountVectorizer shape: (50000, 5000)

Sample processed review:
one reviewer mentioned watching episode youll hooked right exactly happened methe first
```

Splitting the Data:

Divide the dataset into training and testing sets (e.g., 80% training, 20% testing).

Building the Classification Model:

Train a text classification model using Logistic Regression, Naïve Bayes, or any other suitable algorithm.

Implement the model using scikit-learn.

Model Evaluation:

Evaluate the model using accuracy, precision, recall, and F1-score.

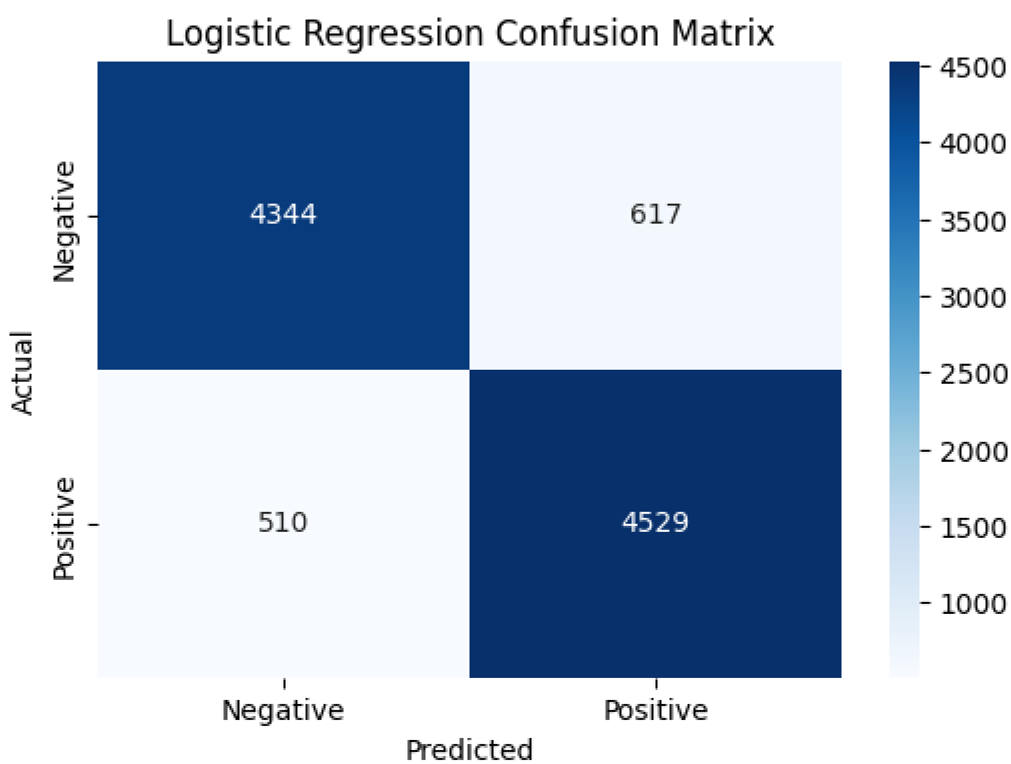
Use a confusion matrix to visualize the results.

```
#code for Part 2

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import (accuracy_score, precision_score,
                           recall_score, f1_score, confusion_matrix,
                           classification_report)
import matplotlib.pyplot as plt
import seaborn as sns

# Split data (using TF-IDF features)
X_train, X_test, y_train, y_test = train_test_split(
    X_tfidf, y, test_size=0.2, random_state=42)

print(f"Training set: {X_train.shape[0]} samples")
print(f"Test set: {X_test.shape[0]} samples")

# Function to evaluate and visualize model performance
def evaluate_model(model, X_test, y_test, model_name):
    y_pred = model.predict(X_test)

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)

    print(f"\n{model_name} Performance:")
    print(classification_report(y_test, y_pred))
    print(f"Accuracy: {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall: {recall:.4f}")
    print(f"F1 Score: {f1:.4f}")

    # Confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=['Negative', 'Positive'],
```

```
                ytticklabels=['Negative', 'Positive'])
    plt.title(f'{model_name} Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

    return {'accuracy': accuracy, 'precision': precision, 'recall': recall, 'f1': f1}

# Logistic Regression Model
print("\nTraining Logistic Regression model...")
lr_model = LogisticRegression(
    max_iter=1000,
    random_state=42,
    class_weight='balanced'  # Handle class imbalance
)
lr_model.fit(X_train, y_train)
lr_metrics = evaluate_model(lr_model, X_test, y_test, "Logistic Regression")

# Naive Bayes Model
print("\nTraining Naive Bayes model...")
nb_model = MultinomialNB()
nb_model.fit(X_train, y_train)
nb_metrics = evaluate_model(nb_model, X_test, y_test, "Naive Bayes")

# Compare with CountVectorizer features
X_train_count, X_test_count, y_train_count, y_test_count = train_test_split(
    X_count, y, test_size=0.2, random_state=42)

print("\nTraining Logistic Regression with CountVectorizer features...")
lr_count_model = LogisticRegression(
    max_iter=1000,
    random_state=42,
    class_weight='balanced'
)
lr_count_model.fit(X_train_count, y_train_count)
lr_count_metrics = evaluate_model(lr_count_model, X_test_count, y_test_count,
                                "Logistic Regression (CountVectorizer)")

# Create comparison table
results = pd.DataFrame({
    'Model': ['Logistic Regression (TF-IDF)', 'Naive Bayes (TF-IDF)',
              'Logistic Regression (CountVectorizer)'],
    'Accuracy': [lr_metrics['accuracy'], nb_metrics['accuracy'], lr_count_metrics['accur
    'Precision': [lr_metrics['precision'], nb_metrics['precision'], lr_count_metrics['pr
    'Recall': [lr_metrics['recall'], nb_metrics['recall'], lr_count_metrics['recall']],
    'F1 Score': [lr_metrics['f1'], nb_metrics['f1'], lr_count_metrics['f1']]
})

print("\nModel Performance Comparison:")
print(results.to_markdown(index=False))

```

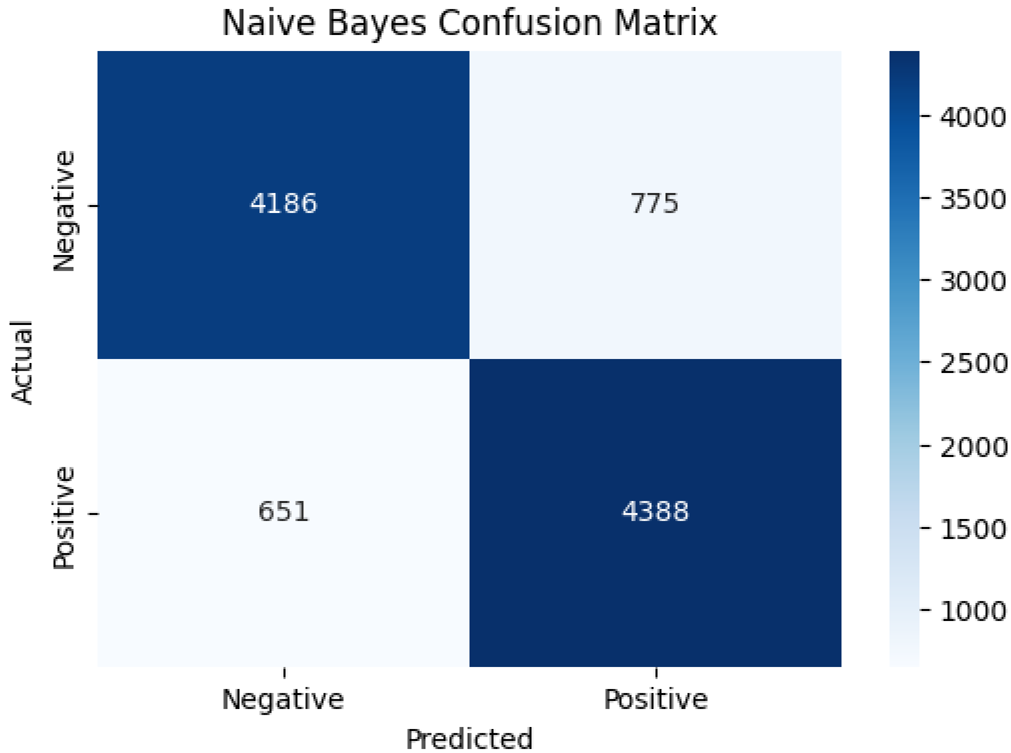
```
# Visualize model comparison
plt.figure(figsize=(10, 6))
results.set_index('Model').plot(kind='bar', rot=45)
plt.title('Model Performance Comparison')
plt.ylabel('Score')
plt.ylim(0.7, 1.0)
plt.tight_layout()
plt.show()
```

```
Test set: 10000 samples

Training Logistic Regression model...

Logistic Regression Performance:
              precision    recall  f1-score   support

           0       0.89      0.88      0.89      4961
           1       0.88      0.90      0.89      5039

    accuracy                           0.89     10000
   macro avg       0.89      0.89      0.89     10000
weighted avg       0.89      0.89      0.89     10000

Accuracy: 0.8873
Precision: 0.8801
Recall: 0.8988
F1 Score: 0.8893
```




```
Training Naive Bayes model...

Naive Bayes Performance:
              precision    recall  f1-score   support

           0       0.87      0.84      0.85      4961
           1       0.85      0.87      0.86      5039

    accuracy                           0.86     10000
   macro avg       0.86      0.86      0.86     10000
weighted avg       0.86      0.86      0.86     10000

Accuracy: 0.8574
Precision: 0.8409
```

```
Precision: 0.8499
Recall: 0.8708
F1 Score: 0.8602
```




```
Training Logistic Regression with CountVectorizer features...

Logistic Regression (CountVectorizer) Performance:
              precision    recall  f1-score   support

           0       0.88      0.87      0.87      4961
           1       0.87      0.88      0.88      5039

    accuracy                           0.87     10000
   macro avg       0.87      0.87      0.87     10000
weighted avg       0.87      0.87      0.87     10000

Accuracy: 0.8747
Precision: 0.8726
Recall: 0.8797
F1 Score: 0.8762
```