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import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model selection import train test split
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
import tensorflow as tf
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, LSTM, Dense, Dropout, Bidirectional
from tensorflow.keras.callbacks import EarlyStopping
import re
import string
import nltk
from nltk.corpus import stopwords
# Set random seeds for reproducibility
np.random.seed(42)
tf.random.set_seed(42)
# Download necessary NLTK data
try:
    nltk.data.find('corpora/stopwords')
except LookupError:
   \verb|print("Downloading NLTK stopwords...")|\\
    nltk.download('stopwords')
# a) Select and load a suitable dataset
print("Loading dataset...")
# Load the IMDB Movie Reviews dataset from Keras
from tensorflow.keras.datasets import imdb
# Load the data with the top 10,000 words
max words = 10000
(X_train_raw, y_train), (X_test_raw, y_test) = imdb.load_data(num_words=max_words)
# Get the word index mapping
word_index = imdb.get_word_index()
# Reverse the word index to get words
reverse_word_index = {value: key for key, value in word_index.items()}
# Function to convert sequences back to text
def seq to text(sequence):
    \# Index offset is 3 because 0 = padding, 1 = start, 2 = unknown
    return ' '.join([reverse_word_index.get(i-3, '?') for i in sequence if i > 3])
# Convert some examples back to text for inspection
train_reviews = [seq_to_text(sequence) for sequence in X_train_raw[:5]]
print("\nSample reviews from the dataset:")
for i, review in enumerate(train_reviews):
   print(f"Review {i+1} (Sentiment: {'Positive' if y_train[i] == 1 else 'Negative'}):")
    print(review[:200] + "...") # Print just the beginning of the review
# Display dataset information
print(f"\nTraining dataset size: {len(X_train_raw)} reviews")
print(f"Testing \ dataset \ size: \ \{len(X\_test\_raw)\} \ reviews")
# Display class distribution
train_sentiment_counts = np.bincount(y_train)
test_sentiment_counts = np.bincount(y_test)
print("\nClass distribution in training data:")
print(f"Negative: {train_sentiment_counts[0]} ({train_sentiment_counts[0]/len(y_train)*100:.1f}%)")
print(f"Positive: {train_sentiment_counts[1]} ({train_sentiment_counts[1]/len(y_train)*100:.1f}%)")
# Visualize class distribution
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
sns.countplot(x=y_train)
plt.title('Sentiment Distribution (Training Data)')
plt.xlabel('Sentiment (0: Negative, 1: Positive)')
plt.xticks([0, 1], ['Negative', 'Positive'])
plt.subplot(1, 2, 2)
sns.countplot(x=y_test)
plt.title('Sentiment Distribution (Test Data)')
plt.xlabel('Sentiment (0: Negative, 1: Positive)')
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plt.tight_layout()
    plt.savefig('sentiment_distribution.png')
    plt.close()
    # Data preprocessing
    print("\nPreprocessing data...")
    # Define the max sequence length
    max_len = 200  # Maximum sequence length
    # Pad the sequences
    X_train = pad_sequences(X_train_raw, maxlen=max_len, padding='post', truncating='post')
    \textbf{X\_test = pad\_sequences}(\textbf{X\_test\_raw, maxlen=max\_len, padding='post', truncating='post'})
    print(f"Training data shape after padding: {X train.shape}")
    print(f"Testing data shape after padding: {X_test.shape}")
    # b) Apply RNN variant (LSTM) for prediction
    print("\nBuilding LSTM model...")
    # Define the model
    def create_lstm_model(vocab_size, embedding_dim=128, lstm_units=64):
        model = Sequential([
            # Embedding layer
            Embedding(input_dim=vocab_size, output_dim=embedding_dim, input_length=max_len),
            # Bidirectional LSTM layer
            Bidirectional(LSTM(lstm_units, return_sequences=True)),
            Dropout(0.3),
            # Second LSTM layer
            Bidirectional(LSTM(lstm_units)),
            Dropout(0.3),
            # Output layer
            Dense(1, activation='sigmoid')
        ])
        # Compile the model
        model.compile(
            loss='binary_crossentropy',
            optimizer='adam',
            metrics=['accuracy']
        )
        return model
    # Create and display the model
    vocab_size = max_words + 1 # +1 for the padding token
    model = create_lstm_model(vocab_size)
    model.summary()
    # Train the model
    early stopping = EarlyStopping(
        monitor='val_loss',
        patience=3,
        restore\_best\_weights=True
    print("\nTraining the model...")
    history = model.fit(
       X_train, y_train,
        epochs=10,
        batch size=64,
        validation_split=0.2,
        callbacks=[early_stopping],
        verbose=1
    # Plot training history
    plt.figure(figsize=(12, 5))
    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label='Training Accuracy')
    plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
    plt.title('Model Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()
    plt.subplot(1, 2, 2)
https://colab.research.google.com/drive/1M1nkGfHcrQW9bMko64VR3ytrrAQhPetG#printMode=true
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plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.savefig('training_history.png')
plt.close()
# Evaluate the model
print("\nEvaluating the model...")
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Loss: {loss:.4f}")
print(f"Test Accuracy: {accuracy:.4f}")
# Make predictions
y_pred_proba = model.predict(X_test)
y_pred = (y_pred_proba > 0.5).astype(int)
# Generate confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Negative', 'Positive'],
            yticklabels=['Negative', 'Positive'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.savefig('confusion_matrix.png')
plt.close()
# Display classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred, target_names=['Negative', 'Positive']))
# Function to predict sentiment on new texts
def predict_sentiment_raw(text, model, max_len=200):
    # Get the word index
    word_index = imdb.get_word_index()
    # Preprocess the text
    text = text.lower()
    # Tokenize
    words = text.split()
    # Convert to sequence
    sequence = []
    for word in words:
        # Add 3 because 0 = padding, 1 = start, 2 = unknown
        idx = word_index.get(word, 0) + 3
        if idx < max_words + 3: # Only include words in our vocabulary</pre>
            sequence.append(idx)
    # Pad the sequence
    padded = pad_sequences([sequence], maxlen=max_len, padding='post', truncating='post')
    # Make prediction
    prediction = model.predict(padded)[0][0]
    return {
        'review': text,
        'sentiment_score': float(prediction),
        'sentiment': 'Positive' if prediction > 0.5 else 'Negative'
# Test the model with a few sample reviews
    "This movie was fantastic! The acting was superb and the plot kept me engaged throughout.",
    "Terrible film. Waste of time and money. The plot made no sense and the acting was wooden.",
    "It was an okay movie. Not great, not terrible, just average entertainment.",
    "I was pleasantly surprised by this film. The reviews weren't great but I really enjoyed it!"
print("\nPredictions on sample reviews:")
for review in sample_reviews:
    result = predict_sentiment_raw(review, model)
    print(f"Review: '{review[:50]}...'")
    print(f"Sentiment: {result['sentiment']} (Score: {result['sentiment_score']:.4f})")
    print()
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# Visualize some examples where predictions match and differ from actual labels
correct_predictions = np.where(y_pred == y_test)[0]
incorrect_predictions = np.where(y_pred != y_test)[0]
if len(correct_predictions) > 0 and len(incorrect_predictions) > 0:
    print("\nAnalyzing correct and incorrect predictions:")
    # Sample reviews with correct predictions
    sampled_correct = np.random.choice(correct_predictions, min(3, len(correct_predictions)), replace=False)
    print("\nExamples of CORRECT predictions:")
    for idx in sampled_correct:
        review_text = seq_to_text(X_test_raw[idx])
        sentiment = "Positive" if y test[idx] == 1 else "Negative"
        print(f"Review: '{review_text[:100]}...'")
        print(f"True sentiment: {sentiment}")
        print(f"Predicted sentiment: {sentiment} (Score: {y_pred_proba[idx][0]:.4f})")
        print()
    # Sample reviews with incorrect predictions
    sampled_incorrect = np.random.choice(incorrect_predictions, min(3, len(incorrect_predictions)), replace=False)
    print("\nExamples of INCORRECT predictions:")
    for idx in sampled_incorrect:
        review_text = seq_to_text(X_test_raw[idx])
        true_sentiment = "Positive" if y_test[idx] == 1 else "Negative"
pred_sentiment = "Positive" if y_pred[idx] == 1 else "Negative"
        print(f"Review: '{review_text[:100]}...'")
        print(f"True sentiment: {true_sentiment}")
        print(f"Predicted sentiment: {pred_sentiment} (Score: {y_pred_proba[idx][0]:.4f})")
        print()
print("Analysis completed.")
```

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→ Downloading NLTK stopwords...
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Loading dataset...

Downloading data from <a href="https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz">https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz</a>

8036352/17464789 0s Ous/step[nltk data] Downloading package stopwords to /root/nltk data...

[nltk\_data] Unzipping corpora/stopwords.zip.

17464789/17464789 -**- 0s** 0us/step

Downloading data from <a href="https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb">https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb</a> word index.ison

1641221/1641221 -0s Ous/step

Sample reviews from the dataset:

Review 1 (Sentiment: Positive):

this film was just brilliant casting location scenery story direction everyone's really suited the part they played and you cou. Review 2 (Sentiment: Negative):

big hair big boobs bad music and a giant safety pin these are the words to best describe this terrible movie i love cheesy horn Review 3 (Sentiment: Negative):

this has to be one of the worst films of the 1990s when my friends i were watching this film being the target audience it was a Review 4 (Sentiment: Positive):

the at storytelling the traditional sort many years after the event i can still see in my eye an elderly lady my friend's mother Review 5 (Sentiment: Negative):

worst mistake of my life br br i picked this movie up at target for 5 because i figured hey it's sandler i can get some cheap  $l\epsilon$ 

Training dataset size: 25000 reviews Testing dataset size: 25000 reviews

Class distribution in training data:

Negative: 12500 (50.0%) Positive: 12500 (50.0%)

Preprocessing data...

Training data shape after padding: (25000, 200) Testing data shape after padding: (25000, 200)

Building LSTM model...

/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/embedding.py:90: UserWarning: Argument `input\_length` is deprecate warnings.warn(

Model: "sequential"

Layer (type)	Output Shape	Param #
embedding (Embedding)	?	0 (unbuilt)
bidirectional (Bidirectional)	?	0 (unbuilt)
dropout (Dropout)	?	0
bidirectional_1 (Bidirectional)	?	0 (unbuilt)
dropout_1 (Dropout)	?	0
dense (Dense)	?	0 (unbuilt)

Total params: 0 (0.00 B) Trainable params: 0 (0.00 B) Non-trainable params: 0 (0.00 B)

Training the model...

Epoch 1/10	
313/313	— <b>204s</b> 628ms/step - accuracy: 0.6815 - loss: 0.5695 - val_accuracy: 0.8188 - val_loss: 0.4001
Epoch 2/10	100a (00ma/shan   200maya 0 0774   lace 0 2004   val   200maya 0 0612   val   lace 0 2701
313/313 — Epoch 3/10	— <b>190s</b> 608ms/step - accuracy: 0.8774 - loss: 0.3004 - val_accuracy: 0.8612 - val_loss: 0.3791
313/313	— <b>203s</b> 613ms/step - accuracy: 0.9014 - loss: 0.2612 - val_accuracy: 0.8490 - val_loss: 0.4233
Epoch 4/10 313/313 —	— 2146 (Films/stan   2001)201   2002   2003   1000   2013   1013   1013   2013
Epoch 5/10	— <b>214s</b> 651ms/step - accuracy: 0.9237 - loss: 0.2012 - val_accuracy: 0.7992 - val_loss: 0.4924
313/313	— <b>251s</b> 617ms/step - accuracy: 0.9388 - loss: 0.1678 - val_accuracy: 0.7970 - val_loss: 0.5030
Evaluating the model	

782/782 -- 57s 73ms/step - accuracy: 0.8429 - loss: 0.4200

Test Loss: 0.4190 Test Accuracy: 0.8426

782/782 - **57s** 72ms/step

Classification Report:

recall f1-score support