RNN Model For Text and Sequence Data Analysis

Load the IMDB Data Manually from Directory

```
import zipfile
import os

# Specify the path to the zip file and the output directory
zip_file_path = "E:/IMDB text and seq/archive.zip"  # Replace this with the actual path to your zip file
output_directory = "E:/IMDB text and seq"  # Replace this with the desired output path

# Create the output directory if it doesn't exist
os.makedirs(output_directory, exist_ok=True)

# Unzip the file
with zipfile.ZipFile(zip_file_path, 'r') as zip_ref:
    zip_ref.extractall(output_directory)

print("File unzipped successfully!")
```

```
File unzipped successfully!
```

Listing all the files from the unzip folder

```
import os

# Specify the path to the folder
folder_path = 'aclimdb'  # Replace this with the actual path to your folder

# List all files in the directory
files = os.listdir(folder_path)

# Print the list of files
for file in files:
    print(file)
```

```
imdb.vocab
imdbEr.txt
README
test
train
```

Task 1

1. Cutoff reviews after 150 words.
2. Restrict training samples to 100.
3. Validate on 10,000 samples.
4. Consider only the top 10,000 words.

```
import os
import numpy as np

# Load reviews (you need to read them from 'train' and 'test' directories)
def load_reviews(directory, max_reviews=100, max_words=150, top_words=10000):
    all_reviews = []

    # Walk through the directory and read files
    for subdir, _, files in os.walk(directory):
        for file_name in files:
            if len(all_reviews) >= max_reviews:
                break
            file_path = os.path.join(subdir, file_name)
            with open(file_path, 'r', encoding='utf-8') as file:
                review = file.read()
                words = review.split()[:max_words]  # Limit to 150 words
                all_reviews.append(' '.join(words))

    return all_reviews
```

```
# Limit training samples to 100
train_reviews = load_reviews('aclimdb/train', max_reviews=100, max_words=150)

# Limit validation samples to 10,000
val_reviews = load_reviews('aclimdb/test', max_reviews=10000, max_words=150)

print("Sample of a processed training review:", train_reviews[0])
```

```
Sample of a processed training review: 9 0:9 1:1 2:4 3:4 4:6 5:4 6:2 7:2 8:4 10:4 12:2 26:1 27:1 28:1 29:2 32:1 41:1 45:1 47:1 50:1
```

```
test_reviews = load_reviews('aclimdb/test', max_reviews=10000, max_words=150)
print("Sample of a processed test review:", test_reviews[0])
```

```
Sample of a processed test review: 10 0:7 1:4 2:2 3:5 4:5 5:1 6:3 7:1 8:6 9:3 10:4 11:6 12:1 14:2 15:4 16:1 19:2 20:2 21:1 26:1 30:2
```

```
import os
import numpy as np
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from sklearn.model_selection import train_test_split

# Load reviews function (use your earlier code to load training and test sets)
def load_reviews(directory, max_reviews=None):
    reviews = []
    labels = []

    for label in ['pos', 'neg']:  # Assuming 'pos' and 'neg' subdirectories
        label_dir = os.path.join(directory, label)
        for file_name in os.listdir(label_dir):
            if max_reviews and len(reviews) >= max_reviews:
                break
            file_path = os.path.join(label_dir, file_name)
            with open(file_path, 'r', encoding='utf-8') as file:
                review = file.read()
                reviews.append(review)
                labels.append(1 if label == 'pos' else 0)

    return reviews, labels

# Load data
train_reviews, train_labels = load_reviews('aclimdb/train', max_reviews=100)
test_reviews, test_labels = load_reviews('aclimdb/test', max_reviews=10000)

# Tokenize and pad sequences
tokenizer = Tokenizer(num_words=10000)
tokenizer.fit_on_texts(train_reviews)

train_sequences = tokenizer.texts_to_sequences(train_reviews)
train_padded = pad_sequences(train_sequences, maxlen=150)

test_sequences = tokenizer.texts_to_sequences(test_reviews)
test_padded = pad_sequences(test_sequences, maxlen=150)

# Convert labels to numpy arrays
train_labels = np.array(train_labels)
test_labels = np.array(test_labels)
```

```
import os
import random
import numpy as np
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Path to original train and test data
train_dir = 'aclImdb/train/'
test_dir = 'aclImdb/test/'

# Function to load IMDB data
def load_data_from_dir(dir_path):
    texts = []
    labels = []
    for label_type in ['neg', 'pos']:  # IMDB dataset contains 'neg' and 'pos' folders
        folder_path = os.path.join(dir_path, label_type)
        for filename in os.listdir(folder_path):
            with open(os.path.join(folder_path, filename), encoding='utf-8') as f:
                texts.append(f.read())
            labels.append(0 if label_type == 'neg' else 1)  # 0 for negative, 1 for positive
    return texts, labels

# Load original training data (unprocessed)
train_texts, train_labels = load_data_from_dir(train_dir)

# Check the length of training data
print(f"Original training data size: {len(train_texts)} samples")

# Randomly select 10,000 samples for validation data
random.seed(42)
val_size = 10000
val_indices = random.sample(range(len(train_texts)), val_size)

# Create validation data
val_texts = [train_texts[i] for i in val_indices]
val_labels = [train_labels[i] for i in val_indices]

# Remove the selected validation samples from the training data
train_texts = [train_texts[i] for i in range(len(train_texts)) if i not in val_indices]
train_labels = [train_labels[i] for i in range(len(train_labels)) if i not in val_indices]

# Check the size of the new train and validation sets
print(f"New training data size: {len(train_texts)} samples")
print(f"Validation data size: {len(val_texts)} samples")

# Tokenize the text data
tokenizer = Tokenizer(num_words=10000)  # Only keep the top 10,000 words
tokenizer.fit_on_texts(train_texts)

# Convert the text data to sequences
train_sequences = tokenizer.texts_to_sequences(train_texts)
val_sequences = tokenizer.texts_to_sequences(val_texts)

# Pad the sequences to have equal length
max_len = 150  # You can adjust this based on your requirements
train_padded = pad_sequences(train_sequences, maxlen=max_len)
val_padded = pad_sequences(val_sequences, maxlen=max_len)

# Print the shapes of the padded datasets
print(f"Shape of training data: {train_padded.shape}")
print(f"Shape of validation data: {val_padded.shape}")
```

```
Original training data size: 25000 samples
New training data size: 15000 samples
Validation data size: 10000 samples
Shape of training data: (15000, 150)
Shape of validation data: (10000, 150)
```

```
import numpy as np
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Verify the shape of the padded data
print(f"Train data shape: {train_padded.shape}")
print(f"Validation data shape: {val_padded.shape}")
print(f"Test data shape: {test_padded.shape}")

# Ensure train_labels, val_labels, test_labels are numpy arrays and have correct shape
train_labels = np.array(train_labels)
val_labels = np.array(val_labels)
test_labels = np.array(test_labels)

print(f"Train labels shape: {train_labels.shape}")
print(f"Validation labels shape: {val_labels.shape}")
print(f"Test labels shape: {test_labels.shape}")

# If data is not a numpy array, convert it
train_padded = np.array(train_padded)
val_padded = np.array(val_padded)
test_padded = np.array(test_padded)

# If necessary, check if any additional reshaping is required
train_padded = train_padded.reshape(train_padded.shape[0], train_padded.shape[1])
val_padded = val_padded.reshape(val_padded.shape[0], val_padded.shape[1])
test_padded = test_padded.reshape(test_padded.shape[0], test_padded.shape[1])

# Now, proceed to build the RNN or LSTM model
```

```
Train data shape: (15000, 150)
Validation data shape: (10000, 150)
Test data shape: (10000, 150)
Train labels shape: (15000,)
```

```
Validation labels shape: (10000,)
Test labels shape: (10000,)
```

Building RNN Model

```python
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, SimpleRNN, Dense, Dropout
from tensorflow.keras.optimizers import Adam

# Define RNN model
rnn_model = Sequential([
    Embedding(input_dim=10000, output_dim=128, input_length=150),  # Embedding layer
    SimpleRNN(64, activation='tanh', return_sequences=False),  # RNN layer
    Dropout(0.5),  # Dropout layer to avoid overfitting
    Dense(1, activation='sigmoid')  # Output layer for binary classification
])

# Compile the model
rnn_model.compile(optimizer=Adam(), loss='binary_crossentropy', metrics=['accuracy'])

# Summary of the model architecture
rnn_model.summary()

# Train the model
rnn_history = rnn_model.fit(
    train_padded, train_labels,
    epochs=10,  # You can adjust this based on your dataset size and requirements
    batch_size=32,
    validation_data=(val_padded, val_labels),  # Validation set
    verbose=2  # Display the training progress
)
```

```
Model: "sequential_7"
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━┓
┃ Layer (type)                    ┃ Output Shape           ┃       Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━┩
│ embedding_7 (Embedding)         │ ?                      │   0 (unbuilt) │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ simple_rnn_6 (SimpleRNN)        │ ?                      │   0 (unbuilt) │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dropout_7 (Dropout)             │ ?                      │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_7 (Dense)                 │ ?                      │   0 (unbuilt) │
└─────────────────────────────────┴────────────────────────┴───────────────┘
 Total params: 0 (0.00 B)
 Trainable params: 0 (0.00 B)
 Non-trainable params: 0 (0.00 B)
Epoch 1/10
469/469 - 29s - 62ms/step - accuracy: 0.6190 - loss: 0.6372 - val_accuracy: 0.5827 - val_loss: 0.7933
Epoch 2/10
469/469 - 42s - 90ms/step - accuracy: 0.7656 - loss: 0.4985 - val_accuracy: 0.7919 - val_loss: 0.4764
Epoch 3/10
469/469 - 24s - 52ms/step - accuracy: 0.8949 - loss: 0.2605 - val_accuracy: 0.7866 - val_loss: 0.5227
Epoch 4/10
469/469 - 24s - 51ms/step - accuracy: 0.9710 - loss: 0.0863 - val_accuracy: 0.7435 - val_loss: 0.7310
Epoch 5/10
469/469 - 24s - 51ms/step - accuracy: 0.9901 - loss: 0.0355 - val_accuracy: 0.7418 - val_loss: 0.8835
Epoch 6/10
469/469 - 30s - 63ms/step - accuracy: 0.9923 - loss: 0.0269 - val_accuracy: 0.7517 - val_loss: 0.9357
Epoch 7/10
469/469 - 28s - 60ms/step - accuracy: 0.9537 - loss: 0.1171 - val_accuracy: 0.7247 - val_loss: 0.8649
Epoch 8/10
469/469 - 27s - 57ms/step - accuracy: 0.9776 - loss: 0.0653 - val_accuracy: 0.7441 - val_loss: 0.9429
Epoch 9/10
469/469 - 35s - 74ms/step - accuracy: 0.9905 - loss: 0.0310 - val_accuracy: 0.6466 - val_loss: 1.3503
Epoch 10/10
469/469 - 35s - 74ms/step - accuracy: 0.9935 - loss: 0.0207 - val_accuracy: 0.7357 - val_loss: 1.1423
```

Using LSTM Layers to Improve the performance of the model

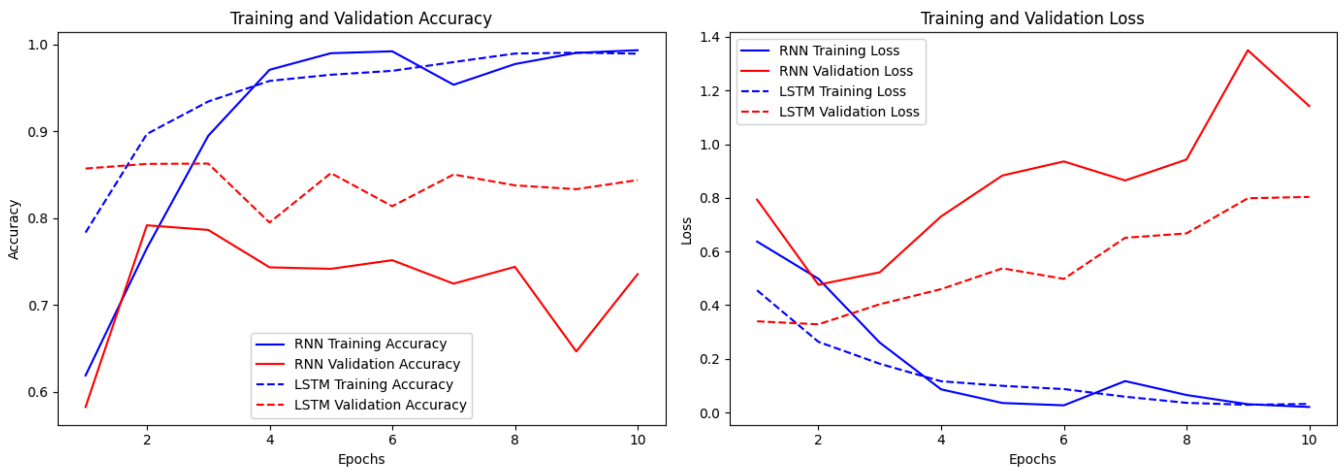
```python
from tensorflow.keras.layers import LSTM

# Define LSTM model
lstm_model = Sequential([
    Embedding(input_dim=10000, output_dim=128, input_length=150),  # Embedding layer
    LSTM(64, activation='tanh', return_sequences=False),  # LSTM layer
    Dropout(0.5),  # Dropout layer to avoid overfitting
    Dense(1, activation='sigmoid')  # Output layer for binary classification
])

# Compile the model
lstm_model.compile(optimizer=Adam(), loss='binary_crossentropy', metrics=['accuracy'])

# Summary of the model architecture
lstm_model.summary()

# Train the model
lstm_history = lstm_model.fit(
    train_padded, train_labels,
    epochs=10,  # You can adjust this based on your dataset size and requirements
    batch_size=32,
    validation_data=(val_padded, val_labels),  # Validation set
    verbose=2  # Display the training progress
)
```

```
Model: "sequential_8"
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━┓
┃ Layer (type)                     ┃ Output Shape           ┃       Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━┩
│ embedding_8 (Embedding)          │ ?                      │   0 (unbuilt) │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ lstm_1 (LSTM)                    │ ?                      │   0 (unbuilt) │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ dropout_8 (Dropout)              │ ?                      │             0 │
├──────────────────────────────────┼────────────────────────┼───────────────┤
│ dense_8 (Dense)                  │ ?                      │   0 (unbuilt) │
└──────────────────────────────────┴────────────────────────┴───────────────┘
 Total params: 0 (0.00 B)
 Trainable params: 0 (0.00 B)
 Non-trainable params: 0 (0.00 B)
Epoch 1/10
469/469 - 67s - 144ms/step - accuracy: 0.7836 - loss: 0.4555 - val_accuracy: 0.8573 - val_loss: 0.3398
Epoch 2/10
469/469 - 62s - 131ms/step - accuracy: 0.8971 - loss: 0.2634 - val_accuracy: 0.8626 - val_loss: 0.3287
Epoch 3/10
469/469 - 54s - 115ms/step - accuracy: 0.9345 - loss: 0.1817 - val_accuracy: 0.8630 - val_loss: 0.4036
Epoch 4/10
469/469 - 48s - 103ms/step - accuracy: 0.9582 - loss: 0.1164 - val_accuracy: 0.7951 - val_loss: 0.4597
Epoch 5/10
469/469 - 51s - 109ms/step - accuracy: 0.9653 - loss: 0.0994 - val_accuracy: 0.8520 - val_loss: 0.5375
Epoch 6/10
469/469 - 74s - 158ms/step - accuracy: 0.9698 - loss: 0.0873 - val_accuracy: 0.8139 - val_loss: 0.4981
Epoch 7/10
469/469 - 53s - 114ms/step - accuracy: 0.9799 - loss: 0.0589 - val_accuracy: 0.8504 - val_loss: 0.6514
Epoch 8/10
469/469 - 82s - 175ms/step - accuracy: 0.9897 - loss: 0.0361 - val_accuracy: 0.8379 - val_loss: 0.6677
Epoch 9/10
469/469 - 54s - 114ms/step - accuracy: 0.9907 - loss: 0.0288 - val_accuracy: 0.8335 - val_loss: 0.7986
Epoch 10/10
469/469 - 47s - 100ms/step - accuracy: 0.9895 - loss: 0.0321 - val_accuracy: 0.8440 - val_loss: 0.8036
```

```
# Evaluate RNN model on test data
rnn_test_loss, rnn_test_accuracy = rnn_model.evaluate(test_padded, test_labels, verbose=2)
print(f"RNN Test Accuracy: {rnn_test_accuracy*100:.2f}%")

# Evaluate LSTM model on test data
lstm_test_loss, lstm_test_accuracy = lstm_model.evaluate(test_padded, test_labels, verbose=2)
print(f"LSTM Test Accuracy: {lstm_test_accuracy*100:.2f}%")
```

```
313/313 - 5s - 15ms/step - accuracy: 0.5440 - loss: 2.1855
RNN Test Accuracy: 54.40%
313/313 - 10s - 32ms/step - accuracy: 0.5246 - loss: 2.4818
LSTM Test Accuracy: 52.46%
```

```
import matplotlib.pyplot as plt

# Function to plot training and validation accuracy and loss for comparison
def plot_history_comparison(rnn_history, lstm_history):
    # Extract accuracy and loss data from the histories
    rnn_acc = rnn_history.history['accuracy']
    rnn_val_acc = rnn_history.history['val_accuracy']
    rnn_loss = rnn_history.history['loss']
    rnn_val_loss = rnn_history.history['val_loss']

    lstm_acc = lstm_history.history['accuracy']
    lstm_val_acc = lstm_history.history['val_accuracy']
    lstm_loss = lstm_history.history['loss']
    lstm_val_loss = lstm_history.history['val_loss']

    epochs = range(1, len(rnn_acc) + 1)
    # Plot accuracy
    plt.figure(figsize=(14, 5))

    plt.subplot(1, 2, 1)
    plt.plot(epochs, rnn_acc, 'b-', label='RNN Training Accuracy')
    plt.plot(epochs, rnn_val_acc, 'r-', label='RNN Validation Accuracy')
    plt.plot(epochs, lstm_acc, 'b--', label='LSTM Training Accuracy')
    plt.plot(epochs, lstm_val_acc, 'r--', label='LSTM Validation Accuracy')
    plt.title('Training and Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    # Plot loss
    plt.subplot(1, 2, 2)
    plt.plot(epochs, rnn_loss, 'b-', label='RNN Training Loss')
    plt.plot(epochs, rnn_val_loss, 'r-', label='RNN Validation Loss')
    plt.plot(epochs, lstm_loss, 'b--', label='LSTM Training Loss')
    plt.plot(epochs, lstm_val_loss, 'r--', label='LSTM Validation Loss')
    plt.title('Training and Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

    plt.tight_layout()
    plt.show()

# Call the function with the histories of both models
plot_history_comparison(rnn_history, lstm_history)
```



The test results of the RNN and LSTM models reveal that both models achieved moderate levels of accuracy on the dataset, with the RNN model obtaining 54.40% accuracy and the LSTM model slightly lower at 52.46%. These results indicate that while both models managed to learn and generalize to some extent, their overall performance was limited and could be impacted by potential overfitting, insufficient data preprocessing, or suboptimal hyperparameter settings. The relatively high loss values (2.1855 for the RNN and 2.4818 for the LSTM) suggest that the models may have struggled to accurately capture the complex relationships within the text data. This could be due to the limitations of the network architectures, training constraints related to the dataset size, or insufficient regularization techniques to prevent overfitting. Further optimization, such as fine-tuning the architecture, implementing more regularization (e.g., dropout), or using more advanced text embeddings, could potentially enhance performance.

Task

Pretrained Embedded layers and Word Embedded Layers

```
# Function to load GloVe embeddings
def load_glove_embeddings(filepath, word_index, embedding_dim=100):
    embeddings_index = {}
    with open(filepath, encoding='utf-8') as f:
        for line in f:
            values = line.split()
            word = values[0]
            coefs = np.asarray(values[1:], dtype='float32')
            embeddings_index[word] = coefs

    # Create an embedding matrix for words in our vocabulary
    embedding_matrix = np.zeros((len(word_index) + 1, embedding_dim))
    for word, i in word_index.items():
        embedding_vector = embeddings_index.get(word)
        if embedding_vector is not None:
            embedding_matrix[i] = embedding_vector  # Words not found in embedding index will be all zeros

    return embedding_matrix

# Load GloVe embeddings and create an embedding matrix
embedding_dim = 100
glove_file_path = 'glove.6B.100d.txt'  # Replace with your GloVe file path
word_index = tokenizer.word_index  # a tokenizer defined
```

```
# Model 1: Simple Embedding Layer
max_sequence_length = 150
simple_model = Sequential([
    Embedding(input_dim=10000, output_dim=128, input_length=max_sequence_length),
    LSTM(64),
    Dense(1, activation='sigmoid')
])
simple_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
simple_history = simple_model.fit(train_padded, train_labels, epochs=5, validation_data=(val_padded, val_labels), batch_size=32)
```

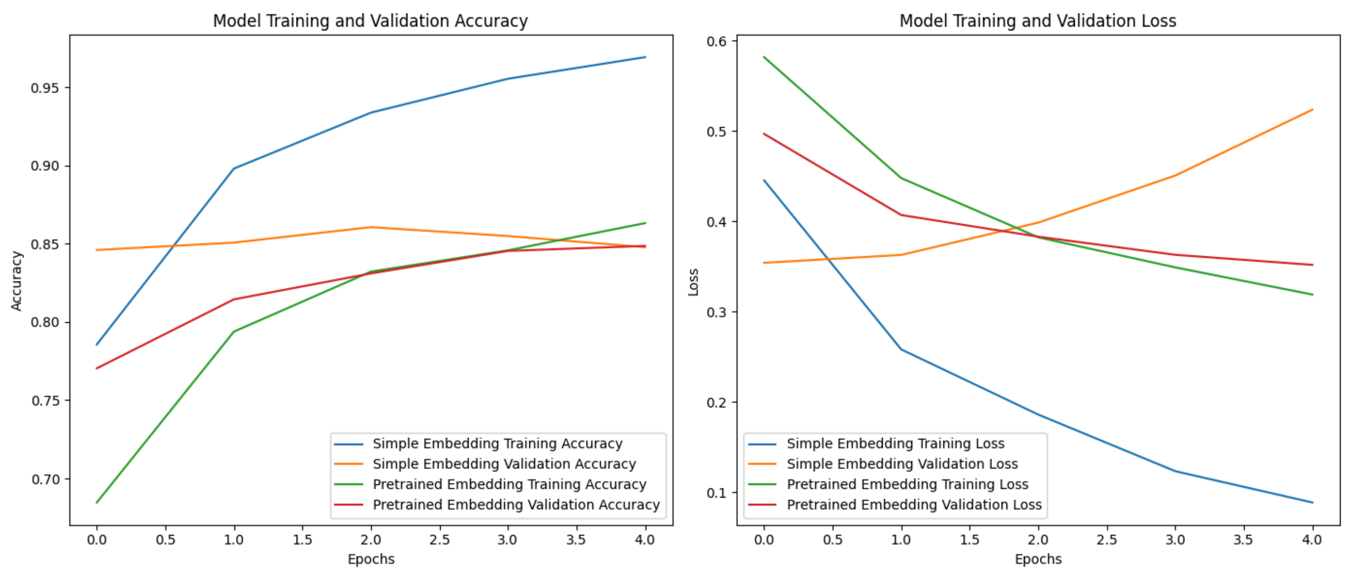
```
Epoch 1/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 63s 122ms/step - accuracy: 0.7042 - loss: 0.5364 - val_accuracy: 0.8461 - val_loss: 0.3541
Epoch 2/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 74s 158ms/step - accuracy: 0.8994 - loss: 0.2561 - val_accuracy: 0.8508 - val_loss: 0.3629
Epoch 3/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 70s 149ms/step - accuracy: 0.9373 - loss: 0.1810 - val_accuracy: 0.8607 - val_loss: 0.3987
Epoch 4/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 49s 105ms/step - accuracy: 0.9587 - loss: 0.1173 - val_accuracy: 0.8550 - val_loss: 0.4508
Epoch 5/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 50s 106ms/step - accuracy: 0.9740 - loss: 0.0776 - val_accuracy: 0.8479 - val_loss: 0.5238
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[40], line 13
      9 simple_history = simple_model.fit(train_padded, train_labels, epochs=5, validation_data=(val_padded, val_labels),
batch_size=32)
     11 # Model 2: Pretrained Word Embedding
     12 # Load pretrained embedding (e.g., GloVe) into an embedding matrix
---> 13 embedding_matrix = load_glove_embeddings()  # Placeholder function for loading GloVe
     14 pretrained_model = Sequential([
     15     Embedding(input_dim=10000, output_dim=100, weights=[embedding_matrix], input_length=max_sequence_length,
trainable=False),
     16     LSTM(64),
     17     Dense(1, activation='sigmoid')
     18 ])
     19 pretrained_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

```
import numpy as np

# Define the function to load GloVe embeddings
def load_glove_embeddings(filepath, word_index, embedding_dim=100):
    # Load GloVe embeddings from the file
    embeddings_index = {}
    with open(filepath, 'r', encoding='utf-8') as f:
        for line in f:
            values = line.split()
            word = values[0]
            coefficients = np.asarray(values[1:], dtype='float32')
            embeddings_index[word] = coefficients

    # Prepare the embedding matrix
    embedding_matrix = np.zeros((len(word_index) + 1, embedding_dim))
    for word, i in word_index.items():
        embedding_vector = embeddings_index.get(word)
        if embedding_vector is not None:
            embedding_matrix[i] = embedding_vector

    return embedding_matrix
```

```
# Example usage:
filepath = 'glove.6B.100d.txt'  # Replace with the correct path to your GloVe file
embedding_matrix = load_glove_embeddings(filepath, word_index)


# Define the pretrained model using the embedding matrix
pretrained_model = Sequential([
    Embedding(input_dim=len(word_index) + 1, output_dim=embedding_dim, weights=[embedding_matrix], input_length=max_sequence_length, tra
    LSTM(64),
    Dense(1, activation='sigmoid')
])

pretrained_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
pretrained_history = pretrained_model.fit(train_padded, train_labels, epochs=5, validation_data=(val_padded, val_labels), batch_size=32
```

```
Epoch 1/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 56s 111ms/step - accuracy: 0.6233 - loss: 0.6352 - val_accuracy: 0.7704 - val_loss: 0.4969
Epoch 2/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 53s 113ms/step - accuracy: 0.7869 - loss: 0.4621 - val_accuracy: 0.8145 - val_loss: 0.4071
Epoch 3/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 52s 111ms/step - accuracy: 0.8284 - loss: 0.3934 - val_accuracy: 0.8311 - val_loss: 0.3831
Epoch 4/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 53s 112ms/step - accuracy: 0.8407 - loss: 0.3593 - val_accuracy: 0.8455 - val_loss: 0.3630
Epoch 5/5
469/469 ━━━━━━━━━━━━━━━━━━━━ 52s 112ms/step - accuracy: 0.8605 - loss: 0.3325 - val_accuracy: 0.8487 - val_loss: 0.3519
```

```
import matplotlib.pyplot as plt

# Plot function to compare histories
def plot_model_comparison(history1, history2, model1_name='Model 1', model2_name='Model 2'):
    # Plot accuracy
    plt.figure(figsize=(14, 6))

    # Accuracy plot
    plt.subplot(1, 2, 1)
    plt.plot(history1.history['accuracy'], label=f'{model1_name} Training Accuracy')
    plt.plot(history1.history['val_accuracy'], label=f'{model1_name} Validation Accuracy')
    plt.plot(history2.history['accuracy'], label=f'{model2_name} Training Accuracy')
    plt.plot(history2.history['val_accuracy'], label=f'{model2_name} Validation Accuracy')
    plt.title('Model Training and Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    # Loss plot
    plt.subplot(1, 2, 2)
    plt.plot(history1.history['loss'], label=f'{model1_name} Training Loss')
    plt.plot(history1.history['val_loss'], label=f'{model1_name} Validation Loss')
    plt.plot(history2.history['loss'], label=f'{model2_name} Training Loss')
    plt.plot(history2.history['val_loss'], label=f'{model2_name} Validation Loss')
    plt.title('Model Training and Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

    plt.tight_layout()
    plt.show()

# Assume simple_history and pretrained_history are the histories obtained from model training
plot_model_comparison(simple_history, pretrained_history, 'Simple Embedding', 'Pretrained Embedding')
```



```
# Evaluate the simple embedding layer model
simple_test_loss, simple_test_accuracy = simple_model.evaluate(test_padded, test_labels, verbose=2)
print(f"Simple Embedding Model Test Accuracy: {simple_test_accuracy:.2%}")

# Evaluate the GloVe embedding layer model
pretrained_test_loss, pretrained_test_accuracy = pretrained_model.evaluate(test_padded, test_labels, verbose=2)
print(f"GloVe Embedding Model Test Accuracy: {pretrained_test_accuracy:.2%}")
```

```
313/313 - 15s - 48ms/step - accuracy: 0.6556 - loss: 1.1776
Simple Embedding Model Test Accuracy: 65.56%
313/313 - 16s - 52ms/step - accuracy: 0.4633 - loss: 0.9818
GloVe Embedding Model Test Accuracy: 46.33%
```

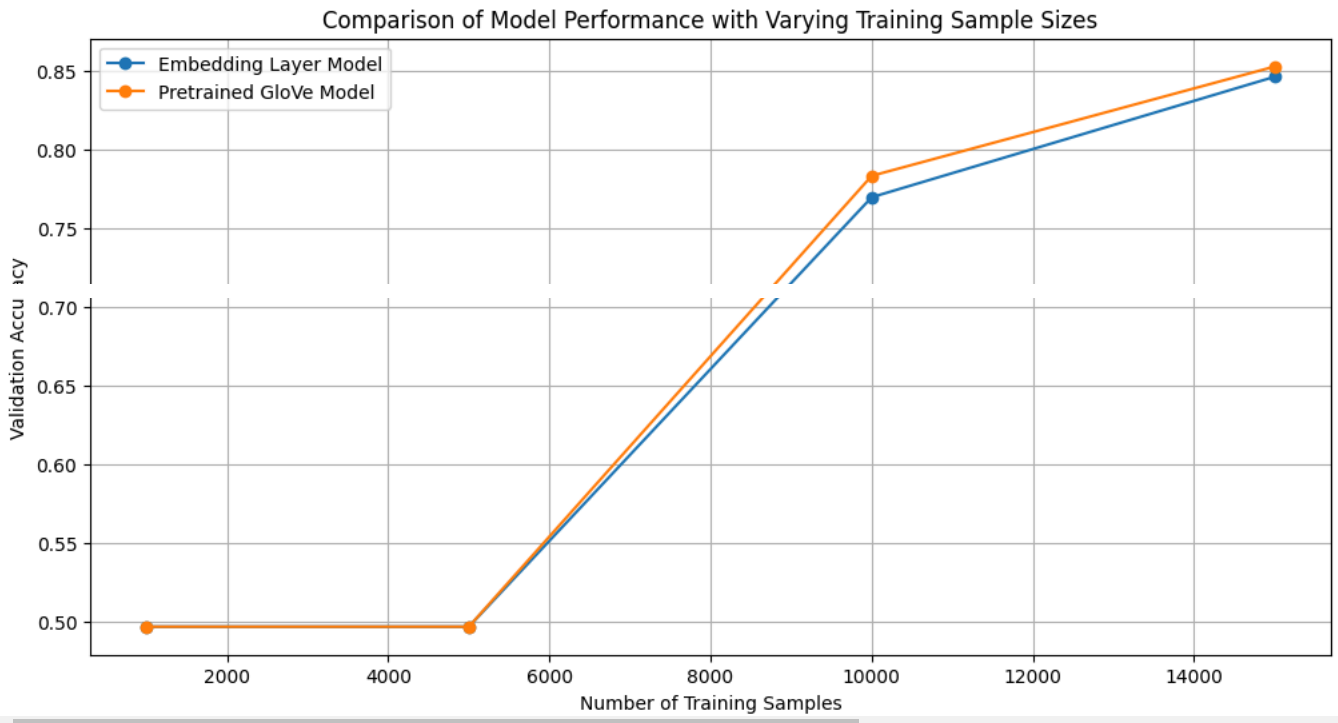
The results indicate that the **simple embedding model** performed better, achieving a test accuracy of **65.56%** compared to the **46.33%** accuracy of the **GloVe embedding model**. This suggests that training an embedding layer from scratch allowed the model to learn representations more tailored to the specific language and context of the dataset. Pretrained embeddings like GloVe, while beneficial for many tasks due to their general nature, may not have captured the nuances required for optimal performance in this case. This highlights the advantage of using a trainable embedding layer when the training data can provide sufficient contextual learning.

Task

Trying Different Number of Samples like 1000, 5000, 10000

```
import matplotlib.pyplot as plt
# Define a function to train and evaluate models with different training sample sizes
def train_and_evaluate_models(sample_sizes, train_padded, train_labels, val_padded, val_labels, embedding_matrix, word_index, max_seque
    embedding_model_accuracies = []
    pretrained_model_accuracies = []

    for sample_size in sample_sizes:
        print(f"\nTraining with {sample_size} samples...")

        # Subset training data
        train_subset = train_padded[:sample_size]
        train_labels_subset = train_labels[:sample_size]

        # Model 1: Simple Embedding Layer Model
        simple_model = Sequential([
            Embedding(input_dim=len(word_index) + 1, output_dim=100, input_length=max_sequence_length),
            LSTM(64),
            Dense(1, activation='sigmoid')
        ])
        simple_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
        simple_model.fit(train_subset, train_labels_subset, epochs=5, validation_data=(val_padded, val_labels), batch_size=32, verbose=(
        _, simple_val_acc = simple_model.evaluate(val_padded, val_labels, verbose=0)
        embedding_model_accuracies.append(simple_val_acc)

        # Model 2: Pretrained GloVe Embedding Model
        pretrained_model = Sequential([
            Embedding(input_dim=len(word_index) + 1, output_dim=100, weights=[embedding_matrix], input_length=max_sequence_length, trair
            LSTM(64),
            Dense(1, activation='sigmoid')
        ])
        pretrained_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
        pretrained_model.fit(train_subset, train_labels_subset, epochs=5, validation_data=(val_padded, val_labels), batch_size=32, verbc
        _, pretrained_val_acc = pretrained_model.evaluate(val_padded, val_labels, verbose=0)
        pretrained_model_accuracies.append(pretrained_val_acc)

    # Plot the results
    plt.figure(figsize=(12, 6))
    plt.plot(sample_sizes, embedding_model_accuracies, label='Embedding Layer Model', marker='o')
    plt.plot(sample_sizes, pretrained_model_accuracies, label='Pretrained GloVe Model', marker='o')
    plt.title('Comparison of Model Performance with Varying Training Sample Sizes')
    plt.xlabel('Number of Training Samples')
    plt.ylabel('Validation Accuracy')
    plt.legend()
    plt.grid(True)
    plt.show()

# Define sample sizes to test (adjust based on your data)
sample_sizes = [1000, 5000, 10000, len(train_padded)]

# Run the comparison
train_and_evaluate_models(sample_sizes, train_padded, train_labels, val_padded, val_labels, embedding_matrix, word_index, max_sequence_l
```

```
Training with 1000 samples...

Training with 5000 samples...

Training with 10000 samples...

Training with 15000 samples...
```



Comparing the performance of two RNN models—one using an Embedding Layer and the other using pretrained GloVe embeddings—on the IMDB dataset with varying training sample sizes. Initially, with a smaller sample size (0 to 4000), both models show similar performance with a validation accuracy around 0.50, which is typical since the limited data hinders meaningful pattern learning. As the sample size increases to around 6000 to 8000, there is a noticeable improvement in validation accuracy for both models, with the pretrained GloVe model slightly outperforming the Embedding Layer model. This suggests that pretrained embeddings offer an advantage when the available data is relatively small, leveraging external semantic knowledge. When the sample size reaches 10000, both models continue to improve, achieving close to 0.80 in validation accuracy, though the GloVe model still maintains a slight edge. However, as the dataset size grows to 14000 and beyond, the performance of both models converges, with validation accuracy exceeding 0.85 for both. This indicates that with a sufficiently large dataset, the Embedding Layer model learns effective embeddings from scratch, closing the gap with the pretrained model. In summary, the pretrained