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import numpy as np
from tensorflow.keras.datasets import imdb
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Load IMDB dataset
max_features = 10000 # number of words to consider as features
maxlen = 150 # cut off reviews after this number of words

(x_train, y_train), (x_test, y_test) =
imdb.load_data(num_words=max_features)
x_train = pad_sequences(x_train, maxlen=maxlen)
x_test = pad_sequences(x_test, maxlen=maxlen)

Downloading data from https://storage.googleapis.com/tensorflow/tf-
keras-datasets/imdb.npz
17464789/17464789 [=====] - 4s 0us/step

# Limit training samples
x_train_limited = x_train[:100]
y_train_limited = y_train[:100]

# Define model
model = Sequential()
model.add(Embedding(max_features, 128, input_length=maxlen))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))

# Compile and train the model
model.compile(optimizer='rmsprop', loss='binary_crossentropy',
metrics=['acc'])
history = model.fit(x_train_limited, y_train_limited, epochs=10,
batch_size=32, validation_data=(x_test, y_test))

Epoch 1/10
4/4 [=====] - 22s 6s/step - loss: 0.6918 -
acc: 0.5600 - val_loss: 0.6942 - val_acc: 0.5000
Epoch 2/10
4/4 [=====] - 17s 6s/step - loss: 0.6804 -
acc: 0.5800 - val_loss: 0.6944 - val_acc: 0.5000
Epoch 3/10
4/4 [=====] - 17s 6s/step - loss: 0.6696 -
acc: 0.5800 - val_loss: 0.6950 - val_acc: 0.5000
Epoch 4/10
4/4 [=====] - 17s 6s/step - loss: 0.6587 -
acc: 0.5800 - val_loss: 0.7005 - val_acc: 0.5000
Epoch 5/10
4/4 [=====] - 16s 5s/step - loss: 0.6391 -
acc: 0.5800 - val_loss: 0.7130 - val_acc: 0.5000

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Epoch 6/10
4/4 [=====] - 16s 5s/step - loss: 0.6172 -
acc: 0.5800 - val_loss: 0.7190 - val_acc: 0.5000
Epoch 7/10
4/4 [=====] - 20s 7s/step - loss: 0.5904 -
acc: 0.5800 - val_loss: 0.6989 - val_acc: 0.5041
Epoch 8/10
4/4 [=====] - 22s 7s/step - loss: 0.5558 -
acc: 0.7900 - val_loss: 0.7108 - val_acc: 0.5052
Epoch 9/10
4/4 [=====] - 25s 8s/step - loss: 0.5040 -
acc: 0.8000 - val_loss: 0.7953 - val_acc: 0.5023
Epoch 10/10
4/4 [=====] - 20s 7s/step - loss: 0.4515 -
acc: 0.8200 - val_loss: 0.7051 - val_acc: 0.5452

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*# Define the dimensionality of the GloVe word embeddings*

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embedding_dim = 100
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*# Load GloVe word embeddings*

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glove_dir = 'glove.6B.100d.txt'
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embeddings_index = {}
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with open(glove_dir, 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

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*# Prepare the embedding matrix*

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embedding_matrix = np.zeros((max_features, embedding_dim))
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for word, i in imdb.get_word_index().items():
    if i < max_features:
        embedding_vector = embeddings_index.get(word)
        if embedding_vector is not None:
            embedding_matrix[i] = embedding_vector

```

Downloading data from [https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb\\_word\\_index.json](https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb_word_index.json)

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1641221/1641221 [=====] - 1s 1us/step
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*# Define model with GloVe embeddings*

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model_glove = Sequential()
model_glove.add(Embedding(max_features, embedding_dim,
input_length=maxlen, weights=[embedding_matrix], trainable=False))
model_glove.add(LSTM(32))
model_glove.add(Dense(1, activation='sigmoid'))

```

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# Compile and train the model
model_glove.compile(optimizer='rmsprop', loss='binary_crossentropy',
metrics=['acc'])
history_glove = model_glove.fit(x_train_limited, y_train_limited,
epochs=10, batch_size=32, validation_data=(x_test, y_test))

Epoch 1/10
4/4 [=====] - 17s 5s/step - loss: 0.6915 -
acc: 0.5200 - val_loss: 0.7039 - val_acc: 0.5009
Epoch 2/10
4/4 [=====] - 14s 5s/step - loss: 0.6666 -
acc: 0.5900 - val_loss: 0.6947 - val_acc: 0.5066
Epoch 3/10
4/4 [=====] - 15s 5s/step - loss: 0.6587 -
acc: 0.6100 - val_loss: 0.6962 - val_acc: 0.5071
Epoch 4/10
4/4 [=====] - 14s 5s/step - loss: 0.6487 -
acc: 0.6500 - val_loss: 0.6955 - val_acc: 0.5073
Epoch 5/10
4/4 [=====] - 16s 5s/step - loss: 0.6463 -
acc: 0.6900 - val_loss: 0.7177 - val_acc: 0.5006
Epoch 6/10
4/4 [=====] - 17s 5s/step - loss: 0.6342 -
acc: 0.6000 - val_loss: 0.7285 - val_acc: 0.5002
Epoch 7/10
4/4 [=====] - 17s 6s/step - loss: 0.6252 -
acc: 0.5900 - val_loss: 0.7021 - val_acc: 0.5102
Epoch 8/10
4/4 [=====] - 17s 6s/step - loss: 0.6134 -
acc: 0.7200 - val_loss: 0.7002 - val_acc: 0.5113
Epoch 9/10
4/4 [=====] - 15s 5s/step - loss: 0.6084 -
acc: 0.7000 - val_loss: 0.7322 - val_acc: 0.5016
Epoch 10/10
4/4 [=====] - 16s 5s/step - loss: 0.5963 -
acc: 0.6200 - val_loss: 0.6972 - val_acc: 0.5148

# Evaluate both models on the validation set
eval_custom_embedding = model.evaluate(x_test, y_test)
eval_glove_embedding = model_glove.evaluate(x_test, y_test)

# Print evaluation results
print("Custom Embedding Model - Loss: {:.4f}, Accuracy:
{:.4f}".format(eval_custom_embedding[0], eval_custom_embedding[1]))
print("GloVe Embedding Model - Loss: {:.4f}, Accuracy:
{:.4f}".format(eval_glove_embedding[0], eval_glove_embedding[1]))

# Optionally, plot the training history for a better comparison
import matplotlib.pyplot as plt

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```
def plot_history(histories, key='acc'):
    plt.figure(figsize=(16,10))

    for name, history in histories:
        val = plt.plot(history.epoch, history.history['val_'+key],
                        '--', label=name.title()+' Val')
        plt.plot(history.epoch, history.history[key],
                 color=val[0].get_color(),
                 label=name.title()+' Train')

    plt.xlabel('Epochs')
    plt.ylabel(key.replace('_', ' ').title())
    plt.legend()

    plt.xlim([0,max(history.epoch)])

# Plot accuracy
plot_history([('Custom Embedding', history), ('GloVe Embedding',
history_glove)])

782/782 [=====] - 18s 23ms/step - loss:
0.7051 - acc: 0.5452
782/782 [=====] - 17s 22ms/step - loss:
0.6972 - acc: 0.5148
Custom Embedding Model - Loss: 0.7051, Accuracy: 0.5452
GloVe Embedding Model - Loss: 0.6972, Accuracy: 0.5148
```



