experiment_11

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Course Name:	Deep Learning Lab
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Experiment:	11
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0.1 Question 1

[2]:
```
import numpy as np
import tensorflow as tf
from tensorflow.keras.datasets import imdb
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Bidirectional, LSTM, GRU,␣
↪SimpleRNN, Dense, TimeDistributed
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import mean_squared_error, r2_score, accuracy_score
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import random

seed = 42
np.random.seed(seed)
tf.random.set_seed(seed)
random.seed(seed)
```

```
2025-10-24 08:17:15.688890: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:477] Unable to register
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
E0000 00:00:1761293836.123432     759 cuda_dnn.cc:8310] Unable to register cuDNN
factory: Attempting to register factory for plugin cuDNN when one has already
been registered
E0000 00:00:1761293836.249005     759 cuda_blas.cc:1418] Unable to register
```

```
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
already been registered
```

[3]:
```python
vocab_size = 10000
maxlen = 500
embedding_dim = 100
val_size = 1000

### Loading the dataset
(x_train_raw,y_train_raw),(x_test_raw,y_test_raw) = imdb.
 ↪load_data(num_words=vocab_size)

lengths = [len(r) for r in x_train_raw+x_test_raw]
print("Min review length (words):", np.min(lengths))
print("Max review length (words):", np.max(lengths))
print("Mean review length (words):", int(np.mean(lengths)))

x_train_padded = pad_sequences(x_train_raw, maxlen = maxlen, padding = 'pre',␣
 ↪truncating='pre')
x_test_padded = pad_sequences(x_test_raw, maxlen = maxlen, padding = 'pre',␣
 ↪truncating='pre')

## Creating validation split

x_val = x_train_padded[:val_size]
y_val = np.array(y_train_raw[:val_size])

x_train = x_train_padded[val_size:]
y_train = np.array(y_train_raw[val_size:])

x_test = x_test_padded
y_test = np.array(y_test_raw)

print("\nShapes after padding and split:")
print("X_train:", x_train.shape,"y_train",y_train.shape)
print("X_val:", x_val.shape,"y_val",y_val.shape)
print("X_test:", x_test.shape,"y_test",y_test.shape)
```

```
Min review length (words): 70
Max review length (words): 2697
Mean review length (words): 469

Shapes after padding and split:
X_train: (24000, 500) y_train (24000,)
X_val: (1000, 500) y_val (1000,)
X_test: (25000, 500) y_test (25000,)
```

[4]:
```python
BiLSTM_model = Sequential()
BiLSTM_model.add(Embedding(input_dim=vocab_size,
                           output_dim=embedding_dim,
                           input_shape=(maxlen,)))
BiLSTM_model.add(Bidirectional(LSTM(128, return_sequences=True)))
BiLSTM_model.add(Bidirectional(LSTM(64)))
BiLSTM_model.add(Dense(1, activation='sigmoid'))

BiLSTM_model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics␣
 ↪= ['accuracy'])
BiLSTM_model.summary()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/embedding.py:93:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(**kwargs)
I0000 00:00:1761293854.890814     759 gpu_device.cc:2022] Created device
/job:localhost/replica:0/task:0/device:GPU:0 with 13942 MB memory:  -> device:
0, name: Tesla T4, pci bus id: 0000:00:04.0, compute capability: 7.5
I0000 00:00:1761293854.891536     759 gpu_device.cc:2022] Created device
/job:localhost/replica:0/task:0/device:GPU:1 with 13942 MB memory:  -> device:
1, name: Tesla T4, pci bus id: 0000:00:05.0, compute capability: 7.5
```

Model: "sequential"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 500, 100)	1,000,000
bidirectional (Bidirectional)	(None, 500, 256)	234,496
bidirectional_1 (Bidirectional)	(None, 128)	164,352
dense (Dense)	(None, 1)	129

Total params: 1,398,977 (5.34 MB)

Trainable params: 1,398,977 (5.34 MB)

Non-trainable params: 0 (0.00 B)

[5]:
```
es = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True,␣
↪verbose=1)
history_bilstm = BiLSTM_model.fit(
    x_train, y_train,
    validation_data=(x_val, y_val),
    epochs=20,
    batch_size=64,
    callbacks=[es],
    verbose=1
)
```

```
Epoch 1/20

I0000 00:00:1761293862.825005     796 cuda_dnn.cc:529] Loaded cuDNN version
90300

375/375              41s 90ms/step -
accuracy: 0.6893 - loss: 0.5663 - val_accuracy: 0.8660 - val_loss: 0.3362
Epoch 2/20
375/375              34s 90ms/step -
accuracy: 0.8744 - loss: 0.3049 - val_accuracy: 0.8890 - val_loss: 0.2718
Epoch 3/20
375/375              33s 89ms/step -
accuracy: 0.8914 - loss: 0.2707 - val_accuracy: 0.8780 - val_loss: 0.3179
Epoch 4/20
375/375              33s 89ms/step -
accuracy: 0.9224 - loss: 0.2030 - val_accuracy: 0.8610 - val_loss: 0.3414
Epoch 5/20
375/375              34s 89ms/step -
accuracy: 0.9394 - loss: 0.1633 - val_accuracy: 0.8610 - val_loss: 0.3654
Epoch 6/20
375/375              33s 89ms/step -
accuracy: 0.9534 - loss: 0.1281 - val_accuracy: 0.8650 - val_loss: 0.3818
Epoch 7/20
375/375              33s 89ms/step -
accuracy: 0.9552 - loss: 0.1201 - val_accuracy: 0.8750 - val_loss: 0.4145
Epoch 7: early stopping
Restoring model weights from the end of the best epoch: 2.
```

[6]:
```
loss_bilstm, acc_bilstm = BiLSTM_model.evaluate(x_test, y_test, verbose=1)
print(f"\nBi-LSTM Test Loss: {loss_bilstm:.4f}, Test Accuracy: {acc_bilstm:.
↪4f}")
```

```
782/782              21s 27ms/step -
accuracy: 0.8709 - loss: 0.3130

Bi-LSTM Test Loss: 0.3118, Test Accuracy: 0.8721
```

0.2 Question 2: Next, build an Bi-GRU model and try the same problem and compare the outputs of the models.

[7]:
```
BiGRU_model = Sequential()
BiGRU_model.add(Embedding(input_dim=vocab_size,
                          output_dim=embedding_dim,
                          input_shape=(maxlen,)))
BiGRU_model.add(Bidirectional(GRU(128, return_sequences=True)))
BiGRU_model.add(Bidirectional(GRU(64)))
BiGRU_model.add(Dense(1, activation='sigmoid'))

BiGRU_model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics =␣
 ↪['accuracy'])
BiGRU_model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 500, 100)	1,000,000
bidirectional_2 (Bidirectional)	(None, 500, 256)	176,640
bidirectional_3 (Bidirectional)	(None, 128)	123,648
dense_1 (Dense)	(None, 1)	129

Total params: 1,300,417 (4.96 MB)

Trainable params: 1,300,417 (4.96 MB)

Non-trainable params: 0 (0.00 B)

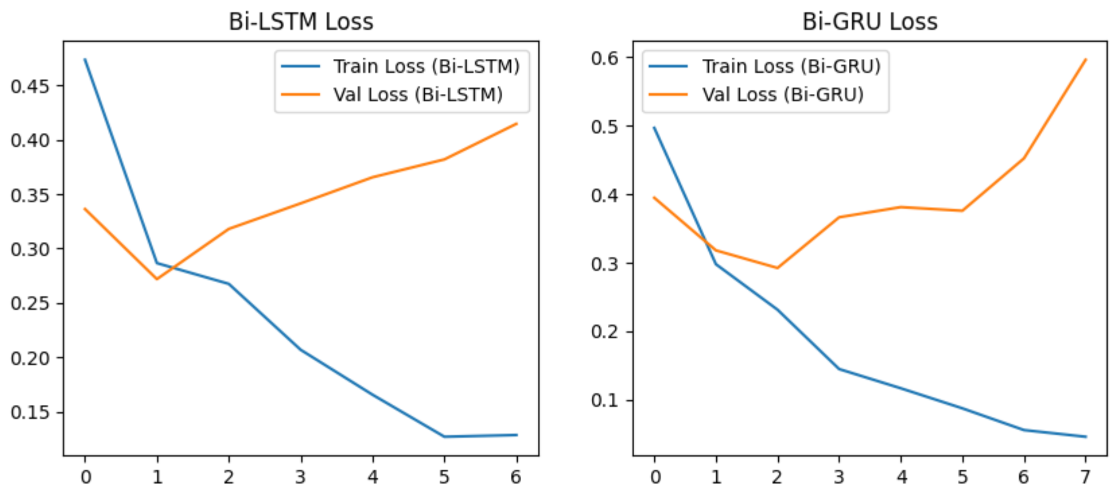
[8]:
```
es = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True,␣
 ↪verbose=1)
history_bigru = BiGRU_model.fit(
    x_train, y_train,
    validation_data=(x_val, y_val),
    epochs=20,
    batch_size=64,
    callbacks=[es],
    verbose=1
)
```

```
Epoch 1/20
375/375            36s 84ms/step -
accuracy: 0.6687 - loss: 0.5861 - val_accuracy: 0.8210 - val_loss: 0.3948
Epoch 2/20
375/375            31s 83ms/step -
accuracy: 0.8682 - loss: 0.3170 - val_accuracy: 0.8750 - val_loss: 0.3180
Epoch 3/20
375/375            31s 83ms/step -
accuracy: 0.9048 - loss: 0.2416 - val_accuracy: 0.8930 - val_loss: 0.2923
Epoch 4/20
375/375            31s 83ms/step -
accuracy: 0.9417 - loss: 0.1567 - val_accuracy: 0.8850 - val_loss: 0.3664
Epoch 5/20
375/375            31s 83ms/step -
accuracy: 0.9582 - loss: 0.1174 - val_accuracy: 0.8820 - val_loss: 0.3812
Epoch 6/20
375/375            31s 83ms/step -
accuracy: 0.9691 - loss: 0.0873 - val_accuracy: 0.8890 - val_loss: 0.3759
Epoch 7/20
375/375            31s 83ms/step -
accuracy: 0.9818 - loss: 0.0539 - val_accuracy: 0.8790 - val_loss: 0.4524
Epoch 8/20
375/375            31s 83ms/step -
accuracy: 0.9856 - loss: 0.0447 - val_accuracy: 0.8520 - val_loss: 0.5963
Epoch 8: early stopping
Restoring model weights from the end of the best epoch: 3.
```

[9]:

```python
loss_bigru, acc_bigru = BiGRU_model.evaluate(x_test, y_test, verbose=1)
print(f"\nBi-GRU Test Loss: {loss_bigru:.4f}, Test Accuracy: {acc_bigru:.4f}")

print("\n--- Comparison (Test set) ---")
print(f"Bi-LSTM -> Loss: {loss_bilstm:.4f}, Acc: {acc_bilstm:.4f}")
print(f"Bi-GRU  -> Loss: {loss_bigru:.4f}, Acc: {acc_bigru:.4f}")




plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
plt.plot(history_bilstm.history['loss'], label='Train Loss (Bi-LSTM)')
plt.plot(history_bilstm.history['val_loss'], label='Val Loss (Bi-LSTM)')
plt.legend(); plt.title('Bi-LSTM Loss')

plt.subplot(1,2,2)
plt.plot(history_bigru.history['loss'], label='Train Loss (Bi-GRU)')
plt.plot(history_bigru.history['val_loss'], label='Val Loss (Bi-GRU)')
plt.legend(); plt.title('Bi-GRU Loss')
plt.show()
```

```
782/782              20s 26ms/step -
accuracy: 0.8755 - loss: 0.3214

Bi-GRU Test Loss: 0.3207, Test Accuracy: 0.8751

--- Comparison (Test set) ---
Bi-LSTM -> Loss: 0.3118, Acc: 0.8721
Bi-GRU  -> Loss: 0.3207, Acc: 0.8751
```



0.3 Questions 3: Think how you can create a simple model with RNN to predict the next word once you give a sentence to the model. Try to create one such model that can do this task. Use the same imdb dataset for the task. (Hint: Try to first prepare the sequences for training just like we did in gold price prediction, Sequences in which we have say 10 words as inputs and the next word as output. And we can plan like we can in our model the final layer with vocal size you have fixed that many number of neurons so that you can run with a softmax function to predict the probability of next word and train the model accordingly)

0.3.1 Importing necessary libraries

[10]:
```python
import numpy as np
from tensorflow.keras.datasets import imdb
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, SimpleRNN, Dense
from tensorflow.keras.utils import to_categorical
```

0.3.2 Loading the dataset

[11]:
```python
vocab_size = 5000
sequence_length = 10

(x_train,_),(_,_) = imdb.load_data(num_words = vocab_size)

all_words = [word for review in x_train for word in review]

sequences = []
next_words = []

for i in range(len(all_words) - sequence_length):
    seq = all_words[i:i+sequence_length]
    next_word = all_words[i+sequence_length]
    sequences.append(seq)
    next_words.append(next_word)

sequences = np.array(sequences)
next_words = to_categorical(next_words, num_classes = vocab_size)

print("Input shape:", sequences.shape)
print("Output shape:", next_words.shape)
```

```
Input shape: (5967831, 10)
Output shape: (5967831, 5000)
```

[12]:
```python
model = Sequential()
model.add(Embedding(input_dim=vocab_size, output_dim=50,␣
↪input_shape=(sequence_length,)))
model.add(SimpleRNN(128))
model.add(Dense(vocab_size, activation='softmax'))

model.compile(loss='categorical_crossentropy', optimizer='adam',␣
↪metrics=['accuracy'])
model.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(None, 10, 50)	250,000
simple_rnn (SimpleRNN)	(None, 128)	22,912
dense_2 (Dense)	(None, 5000)	645,000

Total params: 917,912 (3.50 MB)

Trainable params: 917,912 (3.50 MB)

Non-trainable params: 0 (0.00 B)

[13]:
```
es = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True,␣
 ↪verbose=1)
model.fit(sequences[:50000], next_words[:50000], epochs=50, batch_size=128,␣
 ↪callbacks = [es], verbose = 1)
```

```
Epoch 1/50

WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
I0000 00:00:1761294434.450323     795 service.cc:148] XLA service 0x7867040d2a70
initialized for platform CUDA (this does not guarantee that XLA will be used).
Devices:
I0000 00:00:1761294434.455911     795 service.cc:156]   StreamExecutor device
(0): Tesla T4, Compute Capability 7.5
I0000 00:00:1761294434.455936     795 service.cc:156]   StreamExecutor device
(1): Tesla T4, Compute Capability 7.5

 42/391              1s 4ms/step -
accuracy: 0.0661 - loss: 7.8775

I0000 00:00:1761294436.150933     795 device_compiler.h:188] Compiled cluster
using XLA!  This line is logged at most once for the lifetime of the process.

391/391              6s 7ms/step -
accuracy: 0.0992 - loss: 6.5719
Epoch 2/50
 43/391              1s 4ms/step -
accuracy: 0.1027 - loss: 5.9133

/usr/local/lib/python3.11/dist-
packages/keras/src/callbacks/early_stopping.py:153: UserWarning: Early stopping
conditioned on metric `val_loss` which is not available. Available metrics are:
accuracy,loss
  current = self.get_monitor_value(logs)

391/391              1s 4ms/step -
accuracy: 0.1123 - loss: 5.8558
Epoch 3/50
391/391              2s 4ms/step -
accuracy: 0.1321 - loss: 5.6136
Epoch 4/50
```

```
391/391             2s 4ms/step -
accuracy: 0.1489 - loss: 5.3731
Epoch 5/50
391/391             2s 4ms/step -
accuracy: 0.1590 - loss: 5.1967
Epoch 6/50
391/391             2s 4ms/step -
accuracy: 0.1648 - loss: 5.0751
Epoch 7/50
391/391             2s 4ms/step -
accuracy: 0.1677 - loss: 4.9613
Epoch 8/50
391/391             2s 4ms/step -
accuracy: 0.1721 - loss: 4.8832
Epoch 9/50
391/391             2s 4ms/step -
accuracy: 0.1749 - loss: 4.7759
Epoch 10/50
391/391             2s 4ms/step -
accuracy: 0.1801 - loss: 4.6786
Epoch 11/50
391/391             2s 4ms/step -
accuracy: 0.1844 - loss: 4.5799
Epoch 12/50
391/391             2s 4ms/step -
accuracy: 0.1911 - loss: 4.4808
Epoch 13/50
391/391             2s 4ms/step -
accuracy: 0.1946 - loss: 4.3899
Epoch 14/50
391/391             1s 4ms/step -
accuracy: 0.2019 - loss: 4.2916
Epoch 15/50
391/391             1s 4ms/step -
accuracy: 0.2082 - loss: 4.1808
Epoch 16/50
391/391             2s 4ms/step -
accuracy: 0.2162 - loss: 4.0905
Epoch 17/50
391/391             1s 4ms/step -
accuracy: 0.2231 - loss: 4.0276
Epoch 18/50
391/391             1s 4ms/step -
accuracy: 0.2311 - loss: 3.9502
Epoch 19/50
391/391             2s 4ms/step -
accuracy: 0.2419 - loss: 3.8620
Epoch 20/50
```

```
391/391              2s 4ms/step -
accuracy: 0.2557 - loss: 3.7380
Epoch 21/50
391/391              2s 4ms/step -
accuracy: 0.2700 - loss: 3.6187
Epoch 22/50
391/391              2s 4ms/step -
accuracy: 0.2850 - loss: 3.5032
Epoch 23/50
391/391              2s 4ms/step -
accuracy: 0.3001 - loss: 3.3936
Epoch 24/50
391/391              2s 4ms/step -
accuracy: 0.3150 - loss: 3.2961
Epoch 25/50
391/391              2s 4ms/step -
accuracy: 0.3276 - loss: 3.2143
Epoch 26/50
391/391              2s 4ms/step -
accuracy: 0.3411 - loss: 3.1383
Epoch 27/50
391/391              2s 4ms/step -
accuracy: 0.3516 - loss: 3.0724
Epoch 28/50
391/391              2s 4ms/step -
accuracy: 0.3638 - loss: 3.0046
Epoch 29/50
391/391              2s 4ms/step -
accuracy: 0.3765 - loss: 2.9366
Epoch 30/50
391/391              2s 4ms/step -
accuracy: 0.3866 - loss: 2.8624
Epoch 31/50
391/391              2s 4ms/step -
accuracy: 0.3955 - loss: 2.8067
Epoch 32/50
391/391              2s 4ms/step -
accuracy: 0.4034 - loss: 2.7543
Epoch 33/50
391/391              2s 4ms/step -
accuracy: 0.4137 - loss: 2.7073
Epoch 34/50
391/391              2s 4ms/step -
accuracy: 0.4239 - loss: 2.6447
Epoch 35/50
391/391              2s 4ms/step -
accuracy: 0.4350 - loss: 2.5831
Epoch 36/50
```

```
391/391              2s 4ms/step -
accuracy: 0.4442 - loss: 2.5384
Epoch 37/50
391/391              2s 4ms/step -
accuracy: 0.4515 - loss: 2.4964
Epoch 38/50
391/391              2s 4ms/step -
accuracy: 0.4628 - loss: 2.4421
Epoch 39/50
391/391              2s 4ms/step -
accuracy: 0.4748 - loss: 2.3861
Epoch 40/50
391/391              2s 4ms/step -
accuracy: 0.4819 - loss: 2.3363
Epoch 41/50
391/391              2s 4ms/step -
accuracy: 0.4911 - loss: 2.2901
Epoch 42/50
391/391              2s 4ms/step -
accuracy: 0.4961 - loss: 2.2548
Epoch 43/50
391/391              2s 4ms/step -
accuracy: 0.5049 - loss: 2.2205
Epoch 44/50
391/391              2s 4ms/step -
accuracy: 0.5081 - loss: 2.2010
Epoch 45/50
391/391              2s 4ms/step -
accuracy: 0.5114 - loss: 2.1715
Epoch 46/50
391/391              2s 4ms/step -
accuracy: 0.5130 - loss: 2.1510
Epoch 47/50
391/391              2s 4ms/step -
accuracy: 0.5170 - loss: 2.1339
Epoch 48/50
391/391              2s 4ms/step -
accuracy: 0.5190 - loss: 2.1155
Epoch 49/50
391/391              2s 4ms/step -
accuracy: 0.5227 - loss: 2.0943
Epoch 50/50
391/391              2s 4ms/step -
accuracy: 0.5273 - loss: 2.0676
```

```
[13]: <keras.src.callbacks.history.History at 0x7867c193a990>
```

[21]:
```
word_index = imdb.get_word_index()

index_word = {index + 3: word for word, index in word_index.items() if index+3␣
↪< vocab_size}
index_word[0] = '<PAD>'
index_word[1] = '<START>'
index_word[2] = '<UNK>'
```

[30]:
```
def predict_next_word(model, seed_seq, index_word, sequence_length=10):

    seq_input = pad_sequences([seed_seq], maxlen=sequence_length)

    pred_probs = model.predict(seq_input, verbose=0)[0]

    next_word_index = np.argmax(pred_probs)

    next_word = index_word.get(next_word_index, '<UNK>')

    return next_word
```

[33]:
```
num_samples = 5  # number of sequences to test
seed_sequences = [all_words[i:i+sequence_length] for i in range(num_samples)]

# Convert seed sequences to actual words for display
seed_words_list = [[index_word.get(idx, '<UNK>') for idx in seq] for seq in␣
↪seed_sequences]


predicted_next_words = []

for seq in seed_sequences:
    next_word = predict_next_word(model, seq, index_word,␣
↪sequence_length=sequence_length)
    predicted_next_words.append(next_word)


for i in range(num_samples):
    print(f"Seed sequence {i+1}: {' '.join(seed_words_list[i])}")
    print(f"Predicted next word: {predicted_next_words[i]}")
    print("-" * 50)
```

```
Seed sequence 1: <START> this film was just brilliant casting location scenery
story
Predicted next word: as
--------------------------------------------------
Seed sequence 2: this film was just brilliant casting location scenery story
direction
Predicted next word: everyone's
```

```
--------------------------------------------------
Seed sequence 3: film was just brilliant casting location scenery story
direction everyone's
Predicted next word: be
--------------------------------------------------
Seed sequence 4: was just brilliant casting location scenery story direction
everyone's really
Predicted next word: suited
--------------------------------------------------
Seed sequence 5: just brilliant casting location scenery story direction
everyone's really suited
Predicted next word: to
--------------------------------------------------
```