Assessment No.	Date	Question	Marks	Weightage
5	1-10-2024	**1. Text processing, Language Modeling using RNN.**	10	10%

1. Text processing, Language Modeling using RNN (LSTM/GRU).

- In this experiment, we will learn how we can use **recurrent neural networks (RNNs)** for **text classification** tasks in **natural language processing (NLP)**.
- We would be performing sentiment analysis, one of the text classification techniques on the IMDB movie review dataset.
- We would implement the network from scratch and train it to identify if the review is positive or negative.

→RNN for Text Classifications in NLP

- In Natural Language Processing (NLP), Recurrent Neural Networks (RNNs) are a potent family of artificial neural networks that are crucial, especially for text classification tasks.
- RNNs are uniquely able to capture sequential dependencies in data, which sets them apart from standard feedforward networks and makes them ideal for processing and comprehending sequential information, like language.
- RNNs are particularly good at evaluating the contextual links between words in NLP text classification, which helps them identify patterns and semantics that are essential for correctly classifying textual information.
- Because of their versatility, RNNs are essential for creating complex models for tasks like document classification, spam detection, and sentiment analysis.

→Recurrent Neural Networks (RNNs)

- Recurrent neural networks are a specific kind of artificial neural network created to work with sequential data.

- It is utilized particularly in activities involving natural language processing, such as language translation, speech recognition, sentiment analysis, natural language generation, and summary writing.
- Unlike feedforward neural networks, RNNs include a loop or cycle built into their architecture that acts as a "memory" to hold onto information over time.
- This distinguishes them from feedforward neural networks.

→**Implementation of RNN for Text Classifications:** First, we will need the following dependencies to be imported.

```
import tensorflow as tf
import tensorflow_datasets as tfds

import numpy as np
import matplotlib.pyplot as plt
```

The code imports the TensorFlow library (tf) along with its dataset module (tensorflow_datasets as tfds). Additionally, it imports NumPy (np) for numerical operations and Matplotlib (plt) for plotting. These libraries are commonly used for machine learning tasks and data visualization.

1. Load the dataset

IMDB movies review dataset is the dataset for binary sentiment classification containing 25,000 highly polar movie reviews for training, and 25,000 for testing. This dataset can be acquired from this website or we can also use *tensorflow_datasets* library to acquire it.

```
# Obtain the imdb review dataset from tensorflow datasets
dataset = tfds.load('imdb_reviews', as_supervised=True)

# Seperate test and train datasets
train_dataset, test_dataset = dataset['train'], dataset['test']

# Split the test and train data into batches of 32
# and shuffling the training set
batch_size = 32
train_dataset = train_dataset.shuffle(10000)
train_dataset = train_dataset.batch(batch_size)
test_dataset = test_dataset.batch(batch_size)
```

The code loads the IMDb review dataset using TensorFlow Datasets (tfds.load('imdb_reviews', as_supervised=True)). It then separates the dataset into training and testing sets (train_dataset and test_dataset). Finally, it batches the training and testing data into sets of 32 samples each, and shuffles the training set to enhance the learning process by preventing the model from memorizing the order of

the training samples. The batch_size variable determines the size of each batch. Printing a sample review and its label from the training set.

```
example, label = next(iter(train_dataset))
print('Text:\n', example.numpy()[0])
print('\nLabel: ', label.numpy()[0])
```

Output:

```
Text:
 b'Stumbling upon this HBO special late one night, I was absolutely taken by
this
 attractive British "executive transvestite." I have never laughed so hard
over
 European History or any of the other completely worthwhile point Eddie
Izzard made.
  I laughed so much that I woke up my mother sleeping at the other end of
the house...'
Label:  1
```

The code uses the iter function to create an iterator for the training dataset and then extracts the first batch using next(iter(train_dataset)). It prints the text of the first example in the batch (example.numpy()[0]) and its corresponding label (label.numpy()[0]). This provides a glimpse into the format of the training data, helping to understand how the text and labels are structured in the IMDb review dataset.

2. Build the Model

In this section, we will define the model we will use for sentiment analysis. The initial layer of this architecture is the text factorization layer, responsible for encoding the input text into a sequence of token indices. These tokens are subsequently fed into the embedding layer, where each word is assigned a trainable vector. After enough training, these vectors tend to adjust themselves such that words with similar meanings have similar vectors. This data is then passed to RNN layers which process these sequences and finally convert it to a single logit as the classification output.

Text Vectorization

We will first perform text factorization and let the encoder map all the words in the training dataset to a token. We can also see in the example below how we can encode and decode the sample review into a vector of integers.

```
# Using the TextVectorization layer to normalize, split, and map strings
# to integers.
```

```
encoder = tf.keras.layers.TextVectorization(max_tokens=10000)
encoder.adapt(train_dataset.map(lambda text, _: text))

# Extracting the vocabulary from the TextVectorization layer.
vocabulary = np.array(encoder.get_vocabulary())

# Encoding a test example and decoding it back.
original_text = example.numpy()[0]
encoded_text = encoder(original_text).numpy()
decoded_text = ' '.join(vocabulary[encoded_text])

print('original: ', original_text)
print('encoded: ', encoded_text)
print('decoded: ', decoded_text)
```

Output:

```
original:
 b'Stumbling upon this HBO special late one night, I was absolutely taken by
this
 attractive British "executive transvestite." I have never laughed so hard
over
 European History or any of the other completely worthwhile point Eddie
Izzard made.
 I laughed so much that I woke up my mother sleeping at the other end of the
house...'
encoded:
 [9085  720   11 4335  309  534   29  311   10   14  412  602   33   11
 1523  683 3505    1   10   26  110 1434   38  264  126 1835  489   42
   99    5    2   81  325 2601  215 1781 9352   91   10 1434   38   73
   12   10 9259   58   56  462 2703   31    2   81  129    5    2  313]
decoded:
 stumbling upon this hbo special late one night i was absolutely taken by
this
 attractive british executive [UNK] i have never laughed so hard over
european history
  or any of the other completely worthwhile point eddie izzard made i
laughed so much
  that i woke up my mother sleeping at the other end of the house
```

The code defines a TextVectorization layer (encoder) with a vocabulary size limit of 10,000 tokens and adapts it to the training dataset. It then extracts the vocabulary from the TextVectorization layer. The code encodes an example text using the TextVectorization layer (encoder(original_text).numpy()) and decodes it back to the original form using the vocabulary. This demonstrates how the TextVectorization layer can normalize, tokenize, and map strings to integers, facilitating text processing for machine learning models.

Create the model

Now, we will use this trained encoder along with other layers to define a model as discussed earlier. In TensorFlow, while the RNN layers cannot be directly used with a Bidirectional wrapper and Embedding layer, we can employ its derivatives, like LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit). In this example, we will use LSTM layers to define the model.

```
# Creating the model
model = tf.keras.Sequential([
    encoder,
    tf.keras.layers.Embedding(
        len(encoder.get_vocabulary()), 64, mask_zero=True),
    tf.keras.layers.Bidirectional(
        tf.keras.layers.LSTM(64,  return_sequences=True)),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(32)),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(1)
])

# Summary of the model
model.summary()

# Compile the model
model.compile(
    loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
    optimizer=tf.keras.optimizers.Adam(),
    metrics=['accuracy']
)
```

Output:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 text_vectorization (TextVe  (None, None)              0
 ctorization)

 embedding (Embedding)       (None, None, 64)          640000

 bidirectional (Bidirection  (None, None, 128)         66048
 al)

 bidirectional_1 (Bidirecti  (None, 64)                41216
 onal)

 dense (Dense)               (None, 64)                4160

 dense_1 (Dense)             (None, 1)                 65
```

```
=================================================================
Total params: 751489 (2.87 MB)
Trainable params: 751489 (2.87 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

The code defines a Sequential model using TensorFlow's Keras API. It includes a TextVectorization layer (encoder) for tokenization, an Embedding layer with 64 units, two Bidirectional LSTM layers with 64 and 32 units, respectively, a Dense layer with 64 units and ReLU activation, and a final Dense layer with a single unit for binary classification. The model is compiled using binary cross-entropy loss, the Adam optimizer, and accuracy as the evaluation metric. The summary provides an overview of the model architecture, showcasing the layers and their parameters.

3. Training the model

Now, we will train the model we defined in the previous step.

```
# Training the model and validating it on test set
history = model.fit(
    train_dataset,
    epochs=5,
    validation_data=test_dataset,
)
```

Output:

```
Epoch 1/5
782/782 [==============================] - 1209s 2s/step - loss: 0.3657 -
accuracy: 0.8266 - val_loss: 0.3110 - val_accuracy: 0.8441
Epoch 2/5
782/782 [==============================] - 1269s 2s/step - loss: 0.2147 -
accuracy: 0.9126 - val_loss: 0.3566 - val_accuracy: 0.8590
Epoch 3/5
782/782 [==============================] - 1146s 1s/step - loss: 0.1616 -
accuracy: 0.9380 - val_loss: 0.3764 - val_accuracy: 0.8670
Epoch 4/5
782/782 [==============================] - 1963s 3s/step - loss: 0.0962 -
accuracy: 0.9647 - val_loss: 0.4271 - val_accuracy: 0.8564
Epoch 5/5
782/782 [==============================] - 1121s 1s/step - loss: 0.0573 -
accuracy: 0.9796 - val_loss: 0.5516 - val_accuracy: 0.8575
```

The code trains the defined model (model) using the training dataset (train_dataset) for 5 epochs. It also validates the model on the test dataset (test_dataset). The training progress and performance metrics are stored in the history variable for further analysis or visualization.

4. Plotting the results

Plotting the training and validation accuracy and loss plots.

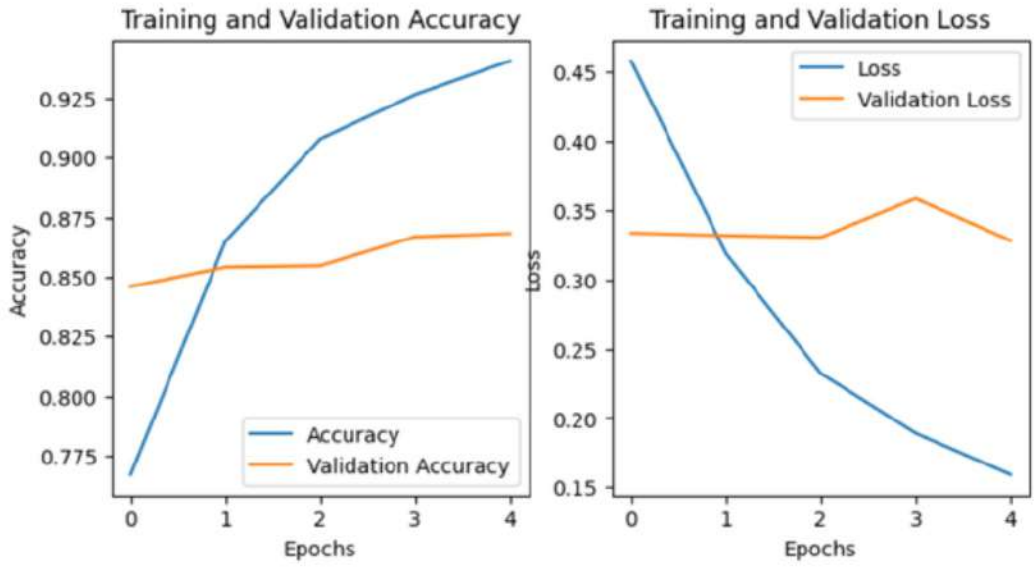
```
# Plotting the accuracy and loss over time
# Training history
history_dict = history.history

# Seperating validation and training accuracy
acc = history_dict['accuracy']
val_acc = history_dict['val_accuracy']

# Seperating validation and training loss
loss = history_dict['loss']
val_loss = history_dict['val_loss']

# Plotting
plt.figure(figsize=(8, 4))
plt.subplot(1, 2, 1)
plt.plot(acc)
plt.plot(val_acc)
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend(['Accuracy', 'Validation Accuracy'])
plt.subplot(1, 2, 2)
plt.plot(loss)
plt.plot(val_loss)
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend(['Loss', 'Validation Loss'])
plt.show()
```

Output:



The code visualizes the training and validation accuracy as well as the training and validation loss over epochs. It extracts accuracy and loss values from the training history (history_dict). The matplotlib library is then used to create a side-by-side subplot, where the left subplot displays accuracy trends, and the right subplot shows loss trends over epochs.

5. Testing the trained model

Now, we will test the trained model with a random review and check its output.

```
# Making predictions
sample_text = (
    '''The movie by GeeksforGeeks was so good and the animation are so dope.
    I would recommend my friends to watch it.'''
)
predictions = model.predict(np.array([sample_text]))
print(*predictions[0])

# Print the label based on the prediction
if predictions[0] > 0:
    print('The review is positive')
else:
    print('The review is negative')
```

Output:

```
1/1 [==============================] - 0s 33ms/step
5.414222
The review is positive
```

Note: Also refer the following link for the detailed experimentations.

1. Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. (2011). Learning Word Vectors for Sentiment Analysis. *The 49th Annual Meeting of the Association for Computational Linguistics (ACL 2011)*.

2. https://www.kaggle.com/code/quadeer15sh/introduction-to-language-modelling-using-rnns