# NN and Neural Networks Assignment 1 Report

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### Part A

1. Sanity Check after pre-processing:

```
[['[', 'Sense', 'and', 'Sensibility', 'by', 'Jane', 'Austen', '1811', ']'], ['CHAPTER', '1'], ...]
The new length of the preprocessed output
13660
[['Sense', 'Sensibility', 'Jane', 'Austen'], ['The', 'family', 'Dashwood', 'long', 'settled', 'Sussex'],
```

2. Sanity Check after Creating the Corpus Vocabulary and Preparing the Data:

```
print('Number of unique words:', len(word2idx))

Number of unique words: 10808

[ ] print('\nSample word2idx: ', list(word2idx.items())[:10])

Sample word2idx: [('Sense', 1), ('Sensibility', 2), ('Jane', 3), ('Austen', 4), ('The', 5), ('family', 6)

[ ] print('\nSample idx2word:', list(idx2word.items())[:10])

Sample idx2word: [(1, 'Sense'), (2, 'Sensibility'), (3, 'Jane'), (4, 'Austen'), (5, 'The'), (6, 'family'),

[ ] print('\nSample sents_as_id:', prepareSentsAsId(preprocessed_sample))

Sample sents_as_id: [[1, 2, 3, 4], [5, 6, 7, 8, 9, 10, 11, 12, 13]]
```

3. model.summary Sanity Check:

model.summary()			
Model: "model"			
Layer (type)	Output Shape	Param #	Connected to
input_2 (InputLayer)	[(None, 1)]	0	
input_3 (InputLayer)	[(None, 1)]	0	
target_embed_layer (Embedding)	(None, 1, 100)	1080800	input_2[0][0]
context_embed_layer (Embedding)	(None, 1, 100)	1080800	input_3[0][0]
reshape (Reshape)	(None, 100)	0	target_embed_layer[0][0]
reshape_1 (Reshape)	(None, 100)	0	context_embed_layer[0][0]
dot (Dot)	(None, 1)	0	reshape[0][0] reshape_1[0][0]
activation (Activation)	(None, 1)	0	dot[0][0]

Total params: 2,161,600 Trainable params: 2,161,600 Non-trainable params: 0

4. What would be the Inputs and Outputs to the model be?

Inputs are wordtoindex of context word and target word. Outputs are probability of pair is positive or negative

How would you use the Keras framework to create this architecture?

Define the layers in the model. Connect the flow of input and outputs through each layer. Fit the model and then evaluate on test data to get fast and accurate results.

What are the reasons this training approach is considered inefficient?

Sometimes when we use two different embedding Matrices, same word may have different vectors.

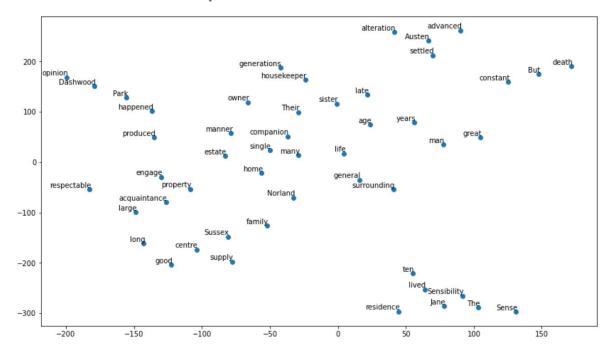
5. Printing the dataframe for word embeddings

# [ ] from pandas import DataFrame print(DataFrame(word\_embeddings, index=idx2word.values()).head(10))

```
98
                                                                           99
Sense
             0.010083 -0.012033 -0.016542
                                                 0.003729 -0.014503
                                                                     0.019011
                                            . . .
                                 0.008540
Sensibility 0.010376 -0.023291
                                                 0.030873 -0.024183
                                                                     0.011487
Jane
             0.016210 -0.014352
                                 0.023118
                                                 0.020753 -0.014591
Austen
             0.011112 -0.078037
                                 0.038333
                                                0.008071
                                                          0.010603
                                                                     0.035187
                                            . . .
The
             0.005096 -0.014580 -0.007197
                                                0.015193 -0.015456
                                                                     0.022403
family
             0.027164 -0.017446 -0.005271
                                            ... -0.011948
                                                          0.054367
Dashwood
            -0.145946 -0.032238
                                 0.018873
                                                0.052960 -0.162810
                                                                     0.091453
                                            . . .
            -0.236915 -0.052849
long
                                 0.114623
                                                0.102109 -0.154706 -0.048957
settled
             0.067867 -0.000789 -0.019915
                                                0.061657 -0.019171
Sussex
             0.053522 -0.021792 0.059648
                                                0.058734 -0.012536
```

[10 rows x 100 columns]

### 6. Plt.annotate Output:



# Part B

1. Readying the inputs for the LSTM Sanity Check:

Length	of s	sample	trai	in_data	befo	re p	repro	cessi	ing: 2	218							
Length	of	sample	trai	in_data	afte	er pr	eprod	essir	ng: 50	90							
Sample	tra:	in dat	a: [	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	0	0	0	0	0	0	0	0	0	0	0	0				
0	0	1	13	21	15	42	529		1621		64		4467				
	3940	3	172		255	4	24	99	42	837	111	49	669				
2	8	34	479	283	4	149	3	171	111	166	2	335	384				
38	3			1110	16	545	37	12	446	3	191	49	15				
5	146	2024	18	13	21	3	1919	4612	468	3	21	70	86				

# 2. Structure of the model obtained:

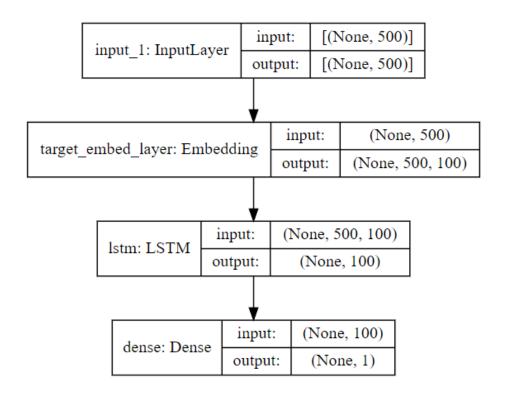
### model.summary()

Model: "model"

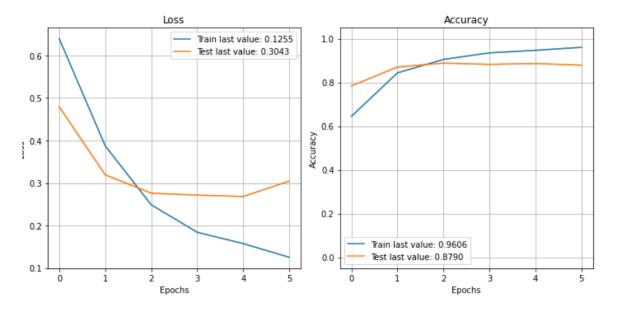
Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 500)]	0
target_embed_layer (Embeddin	(None, 500, 100)	1000000
lstm (LSTM)	(None, 100)	80400
dense (Dense)	(None, 1)	101

Total params: 1,080,501 Trainable params: 1,080,501 Non-trainable params: 0

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# 3. Plot of training and validation accuracy and loss data:



The optimal stopping point should be about 2 epochs where both validation and training data converge so that we don't get any overfitting.

# 4. Output of the test accuracy and test loss:

### 5. model.summary

model.summary()

(10000, 100) Model: "model 2"		
Layer (type)	Output Shape	Param #
<pre>input_3 (InputLayer)</pre>	[(None, 500)]	 0

target\_embed\_layer (Embeddin (None, 500, 100) 1000000

lstm\_2 (LSTM) (None, 100) 80400

dense\_2 (Dense) (None, 1) 101

Trainable params: 1,080,501 Non-trainable params: 0

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#### Sanity Check

Print the shape of the word embeddings using the line of code below. It should return (VOCAB

```
[17] print('Shape of word_embeddings:', word_embeddings.shape)

Shape of word_embeddings: (10000, 100)
```

# **6.** Visualizing the reviews:

### Step 3: Visualize sample review

View a sample review text using the lines of code below:

```
[20] print(' '.join(idx2word[idx] for idx in train_data[0]))

<START> this film was just brilliant casting location scenery story direction everyone's really suited the part they played and
```

# 7. Visualizing the word embeddings:

### 8. Visualizing the Word\_Embeddings

Visualize the word embeddings for 10 of the words using pandas DataFrame like we did in lab 3

```
[21] from pandas import DataFrame
    print(DataFrame(word_embeddings, index=idx2word.values()).head(10))
                                2 ...
                                                         98
                   0
                                                97
            -0.018422 -0.028894 0.044005 ... 0.042796 -0.003599 0.045664
    woods
    hanging -0.050355 0.019669 -0.023673 ... 0.050463 0.028757 0.005433
    woodv
             \hbox{-0.032700 -0.030171 -0.001717 } \dots \hbox{-0.027080 } \hbox{0.004520 -0.017445}
    arranged -0.045771 -0.032585 0.026716 ... -0.035090 0.019204 0.026020
    bringing -0.024623 0.004106 -0.001668 ... 0.027033 -0.022006 0.025479
    wooden
             0.032191 0.002833 0.033943 ... -0.006398 -0.003582 0.011662
    errors
            dialogs -0.011855 -0.045498 -0.023849 ... -0.029265 -0.040318 -0.026097
    kids -0.022314 -0.028868 -0.038487 ... -0.016460 0.025459 0.007085
    uplifting -0.028250 0.007414 0.048871 ... -0.047134 0.028057 0.025444
    [10 rows x 100 columns]
```

8. Create a new model that is a copy of the model step 3. To this new model, add two dropout layers, one between the embedding layer and the LSTM layer and another between the LSTM layer and the output layer. Repeat steps 4 and 5 for this model. What do you observe?

Answer: Dropout is a technique used to prevent a model from overfitting. Dropout works by randomly setting the outgoing edges of hidden units (neurons that make up hidden layers) to 0 at each update of the training phase. I observed that the validation and training accuracy came out to be similar about around 51%. I can clearly observe that there is no overfitting now and adding these dropout layers increased the reliability of the model.

Q: Experiment with training the model with batch sizes of 1, 32, len(training\_data). What do you observe?

Answer: Although with smaller batch size, I got a much more accurate test result, it took so much computational power and time as the batch size was decreased. Another downside of using

a smaller batch size is that the model is not guaranteed to converge to the global optima. It will bounce around the global optima.

### With Batch size = 32

```
Total params: 1,080,501
Trainable params: 1,080,501
Non-trainable params: 0
```

#### With Batch Size = 1

As you can see with a smaller batch size, it took even longer for a single epoch.

# Part C

1. model.summary and plotting of the graph:

# model.summary()

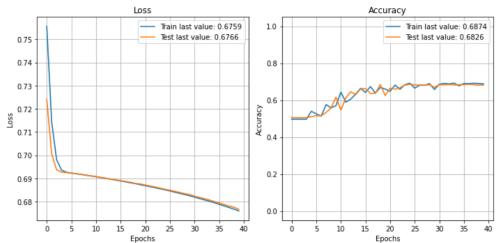
Model: "model"

Layer (type)	Output Shape	Param #
input_4 (InputLayer)	[(None, 256)]	0
lambda_3 (Lambda)	(None, 256, 10000)	0
global_average_pooling1d_mas	(None, 10000)	0
dense (Dense)	(None, 16)	160016
dense_1 (Dense)	(None, 1)	17

Total params: 160,033 Trainable params: 160,033 Non-trainable params: 0

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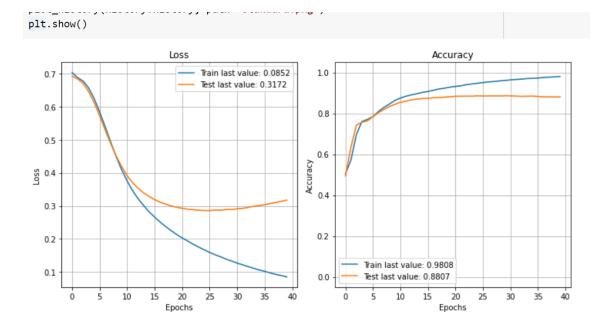


# 2. model2.summary and plotting of training and validation loss:

Model: "model\_2"

Layer (type)	Output Shape	Param #
input_7 (InputLayer)	[(None, 256)]	0
target_embed_layer (Embeddin	(None, 256, 100)	1000000
global_average_pooling1d_mas	(None, 100)	0
dense_4 (Dense)	(None, 16)	1616
dense_5 (Dense)	(None, 1)	17

Total params: 1,001,633 Trainable params: 1,001,633 Non-trainable params: 0



# 3. model3.summary and plotting the validation and training loss:

# With freezing the weights:

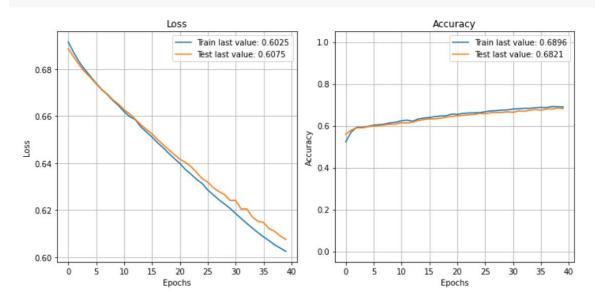
```
model = Model (inputs=[input_review], outputs=[label])
model.summary()
```

Model: "model\_4"

Layer (type)	Output Shape	Param #
input_9 (InputLayer)	[(None, 256)]	0
GloVe_Embeddings (Embedding)	(None, 256, 300)	120000300
global_average_pooling1d_mas	(None, 300)	0
dense_8 (Dense)	(None, 16)	4816
dense_9 (Dense)	(None, 1)	17

Total params: 120,005,133 Trainable params: 4,833

Non-trainable params: 120,000,300



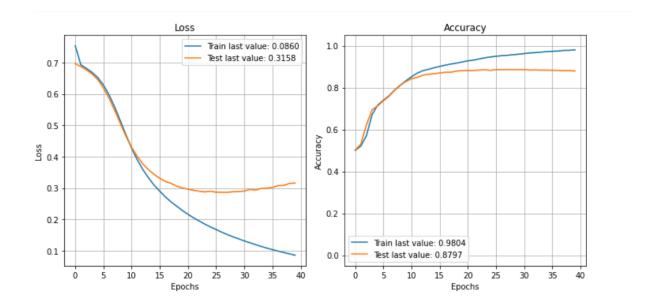
# With fine tuning:

Model: "model\_3"

Layer (type)	Output Shape	Param #
input_4 (InputLayer)	[(None, 256)]	0
GloVe_Embeddings (Embedding)	(None, 256, 300)	120000300
global_average_pooling1d_mas	(None, 300)	0
dense_6 (Dense)	(None, 16)	4816
dense_7 (Dense)	(None, 1)	17

Total params: 120,005,133 Trainable params: 120,005,133

Non-trainable params: 0



# LSTM with pre-trained word embeddings:

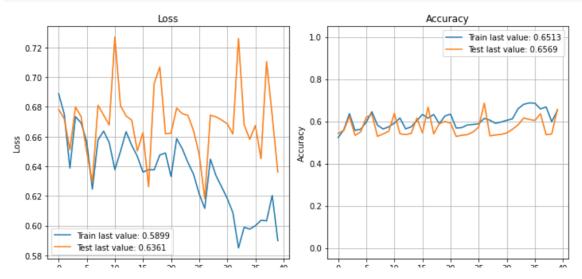
Model: "model 4"
------------------

Layer (type)	Output Shape	Param #
input_5 (InputLayer)	[(None, 256)]	0
GloVe_Embeddings (Embedding)	(None, 256, 300)	120000300
lstm (LSTM)	(None, 100)	160400
dense_8 (Dense)	(None, 1)	101

Total params: 120,160,801 Trainable params: 160,501

Non-trainable params: 120,000,300

```
from plot_keras_history import plot_history
import matplotlib.pyplot as plt
plot_history(history.history, path="standard.png")
plt.show()
```



4. model.summary and plotting of the validation and training loss:

# Adding a dense layer:

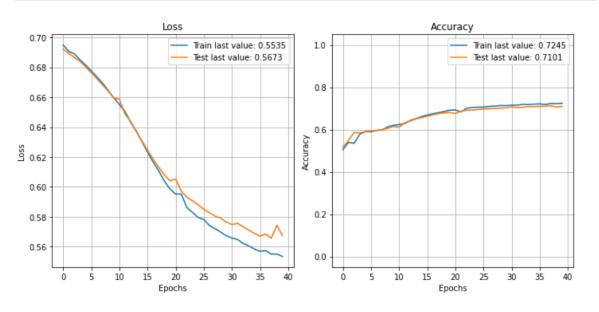
### model4.summary()

Model: "model\_5"

Layer (type)	Output Shape	Param #
input_6 (InputLayer)	[(None, 256)]	0
GloVe_Embeddings (Embedding)	(None, 256, 300)	120000300
global_average_pooling1d_mas	(None, 300)	0
dense_9 (Dense)	(None, 100)	30100
dense_10 (Dense)	(None, 16)	1616
dense_11 (Dense)	(None, 1)	17

Total params: 120,032,033 Trainable params: 31,733

Non-trainable params: 120,000,300



# Adding another dense layer:

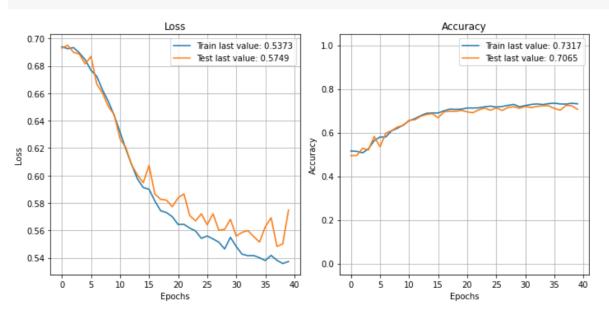
Model: "model\_6"

Layer (type)	Output Shape	Param #
input_7 (InputLayer)	[(None, 256)]	0
GloVe_Embeddings (Embedding)	(None, 256, 300)	120000300
global_average_pooling1d_mas	(None, 300)	0
dense_12 (Dense)	(None, 300)	90300
dense_13 (Dense)	(None, 100)	30100
dense_14 (Dense)	(None, 16)	1616
dense_15 (Dense)	(None, 1)	17

Total params: 120,122,333 Trainable params: 122,033

Non-trainable params: 120,000,300





After comparing we can see that there is improvement in performance when adding an extra dense layer. The loss value decreases and accuracy increases.

These two experiments show that adding extra dense layers can slightly improve accuracy over model 3-1.

# 5. Model.summary and plotting the validation and training loss:

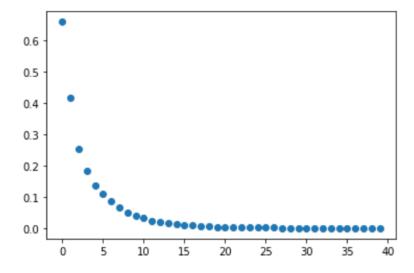
Model: "model\_7"

Layer (type)	Output Shape	Param #
input_8 (InputLayer)	[(None, 256)]	0
embed_layer (Embedding)	(None, 256, 300)	3000000
conv1d (Conv1D)	(None, 251, 100)	180100
global_average_pooling1d_mas	(None, 100)	0
dense_16 (Dense)	(None, 1)	101
=======================================		========

Total params: 3,180,201 Trainable params: 3,180,201 Non-trainable params: 0

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```
# your code goes here
plt.scatter(history.epoch, history.history['loss'])
plt.show()
```



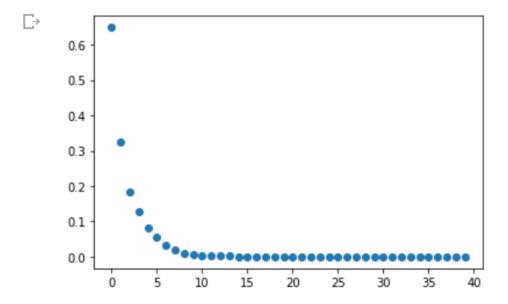
# Adding extra convolutional layer:

Model: "model\_8"

Layer (type)	Output Shape	Param #
input_9 (InputLayer)	[(None, 256)]	0
embed_layer (Embedding)	(None, 256, 300)	3000000
conv1d_1 (Conv1D)	(None, 251, 100)	180100
conv1d_2 (Conv1D)	(None, 246, 100)	60100
global_average_pooling1d_mas	(None, 100)	0
dense_17 (Dense)	(None, 1)	101

Total params: 3,240,301 Trainable params: 3,240,301 Non-trainable params: 0

[49] # your code goes here
 plt.scatter(history.epoch, history.history['loss'])
 plt.show()



I observed that adding an extra convolutional layer here reduces the training loss but the evaluation accuracy is worse than the model without the extra convolutional layer.

Adding more layers can help to extract more features. But we can do that up to a certain extent. After some point, instead of extracting features, we tend to overfit the data. Overfitting can lead to errors in one form or another, such as false positives.

# Part D

### 1. Preprocessing the data:

```
['jay', 'z', 'j
x_dev_topic[0]:
             .
joins', 'instagram', 'with', 'nostalgic', 'tribute', 'to', 'michael', 'jackson', 'jay', 'z', 'apparently', 'joined', 'i
['michael',
x_dev_tweet_int[0]:
[7269, 7022, 1054, 25880, 24821, 28295, 25462, 16889, 15313, 7882, 7269, 7022, 25999, 14715, 25880, 25333, 16110, 4229, 21320, 21173,
x_dev_topic_int[0]:
[15313, 7882]
Before paded:
['microsoft', '<START>', 'dear', 'microsoft', 'the', 'newooffice', 'for', 'mac', 'is', 'great', 'and', 'all', 'but', 'I
[31463, 1, 3310, 31463, 29114, 6170, 20972, 9602, 30518, 5879, 4229, 18197, 5883, 13993, 8537, 19463, 16854]
          1 3310 31463 29114 6170 20972 9602 30518 5879 4229 18197
  5883 13993 8537 19463 16854
    0
                                   0
                                         0
                                               0
                   0 0
     0
                                   0
                                               0
```

# 2.model.summary() command to show your model structure, and training epochs, and evaluation results:

Model:	"model"	

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 128)]	0
target_embed_layer (Embeddin	(None, 128, 100)	3257500
global_average_pooling1d_mas	(None, 100)	0
dense (Dense)	(None, 16)	1616
dense_1 (Dense)	(None, 1)	17

Total params: 3,259,133 Trainable params: 3,259,133 Non-trainable params: 0

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### **Epochs:**

```
35/35 [====
   Enoch 2/30
   35/35 [=====
Epoch 3/30
Epoch 4/30
Epoch 5/30
35/35 [====
   Epoch 6/30
   35/35 [=====
Epoch 7/30
Epoch 8/30
35/35 [============] - 1s 27ms/step - loss: 0.4723 - accuracy: 0.7874 - val_loss: 0.5390 - val_accuracy: 0.7442
Epoch 9/30
   Epoch 10/30
   35/35 [=====
Epoch 11/30
35/35 [=============] - 1s 26ms/step - loss: 0.3552 - accuracy: 0.8378 - val_loss: 0.4778 - val_accuracy: 0.7570
```

#### **Evaluation:**

# CNN or LSTM without pre-trained word embeddings:

### **Summary:**

Model: "model\_1"

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 128)]	0
embed_layer (Embedding)	(None, 128, 100)	3257500
conv1d (Conv1D)	(None, 123, 100)	60100
global_average_pooling1d (Gl	(None, 100)	0
dense_2 (Dense)	(None, 16)	1616
dense_3 (Dense)	(None, 1)	17

Total params: 3,319,233 Trainable params: 3,319,233 Non-trainable params: 0

```
Epoch 20/30
Epoch 21/30
     Epoch 22/30
Epoch 23/30
35/35 [=====
      :==========] - 1s 41ms/step - loss: 0.0138 - accuracy: 0.9989 - val_loss: 0.9512 - val_accuracy: 0.7434
Epoch 24/30
35/35 [============] - 1s 42ms/step - loss: 0.0151 - accuracy: 0.9986 - val loss: 0.9591 - val accuracy: 0.7457
Epoch 25/30
35/35 [====:
      ===========] - 1s 41ms/step - loss: 0.0129 - accuracy: 0.9986 - val_loss: 0.9781 - val_accuracy: 0.7374
Epoch 26/30
Epoch 27/30
35/35 [=====
     =================] - 1s 42ms/step - loss: 0.0128 - accuracy: 0.9987 - val_loss: 1.0107 - val_accuracy: 0.7419
Epoch 28/30
Epoch 29/30
Epoch 30/30
```

### **Evaluation:**

### 3. model.summary, epochs and evaluation for Model 2:

### Using pre-trained word embeddings:

### **Preprocess Part:**

```
x_dev_tweet_glove[0]:
[196237, 395262, 198486, 190716, 388711, 264529, 365027, 360915, 242891, 194733,
x_dev_topic_glove[0]:
[242891, 194733]
Before paded:
[243317, 1, 118309, 243317, 357266, 2, 151349, 229153, 192973, 166369, 54718, 51582, 87775, 262350, 228306, 373375, 88558]
After paded:
           1 118309 243317 357266
                                    2 151349 229153 192973 166369
[243317
       51582 87775 262350 228306 373375 88558
  54718
     0
           0
                 0
                        0
                              a
                                    0
                                           0
                                                 0
                                                       0
     0
                                           0
                                                 0
                                    0
           0
                              0
                                    0
                                           0
                 0
                                                 0
                                                       0
                                                              0
           0
                        0
                              0
                                    0
                                           0
                                                       0
     0
           0
                 0
                        0
                              0
                                    0
                                           0
                                                 0
                                                       0
                                                              0
     0
           0
                 0
                        0
                              0
                                    0
                                           0
                                                 0
                                                       0
                                                              0
     0
                        0
                              0
                                    0
                                           0
                                                 0]
```

# **Summary:**

Model: "model\_3"

Layer (type)	Output Shape	Param #
input_5 (InputLayer)	[(None, 128)]	0
GloVe_Embeddings (Embedding)	(None, 128, 300)	120000300
global_average_pooling1d_mas	(None, 300)	0
dense_8 (Dense)	(None, 16)	4816
dense_9 (Dense)	(None, 1)	17

Total params: 120,005,133 Trainable params: 4,833

Non-trainable params: 120,000,300

### **Epochs:**

```
Epoch 189/200
Epoch 190/200
35/35 [======
      ==========] - 1s 23ms/step - loss: 0.3088 - accuracy: 0.8736 - val_loss: 0.4022 - val_accuracy: 0.8219
Epoch 191/200
Epoch 192/200
35/35 [======
      ==========] - 1s 24ms/step - loss: 0.3101 - accuracy: 0.8721 - val_loss: 0.4024 - val_accuracy: 0.8189
Epoch 193/200
35/35 [======
     Epoch 194/200
Epoch 195/200
      Epoch 196/200
Epoch 197/200
       =========] - 1s 23ms/step - loss: 0.3050 - accuracy: 0.8732 - val_loss: 0.4027 - val_accuracy: 0.8204
Epoch 198/200
Epoch 199/200
      ===========] - 1s 23ms/step - loss: 0.3082 - accuracy: 0.8716 - val_loss: 0.4025 - val_accuracy: 0.8211
Epoch 200/200
```

### **Evaluation:**

# Model 2-2: CNN or LSTM with pre-trained word embeddings: Summary:

Model: "model\_12"

Layer (type)	Output Shape	Param #
input_21 (InputLayer)	[(None, 128)]	0
GloVe_Embeddings (Embedding)	(None, 128, 300)	120000300
conv1d_11 (Conv1D)	(None, 123, 100)	180100
global_average_pooling1d_11	(None, 100)	0
dense_28 (Dense)	(None, 1)	101

Total params: 120,180,501 Trainable params: 180,201

Non-trainable params: 120,000,300

\_\_\_\_\_

# **Epochs:**

```
Epoch 189/200
        Epoch 190/200
35/35 [===========] - 1s 32ms/step - loss: 0.2635 - accuracy: 0.8921 - val_loss: 0.4436 - val_accuracy: 0.8098
Epoch 191/200
Epoch 192/200
35/35 [======
          :=========] - 1s 32ms/step - loss: 0.2664 - accuracy: 0.8918 - val loss: 0.4351 - val accuracy: 0.8113
Epoch 193/200
35/35 [======
       Epoch 194/200
35/35 [===========] - 1s 32ms/step - loss: 0.2630 - accuracy: 0.8933 - val_loss: 0.4350 - val_accuracy: 0.8008
Epoch 195/200
Epoch 196/200
35/35 [=====
          =========] - 1s 32ms/step - loss: 0.2696 - accuracy: 0.8883 - val_loss: 0.4379 - val_accuracy: 0.7970
Epoch 197/200
       35/35 [=====
Epoch 198/200
Epoch 199/200
Epoch 200/200
          :=========] - 1s 32ms/step - loss: 0.2630 - accuracy: 0.8941 - val_loss: 0.4512 - val_accuracy: 0.7857
```

### **Evaluation:**

**4.** model.summary() command to show your model structure, and training epochs, and evaluation results:

# Neural bag of words model with multiple-input:

### **Summary:**

Model: "model_6"			
Layer (type)	Output Shape	Param #	Connected to
input_10 (InputLayer)	[(None, 16)]	0	
input_11 (InputLayer)	[(None, 128)]	0	
GloVe_Embeddings (Embedding)	multiple	120000300	input_10[0][0] input_11[0][0]
global_average_pooling1d_masked	(None, 300)	0	GloVe_Embeddings[6][0]
global_average_pooling1d_masked	(None, 300)	0	GloVe_Embeddings[7][0]
dense_14 (Dense)	(None, 16)	4816	global_average_pooling1d_masked_6
dense_15 (Dense)	(None, 16)	4816	global_average_pooling1d_masked_7
concatenate_1 (Concatenate)	(None, 32)	0	dense_14[0][0] dense_15[0][0]
dense_16 (Dense)	(None, 1)	33	concatenate_1[0][0]

Total params: 120,009,965 Trainable params: 9,665

Non-trainable params: 120,000,300

### **Epochs:**

```
Epoch 188/200
35/35 [===========] - 1s 25ms/step - loss: 0.2705 - accuracy: 0.8879 - val loss: 0.4602 - val accuracy: 0.7789
Epoch 190/200
        35/35 [=====
Epoch 191/200
35/35 [=============] - 1s 25ms/step - loss: 0.2729 - accuracy: 0.8875 - val_loss: 0.4624 - val_accuracy: 0.7766
Epoch 192/200
35/35 [===========] - 1s 25ms/step - loss: 0.2771 - accuracy: 0.8851 - val loss: 0.4628 - val accuracy: 0.7789
Epoch 193/200
         ===========] - 1s 25ms/step - loss: 0.2692 - accuracy: 0.8890 - val_loss: 0.4600 - val_accuracy: 0.7804
Epoch 194/200
Epoch 195/200
35/35 [=============] - 1s 25ms/step - loss: 0.2768 - accuracy: 0.8859 - val_loss: 0.4607 - val_accuracy: 0.7789
Epoch 196/200
Epoch 197/200
        :=============] - 1s 25ms/step - loss: 0.2814 - accuracy: 0.8855 - val_loss: 0.4606 - val_accuracy: 0.7804
Epoch 198/200
Epoch 199/200
35/35 [=============] - 1s 25ms/step - loss: 0.2753 - accuracy: 0.8859 - val_loss: 0.4639 - val_accuracy: 0.7766
Epoch 200/200
35/35 [============] - 1s 25ms/step - loss: 0.2738 - accuracy: 0.8867 - val_loss: 0.4640 - val_accuracy: 0.7774
```

### **Evaluation:**

```
results_5 = model_5.evaluate([x_test_topic_pad_glove, x_test_tweet_pad_glove], y_test)
print(results_5)
```

### Model 3-2: CNN or LSTM model with multiple-input

### **Summary:**

Model: "model\_7"

Layer (type)	Output Shape	Param #	Connected to
input_12 (InputLayer)	[(None, 16)]	0	
input_13 (InputLayer)	[(None, 128)]	0	
GloVe_Embeddings (Embedding)	multiple	120000300	input_12[0][0] input_13[0][0]
conv1d_2 (Conv1D)	(None, 11, 100)	180100	GloVe_Embeddings[8][0]
conv1d_3 (Conv1D)	(None, 123, 100)	180100	GloVe_Embeddings[9][0]
global_average_pooling1d_2 (Glo	(None, 100)	0	conv1d_2[0][0]
global_average_pooling1d_3 (Glo	(None, 100)	0	conv1d_3[0][0]
dense_17 (Dense)	(None, 16)	1616	global_average_pooling1d_2[0][0]
dense_18 (Dense)	(None, 16)	1616	global_average_pooling1d_3[0][0]
concatenate_2 (Concatenate)	(None, 32)	0	dense_17[0][0] dense_18[0][0]
dense_19 (Dense)	(None, 1)	33	concatenate_2[0][0]

.\_\_\_\_\_\_

Total params: 120,363,765 Trainable params: 363,465

Non-trainable params: 120,000,300

### **Epochs:**

```
Epoch 188/200
Epoch 189/200
35/35 [=============] - 1s 36ms/step - loss: 0.2050 - accuracy: 0.9194 - val_loss: 0.5362 - val_accuracy: 0.7811
Epoch 190/200
35/35 [=============] - 1s 36ms/step - loss: 0.2094 - accuracy: 0.9191 - val_loss: 0.5465 - val_accuracy: 0.7721
Epoch 191/200
35/35 [===========] - 1s 35ms/step - loss: 0.2071 - accuracy: 0.9174 - val_loss: 0.5466 - val_accuracy: 0.7766
Epoch 192/200
35/35 [============] - 1s 35ms/step - loss: 0.2076 - accuracy: 0.9170 - val_loss: 0.5623 - val_accuracy: 0.7736
Epoch 193/200
Epoch 194/200
Epoch 195/200
Epoch 196/200
      35/35 [======
Epoch 197/200
35/35 [=====
      Epoch 198/200
35/35 [===========] - 1s 36ms/step - loss: 0.2011 - accuracy: 0.9218 - val_loss: 0.5596 - val_accuracy: 0.7706
Epoch 199/200
Epoch 200/200
```

### **Evaluation:**

**5.**Try to improve your overall accuracy over 81% on this task. You could try one or more of: using a CNN instead; using a different classifier; modify embeddings, loss function etc - see ideas in Week 5 & 6 lectures. Please discuss your model and results in your report. [6 marks].

# Summary of the best model:

Model: "model_3"				
Layer (type)	Output	Shape	Param #	Connected to
input_3 (InputLayer)	[(None	, 16)]	0	
input_4 (InputLayer)	[(None	, 128)]	0	
GloVe_Embeddings (Embedding)	multip:	le	120000300	input_3[0][0] input_4[0][0]
conv1d_2 (Conv1D)	(None,	11, 100)	180100	GloVe_Embeddings[2][0]
conv1d_3 (Conv1D)	(None,	123, 100)	180100	GloVe_Embeddings[3][0]
global_max_pooling1d (GlobalMax	(None,	100)	0	conv1d_2[0][0]
<pre>global_max_pooling1d_1 (GlobalM</pre>	(None,	100)	0	conv1d_3[0][0]
dense_5 (Dense)	(None,	16)	1616	global_max_pooling1d[0][0]
dense_6 (Dense)	(None,	16)	1616	global_max_pooling1d_1[0][0]
concatenate_1 (Concatenate)	(None,	32)	0	dense_5[0][0] dense_6[0][0]
dense_7 (Dense)	(None,	1)	33	concatenate_1[0][0]

Total params: 120,363,765 Trainable params: 363,465

Non-trainable params: 120,000,300

# **Epochs:**

```
Epoch 188/200
    35/35 [======
Epoch 189/200
35/35 [======
     Epoch 190/200
Epoch 191/200
35/35 [============] - 23s 644ms/step - loss: 0.0024 - accuracy: 0.9976 - val loss: 0.1705 - val accuracy: 0.8128
Epoch 192/200
Fnoch 193/200
Epoch 194/200
35/35 [============] - 23s 644ms/step - loss: 0.0021 - accuracy: 0.9979 - val_loss: 0.1706 - val_accuracy: 0.8128
Epoch 195/200
Epoch 196/200
Epoch 197/200
Epoch 198/200
Epoch 199/200
35/35 [============] - 22s 638ms/step - loss: 0.0019 - accuracy: 0.9981 - val loss: 0.1706 - val accuracy: 0.8128
Epoch 200/200
```

# **Evaluation:**

```
results_7 = final_model.evaluate([x_test_topic_pad_glove, x_test_tweet_pad_glove], y_test)
print(results_7)
```