Week 3: Exploring Overfitting in NLP

Welcome to this assignment! During this week you saw different ways to handle sequence-like data. You saw how some Keras' layers such as `GRU`, `Conv` and `LSTM` can be used to tackle problems in this space. Now you will put this knowledge into practice by creating a model architecture that does not overfit.

For this assignment you will be using a variation of the Sentiment140 dataset, which contains 1.6 million tweets alongside their respective sentiment (0 for negative and 4 for positive).

You will also need to create the helper functions very similar to the ones you coded in previous assignments pre-process data and to tokenize sentences. However the objective of the assignment is to find a model architecture that will not overfit.

Let's get started!

```
# IMPORTANT: This will check your notebook's metadata for grading.
# Please do not continue the lab unless the output of this cell tells
you to proceed.
!python add_metadata.py --filename C3W3_Assignment.ipynb

Grader metadata detected! You can proceed with the lab!
```

NOTE: *To prevent errors from the autograder, you are not allowed to edit or delete non-graded cells in this notebook . Please only put your solutions in between the* `### START CODE HERE` *and* `### END CODE HERE` *code comments, and also refrain from adding any new cells.* ***Once you have passed this assignment*** *and want to experiment with any of the non-graded code, you may follow the instructions at the bottom of this notebook.*

```
# grader-required-cell

import csv
import random
import pickle
import numpy as np
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
import matplotlib.pyplot as plt
from scipy.stats import linregress
```

Defining some useful global variables

Next you will define some global variables that will be used throughout the assignment.

- `EMBEDDING_DIM`: Dimension of the dense embedding, will be used in the embedding layer of the model. Defaults to 100.

- `MAXLEN`: Maximum length of all sequences. Defaults to 16.
- `TRUNCATING`: Truncating strategy (truncate either before or after each sequence.). Defaults to 'post'.
- `PADDING`: Padding strategy (pad either before or after each sequence.). Defaults to 'post'.
- `OOV_TOKEN`: Token to replace out-of-vocabulary words during text_to_sequence calls. Defaults to "<OOV>".
- `MAX_EXAMPLES`: Max number of examples to use. Defaults to 160000 (10% of the original number of examples)
- `TRAINING_SPLIT`: Proportion of data used for training. Defaults to 0.9

For now leave them unchanged but after submitting your assignment for grading you are encouraged to come back here and play with these parameters to see the impact they have in the classification process.

```
# grader-required-cell

EMBEDDING_DIM = 100
MAXLEN = 16
TRUNCATING = 'post'
PADDING = 'post'
OOV_TOKEN = "<OOV>"
MAX_EXAMPLES = 160000
TRAINING_SPLIT = 0.9
```

Explore the dataset

The dataset is provided in a csv file.

Each row of this file contains the following values separated by commas:

- target: the polarity of the tweet (0 = negative, 4 = positive)
- ids: The id of the tweet
- date: the date of the tweet
- flag: The query. If there is no query, then this value is NO_QUERY.
- user: the user that tweeted
- text: the text of the tweet

Take a look at the first two examples:

```
# grader-required-cell

SENTIMENT_CSV = "./data/training_cleaned.csv"

with open(SENTIMENT_CSV, 'r') as csvfile:
    print(f"First data point looks like this:\n\
n{csvfile.readline()}")
    print(f"Second data point looks like this:\n\
n{csvfile.readline()}")
```

```
First data point looks like this:

"0","1467810369","Mon Apr 06 22:19:45 PDT
2009","NO_QUERY","_TheSpecialOne_","@switchfoot
http://twitpic.com/2y1zl - Awww, that's a bummer.  You shoulda got
David Carr of Third Day to do it. ;D"

Second data point looks like this:

"0","1467810672","Mon Apr 06 22:19:49 PDT
2009","NO_QUERY","scotthamilton","is upset that he can't update his
Facebook by texting it... and might cry as a result  School today
also. Blah!"
```

Notice that this file does not have a header so you won't need to skip the first row when parsing the file.

For the task at hand you will only need the information of the target and the text, which are the first and last element of each row.

Parsing the raw data

Now you need to read the data from the csv file. To do so, complete the `parse_data_from_file` function.

A couple of things to note:

- You should NOT omit the first line as the file does not contain headers.
- There is no need to save the data points as numpy arrays, regular lists is fine.
- To read from csv files use `csv.reader` by passing the appropriate arguments.
- `csv.reader` returns an iterable that returns each row in every iteration. So the label can be accessed via `row[0]` and the text via `row[5]`.
- The labels are originally encoded as strings ('0' representing negative and '4' representing positive). **You need to change this so that the labels are integers and 0 is used for representing negative, while 1 should represent positive.**

```
# grader-required-cell

# GRADED FUNCTION: parse_data_from_file
```

```python
def parse_data_from_file(filename):
    """
    Extracts sentences and labels from a CSV file

    Args:
        filename (string): path to the CSV file

    Returns:
        sentences, labels (list of string, list of string): tuple
containing lists of sentences and labels
    """

    sentences = []
    labels = []

    with open(filename, 'r') as csvfile:
        ### START CODE HERE
        reader = csv.reader(csvfile, delimiter=",")

        for row in reader:
            sentences.append(row[5])
            for_label = row[0]

            if for_label =="0":
                labels.append(0)
            else:
                labels.append(1)
        ### END CODE HERE

    return sentences, labels

# grader-required-cell

# Test your function
sentences, labels = parse_data_from_file(SENTIMENT_CSV)

print(f"dataset contains {len(sentences)} examples\n")

print(f"Text of second example should look like this:\n{sentences[1]}\
n")
print(f"Text of fourth example should look like this:\
n{sentences[3]}")

print(f"\nLabels of last 5 examples should look like this:\n{labels[-
5:]}")
```

```
dataset contains 1600000 examples

Text of second example should look like this:
is upset that he can't update his Facebook by texting it... and might
```

```
cry as a result  School today also. Blah!

Text of fourth example should look like this:
my whole body feels itchy and like its on fire

Labels of last 5 examples should look like this:
[1, 1, 1, 1, 1]
```

Expected Output:

```
dataset contains 1600000 examples

Text of second example should look like this:
is upset that he can't update his Facebook by texting it... and might
cry as a result  School today also. Blah!

Text of fourth example should look like this:
my whole body feels itchy and like its on fire

Labels of last 5 examples should look like this:
[1, 1, 1, 1, 1]
```

You might have noticed that this dataset contains a lot of examples. In order to keep a low execution time of this assignment you will be using only 10% of the original data. The next cell does this while also randomnizing the datapoints that will be used:

```
# grader-required-cell

# Bundle the two lists into a single one
sentences_and_labels = list(zip(sentences, labels))

# Perform random sampling
random.seed(42)
sentences_and_labels = random.sample(sentences_and_labels,
MAX_EXAMPLES)

# Unpack back into separate lists
sentences, labels = zip(*sentences_and_labels)

print(f"There are {len(sentences)} sentences and {len(labels)} labels
after random sampling\n")

There are 160000 sentences and 160000 labels after random sampling
```

Expected Output:

```
There are 160000 sentences and 160000 labels after random sampling
```

Training - Validation Split

Now you will code the `train_val_split`, which given the list of sentences, the list of labels and the proportion of data for the training set, should return the training and validation sentences and labels:

```
# grader-required-cell

# GRADED FUNCTION: train_val_split
def train_val_split(sentences, labels, training_split):
    """
    Splits the dataset into training and validation sets

    Args:
        sentences (list of string): lower-cased sentences without
stopwords
        labels (list of string): list of labels
        training split (float): proportion of the dataset to convert
to include in the train set

    Returns:
        train_sentences, validation_sentences, train_labels,
validation_labels - lists containing the data splits
    """
    ### START CODE HERE

    # Compute the number of sentences that will be used for training
(should be an integer)
    train_size = int(len(sentences)*training_split)

    # Split the sentences and labels into train/validation splits
    train_sentences = sentences[:train_size]
    train_labels = labels[:train_size]

    validation_sentences = sentences[train_size:]
    validation_labels = labels[train_size:]

    ### END CODE HERE

    return train_sentences, validation_sentences, train_labels,
validation_labels

# grader-required-cell

# Test your function
train_sentences, val_sentences, train_labels, val_labels =
train_val_split(sentences, labels, TRAINING_SPLIT)

print(f"There are {len(train_sentences)} sentences for training.\n")
print(f"There are {len(train_labels)} labels for training.\n")
```

```
print(f"There are {len(val_sentences)} sentences for validation.\n")
print(f"There are {len(val_labels)} labels for validation.")
```

```
There are 144000 sentences for training.

There are 144000 labels for training.

There are 16000 sentences for validation.

There are 16000 labels for validation.
```

Expected Output:

```
There are 144000 sentences for training.

There are 144000 labels for training.

There are 16000 sentences for validation.

There are 16000 labels for validation.
```

Tokenization - Sequences, truncating and padding

Now that you have sets for training and validation it is time for you to begin the tokenization process.

Begin by completing the `fit_tokenizer` function below. This function should return a Tokenizer that has been fitted to the training sentences.

```
# grader-required-cell

# GRADED FUNCTION: fit_tokenizer
def fit_tokenizer(train_sentences, oov_token):
    """
    Instantiates the Tokenizer class on the training sentences

    Args:
        train_sentences (list of string): lower-cased sentences
without stopwords to be used for training
        oov_token (string) - symbol for the out-of-vocabulary token

    Returns:
        tokenizer (object): an instance of the Tokenizer class
containing the word-index dictionary
    """
    ### START CODE HERE

    # Instantiate the Tokenizer class, passing in the correct value
for oov_token
```

```
    tokenizer = Tokenizer(num_words=len(train_sentences),
oov_token="")

    # Fit the tokenizer to the training sentences
    tokenizer.fit_on_texts(train_sentences)


    ### END CODE HERE

    return tokenizer
```

```
# grader-required-cell

# Test your function
tokenizer = fit_tokenizer(train_sentences, OOV_TOKEN)

word_index = tokenizer.word_index
VOCAB_SIZE = len(word_index)

print(f"Vocabulary contains {VOCAB_SIZE} words\n")
print("<OOV> token included in vocabulary" if "<OOV>" in word_index
else "<OOV> token NOT included in vocabulary")
print(f"\nindex of word 'i' should be {word_index['i']}")
```

```
Vocabulary contains 128293 words

<OOV> token NOT included in vocabulary

index of word 'i' should be 2
```

Expected Output:

```
Vocabulary contains 128293 words

<OOV> token included in vocabulary

index of word 'i' should be 2
```

```
# grader-required-cell

# GRADED FUNCTION: seq_pad_and_trunc
def seq_pad_and_trunc(sentences, tokenizer, padding, truncating,
maxlen):
    """
    Generates an array of token sequences and pads them to the same
length

    Args:
        sentences (list of string): list of sentences to tokenize and
pad
```

```
        tokenizer (object): Tokenizer instance containing the word-
index dictionary
        padding (string): type of padding to use
        truncating (string): type of truncating to use
        maxlen (int): maximum length of the token sequence

    Returns:
        pad_trunc_sequences (array of int): tokenized sentences padded
to the same length
    """
    ### START CODE HERE

    # Convert sentences to sequences
    sequences = tokenizer.texts_to_sequences(sentences)

    # Pad the sequences using the correct padding, truncating and
maxlen
    pad_trunc_sequences = pad_sequences(sequences, maxlen=maxlen,
padding=padding, truncating=truncating)

    ### END CODE HERE

    return pad_trunc_sequences

# grader-required-cell

# Test your function
train_pad_trunc_seq = seq_pad_and_trunc(train_sentences, tokenizer,
PADDING, TRUNCATING, MAXLEN)
val_pad_trunc_seq = seq_pad_and_trunc(val_sentences, tokenizer,
PADDING, TRUNCATING, MAXLEN)

print(f"Padded and truncated training sequences have shape:
{train_pad_trunc_seq.shape}\n")
print(f"Padded and truncated validation sequences have shape:
{val_pad_trunc_seq.shape}")

Padded and truncated training sequences have shape: (144000, 16)

Padded and truncated validation sequences have shape: (16000, 16)
```

Expected Output:

```
Padded and truncated training sequences have shape: (144000, 16)

Padded and truncated validation sequences have shape: (16000, 16)
```

Remember that the `pad_sequences` function returns numpy arrays, so your training and validation sequences are already in this format.

However the labels are still Python lists. Before going forward you should convert them numpy arrays as well. You can do this by running the following cell:

```
# grader-required-cell

train_labels = np.array(train_labels)
val_labels = np.array(val_labels)
```

Using pre-defined Embeddings

This time you will not be learning embeddings from your data but you will be using pre-trained word vectors.

In particular you will be using the 100 dimension version of GloVe from Stanford.

```
# grader-required-cell

# Define path to file containing the embeddings
GLOVE_FILE = './data/glove.6B.100d.txt'

# Initialize an empty embeddings index dictionary
GLOVE_EMBEDDINGS = {}

# Read file and fill GLOVE_EMBEDDINGS with its contents
with open(GLOVE_FILE) as f:
    for line in f:
        values = line.split()
        word = values[0]
        coefs = np.asarray(values[1:], dtype='float32')
        GLOVE_EMBEDDINGS[word] = coefs
```

Now you have access to GloVe's pre-trained word vectors. Isn't that cool?

Let's take a look at the vector for the word **dog**:

```
# grader-required-cell

test_word = 'dog'

test_vector = GLOVE_EMBEDDINGS[test_word]

print(f"Vector representation of word {test_word} looks like this:\n\
n{test_vector}")
```

```
Vector representation of word dog looks like this:

[ 0.30817     0.30938     0.52803    -0.92543    -0.73671     0.63475
  0.44197     0.10262    -0.09142    -0.56607    -0.5327      0.2013
```

```
 0.7704     -0.13983    0.13727    1.1128     0.89301   -0.17869
-0.0019722  0.57289    0.59479    0.50428   -0.28991   -1.3491
 0.42756    1.2748    -1.1613    -0.41084    0.042804   0.54866
 0.18897    0.3759     0.58035    0.66975    0.81156    0.93864
-0.51005   -0.070079   0.82819   -0.35346    0.21086   -0.24412
-0.16554   -0.78358   -0.48482    0.38968   -0.86356   -0.016391
 0.31984   -0.49246   -0.069363   0.018869  -0.098286   1.3126
-0.12116   -1.2399    -0.091429   0.35294    0.64645    0.089642
 0.70294    1.1244     0.38639    0.52084    0.98787    0.79952
-0.34625    0.14095    0.80167    0.20987   -0.86007   -0.15308
 0.074523   0.40816    0.019208   0.51587   -0.34428   -0.24525
-0.77984    0.27425    0.22418    0.20164    0.017431  -0.014697
-1.0235    -0.39695   -0.0056188  0.30569    0.31748    0.021404
 0.11837   -0.11319    0.42456    0.53405   -0.16717   -0.27185
-0.6255     0.12883    0.62529   -0.52086  ]
```

Feel free to change the `test_word` to see the vector representation of any word you can think of.

Also, notice that the dimension of each vector is 100. You can easily double check this by running the following cell:

```
# grader-required-cell

print(f"Each word vector has shape: {test_vector.shape}")

Each word vector has shape: (100,)
```

Represent the words in your vocabulary using the embeddings

Save the vector representation of each word in the vocabulary in a numpy array.

A couple of things to notice:

- If a word in your vocabulary is not present in `GLOVE_EMBEDDINGS` the representation for that word is left as a column of zeros.
- `word_index` starts counting at 1, because of this you will need to add an extra column at the left-most side of the `EMBEDDINGS_MATRIX` array. This is the reason why you add 1 to `VOCAB_SIZE` in the cell below:

```
# grader-required-cell

# Initialize an empty numpy array with the appropriate size
EMBEDDINGS_MATRIX = np.zeros((VOCAB_SIZE+1, EMBEDDING_DIM))

# Iterate all of the words in the vocabulary and if the vector
representation for
# each word exists within GloVe's representations, save it in the
```

```
EMBEDDINGS_MATRIX array
for word, i in word_index.items():
    embedding_vector = GLOVE_EMBEDDINGS.get(word)
    if embedding_vector is not None:
        EMBEDDINGS_MATRIX[i] = embedding_vector
```

Now you have the pre-trained embeddings ready to use!

Define a model that does not overfit

Now you need to define a model that will handle the problem at hand while not overfitting.

A couple of things to note / hints:

- The first layer is provided so you can see how the Embedding layer is configured when using pre-trained embeddings
- You can try different combinations of layers covered in previous ungraded labs such as:
  - `Conv1D`
  - `Dropout`
  - `GlobalMaxPooling1D`
  - `MaxPooling1D`
  - `LSTM`
  - `Bidirectional(LSTM)`
- The last two layers should be `Dense` layers.
- There multiple ways of solving this problem. So try an architecture that you think will not overfit.
- Try simpler architectures first to avoid long training times. Architectures that are able to solve this problem usually have around 3-4 layers (excluding the last two `Dense` ones)
- Include at least one `Dropout` layer to mitigate overfitting.

```
# grader-required-cell

# GRADED FUNCTION: create_model
def create_model(vocab_size, embedding_dim, maxlen,
embeddings_matrix):
    """
    Creates a binary sentiment classifier model
```

```
    Args:
        vocab_size (int): size of the vocabulary for the Embedding
layer input
        embedding_dim (int): dimensionality of the Embedding layer
output
        maxlen (int): length of the input sequences
        embeddings_matrix (array): predefined weights of the
embeddings

    Returns:
        model (tf.keras Model): the sentiment classifier model
    """
    ### START CODE HERE

    model = tf.keras.Sequential([
        # This is how you need to set the Embedding layer when using
pre-trained embeddings
        tf.keras.layers.Embedding(vocab_size+1, embedding_dim,
input_length=maxlen, weights=[embeddings_matrix], trainable=False),
        tf.keras.layers.Dropout(0.2),
        tf.keras.layers.Conv1D(64, 5, activation='relu'),
        tf.keras.layers.MaxPooling1D(pool_size=4),
        tf.keras.layers.LSTM(64),
        tf.keras.layers.Dense(1, activation='sigmoid')
    ])

    model.compile(loss='binary_crossentropy',
                  optimizer='adam',
                  metrics=['accuracy'])

    ### END CODE HERE

    return model

# grader-required-cell

# Create your untrained model
model = create_model(VOCAB_SIZE, EMBEDDING_DIM, MAXLEN,
EMBEDDINGS_MATRIX)

# Train the model and save the training history
history = model.fit(train_pad_trunc_seq, train_labels, epochs=20,
validation_data=(val_pad_trunc_seq, val_labels))

Epoch 1/20
4500/4500 [==============================] - 36s 8ms/step - loss:
0.5681 - accuracy: 0.6978 - val_loss: 0.5200 - val_accuracy: 0.7387
Epoch 2/20
4500/4500 [==============================] - 35s 8ms/step - loss:
0.5283 - accuracy: 0.7295 - val_loss: 0.5103 - val_accuracy: 0.7441
```

```
Epoch 3/20
4500/4500 [==============================] - 35s 8ms/step - loss:
0.5119 - accuracy: 0.7429 - val_loss: 0.5036 - val_accuracy: 0.7535
Epoch 4/20
4500/4500 [==============================] - 33s 7ms/step - loss:
0.4999 - accuracy: 0.7502 - val_loss: 0.5006 - val_accuracy: 0.7535
Epoch 5/20
4500/4500 [==============================] - 34s 7ms/step - loss:
0.4913 - accuracy: 0.7569 - val_loss: 0.4991 - val_accuracy: 0.7545
Epoch 6/20
4500/4500 [==============================] - 33s 7ms/step - loss:
0.4845 - accuracy: 0.7600 - val_loss: 0.5025 - val_accuracy: 0.7553
Epoch 7/20
4500/4500 [==============================] - 35s 8ms/step - loss:
0.4790 - accuracy: 0.7648 - val_loss: 0.4951 - val_accuracy: 0.7576
Epoch 8/20
4500/4500 [==============================] - 34s 8ms/step - loss:
0.4728 - accuracy: 0.7682 - val_loss: 0.4966 - val_accuracy: 0.7598
Epoch 9/20
4500/4500 [==============================] - 33s 7ms/step - loss:
0.4699 - accuracy: 0.7686 - val_loss: 0.5054 - val_accuracy: 0.7524
Epoch 10/20
4500/4500 [==============================] - 33s 7ms/step - loss:
0.4648 - accuracy: 0.7739 - val_loss: 0.5043 - val_accuracy: 0.7560
Epoch 11/20
4500/4500 [==============================] - 36s 8ms/step - loss:
0.4629 - accuracy: 0.7744 - val_loss: 0.5070 - val_accuracy: 0.7566
Epoch 12/20
4500/4500 [==============================] - 35s 8ms/step - loss:
0.4588 - accuracy: 0.7778 - val_loss: 0.5045 - val_accuracy: 0.7533
Epoch 13/20
4500/4500 [==============================] - 35s 8ms/step - loss:
0.4570 - accuracy: 0.7788 - val_loss: 0.5113 - val_accuracy: 0.7519
Epoch 14/20
4500/4500 [==============================] - 35s 8ms/step - loss:
0.4540 - accuracy: 0.7795 - val_loss: 0.5063 - val_accuracy: 0.7583
Epoch 15/20
4500/4500 [==============================] - 36s 8ms/step - loss:
0.4516 - accuracy: 0.7812 - val_loss: 0.5069 - val_accuracy: 0.7582
Epoch 16/20
4500/4500 [==============================] - 36s 8ms/step - loss:
0.4495 - accuracy: 0.7838 - val_loss: 0.5030 - val_accuracy: 0.7541
Epoch 17/20
4500/4500 [==============================] - 36s 8ms/step - loss:
0.4467 - accuracy: 0.7834 - val_loss: 0.5086 - val_accuracy: 0.7571
Epoch 18/20
4500/4500 [==============================] - 36s 8ms/step - loss:
0.4458 - accuracy: 0.7855 - val_loss: 0.5114 - val_accuracy: 0.7560
Epoch 19/20
```

```
4500/4500 [==============================] - 35s 8ms/step - loss: 
0.4439 - accuracy: 0.7861 - val_loss: 0.5123 - val_accuracy: 0.7538
Epoch 20/20
4500/4500 [==============================] - 36s 8ms/step - loss: 
0.4440 - accuracy: 0.7864 - val_loss: 0.5103 - val_accuracy: 0.7552
```

To pass this assignment your `val_loss` (validation loss) should either be flat or decreasing.

Although a flat `val_loss` and a lowering `train_loss` (or just `loss`) also indicate some overfitting what you really want to avoid is having a lowering `train_loss` and an increasing `val_loss`.

With this in mind, the following three curves will be acceptable solutions:

While the following would not be able to pass the grading:

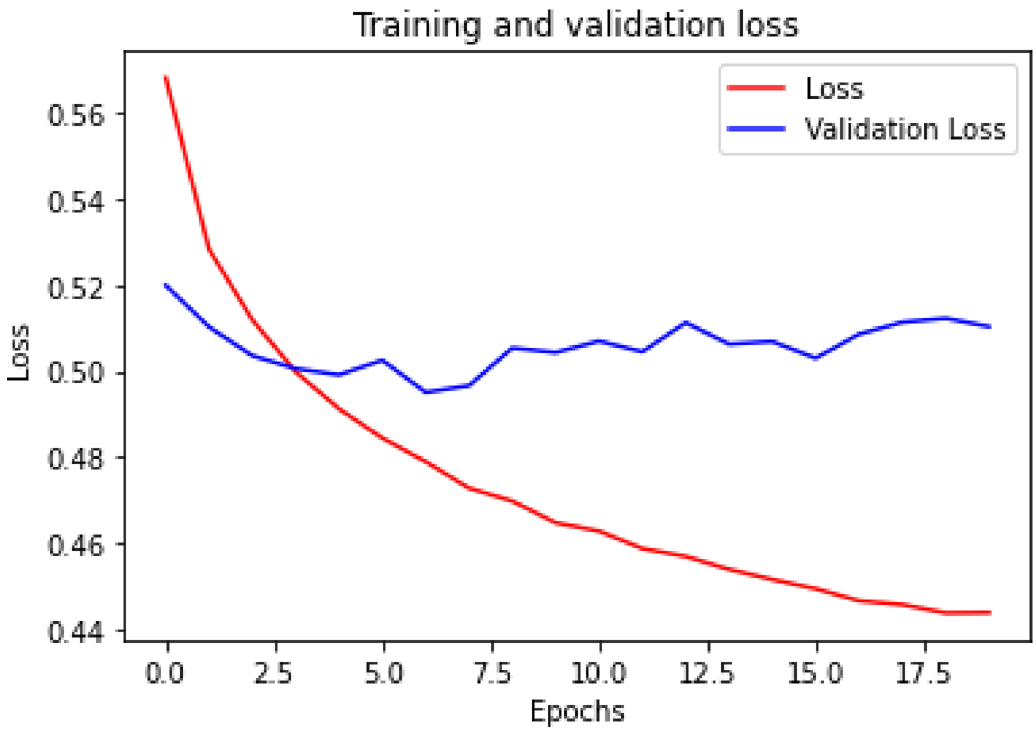
Run the following cell to check your loss curves:

```
# grader-required-cell

#-----------------------------------------------------------
# Retrieve a list of list results on training and test data
# sets for each training epoch
#-----------------------------------------------------------
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = [*range(20)]

#------------------------------------------------
# Plot training and validation loss per epoch
#------------------------------------------------
plt.plot(epochs, loss, 'r')
plt.plot(epochs, val_loss, 'b')
plt.title('Training and validation loss')
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend(["Loss", "Validation Loss"])
plt.show()
```

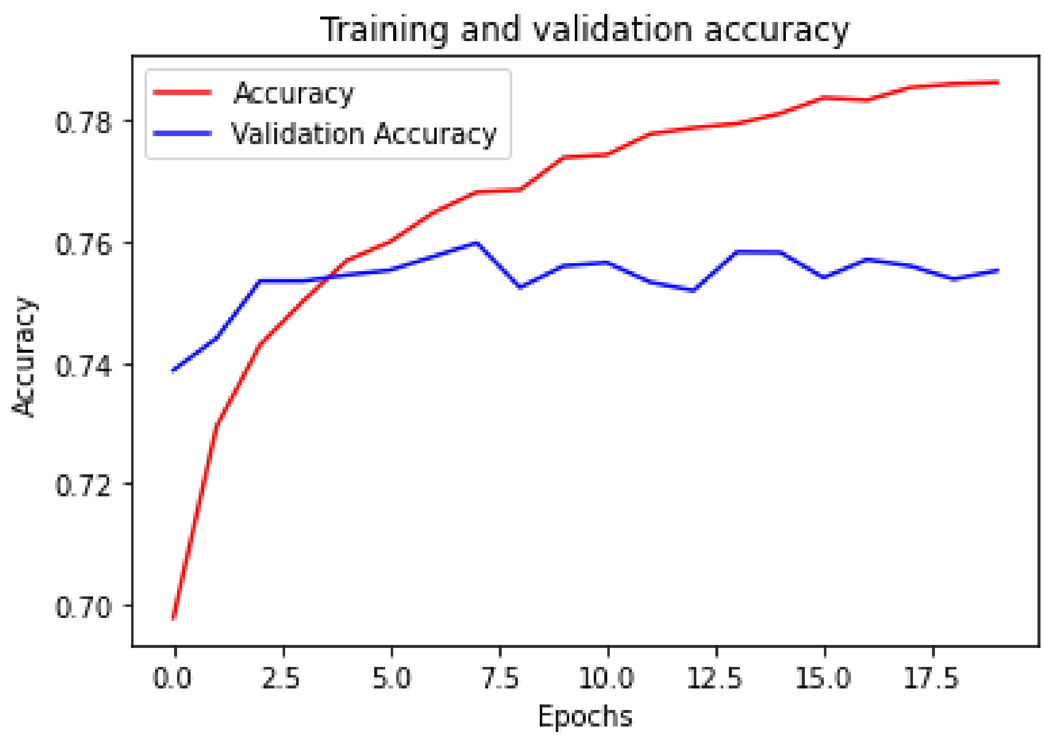


If you wish so, you can also check the training and validation accuracies of your model:

```
# grader-required-cell

acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

#------------------------------------------------
# Plot training and validation accuracy per epoch
#------------------------------------------------
plt.plot(epochs, acc, 'r')
plt.plot(epochs, val_acc, 'b')
plt.title('Training and validation accuracy')
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend(["Accuracy", "Validation Accuracy"])
plt.show()
```



A more rigorous way of setting the passing threshold of this assignment is to use the slope of your `val_loss` curve.

To pass this assignment the slope of your `val_loss` curve should be 0.0005 at maximum.

```
# grader-required-cell

# Test the slope of your val_loss curve
slope, *_ = linregress(epochs, val_loss)
print(f"The slope of your validation loss curve is {slope:.5f}")
```

```
The slope of your validation loss curve is 0.00023
```

If your model generated a validation loss curve that meets the criteria above, run the following cell and then submit your assignment for grading. Otherwise, try with a different architecture.

```
# grader-required-cell

with open('history.pkl', 'wb') as f:
    pickle.dump(history.history, f)
```

Congratulations on finishing this week's assignment!

You have successfully implemented a neural network capable of classifying sentiment in text data while doing a fairly good job of not overfitting! Nice job!

Keep it up!