```
import tensorflow_datasets as tfds
import tensorflow as tf
```

The IMDB movie reviews dataset comes packaged in tfds. It has already been preprocessed so that the reviews (sequences of words) have been converted to sequences of integers, where each integer represents a specific word in a dictionary.

dataset, info = tfds.load('imdb\_reviews/subwords8k', with\_info=True, as\_supervised=True)
train\_dataset, test\_dataset = dataset['train'], dataset['test']



Downloading and preparing dataset imdb\_reviews/subwords8k/1.0.0 (download: 80.23 MiB, ge

DI Completed...: 100% 1/1 [00:03<00:00, 3.11s/ url]

DI Size...: 100% 80/80 [00:03<00:00, 25.98 MiB/s]

```
25000/0 [00:35<00:00, 838.81 examples/s]
```

Shuffling and writing examples to /root/tensorflow\_datasets/imdb\_reviews/subwords8k/1.0 50% 12431/25000 [00:00<00:00, 124307.75 examples/s]

25000/0 [00:33<00:00, 916.86 examples/s]

Shuffling and writing examples to /root/tensorflow\_datasets/imdb\_reviews/subwords8k/1.0 13808/25000 [00:00<00:00, 138077.17 examples/s]

50000/0 [01:01<00:00, 869.27 examples/s]

Shuffling and writing examples to /root/tensorflow\_datasets/imdb\_reviews/subwords8k/1.0 68% 33766/50000 [00:00<20:20, 13.30 examples/s]

Dataset imdb\_reviews downloaded and prepared to /root/tensorflow\_datasets/imdb\_reviews/s

```
train_examples_batch, train_labels_batch = next(iter(train_dataset))
print(train_examples_batch)
print(train_labels_batch)
```

```
tf.Tensor(
                                                         35 5096
   62
        18
              41
                  604
                       927
                              65
                                     3
                                        644 7968
                                                    21
                                                                    36
                                                                          11
   43 2948 5240
                  102
                         50
                             681 7862 1244
                                                3 3266
                                                         29
                                                              122
                                                                   640
                                                                           2
   26
        14
             279
                  438
                         35
                              79
                                  349
                                        384
                                               11 1991
                                                           3
                                                              492
                                                                    79
                                                                         122
                                    65 7968
  188
       117
              33 4047 4531
                                                8 1819 3947
                                                                    62
                                                                          27
                              14
                                                                3
    9
             577 5044 2629 2552 7193 7961 3642
                                                     3
                                                         19
                                                              107 3903
                                                                         225
   85
       198
              72
                                        102 6245
                                                         85
                                                              308
                                                                    79 6936
                    1 1512
                             738 2347
                                                     8
        23 4981 8044
                          3 6429 7961 1141 1335 1848 4848
                                                               55 3601 4217
 7961
 8050
                   59 3831 1484 8040 7974
                                             174 5773
                                                         22 5240
                                                                   102
                                                                          18
         2
               5
  247
        26
               4 3903 1612 3902
                                  291
                                         11
                                                4
                                                    27
                                                         13
                                                               18 4092 4008
```

```
7961
                                12
                                    258 2306
        6 119 213 2774
                            3
                                               13
                                                    91
                                                         29
 229
        2 1245 5790 995 7968
                               8
                                     52 2948 5240 8039 7968
                                                               8
                                                                   74
            12 117 2438 1369 192
                                     39 7975], shape=(163,), dtype=int64)
tf.Tensor(0, shape=(), dtype=int64)
```

# ▼ Text Encoding

The dataset info includes the encoder (a tfds.features.text.SubwordTextEncoder). This text encoder will reversibly encode any string, falling back to byte-encoding if necessary.

```
encoder = info.features['text'].encoder
print('Vocabulary size: {}'.format(encoder.vocab_size))
     Vocabulary size: 8185
sample string = 'Hello TensorFlow.'
encoded string = encoder.encode(sample string)
print('Encoded string is {}'.format(encoded string))
original string = encoder.decode(encoded string)
print('The original string: "{}"'.format(original_string))
     Encoded string is [4025, 222, 6307, 2327, 4043, 2120, 7975]
     The original string: "Hello TensorFlow."
assert original_string == sample_string
for index in encoded string:
 print('{} ----> {}'.format(index, encoder.decode([index])))
     4025 ----> Hell
     222 ----> o
     6307 ---> Ten
     2327 ----> sor
     4043 ---> F1
     2120 ---> ow
     7975 ----> .
```

Create batches of training data for your model. The reviews are all different lengths, so use padded batch to zero pad the sequences while batching.

```
BUFFER_SIZE = 10000

BATCH_SIZE = 64

train_dataset = train_dataset.shuffle(BUFFER_SIZE)

train_dataset = train_dataset.padded_batch(BATCH_SIZE)

test dataset = test dataset.padded batch(BATCH SIZE)

https://colab.research.google.com/github/Tanya-vats/Tanya/blob/master/Sentiment Analysis RNN LSTM 1.ipynb#printMode=true
```

## **Build Model with an LSTM layer**

Creating a tf.keras.Sequential model and start with an embedding layer. An embedding layer stores one vector per word. When called, it converts the sequences of word indices to sequences of vectors. These vectors are trainable. After training (on enough data), words with similar meanings often have similar vectors.

This index-lookup is much more efficient than the equivalent operation of passing a one-hot encoded vector through a tf.keras.layers.Dense layer.

A recurrent neural network (RNN) processes sequence input by iterating through the elements. RNNs pass the outputs from one timestep to their input—and then to the next.

The tf.keras.layers.Bidirectional wrapper can also be used with an RNN layer. This propagates the input forward and backwards through the RNN layer and then concatenates the output. This helps the RNN to learn long range dependencies. Keras sequential model here since all the layers in the model only have single input and produce single output.

```
model = tf.keras.Sequential([
    tf.keras.layers.Embedding(encoder.vocab_size, 64),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(64)),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(1)
])
model.summary()
```

Model: "sequential"

| Layer (type)                 | Output Shap | pe         | Param # |
|------------------------------|-------------|------------|---------|
| embedding (Embedding)        | (None, None | e, 64)     | 523840  |
| bidirectional (Bidirectional | (None, 128) | )          | 66048   |
| dense (Dense)                | (None, 64)  |            | 8256    |
| dense_1 (Dense)              | (None, 1)   | ========== | 65      |

Total params: 598,209 Trainable params: 598,209 Non-trainable params: 0

Since this is a binary classification problem and the model outputs logits (a single-unit layer with a linear activation), we'll use the binary\_crossentropy loss function. It is better for dealing with

probabilities—it measures the "distance" between probability distributions, or in our case, between

Train the model for 10 epochs. This is 10 iterations over all samples in the train dataset tensors.

```
history = model.fit(train_dataset, epochs = 10, validation_data = test_dataset, validation_st
```

```
Epoch 1/10
Epoch 2/10
Epoch 3/10
391/391 [================== ] - 859s 2s/step - loss: 0.2509 - accuracy: 0.904
Epoch 4/10
Epoch 5/10
391/391 [================== ] - 862s 2s/step - loss: 0.1843 - accuracy: 0.934
Epoch 6/10
391/391 [============== ] - 863s 2s/step - loss: 0.1591 - accuracy: 0.94
Epoch 7/10
Epoch 8/10
391/391 [================== ] - 864s 2s/step - loss: 0.1359 - accuracy: 0.954
Epoch 9/10
Epoch 10/10
```

# **Test For Accuracy**

## **Prediction Functions**

```
vec.extenu(zeros)
return vec

def sample_predict(sample_pred_text, pad):
    encoded_sample_pred_text = encoder.encode(sample_pred_text)

if pad:
    encoded_sample_pred_text = pad_to_size(encoded_sample_pred_text, 64)
    encoded_sample_pred_text = tf.cast(encoded_sample_pred_text, tf.float32)
    predictions = model.predict(tf.expand_dims(encoded_sample_pred_text, 0))
    print("Prediction Score: ", predictions)

output = ""
    if predictions[0][0] >= 0.5: output = "POSITIVE"
    elif predictions[0][0] <= -1: output = "NEGATIVE"
    else: output = "NEUTRAL"

return output</pre>
```

### **Prediction with Sample Sentiments**

```
sample pred text = ('The movie was not good. The animation and the graphics were terrible. I
predictions = sample predict(sample pred text, pad = False)
print(predictions)
    Prediction Score: [[-1.2465143]]
    NEGATIVE
sample pred text = ('The movie was cool. The animation and the graphics were out of this worl
predictions = sample predict(sample pred text, pad = False)
print(predictions)
    Prediction Score: [[0.11379167]]
    NEUTRAL
sample_pred_text = ('This movie is awesome. The acting was incredicable. Highly recommend')
predictions = sample predict(sample pred text, pad = False)
print(predictions)
    Prediction Score: [[1.4532732]]
    POSITIVE
sample pred text = ('This movie was so so. The acting was medicore. Kind of recommend')
predictions = sample_predict(sample_pred_text, pad = False)
print(predictions)
    Prediction Score: [[-0.49171886]]
    NEUTRAL
```

#### # AVENGERS: ENDGAME 5 STAR COMMENT

sample\_pred\_text = ("""I loved the movie a lot as I am great fan of marvel! Avengers: Endgame and surely an enthralling experience. The last film of the 'Avengers' franchise is remarkable in one film is just surpassing. Marvel has been working on this grand culmination ever since work and ambition has paid off. The directors, Anthony and Joe Russo, have made sure that it Stephen McFeely have come up with a screenplay full of epic and unpredictable moments. The fi The biggest strength of the film is the emotions. This is the most emotional superhero film I were jaw-dropping. The climatic battle left me amazed. It's just filled with memorable moment and have a great impact on the film. The humour doesn't look exaggerated and manages to enter and suspenseful. The film features many cameos of characters from the previous MCU films, whi gives me goosebumps, though I've listened to it several times. It was really clever to make c But the show-stealer is Robert Downey Jr, who plays the role of Tony Stark/Iron Man. The man can perfect his role. Do not miss his powerful moments in the final battle.""")

predictions = sample\_predict(sample\_pred\_text, pad = False)
print(predictions)

WARNING:tensorflow:5 out of the last 5 calls to <function Model.make\_predict\_function.<]
WARNING:tensorflow:5 out of the last 5 calls to <function Model.make\_predict\_function.<]
Prediction Score: [[7.5766687]]

**POSITIVE** 

#### # AVENGERS: ENDGAME 3 STAR COMMENT

sample\_pred\_text = ("""Overrated Sequel, But Still Good, But Violent! Beloved characters die, stabbings, punching, shooting, and more. The characters swear a bit. Even Captain America doe Black Widow, Hawkeye. Thor not so much because he SPOILER ALERT: got fat and played Fortnite kid wanting to say 'I want to be like the God of Thunder and play fortnite all day'. Characte himself of something but not saying what. With reviewing the movie, the first half hour was g pretty good, but the last hour was epic. From just starting out with Iron Man, Cap, Thor, and really pulled it off. Overall, pretty good for families and a good finale for the Infinity Sa

predictions = sample\_predict(sample\_pred\_text, pad = False)
print(predictions)

WARNING:tensorflow:6 out of the last 6 calls to <function Model.make\_predict\_function.<]
WARNING:tensorflow:6 out of the last 6 calls to <function Model.make\_predict\_function.<]
Prediction Score: [[-3.3150415]]
NEGATIVE

### # AVENGERS: ENDGAME 3 STAR COMMENT

sample\_pred\_text = ("""I don't get why so many people like this movie so much, all they did w
They also just added a whole bunch of scenes of previous marvel movies, and that is how they
Now, getting to the inappropriate content for the parents. This is just your average superhero
There are also strong roll models, but if you have a kid that is in elementary school or high
But. I am not trying to parent your child. I am just giving my personal opinion, so you can c
https://colab.research.google.com/github/Tanya-vats/Tanya/blob/master/Sentiment Analysis RNN LSTM 1.ipynb#printMode=true 6/10

```
Due, I am not crying to partite your critia, I am just giving my personal opinion, so you can t
watching it.""")
predictions = sample predict(sample pred text, pad = False)
print(predictions)
     WARNING:tensorflow:7 out of the last 7 calls to <function Model.make predict function.<]
     WARNING:tensorflow:7 out of the last 7 calls to <function Model.make predict function.<]
```

#### # AVENGERS: ENDGAME 1 STAR COMMENT

**NEGATIVE** 

Prediction Score: [[-2.6585133]]

sample pred text = ("""Disappointing storyline - too many sad crying scenes - too much shit s an adult I don't appreciate swearing in movies. There are MANY people who don't use cuss word To hear Robert Downey jr's 'moment' with his young child using and laughing at the fact that ages watching this, that it is okay when it isn't. They seemed to want to use their cuss word how they get their best laughs from audience. Bring back your creative, quirky writers from t development and writing without resorting to desperate shock value. We have loved every movie was soooo boring in this. All of us watching kept hoping it would improve and it didn't. I th between Quill (StarLord) and Thor. Subtle, but funny. We all could've cared less if anyone di Why! It was torture and I felt robbed of my time in the end.""")

```
predictions = sample predict(sample pred text, pad = False)
print(predictions)
```

```
WARNING:tensorflow:8 out of the last 8 calls to <function Model.make_predict_function.<]
WARNING:tensorflow:8 out of the last 8 calls to <function Model.make predict function.<]
Prediction Score: [[-2.4277794]]
NEGATIVE
```

#### # AVENGERS ENDGAME COMMENT

sample pred text = ("""What a great way to end several major storylines that they invested in I feel like this is just the cherry on the top. My only complaint is something that you can't 'powers' are totally inconsistent from scene to scene, and movie to movie. This is a trope th Captain Marvel, Thor, Scarlet Witch, and Hulk were always as powerful as they show flashes of could destroy Thanos in the blink of an eye, and have done similar feats in other stories (an sometimes 'reduce' their power to a lower level, without an explained mechanism, is pretty la Yes, this constant Ex Machina is needed to maintain the drama and keep the plot going, but it

```
predictions = sample_predict(sample_pred_text, pad = False)
print(predictions)
```

```
WARNING:tensorflow:9 out of the last 9 calls to <function Model.make predict function.<]
WARNING:tensorflow:9 out of the last 9 calls to <function Model.make_predict_function.<]
Prediction Score: [[3.6573927]]
POSITIVE
```

sample\_pred\_text = ("""Superhero comics, and much of their adaptations, have long taken an ou At their best, they can take these fantastical ideas and make them emotionally resonant, even In some respects, Endgame pulls this off beautifully, like how the character Nebula confronts her personal growth. But as fun as the movie is, there's an undeniable hollowness at its core ideas and symbols.""")

predictions = sample\_predict(sample\_pred\_text, pad = False)
print(predictions)

WARNING:tensorflow:10 out of the last 10 calls to <function Model.make\_predict\_function WARNING:tensorflow:10 out of the last 10 calls to <function Model.make\_predict\_function Prediction Score: [[1.5968482]]
POSITIVE

# AUGUST to JUNE: Bringing Life to School (<a href="http://augusttojune.com/press-media/audience-comme">http://augusttojune.com/press-media/audience-comme</a>

sample\_pred\_text = ("""The film's ever-present focus on the 'big picture' of education and li In particular, we really liked seeing how you conferenced with parents, e.g., paraphrased: 'readers and late readers were', the overall approach to literacy- holistically focused rather growth/experiences/conflict resolution, and the fact that you did not choose to hide those mo children when disruptive. There is a whole, whole, whole lot more that I wish to say! It is heart-warming to know that your school carries on.""")

predictions = sample\_predict(sample\_pred\_text, pad = False)
print(predictions)

WARNING:tensorflow:11 out of the last 11 calls to <function Model.make\_predict\_function WARNING:tensorflow:11 out of the last 11 calls to <function Model.make\_predict\_function Prediction Score: [[1.7408558]]
POSITIVE

# AUGUST to JUNE: Bringing Life to School

sample\_pred\_text = ("""After we screened August To June, Boynton, Boca Democratic Party Movie they never seen an audience response so serene. People wanted to stay. No one was angry. Conv who had known each other for years discovered commonalities that previously they did not know The response, in unison, August To June is warm. It touches people. Real life school situati already is. People were reminded of good times and the challenges that helped them grow great reverence.""")

predictions = sample\_predict(sample\_pred\_text, pad = False)
print(predictions)

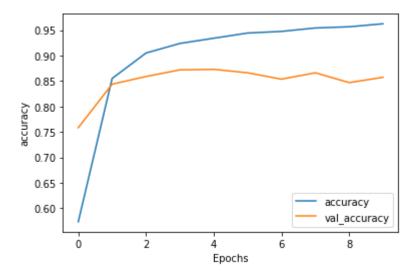
WARNING:tensorflow:11 out of the last 11 calls to <function Model.make\_predict\_function WARNING:tensorflow:11 out of the last 11 calls to <function Model.make\_predict\_function Prediction Score: [[4.970427]]
POSITIVE

# Plotting Acuracy & Loss Function Graphs

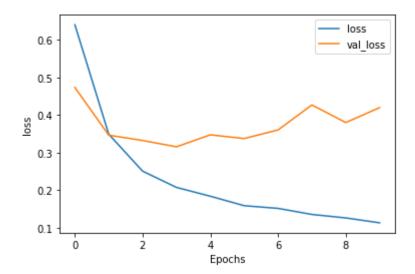
```
import matplotlib.pyplot as plt

def plot_graphs(history, metric):
   plt.plot(history.history[metric])
   plt.plot(history.history['val_'+metric], '')
   plt.xlabel("Epochs")
   plt.ylabel(metric)
   plt.legend([metric, 'val_'+metric])
   plt.show()
```

plot\_graphs(history, 'accuracy')



plot\_graphs(history, 'loss')



×