```
In []: #@title Licensed under the Apache License, Version 2.0 (the "License"
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```

Open in Colab

(https://colab.research.google.com/github/lmoroney/dlaicourse/blob/master/Tensorf%20NLP/Course%203%20-%20Week%202%20-%20Lesson%202.jpynb)

```
In [6]: # Run this to ensure TensorFlow 2.x is used
try:
    # %tensorflow_version only exists in Colab.
    %tensorflow_version 2.x
except Exception:
    pass
```

In [7]: import json
import tensorflow as tf

from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

```
In [8]: vocab_size = 10000
embedding_dim = 16
max_length = 100
trunc_type='post'
padding_type='post'
oov_tok = "<00V>"
training_size = 20000
```

```
In [9]: !wget --no-check-certificate \
    https://storage.googleapis.com/laurencemoroney-blog.appspot.com
    -0 /tmp/sarcasm.json
```

'wget' is not recognized as an internal or external command, operable program or batch file.

```
In [5]: #tokenize sarcarm
        with open("/tmp/sarcasm.json", 'r') as f:
            datastore = json.load(f)
        sentences = []
        labels = []
        #separate the json file
        #each item is an object, so it's really easy to get data
        for item in datastore:
            sentences.append(item['headline'])
            labels.append(item['is_sarcastic'])
In [6]: #separate into testing and training by slicing at indexes
        training_sentences = sentences[0:training_size]
        testing_sentences = sentences[training_size:]
        training_labels = labels[0:training_size]
        testing labels = labels[training size:]
In [7]: tokenizer = Tokenizer(num_words=vocab_size, oov_token=oov_tok)
        tokenizer.fit_on_texts(training_sentences)
        word_index = tokenizer.word_index
        training sequences = tokenizer.texts to sequences(training sentence
        training_padded = pad_sequences(training_sequences, maxlen=max_leng
        #same process, obtain tokenized diciontary of training sentences
        #then try it on the testing sentences
        testing sequences = tokenizer.texts to sequences(testing sentences)
        testing padded = pad sequences(testing sequences, maxlen=max length
In [8]: # Need this block to get it to work with TensorFlow 2.x
        import numpy as np
        training_padded = np.array(training_padded)
        training labels = np.array(training labels)
        testing_padded = np.array(testing_padded)
        testing_labels = np.array(testing_labels)
In [9]: |#the vector shape returned is not easily flattened, so the
        #global average pooling layer is used
        model = tf.keras.Sequential([
            tf.keras.layers.Embedding(vocab_size, embedding_dim, input_leng
            tf.keras.layers.GlobalAveragePooling1D(),
            tf.keras.layers.Dense(24, activation='relu'),
            tf.keras.layers.Dense(1, activation='sigmoid')
        1)
        model.compile(loss='binary crossentropy',optimizer='adam',metrics=[
```

In [10]: model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 100, 16)	160000
global_average_pooling1d (Gl	(None, 16)	0
dense (Dense)	(None, 24)	408
dense_1 (Dense)	(None, 1)	25

Total params: 160,433 Trainable params: 160,433 Non-trainable params: 0

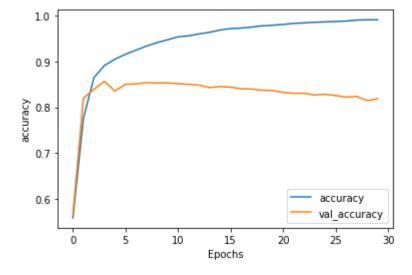
```
In [11]: num epochs = 30
         history = model.fit(training_padded, training_labels, epochs=num_ep
         Epoch 1/30
         625/625 - 2s - loss: 0.6803 - accuracy: 0.5584 - val loss: 0.6548 -
         y: 0.5646
         Epoch 2/30
         625/625 - 2s - loss: 0.5135 - accuracy: 0.7754 - val loss: 0.4231 -
         y: 0.8201
         Epoch 3/30
         625/625 - 2s - loss: 0.3404 - accuracy: 0.8648 - val loss: 0.3699 -
         y: 0.8393
         Epoch 4/30
         625/625 - 2s - loss: 0.2822 - accuracy: 0.8913 - val loss: 0.3457 -
         y: 0.8571
         Epoch 5/30
         625/625 - 2s - loss: 0.2447 - accuracy: 0.9051 - val_loss: 0.3641 -
         y: 0.8356
         Epoch 6/30
         625/625 - 2s - loss: 0.2182 - accuracy: 0.9159 - val_loss: 0.3524 -
         y: 0.8504
         Epoch 7/30
         625/625 - 2s - loss: 0.1947 - accuracy: 0.9249 - val_loss: 0.3497 -
         v: 0.8512
         Epoch 8/30
         625/625 - 2s - loss: 0.1764 - accuracy: 0.9338 - val_loss: 0.3661 -
         y: 0.8538
         Epoch 9/30
         625/625 - 2s - loss: 0.1586 - accuracy: 0.9413 - val_loss: 0.3682 -
         v: 0.8533
         Epoch 10/30
         625/625 - 2s - loss: 0.1462 - accuracy: 0.9475 - val_loss: 0.3833 -
         y: 0.8533
         Epoch 11/30
         625/625 - 2s - loss: 0.1328 - accuracy: 0.9540 - val_loss: 0.4007 -
         y: 0.8518
         Epoch 12/30
         625/625 - 3s - loss: 0.1234 - accuracy: 0.9563 - val_loss: 0.4147 -
         y: 0.8502
         Epoch 13/30
         625/625 - 2s - loss: 0.1138 - accuracy: 0.9604 - val loss: 0.4334 -
         y: 0.8486
         Epoch 14/30
         625/625 - 2s - loss: 0.1054 - accuracy: 0.9639 - val loss: 0.4548 -
         y: 0.8432
         Epoch 15/30
         625/625 - 2s - loss: 0.0955 - accuracy: 0.9689 - val loss: 0.4701 -
         y: 0.8454
         Epoch 16/30
         625/625 - 2s - loss: 0.0876 - accuracy: 0.9720 - val loss: 0.4956 -
         y: 0.8442
         Epoch 17/30
         625/625 - 2s - loss: 0.0831 - accuracy: 0.9732 - val loss: 0.5174 -
         y: 0.8405
         Epoch 18/30
         625/625 - 2s - loss: 0.0764 - accuracy: 0.9754 - val loss: 0.5421 -
```

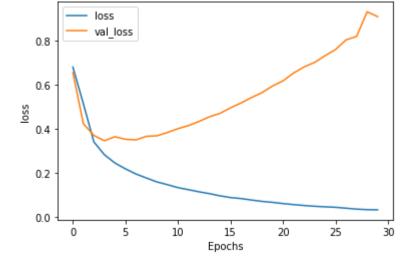
```
y: 0.8401
Epoch 19/30
625/625 - 2s - loss: 0.0702 - accuracy: 0.9780 - val_loss: 0.5645 -
v: 0.8374
Epoch 20/30
625/625 - 2s - loss: 0.0659 - accuracy: 0.9793 - val_loss: 0.5946 -
y: 0.8366
Epoch 21/30
625/625 - 2s - loss: 0.0603 - accuracy: 0.9812 - val_loss: 0.6179 -
y: 0.8326
Epoch 22/30
625/625 - 2s - loss: 0.0556 - accuracy: 0.9834 - val_loss: 0.6535 -
y: 0.8307
Epoch 23/30
625/625 - 2s - loss: 0.0516 - accuracy: 0.9845 - val_loss: 0.6811 -
v: 0.8307
Epoch 24/30
625/625 - 2s - loss: 0.0481 - accuracy: 0.9859 - val_loss: 0.7016 -
y: 0.8269
Epoch 25/30
625/625 - 2s - loss: 0.0455 - accuracy: 0.9867 - val_loss: 0.7322 -
y: 0.8286
Epoch 26/30
625/625 - 2s - loss: 0.0434 - accuracy: 0.9876 - val_loss: 0.7603 -
y: 0.8258
Epoch 27/30
625/625 - 2s - loss: 0.0392 - accuracy: 0.9886 - val loss: 0.8041 -
y: 0.8225
Epoch 28/30
625/625 - 2s - loss: 0.0351 - accuracy: 0.9906 - val_loss: 0.8197 -
y: 0.8238
Epoch 29/30
625/625 - 3s - loss: 0.0328 - accuracy: 0.9913 - val_loss: 0.9317 -
y: 0.8146
Epoch 30/30
625/625 - 3s - loss: 0.0319 - accuracy: 0.9912 - val loss: 0.9097 -
y: 0.8188
```

```
In [12]: import matplotlib.pyplot as plt
#overtime the Loss increases, due to overfitting

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

plot_graphs(history, "accuracy")
    plot_graphs(history, "loss")
```





```
In [13]: reverse word index = dict([(value, key) for (key, value) in word in
        def decode_sentence(text):
            return ' '.join([reverse word index.get(i, '?') for i in text])
        print(decode_sentence(training_padded[0]))
        print(training sentences[2])
        print(labels[2])
        former <00V> store clerk sues over secret 'black <00V> for minority
        , , , , , , ,
        mom starting to fear son's web series closest thing she will have t
In [14]: | e = model.layers[0]
        weights = e.get weights()[0]
        print(weights.shape) # shape: (vocab_size, embedding_dim)
        (10000, 16)
In [15]: import io
        out_v = io.open('vecs.tsv', 'w', encoding='utf-8')
        out_m = io.open('meta.tsv', 'w', encoding='utf-8')
        for word_num in range(1, vocab_size):
          word = reverse word index[word num]
          embeddings = weights[word_num]
          out_m.write(word + "\n")
          out v.write('\t'.join([str(x) for x in embeddings]) + "\n")
        out v.close()
        out_m.close()
In [16]: try:
          from google.colab import files
        except ImportError:
          pass
        else:
          files.download('vecs.tsv')
          files.download('meta.tsv')
        <IPython.core.display.Javascript object>
        <IPython.core.display.Javascript object>
        <IPython.core.display.Javascript object>
        <IPython.core.display.Javascript object>
```

```
In [17]: sentence = ["granny starting to fear spiders in the garden might be
sequences = tokenizer.texts_to_sequences(sentence)
padded = pad_sequences(sequences, maxlen=max_length, padding=paddin
print(model.predict(padded))

[[9.844283e-01]
[8.191375e-04]]
```