Welcome to your assignment this week!

To better understand the adverse use of AI, in this assignment, we will look at a Natural Language Processing use case.

Natural Language Pocessing (NLP) is a branch of Artificial Intelligence (AI) that helps computers to understand, to interpret and to manipulate natural (i.e. human) language. Imagine NLP-powered machines as black boxes that are capable of understanding and evaluating the context of the input documents (i.e. collection of words), outputting meaningful results that depend on the task the machine is designed for.

In this notebook, you will implement a model that uses an LSTM to generate fake tweets and comments. You will also be able to try it to generate your own fake text.

You will learn to:

- Apply an LSTM to generate fake comments.
- Generate your own fake text with deep learning.

Run the following cell to load the packages you will need.

```
import time
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout, Bidirectional
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import regularizers
import tensorflow.keras.utils as ku
import keras.backend as K
import matplotlib.pyplot as plt
import numpy as np
```

Build the model

Let's define a tokenizer and read the data from disk.

```
tokenizer = Tokenizer(filters='"#$%&()*+-/:;<=>@[\\]^_`{|}~\t\n')
data = open('covid19_fake.txt').read().replace(".", " . ").replace(",", " , ").replace("?", " ? ").replace("!", " ! ")
```

Now, let's splits the data into tweets where each line of the input file is a fake tweets.

We also extract the vocabulary of the data.

```
corpus = data.lower().split("\n")
tokenizer.fit_on_texts(corpus)
total_words = len(tokenizer.word_index) + 1
```

You've loaded:

- `corpus`: an array where each entry is a fake post.
- `tokenizer`: which is the object that we will use to vectorize our dataset. This object also contains our word index.
- `total_words`: is the total number of words in the vacabulary.

```
print("Example of fake tweets: ",corpus[:2])
print("Size of the vocabulary = ", total_words)
index = [(k, v) for k, v in tokenizer.word_index.items()]
print("Example of our word index = ", index[0:10])
```

```
Example of fake tweets:  ['there is already a vaccine to treat covid19
. ', 'cleaning hands do not help to prevent covid19 . ']
Size of the vocabulary =  1257
Example of our word index =  [('.', 1), ('the', 2), ('covid19', 3),
('in', 4), ('to', 5), ('a', 6), ('of', 7), (',', 8), ('coronavirus',
9), ('and', 10)]
```

The next step aims to generate the training set of n_grams sequences.

```
input_sequences = []
for line in corpus:
    token_list = tokenizer.texts_to_sequences([line])[0]
    for i in range(1, len(token_list)):
        n_gram_sequence = token_list[:i+1]
        input_sequences.append(n_gram_sequence)
```

You've create:

- `input_sequences`: which is a list of n_grams sequences.

```
sample = 20
reverse_word_map = dict(map(reversed, tokenizer.word_index.items()))
print("The entry ",sample," in 'input_sequences' is: ")
print(input_sequences[sample])
print(" and it corresponds to:")
for i in input_sequences[sample]:
    print(reverse_word_map[i], end=' ')
```

```
The entry  20  in 'input_sequences' is:
[2, 3, 12, 187, 34, 188]
 and it corresponds to:
the covid19 is same as sars
```

Next, we padd our training set to the max length in order to be able to make a batch processing.

```
max_sequence_len = max([len(x) for x in input_sequences])
input_sequences = np.array(pad_sequences(input_sequences,
maxlen=max_sequence_len, padding='pre'))
```

Run the following to see the containt of the padded 'input_sequences' object.

```
reverse_word_map = dict(map(reversed, tokenizer.word_index.items()))
print("The entry ",sample," in 'input_sequences' is: ")
print(input_sequences[sample])
print(" and it corresponds to:")
print("[", end=' ')
for i in input_sequences[sample]:
    if i in reverse_word_map:
        print(reverse_word_map[i], end=' ')
    else:
        print("__", end=' ')
print("]")

The entry  20  in 'input_sequences' is:
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0
   0   2   3  12 187  34 188]
 and it corresponds to:
[ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __
__ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __
__ __ __ __ __ __ __ __ __ the covid19 is same as sars ]
```

Given a sentence like **"the covid19 is same as "**, we want to design a model that can predict the next word -- in the case the word **"sars"**.

Therefore, the next code prepares our input and output to our model consequently.

```
input_to_model, label = input_sequences[:,:-1],input_sequences[:,-1]

print("The entry ",sample," in 'input_sequences' is: ")
print(input_sequences[sample])
print(", it corresponds to the following input to our model:")
print(input_to_model[sample])
print(" and the following output: ", label[sample])

The entry  20  in 'input_sequences' is:
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
```

```
0
   0   2   3  12 187  34 188]
, it corresponds to the following input to our model:
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0
   0   2   3  12 187  34]
 and the following output:  188
```

Finally, we convert our label to categorical labels for being processed by our model.

```
label = ku.to_categorical(label, num_classes=total_words)
```

Here is the architecture of the model we will use:

Task 1: Implement `deep_fake_comment_model()`. You will need to carry out 5 steps:

1. Create a sequencial model using the `Sequential` class
2. Add an embedding layer to the model using the `Embedding` class of size 128
3. Add an LSTM layer to the model using the `LSTM` class of size 128
4. Add a Dense layer to the model using the `Dense` class with a `softmax` activation
5. Set a `categorical_crossentropy` loss function to the model and optimize `accuracy`.

```
#TASK 1
# deep_fake_comment_model

def deep_fake_comment_model():
    ### START CODE HERE ###
    model = Sequential()
    model.add(Embedding(input_dim=total_words, output_dim=128,
input_length=max_sequence_len-1))
    model.add(LSTM(128))
    model.add(Dense(total_words, activation='softmax'))
    model.compile(loss='categorical_crossentropy', optimizer='adam',
metrics=['accuracy'])
    return model
    ### END CODE HERE ###

#Print details of the model.
model = deep_fake_comment_model()

/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/
embedding.py:97: UserWarning: Argument `input_length` is deprecated.
```

```
Just remove it.
  warnings.warn(
```

Now, let's start our training.

```
history = model.fit(input_to_model, label, epochs=200, batch_size=32,
verbose=1)
```

```
Epoch 1/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.0648 - loss:
6.5783
Epoch 2/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.0722 - loss:
5.8723
Epoch 3/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.0801 - loss:
5.7138
Epoch 4/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.1071 - loss:
5.5186
Epoch 5/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.1137 - loss:
5.3972
Epoch 6/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.1424 - loss:
5.1960
Epoch 7/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.1535 - loss:
5.0135
Epoch 8/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.1576 - loss:
4.9083
Epoch 9/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.1766 - loss:
4.6686
Epoch 10/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.1959 - loss:
4.5106
Epoch 11/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.2054 - loss:
4.4144
Epoch 12/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.2183 - loss:
4.2183
Epoch 13/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.2344 - loss:
4.0763
Epoch 14/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.2382 - loss:
```

```
3.9752
Epoch 15/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.2587 - loss:
3.7483
Epoch 16/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.2941 - loss:
3.5651
Epoch 17/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.3019 - loss:
3.4819
Epoch 18/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.3306 - loss:
3.3082
Epoch 19/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.3508 - loss:
3.1559
Epoch 20/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.3674 - loss:
3.0344
Epoch 21/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.3882 - loss:
2.9124
Epoch 22/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.4092 - loss:
2.7784
Epoch 23/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.4341 - loss:
2.6208
Epoch 24/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.4720 - loss:
2.4756
Epoch 25/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.4977 - loss:
2.3682
Epoch 26/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - accuracy: 0.5421 - loss:
2.2133
Epoch 27/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.5612 - loss:
2.1061
Epoch 28/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.5924 - loss:
1.9806
Epoch 29/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - accuracy: 0.6254 - loss:
1.8724
Epoch 30/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.6606 - loss:
1.7347
```

```
Epoch 31/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.6726 - loss:
1.6944
Epoch 32/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.7018 - loss:
1.5942
Epoch 33/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.7324 - loss:
1.4625
Epoch 34/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.7508 - loss:
1.4028
Epoch 35/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - accuracy: 0.7547 - loss:
1.3242
Epoch 36/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.7739 - loss:
1.2387
Epoch 37/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.7971 - loss:
1.1511
Epoch 38/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.8160 - loss:
1.0882
Epoch 39/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.8362 - loss:
1.0042
Epoch 40/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.8358 - loss:
0.9715
Epoch 41/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.8446 - loss:
0.9027
Epoch 42/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.8567 - loss:
0.8473
Epoch 43/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.8681 - loss:
0.7918
Epoch 44/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.8777 - loss:
0.7639
Epoch 45/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.8758 - loss:
0.7276
Epoch 46/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 11ms/step - accuracy: 0.8897 - loss:
0.6803
Epoch 47/200
```

```
126/126 ━━━━━━━━━━━━━━━━━━━━ 3s 11ms/step - accuracy: 0.8961 - loss:
0.6502
Epoch 48/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.8934 - loss:
0.6208
Epoch 49/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9148 - loss:
0.5793
Epoch 50/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9084 - loss:
0.5699
Epoch 51/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9164 - loss:
0.5214
Epoch 52/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9167 - loss:
0.4899
Epoch 53/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9294 - loss:
0.4629
Epoch 54/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9220 - loss:
0.4562
Epoch 55/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 11ms/step - accuracy: 0.9276 - loss:
0.4274
Epoch 56/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - accuracy: 0.9259 - loss:
0.4225
Epoch 57/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9307 - loss:
0.3881
Epoch 58/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9403 - loss:
0.3808
Epoch 59/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9423 - loss:
0.3456
Epoch 60/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9426 - loss:
0.3579
Epoch 61/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9407 - loss:
0.3267
Epoch 62/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9487 - loss:
0.3049
Epoch 63/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9313 - loss:
```

```
0.3289
Epoch 64/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 12ms/step - accuracy: 0.9403 - loss:
0.3066
Epoch 65/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 14ms/step - accuracy: 0.9412 - loss:
0.2848
Epoch 66/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.9465 - loss:
0.2705
Epoch 67/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9424 - loss:
0.2685
Epoch 68/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9465 - loss:
0.2586
Epoch 69/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9494 - loss:
0.2365
Epoch 70/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9446 - loss:
0.2472
Epoch 71/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9448 - loss:
0.2356
Epoch 72/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9467 - loss:
0.2224
Epoch 73/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9540 - loss:
0.2068
Epoch 74/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9508 - loss:
0.2111
Epoch 75/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - accuracy: 0.9494 - loss:
0.2024
Epoch 76/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9424 - loss:
0.2086
Epoch 77/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9518 - loss:
0.1887
Epoch 78/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9589 - loss:
0.1834
Epoch 79/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9471 - loss:
0.2131
```

```
Epoch 80/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9500 - loss:
0.1901
Epoch 81/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9492 - loss:
0.1814
Epoch 82/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9496 - loss:
0.1873
Epoch 83/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9522 - loss:
0.1774
Epoch 84/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 12ms/step - accuracy: 0.9516 - loss:
0.1682
Epoch 85/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - accuracy: 0.9522 - loss:
0.1589
Epoch 86/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9571 - loss:
0.1581
Epoch 87/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9489 - loss:
0.1671
Epoch 88/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9527 - loss:
0.1624
Epoch 89/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9598 - loss:
0.1473
Epoch 90/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9505 - loss:
0.1584
Epoch 91/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9523 - loss:
0.1577
Epoch 92/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9473 - loss:
0.1620
Epoch 93/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9540 - loss:
0.1452
Epoch 94/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9539 - loss:
0.1486
Epoch 95/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9528 - loss:
0.1428
Epoch 96/200
```

```
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9523 - loss:
0.1398
Epoch 97/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9589 - loss:
0.1254
Epoch 98/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9582 - loss:
0.1342
Epoch 99/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9524 - loss:
0.1506
Epoch 100/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9481 - loss:
0.1517
Epoch 101/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9549 - loss:
0.1356
Epoch 102/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - accuracy: 0.9489 - loss:
0.1507
Epoch 103/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9452 - loss:
0.1525
Epoch 104/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9525 - loss:
0.1348
Epoch 105/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9521 - loss:
0.1376
Epoch 106/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9511 - loss:
0.1328
Epoch 107/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9579 - loss:
0.1270
Epoch 108/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9531 - loss:
0.1347
Epoch 109/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9585 - loss:
0.1195
Epoch 110/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9553 - loss:
0.1203
Epoch 111/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9590 - loss:
0.1242
Epoch 112/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9512 - loss:
```

```
0.1400
Epoch 113/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9540 - loss:
0.1326
Epoch 114/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 11ms/step - accuracy: 0.9526 - loss:
0.1298
Epoch 115/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.9548 - loss:
0.1257
Epoch 116/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9568 - loss:
0.1308
Epoch 117/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9522 - loss:
0.1348
Epoch 118/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9496 - loss:
0.1483
Epoch 119/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.9488 - loss:
0.1358
Epoch 120/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9529 - loss:
0.1231
Epoch 121/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9513 - loss:
0.1321
Epoch 122/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9553 - loss:
0.1203
Epoch 123/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9492 - loss:
0.1339
Epoch 124/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9534 - loss:
0.1235
Epoch 125/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9559 - loss:
0.1247
Epoch 126/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9521 - loss:
0.1225
Epoch 127/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9495 - loss:
0.1321
Epoch 128/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9512 - loss:
0.1262
```

```
Epoch 129/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9521 - loss:
0.1302
Epoch 130/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9570 - loss:
0.1188
Epoch 131/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9591 - loss:
0.1205
Epoch 132/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9583 - loss:
0.1170
Epoch 133/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - accuracy: 0.9584 - loss:
0.1114
Epoch 134/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.9537 - loss:
0.1276
Epoch 135/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9596 - loss:
0.1103
Epoch 136/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9513 - loss:
0.1233
Epoch 137/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9539 - loss:
0.1273
Epoch 138/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9526 - loss:
0.1240
Epoch 139/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9511 - loss:
0.1260
Epoch 140/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9534 - loss:
0.1208
Epoch 141/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9515 - loss:
0.1305
Epoch 142/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9465 - loss:
0.1412
Epoch 143/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9482 - loss:
0.1217
Epoch 144/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9511 - loss:
0.1240
Epoch 145/200
```

```
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9537 - loss:
0.1278
Epoch 146/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9480 - loss:
0.1367
Epoch 147/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9476 - loss:
0.1295
Epoch 148/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9562 - loss:
0.1260
Epoch 149/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9570 - loss:
0.1191
Epoch 150/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9510 - loss:
0.1323
Epoch 151/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9494 - loss:
0.1212
Epoch 152/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9535 - loss:
0.1230
Epoch 153/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9556 - loss:
0.1170
Epoch 154/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9544 - loss:
0.1257
Epoch 155/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.9465 - loss:
0.1506
Epoch 156/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9481 - loss:
0.1490
Epoch 157/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9499 - loss:
0.1262
Epoch 158/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9565 - loss:
0.1101
Epoch 159/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9531 - loss:
0.1202
Epoch 160/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9511 - loss:
0.1261
Epoch 161/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9583 - loss:
```

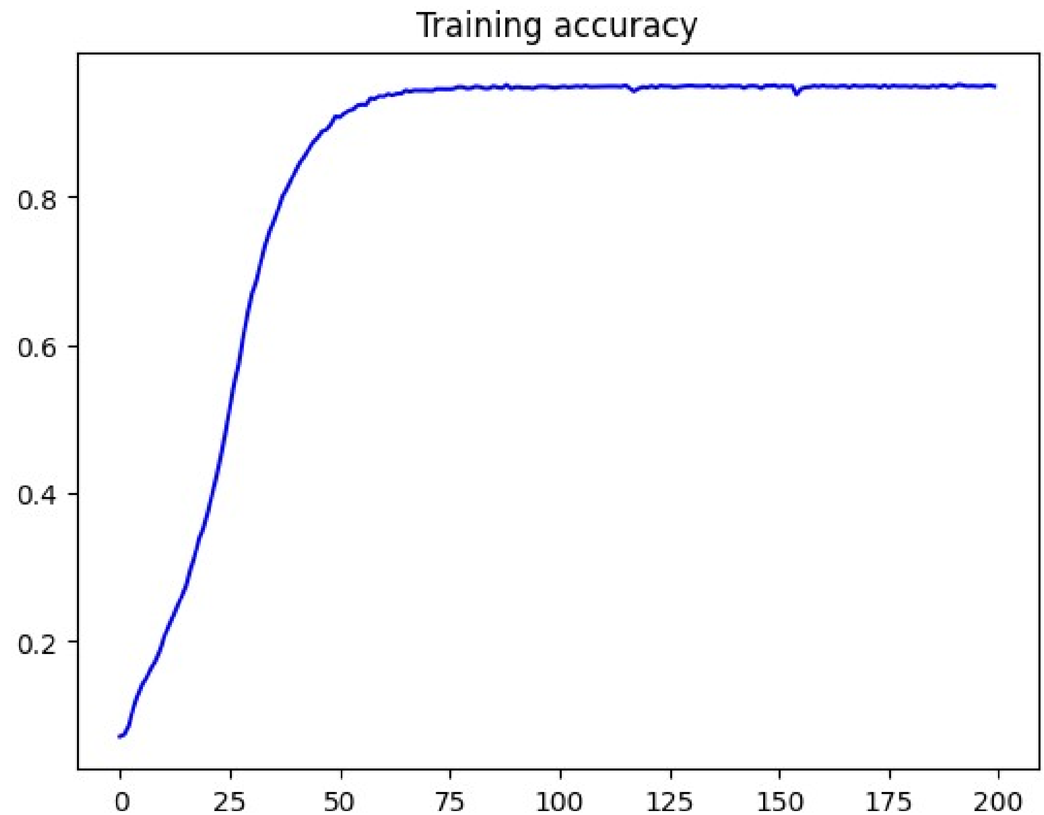
```
0.1050
Epoch 162/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9547 - loss:
0.1288
Epoch 163/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.9535 - loss:
0.1164
Epoch 164/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9517 - loss:
0.1176
Epoch 165/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9529 - loss:
0.1216
Epoch 166/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9520 - loss:
0.1235
Epoch 167/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9551 - loss:
0.1106
Epoch 168/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9537 - loss:
0.1185
Epoch 169/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9508 - loss:
0.1215
Epoch 170/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9479 - loss:
0.1297
Epoch 171/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 11ms/step - accuracy: 0.9538 - loss:
0.1218
Epoch 172/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 3s 12ms/step - accuracy: 0.9517 - loss:
0.1265
Epoch 173/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9535 - loss:
0.1198
Epoch 174/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9518 - loss:
0.1200
Epoch 175/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9529 - loss:
0.1211
Epoch 176/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9469 - loss:
0.1371
Epoch 177/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9524 - loss:
0.1175
Epoch 178/200
```

```
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9546 - loss:
0.1192
Epoch 179/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9559 - loss:
0.1138
Epoch 180/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9566 - loss:
0.1101
Epoch 181/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - accuracy: 0.9550 - loss:
0.1125
Epoch 182/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9521 - loss:
0.1230
Epoch 183/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9503 - loss:
0.1229
Epoch 184/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9468 - loss:
0.1291
Epoch 185/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9506 - loss:
0.1252
Epoch 186/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9499 - loss:
0.1245
Epoch 187/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9539 - loss:
0.1163
Epoch 188/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9496 - loss:
0.1282
Epoch 189/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - accuracy: 0.9548 - loss:
0.1158
Epoch 190/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 2s 10ms/step - accuracy: 0.9556 - loss:
0.1070
Epoch 191/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9543 - loss:
0.1202
Epoch 192/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9564 - loss:
0.1128
Epoch 193/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9578 - loss:
0.1126
Epoch 194/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9550 - loss:
```

```
0.1162
Epoch 195/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9508 - loss:
0.1268
Epoch 196/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9544 - loss:
0.1153
Epoch 197/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9524 - loss:
0.1227
Epoch 198/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9497 - loss:
0.1318
Epoch 199/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9537 - loss:
0.1217
Epoch 200/200
126/126 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9568 - loss:
0.1103
```

Let's plot details of our training.

```
acc = history.history['accuracy']
loss = history.history['loss']
epochs = range(len(acc))
plt.plot(epochs, acc, 'b', label='Training accuracy')
plt.title('Training accuracy')
plt.figure()
plt.plot(epochs, loss, 'b', label='Training Loss')
plt.title('Training loss')
plt.legend()
plt.show()
```


Training accuracy
0.2
0.4
0.6
0.8
0
25
50
75
100
125
150
175
200


Training loss
Training Loss
0
1
2
3
4
5
6
0
25
50
75
100
125
150
175
200

Generating fake comments

To generate fake tweets, we use the below architecture:

The idea is to give one or more starting token(s) to our model, and generate the next tokens until we generate `.`.

At each step, we select the token with the highest probability as our next token and generate the next one similartly using `model.predict_classes()`.

Note: The model takes as input the activation `a` from the previous state of the LSTM and the token chosen, forward propagate by one step, and get a new output activation `a`. The new activation `a` can then be used to generate the output, using the `dense` layer with `softmax` activation as before.

Task 2: Implement `generate()`.

```
#TASK 2
# Implement the generate() function

def generate(seed_text):
    ### START CODE HERE ###
    next_words = 20
    for _ in range(next_words):
        token_list = tokenizer.texts_to_sequences([seed_text])[0]
        token_list = pad_sequences([token_list], 
maxlen=max_sequence_len-1, padding='pre')
        predicted = np.argmax(model.predict(token_list), axis=-1)[0]
        output_word = ""
        for word, index in tokenizer.word_index.items():
            if index == predicted:
                output_word = word
                break
        if output_word == ".":
            break
        seed_text += " " + output_word
    return seed_text
    ### END CODE HERE ###
```

Let's test it:

```
print(generate("COVID19 virus"))
print(generate("COVID19 is the"))
print(generate("The usa is"))
print(generate("The new virus"))
print(generate("China has"))
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 191ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 50ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 50ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step
COVID19 virus survives on surfaces for 7 days
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 40ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
COVID19 is the deadliest virus known to humans
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
The usa is one of the covid19 virus
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
The new virus will not drink corona beer covid19
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
China has made an implanted microchip in humans , and everyone to be
vaccinated
```

Let's test it in an interactive mode:

```
usr_input = input("Write the beginning of your tweet, the algorithm
machine will complete it. Your input is: ")
for w in generate(usr_input).split():
    print(w, end =" ")
    time.sleep(0.4)
```

```
Write the beginning of your tweet, the algorithm machine will complete
it. Your input is: in the america
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 51ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 49ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 68ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
in the america has far fewer covid19 deaths than new york
```

Generating text by sampling

The previous part is generating text by choosing the token with the highest probability. Now, we sill generate text by sampling as shown in the architecture below:

TASK 3: Implement the `generate_sample()` function. To sample a token from the output at each timestep, you need to use the following two functions:

- `model.predict_proba()`: To get probabilities from the output layer.
- `np.random.choice()`: To sample from the token list using the probaility array of each token.

```
#TASK 3
# Implement the generate_sample() function
def generate_sample(seed_text):
    ### START CODE HERE ###
    next_words = 20
    for _ in range(next_words):
        token_list = tokenizer.texts_to_sequences([seed_text])[0]
        token_list = pad_sequences([token_list],
maxlen=max_sequence_len-1, padding='pre')
        probas = model.predict(token_list)[0]
        predicted = np.random.choice(range(total_words), p=probas)
        output_word = ""
        for word, index in tokenizer.word_index.items():
```

```
            if index == predicted:
                output_word = word
                break
        if output_word == ".":
            break
        seed_text += " " + output_word
    return seed_text
    ### END CODE HERE ###
```

Let's test it in an interactive mode:

```
usr_input = input("Write the beginning of your tweet, the algorithm
machine will complete it. Your input is: ")
for w in generate_sample(usr_input).split():
    print(w, end =" ")
    time.sleep(0.4)

Write the beginning of your tweet, the algorithm machine will complete
it. Your input is: in america
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
in america has the sun for two hours kills the 2019 covid19
```

Generate your own text

Below, use you own data to generate content for a different application:
In this case, im createing a fake news generator about news in the USA
Datasets collected from: https://www.kaggle.com/datasets/emineyetm/fake-news-detection-datasets/data

```
tokenizer = Tokenizer(filters='"#$%&()*+-/:;<=>@[\\]^_`{|}~\t\n')
data = open('fakenews.txt', encoding='utf-8').read().replace(".", " .
").replace(",", " , ").replace("?", " ? ").replace("!", " ! ")

corpus = data.lower().split("\n")
tokenizer.fit_on_texts(corpus)
total_words = len(tokenizer.word_index) + 1
```

```
print("Example of fake tweets: ",corpus[:2])
print("Size of the vocabulary = ", total_words)
index = [(k, v) for k, v in tokenizer.word_index.items()]
print("Example of our word index = ", index[0:10])

Example of fake tweets:  [" donald trump sends out embarrassing new
year's eve message; this is disturbing", ' drunk bragging trump
staffer started russian collusion investigation']
Size of the vocabulary =  1243
Example of our word index =  [('trump', 1), ('to', 2), ('the', 3),
('for', 4), ('a', 5), ('is', 6), (',', 7), ('in', 8), ('his', 9),
('and', 10)]

input_sequences = []
for line in corpus:
    token_list = tokenizer.texts_to_sequences([line])[0]
    for i in range(1, len(token_list)):
        n_gram_sequence = token_list[:i+1]
        input_sequences.append(n_gram_sequence)

sample = 20
reverse_word_map = dict(map(reversed, tokenizer.word_index.items()))
print("The entry ",sample," in 'input_sequences' is: ")
print(input_sequences[sample])
print(" and it corresponds to:")
for i in input_sequences[sample]:
    print(reverse_word_map[i], end=' ')

The entry  20  in 'input_sequences' is:
[206, 395, 396, 397]
 and it corresponds to:
sheriff david clarke becomes

max_sequence_len = max([len(x) for x in input_sequences])
input_sequences = np.array(pad_sequences(input_sequences,
maxlen=max_sequence_len, padding='pre'))

reverse_word_map = dict(map(reversed, tokenizer.word_index.items()))
print("The entry ",sample," in 'input_sequences' is: ")
print(input_sequences[sample])
print(" and it corresponds to:")
print("[", end=' ')
for i in input_sequences[sample]:
    if i in reverse_word_map:
        print(reverse_word_map[i], end=' ')
    else:
        print("__", end=' ')
print("]")

The entry  20  in 'input_sequences' is:
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 206
```

```
395
 396 397]
 and it corresponds to:
[ ___ ___ ___ ___ ___ ___ ___ ___ ___ ___ ___ ___ ___ ___ ___ ___ sheriff david clarke
becomes ]

input_to_model, label = input_sequences[:,:-1],input_sequences[:,-1]

print("The entry ",sample," in 'input_sequences' is: ")
print(input_sequences[sample])
print(", it corresponds to the following input to our model:")
print(input_to_model[sample])
print(" and the following output: ", label[sample])

The entry  20  in 'input_sequences' is:
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 206
395
 396 397]
, it corresponds to the following input to our model:
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 206
395
 396]
 and the following output:  397

label = ku.to_categorical(label, num_classes=total_words)

model = deep_fake_comment_model()

history = model.fit(input_to_model, label, epochs=200, batch_size=32,
verbose=1)

Epoch 1/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 7s 6ms/step - accuracy: 0.0238 - loss:
6.9979
Epoch 2/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.0209 - loss:
6.5016
Epoch 3/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.0365 - loss:
6.3595
Epoch 4/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.0359 - loss:
6.1165
Epoch 5/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.0355 - loss:
5.9754
Epoch 6/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.0481 - loss:
5.8331
Epoch 7/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.0444 - loss:
```

```
5.7170
Epoch 8/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.0617 - loss:
5.4487
Epoch 9/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.0556 - loss:
5.3854
Epoch 10/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.0862 - loss:
5.1102
Epoch 11/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.1021 - loss:
4.9719
Epoch 12/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.1136 - loss:
4.7818
Epoch 13/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.1462 - loss:
4.5576
Epoch 14/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.1619 - loss:
4.3866
Epoch 15/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.1944 - loss:
4.1767
Epoch 16/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.2232 - loss:
3.9411
Epoch 17/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.2605 - loss:
3.7978
Epoch 18/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.3014 - loss:
3.6011
Epoch 19/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.3407 - loss:
3.4134
Epoch 20/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.4033 - loss:
3.1962
Epoch 21/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.4561 - loss:
3.0116
Epoch 22/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.5262 - loss:
2.8160
Epoch 23/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.5754 - loss:
2.6378
```

```
Epoch 24/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.6180 - loss:
2.4905
Epoch 25/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.6635 - loss:
2.2938
Epoch 26/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.6854 - loss:
2.1229
Epoch 27/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7246 - loss:
1.9828
Epoch 28/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7648 - loss:
1.8321
Epoch 29/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7853 - loss:
1.6860
Epoch 30/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8203 - loss:
1.5427
Epoch 31/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8494 - loss:
1.4241
Epoch 32/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.8648 - loss:
1.2944
Epoch 33/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.8742 - loss:
1.2097
Epoch 34/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.8926 - loss:
1.0938
Epoch 35/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9003 - loss:
1.0144
Epoch 36/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8971 - loss:
0.9438
Epoch 37/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9203 - loss:
0.8568
Epoch 38/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9327 - loss:
0.7840
Epoch 39/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9351 - loss:
0.6894
Epoch 40/200
```

```
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9345 - loss:
0.6876
Epoch 41/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9367 - loss:
0.6389
Epoch 42/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9464 - loss:
0.5736
Epoch 43/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9479 - loss:
0.5300
Epoch 44/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9496 - loss:
0.4946
Epoch 45/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9534 - loss:
0.4708
Epoch 46/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9445 - loss:
0.4371
Epoch 47/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9542 - loss:
0.4092
Epoch 48/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9572 - loss:
0.3767
Epoch 49/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9551 - loss:
0.3524
Epoch 50/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9565 - loss:
0.3348
Epoch 51/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9547 - loss:
0.3293
Epoch 52/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9634 - loss:
0.2900
Epoch 53/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9654 - loss:
0.2712
Epoch 54/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9612 - loss:
0.2766
Epoch 55/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9596 - loss:
0.2626
Epoch 56/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9616 - loss:
```

```
0.2352
Epoch 57/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9574 - loss:
0.2472
Epoch 58/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9578 - loss:
0.2386
Epoch 59/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9576 - loss:
0.2259
Epoch 60/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9616 - loss:
0.2130
Epoch 61/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9609 - loss:
0.2086
Epoch 62/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9675 - loss:
0.1833
Epoch 63/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9600 - loss:
0.1890
Epoch 64/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9568 - loss:
0.1901
Epoch 65/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9644 - loss:
0.1734
Epoch 66/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9609 - loss:
0.1752
Epoch 67/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9637 - loss:
0.1684
Epoch 68/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9584 - loss:
0.1780
Epoch 69/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9617 - loss:
0.1634
Epoch 70/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9600 - loss:
0.1577
Epoch 71/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9609 - loss:
0.1588
Epoch 72/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9611 - loss:
0.1533
```

```
Epoch 73/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9650 - loss:
0.1401
Epoch 74/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9625 - loss:
0.1394
Epoch 75/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9544 - loss:
0.1527
Epoch 76/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9576 - loss:
0.1494
Epoch 77/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9671 - loss:
0.1246
Epoch 78/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9578 - loss:
0.1543
Epoch 79/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9564 - loss:
0.1483
Epoch 80/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9637 - loss:
0.1283
Epoch 81/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9591 - loss:
0.1290
Epoch 82/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9643 - loss:
0.1176
Epoch 83/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9665 - loss:
0.1216
Epoch 84/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9575 - loss:
0.1382
Epoch 85/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9666 - loss:
0.1172
Epoch 86/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9638 - loss:
0.1270
Epoch 87/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9609 - loss:
0.1241
Epoch 88/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9686 - loss:
0.1070
Epoch 89/200
```

```
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9568 - loss:
0.1206
Epoch 90/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9628 - loss:
0.1115
Epoch 91/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9628 - loss:
0.1094
Epoch 92/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9540 - loss:
0.1244
Epoch 93/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9583 - loss:
0.1174
Epoch 94/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9598 - loss:
0.1214
Epoch 95/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9581 - loss:
0.1194
Epoch 96/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9553 - loss:
0.1237
Epoch 97/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9622 - loss:
0.1115
Epoch 98/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9574 - loss:
0.1181
Epoch 99/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9645 - loss:
0.1034
Epoch 100/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9461 - loss:
0.1497
Epoch 101/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9600 - loss:
0.1359
Epoch 102/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9543 - loss:
0.1351
Epoch 103/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9593 - loss:
0.1043
Epoch 104/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9605 - loss:
0.1125
Epoch 105/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9653 - loss:
```

```
0.1091
Epoch 106/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9545 - loss:
0.1188
Epoch 107/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9596 - loss:
0.1046
Epoch 108/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9597 - loss:
0.1093
Epoch 109/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9593 - loss:
0.1070
Epoch 110/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9606 - loss:
0.1096
Epoch 111/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9619 - loss:
0.1021
Epoch 112/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9619 - loss:
0.1098
Epoch 113/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9603 - loss:
0.1127
Epoch 114/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9622 - loss:
0.1054
Epoch 115/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9626 - loss:
0.0993
Epoch 116/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9612 - loss:
0.1054
Epoch 117/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9591 - loss:
0.1102
Epoch 118/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9565 - loss:
0.1109
Epoch 119/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9607 - loss:
0.1011
Epoch 120/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9644 - loss:
0.0967
Epoch 121/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9588 - loss:
0.1133
```

```
Epoch 122/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9669 - loss:
0.0881
Epoch 123/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9615 - loss:
0.1085
Epoch 124/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9578 - loss:
0.1011
Epoch 125/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9613 - loss:
0.1002
Epoch 126/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9643 - loss:
0.0902
Epoch 127/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9665 - loss:
0.0909
Epoch 128/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9569 - loss:
0.1027
Epoch 129/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9629 - loss:
0.0901
Epoch 130/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9611 - loss:
0.0992
Epoch 131/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9624 - loss:
0.1050
Epoch 132/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9600 - loss:
0.1107
Epoch 133/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9622 - loss:
0.0979
Epoch 134/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9581 - loss:
0.1059
Epoch 135/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9581 - loss:
0.1080
Epoch 136/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9574 - loss:
0.1061
Epoch 137/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9581 - loss:
0.0966
Epoch 138/200
```

```
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9585 - loss:
0.1123
Epoch 139/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9569 - loss:
0.1068
Epoch 140/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 2s 12ms/step - accuracy: 0.9584 - loss:
0.1030
Epoch 141/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9637 - loss:
0.0963
Epoch 142/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9542 - loss:
0.1059
Epoch 143/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9602 - loss:
0.0982
Epoch 144/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9615 - loss:
0.0950
Epoch 145/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9579 - loss:
0.1053
Epoch 146/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9588 - loss:
0.1116
Epoch 147/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9566 - loss:
0.1068
Epoch 148/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9534 - loss:
0.1124
Epoch 149/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9586 - loss:
0.1062
Epoch 150/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9634 - loss:
0.0945
Epoch 151/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9540 - loss:
0.1096
Epoch 152/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9617 - loss:
0.1002
Epoch 153/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9612 - loss:
0.1071
Epoch 154/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9632 - loss:
```

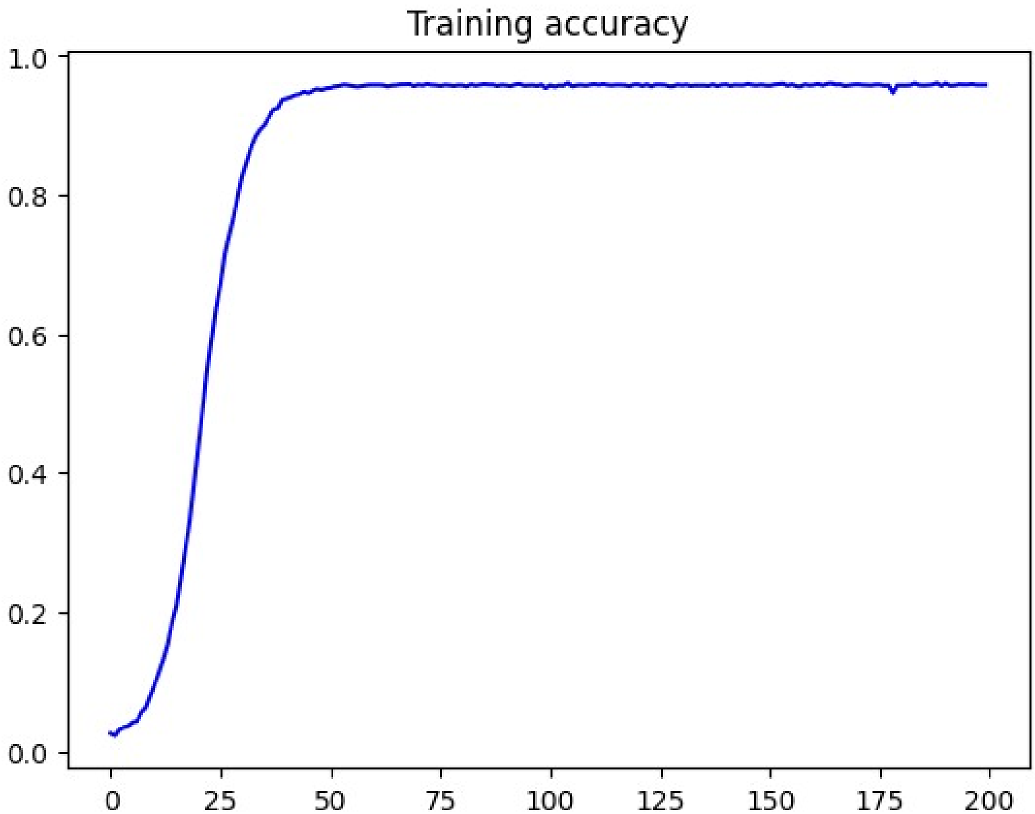
```
0.1028
Epoch 155/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9563 - loss:
0.1065
Epoch 156/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9650 - loss:
0.0939
Epoch 157/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9579 - loss:
0.0947
Epoch 158/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.9500 - loss:
0.1126
Epoch 159/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9690 - loss:
0.0822
Epoch 160/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9649 - loss:
0.0830
Epoch 161/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9638 - loss:
0.1010
Epoch 162/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9641 - loss:
0.1026
Epoch 163/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9613 - loss:
0.0970
Epoch 164/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9640 - loss:
0.0914
Epoch 165/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9595 - loss:
0.1157
Epoch 166/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9639 - loss:
0.0900
Epoch 167/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9631 - loss:
0.0900
Epoch 168/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9588 - loss:
0.1018
Epoch 169/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9618 - loss:
0.0884
Epoch 170/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9633 - loss:
0.0861
Epoch 171/200
```

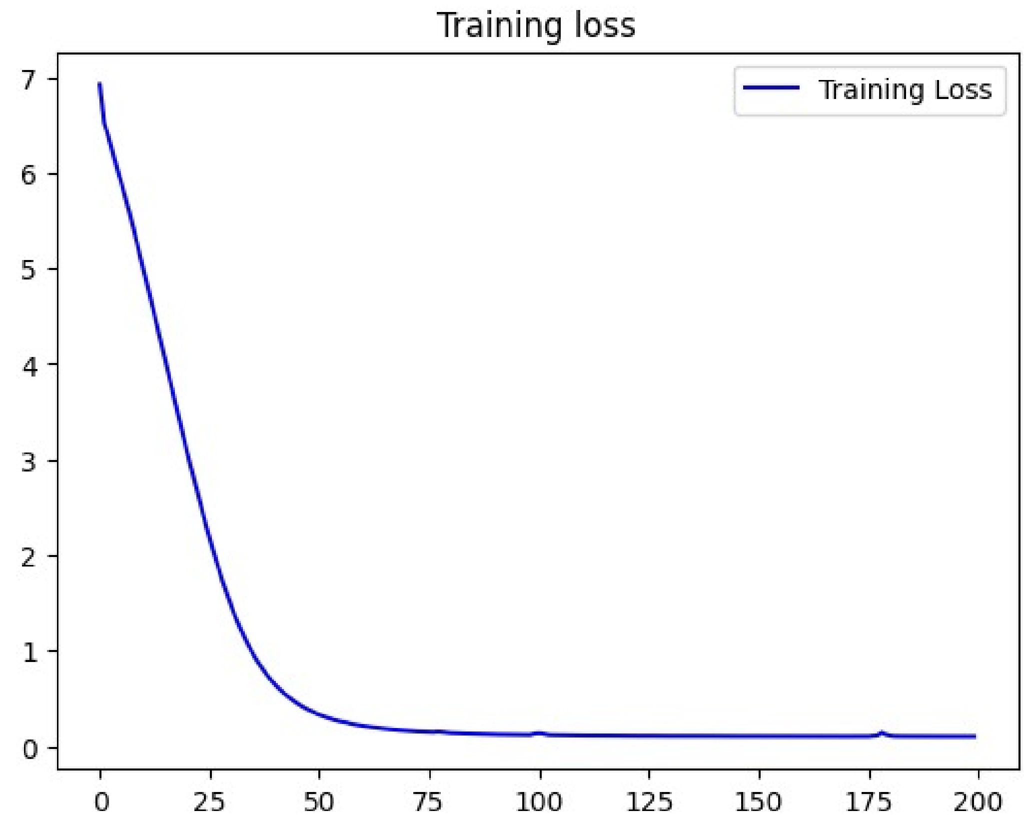
```
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9673 - loss:
0.0819
Epoch 172/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9586 - loss:
0.0984
Epoch 173/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9561 - loss:
0.1031
Epoch 174/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.9594 - loss:
0.0973
Epoch 175/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - accuracy: 0.9619 - loss:
0.1008
Epoch 176/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9622 - loss:
0.0912
Epoch 177/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9595 - loss:
0.0978
Epoch 178/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9663 - loss:
0.0907
Epoch 179/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9458 - loss:
0.1518
Epoch 180/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9653 - loss:
0.1020
Epoch 181/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9560 - loss:
0.1215
Epoch 182/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9622 - loss:
0.0891
Epoch 183/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9620 - loss:
0.0943
Epoch 184/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9644 - loss:
0.1043
Epoch 185/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9628 - loss:
0.0961
Epoch 186/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9551 - loss:
0.1082
Epoch 187/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9577 - loss:
```

```
0.1126
Epoch 188/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9607 - loss:
0.1049
Epoch 189/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9672 - loss:
0.0896
Epoch 190/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9578 - loss:
0.0908
Epoch 191/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9637 - loss:
0.1021
Epoch 192/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9555 - loss:
0.1046
Epoch 193/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.9650 - loss:
0.0873
Epoch 194/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.9587 - loss:
0.1063
Epoch 195/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9601 - loss:
0.1037
Epoch 196/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9649 - loss:
0.0872
Epoch 197/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9631 - loss:
0.0987
Epoch 198/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9626 - loss:
0.0972
Epoch 199/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9649 - loss:
0.0933
Epoch 200/200
82/82 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9583 - loss:
0.1051

acc = history.history['accuracy']
loss = history.history['loss']
epochs = range(len(acc))
plt.plot(epochs, acc, 'b', label='Training accuracy')
plt.title('Training accuracy')
plt.figure()
plt.plot(epochs, loss, 'b', label='Training Loss')
plt.title('Training loss')
```

```
plt.legend()
plt.show()
```






```
print(generate("Trump is"))
print(generate("Asian"))
print(generate("Biden"))
print(generate("Black"))
print(generate("Crime"))
print(generate("Watch this"))
print(generate("Breaking news"))
print(generate("Joe"))
print(generate("Today"))
print(generate("Tax"))
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 141ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
Trump is throwing jared kushner under the bus over mueller indictments
a 13 year old girl the baboon' heartless biden deaf hero
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
Asian house it wasn't sexist for trump to slut shame sen
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 62ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step
Biden just banned a major trump ally for threatening journalists
screenshots furious gets taken to the cleaners anniversary 25
heartless reminder
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 39ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
Black obama photographer takes trolling trump to a whole new level
tweets tweets the passed 25 years ago ago malia malia
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 56ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 49ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 59ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
Crime is throwing a stage 4 temper tantrum over the photo he posed for
image image paul manafort them rick reminder
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 38ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 36ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
Watch this awesome mashup of michael flynn leading the 'lock her up'
chant as he goes off to court video video video
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
Breaking news his sh t , trump says he's done more than any president
ever like the baboon' ago biden deaf hero
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 40ms/step
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
Joe scarborough it's not our imagination — trump really is losing his
mind video video video video video pence another heartless
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 39ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 36ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
Today republican just defended pedophilia using the bible that the
bible it gets his state office tweet video video heartless heartless
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
Tax national security adviser reportedly trashed him — this is epic f
ck you a u
```

Export your notebook to a pdf document

```
# !jupyter nbconvert --to pdf "C:\Users\micha\Desktop\deakin stuff\
deakintrimester3\SIT799 - Human Aligned\\task5.2\\5.2D -
DeepFakeComments Generator.ipynb"
```

Congratulations!

You've come to the end of this assignment, and have seen how to build a deep learning architecture that generate fake tweets/comments.

Congratulations on finishing this notebook!