Transformer (2)

April 14, 2024

[1]:
```
!nvidia-smi
```

```
Sun Apr 14 19:15:49 2024
+---------------------------------------------------------------------------------------+
| NVIDIA-SMI 535.104.05             Driver Version: 535.104.05   CUDA Version: 12.2     |
|-----------------------------------------+----------------------+----------------------+
| GPU  Name                 Persistence-M | Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |         Memory-Usage | GPU-Util  Compute M. |
|                                         |                      |               MIG M. |
|=========================================+======================+======================|
|   0  Tesla V100-SXM2-16GB           Off | 00000000:00:04.0 Off |                    0 |
| N/A   34C    P0              23W / 300W |      0MiB / 16384MiB |      0%      Default |
|                                         |                      |                  N/A |
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+---------------------------------------------------------------------------------------+
| Processes:                                                                            |
|  GPU   GI   CI        PID   Type   Process name                            GPU Memory |
|        ID   ID                                                             Usage      |
|=======================================================================================|
|  No running processes found
```

```
|
+-----------------------------------------------------------------------------
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```

[2]:
```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import *
from tensorflow.keras.regularizers import L1, L2
from keras.callbacks import EarlyStopping
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras import Model

import json
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
```

[16]:
```
df = pd.read_csv('emotion_dataset.csv')
df = df.drop_duplicates()
df = df.dropna()
df.head()
```

[16]:

	text	Emotion
0	awww bummer shoulda got david carr third day	0
1	upset update facebook texting might cry result…	0
2	dived many times ball managed save 50 rest go …	0
3	whole body feels itchy like fire	0
4	behaving mad see	0

[17]:
```
df
```

[17]:

	text	Emotion
0	awww bummer shoulda got david carr third day	0
1	upset update facebook texting might cry result…	0
2	dived many times ball managed save 50 rest go …	0
3	whole body feels itchy like fire	0
4	behaving mad see	0
…	…	…
1599995	woke school best feeling ever	4
1599996	thewdb com cool hear old walt interviews	4

```
1599997                    ready mojo makeover ask details        4
1599998  happy 38th birthday boo alll time tupac amaru …        4
1599999  happy charitytuesday thenspcc sparkscharity sp…        4

[1489715 rows x 2 columns]
```

[19]:
```
def safe_lower(input_text):
    if pd.isnull(input_text):
        return None  # Choose how to handle nulls based on your context
    return str(input_text).lower()

df['text'] = df['text'].apply(safe_lower)
```

[20]:
```
print(f"Unique emotions: {df['Emotion'].unique()}\n Number of unique emotions:␣
 ↪{df['Emotion'].nunique()}")
```

```
Unique emotions: [0 4]
 Number of unique emotions: 2
```

We need to convert our labels into numeric values so the model can work with them

[21]:
```
df['Label'], Emotions = pd.factorize(df['Emotion'])
```

[22]:
```
X = df['text']
y = df['Label']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=37)
```

Before we can feed our inputs into the model, we need to convert them into a form the computer can read: numbers. Tensorflow has a tokenizer method built in, which essentially creates a dictionary of words from a series of texts.

Once we have all of our tokens, we can transform our lines of text into sequences of tokens which can be fed into the model.

[23]:
```
tokenizer = Tokenizer(num_words = 60000, oov_token = "<OOV>")
tokenizer.fit_on_texts(X_train)
tokenizer.fit_on_texts(X_test)

X_train_sequences = tokenizer.texts_to_sequences(X_train)
X_test_sequences = tokenizer.texts_to_sequences(X_test)
```

Our model expects a uniform input size. To accomplish this we pad the sequences with 0's so that each input is equal in size to our largest input.

[24]:
```
maxlen = max(len(tokens) for tokens in X_train_sequences)
print("Maximum sequence length (maxlen):", maxlen)

X_train_padded = pad_sequences(X_train_sequences, maxlen=maxlen, padding='post')
```

```
X_test_padded = pad_sequences(X_test_sequences, maxlen=maxlen, padding='post')
```

```
Maximum sequence length (maxlen): 50
```

[25]:
```
np.max(X_train_padded) + 1
```

[25]:
```
60000
```

[26]:
```
def positional_encoding(length, depth):
  depth = depth/2

  positions = np.arange(length)[:, np.newaxis]     # (seq, 1)
  depths = np.arange(depth)[np.newaxis, :]/depth   # (1, depth)

  angle_rates = 1 / (10000**depths)         # (1, depth)
  angle_rads = positions * angle_rates      # (pos, depth)

  pos_encoding = np.concatenate(
      [np.sin(angle_rads), np.cos(angle_rads)],
      axis=-1)

  return tf.cast(pos_encoding, dtype=tf.float32)

class PositionalEmbedding(tf.keras.layers.Layer):
  def __init__(self, vocab_size, d_model):
    super().__init__()
    self.d_model = d_model
    self.embedding = tf.keras.layers.Embedding(vocab_size, d_model,␣
 ↪mask_zero=True)
    self.pos_encoding = positional_encoding(length=178, depth=d_model)

  def compute_mask(self, *args, **kwargs):
    return self.embedding.compute_mask(*args, **kwargs)

  def call(self, x):
    length = tf.shape(x)[1]
    x = self.embedding(x)
    # This factor sets the relative scale of the embedding and␣
 ↪positonal_encoding.
    x *= tf.math.sqrt(tf.cast(self.d_model, tf.float32))
    x = x + self.pos_encoding[tf.newaxis, :length, :]
    return x
```

[27]:
```
class TransformerBlock(Layer):
    def __init__(self, embed_dim, num_heads, ff_dim, rate=0.1):
        super(TransformerBlock, self).__init__()
        self.att = MultiHeadAttention(num_heads=num_heads, key_dim=embed_dim)
```

```
        self.ffn = Sequential(
            [Dense(ff_dim, activation="relu"),
             Dense(embed_dim),]
        )
        self.layernorm1 = LayerNormalization(epsilon=1e-6)
        self.layernorm2 = LayerNormalization(epsilon=1e-6)
        self.dropout1 = Dropout(rate)
        self.dropout2 = Dropout(rate)

    def call(self, inputs, training):
        attn_output = self.att(inputs, inputs)
        attn_output = self.dropout1(attn_output, training=training)
        out1 = self.layernorm1(inputs + attn_output)
        ffn_output = self.ffn(out1)
        ffn_output = self.dropout2(ffn_output, training=training)
        return self.layernorm2(out1 + ffn_output)
```

[28]:
```
model = Sequential()
model.add(Input(shape=(maxlen,),dtype='float64'))
model.add(PositionalEmbedding(vocab_size = np.max(X_train_padded) + 1, d_model␣
 ↪= 100))
model.add(TransformerBlock(embed_dim = 100, num_heads = 2, ff_dim = 64))
model.add(GlobalAveragePooling1D())
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu',
                kernel_regularizer=L1(0.01),
                activity_regularizer=L2(0.01)))
model.add(Dropout(0.5))
model.add(Dense(13, activation='softmax'))
```

[29]:
```
# Now compile and summarize your model
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',␣
 ↪metrics=['accuracy'])
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 positional_embedding (Posi  (None, 50, 100)           6000000
 tionalEmbedding)

 transformer_block (Transfo  (None, 50, 100)           94064
 rmerBlock)

 global_average_pooling1d (  (None, 100)               0
 GlobalAveragePooling1D)
```

```
 dropout_2 (Dropout)         (None, 100)               0

 dense_2 (Dense)             (None, 64)                6464

 dropout_3 (Dropout)         (None, 64)                0

 dense_3 (Dense)             (None, 13)                845

=================================================================
Total params: 6101373 (23.27 MB)
Trainable params: 6101373 (23.27 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[30]:
```
history = model.fit(X_train_padded, y_train, epochs=5, batch_size=32,
                    validation_data=(X_test_padded, y_test))
```

```
Epoch 1/5
37243/37243 [==============================] - 353s 9ms/step - loss: 0.6001 -
accuracy: 0.7530 - val_loss: 0.5247 - val_accuracy: 0.7710
Epoch 2/5
37243/37243 [==============================] - 329s 9ms/step - loss: 0.5323 -
accuracy: 0.7787 - val_loss: 0.5243 - val_accuracy: 0.7713
Epoch 3/5
37243/37243 [==============================] - 316s 8ms/step - loss: 0.5215 -
accuracy: 0.7832 - val_loss: 0.5172 - val_accuracy: 0.7740
Epoch 4/5
37243/37243 [==============================] - 318s 9ms/step - loss: 0.5176 -
accuracy: 0.7842 - val_loss: 0.5148 - val_accuracy: 0.7719
Epoch 5/5
37243/37243 [==============================] - 322s 9ms/step - loss: 0.5163 -
accuracy: 0.7813 - val_loss: 0.5122 - val_accuracy: 0.7712
```

[31]:
```
history_dict = history.history
json.dump(history_dict, open('transformer_history','w'))
```

[32]:
```
model.save('Transformer_Model')
```

[33]:
```
model = tf.keras.models.load_model("Transformer_Model")
```

[34]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 positional_embedding (Posi  (None, 50, 100)           6000000
```

```
 tionalEmbedding)

 transformer_block (Transfo  (None, 50, 100)           94064
 rmerBlock)

 global_average_pooling1d (  (None, 100)               0
 GlobalAveragePooling1D)

 dropout_2 (Dropout)         (None, 100)               0

 dense_2 (Dense)             (None, 64)                6464

 dropout_3 (Dropout)         (None, 64)                0

 dense_3 (Dense)             (None, 13)                845

=================================================================
Total params: 6101373 (23.27 MB)
Trainable params: 6101373 (23.27 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[36]:
```
history = json.load(open("transformer_history",'r'))
```

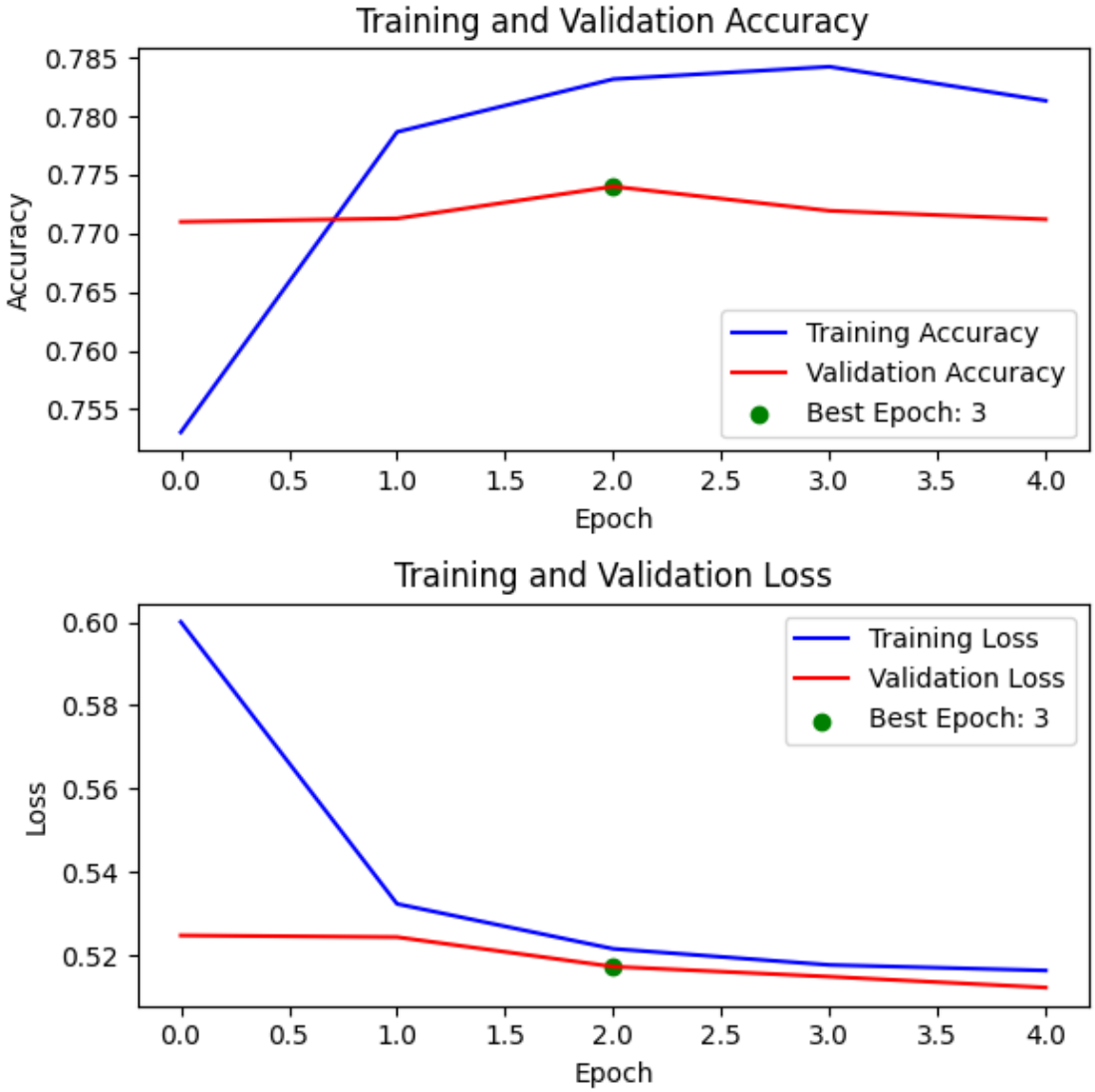
[37]:
```
best_epoch = history['val_accuracy'].index(max(history['val_accuracy'])) + 1

fig, axs = plt.subplots(2, 1, figsize=(6, 6))

# Plot training and validation accuracy
axs[0].plot(history['accuracy'], label='Training Accuracy', color='blue')
axs[0].plot(history['val_accuracy'], label='Validation Accuracy', color='red')
axs[0].scatter(best_epoch - 1, history['val_accuracy'][best_epoch - 1],␣
 ↪color='green', label=f'Best Epoch: {best_epoch}')
axs[0].set_xlabel('Epoch')
axs[0].set_ylabel('Accuracy')
axs[0].set_title('Training and Validation Accuracy')
axs[0].legend()

# Plot training and validation loss
axs[1].plot(history['loss'], label='Training Loss', color='blue')
axs[1].plot(history['val_loss'], label='Validation Loss', color='red')
axs[1].scatter(best_epoch - 1, history['val_loss'][best_epoch - 1],␣
 ↪color='green',label=f'Best Epoch: {best_epoch}')
axs[1].set_xlabel('Epoch')
axs[1].set_ylabel('Loss')
axs[1].set_title('Training and Validation Loss')
axs[1].legend()
```

```
plt.tight_layout()
plt.show()
```



[38]:
```
y_pred = model.predict(X_test_padded)
y_pred = np.argmax(y_pred, axis=1)
```

```
9311/9311 [==============================] - 26s 3ms/step
```

[40]:
```
print(classification_report(y_test,y_pred,labels = list(np.
↪arange(2)),target_names = ['0', '4'], zero_division = 0.0))
```

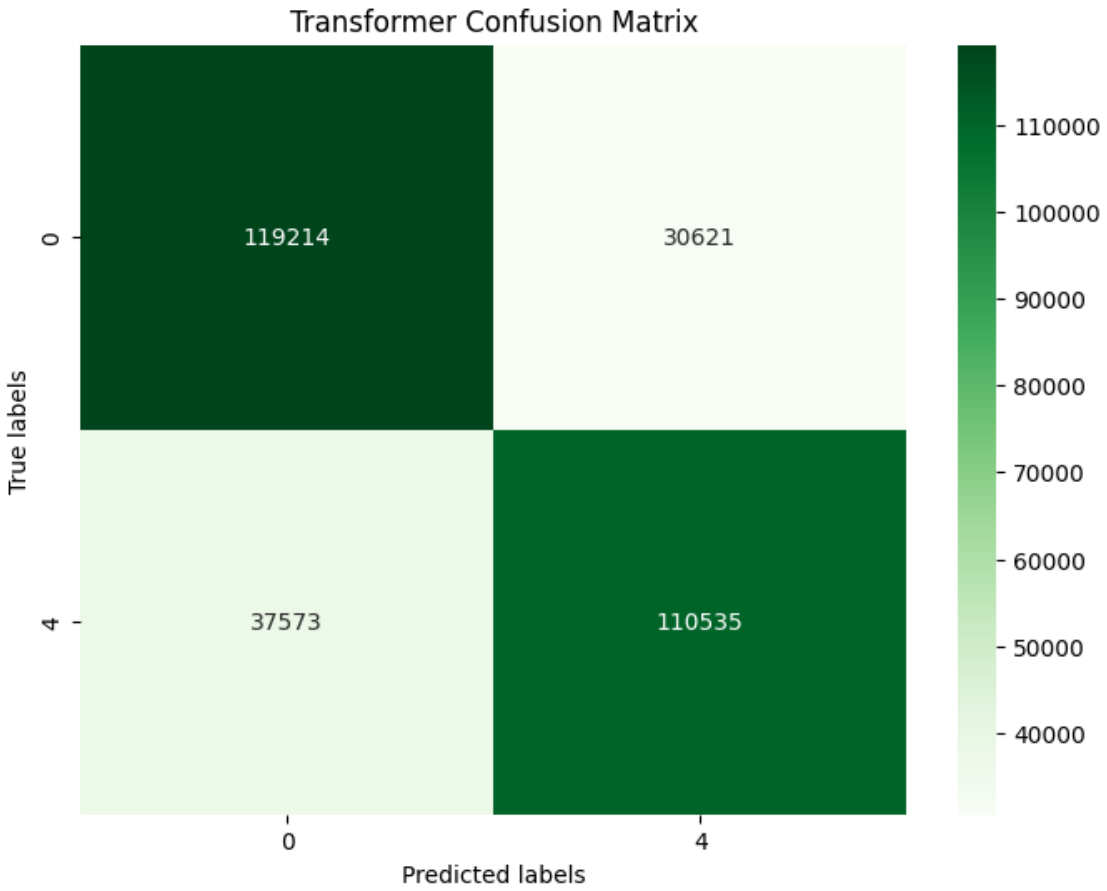
```
              precision    recall  f1-score   support
```

```
              0       0.76      0.80      0.78    149835
              4       0.78      0.75      0.76    148108

       accuracy                           0.77    297943
      macro avg       0.77      0.77      0.77    297943
   weighted avg       0.77      0.77      0.77    297943
```

[41]:
```
# y_test and y_pred are your true and predicted labels
cm = confusion_matrix(y_test, y_pred)

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot = True, fmt='d', cmap = 'Greens',
            xticklabels = ['0', '4'],
            yticklabels = ['0', '4'])
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Transformer Confusion Matrix')
plt.show()
```



[ ]:

0.0.1 Generative Model

[ ]:
```
songs = pd.read_csv(r"C:\Users\danfe\OneDrive\Desktop\School_Work\MATH␣
 ↪6373\Project\Song Data\lyrics-data.csv")
songs_en = songs[songs.language == 'en']
songs_en = songs_en[:250]
```

[ ]:
```
tokenizer = Tokenizer()
tokenizer.fit_on_texts(songs_en['Lyric'].astype(str).str.lower())

total_words = len(tokenizer.word_index)+1
tokenized_sentences = tokenizer.texts_to_sequences(songs_en['Lyric'].
 ↪astype(str))
tokenized_sentences[0]
```

[ ]:
```
[2,
 63,
 22,
 2952,
 149,
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 62,
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 7,
 868,
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 255]
```

[ ]:
```
# Create n-gram sequences
input_sequences = list()
for i in tokenized_sentences:
    for t in range(1, len(i)):
        n_gram_sequence = i[:t+1]
        input_sequences.append(n_gram_sequence)

# Pre-padding
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'))
```

[ ]:
```
# Creating predictors and labels
X, labels = input_sequences[:,:-1],input_sequences[:,-1]
y = tf.keras.utils.to_categorical(labels, num_classes=total_words)
```

[ ]:
```
model = Sequential()
model.add(Embedding(input_dim=total_words,␣
 ↪output_dim=100,input_length=max_sequence_len - 1))
model.add(TransformerBlock(embed_dim = 100, num_heads = 2, ff_dim = 64))
model.add(GlobalAveragePooling1D())
model.add(Dropout(0.2))
model.add(Dense(total_words, activation='softmax'))
```

[ ]:
```
model.compile(
    loss='categorical_crossentropy',
    optimizer=tf.keras.optimizers.Adam(learning_rate=.01),
    metrics=['accuracy']
    )
earlystop = EarlyStopping(monitor='loss', min_delta = 0, patience = 3, verbose␣
 ↪= 0, mode='auto')
```

[ ]:
```
history = model.fit(X,y, epochs = 10, verbose = 1, callbacks = [earlystop])
```

```
Epoch 1/10
2972/2972 [==============================] - 310s 103ms/step - loss: 6.2141 -
accuracy: 0.0473
Epoch 2/10
2972/2972 [==============================] - 308s 104ms/step - loss: 5.8552 -
accuracy: 0.0564
Epoch 3/10
2972/2972 [==============================] - 308s 104ms/step - loss: 5.6226 -
accuracy: 0.0631
Epoch 4/10
2972/2972 [==============================] - 305s 103ms/step - loss: 5.4442 -
accuracy: 0.0676
Epoch 5/10
2972/2972 [==============================] - 304s 102ms/step - loss: 5.3066 -
accuracy: 0.0692
Epoch 6/10
2972/2972 [==============================] - 303s 102ms/step - loss: 5.1944 -
accuracy: 0.0734
Epoch 7/10
2972/2972 [==============================] - 306s 103ms/step - loss: 5.0997 -
accuracy: 0.0745
Epoch 8/10
```

```
2972/2972 [==============================] - 304s 102ms/step - loss: 5.0244 -
accuracy: 0.0761
Epoch 9/10
2972/2972 [==============================] - 309s 104ms/step - loss: 4.9555 -
accuracy: 0.0777
Epoch 10/10
2972/2972 [==============================] - 337s 113ms/step - loss: 4.9009 -
accuracy: 0.0793
```

[ ]:
```
def generate_lyrics(seed_text, next_words):
    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')
        predictions = model.predict(token_list, verbose=0)
        choice = np.random.choice([1,2,3])
        # sort ascending and select from 3 highest probabilities
        predicted = np.argsort(predictions)[0][-choice]

        output_word = ""
        for word, index in tokenizer.word_index.items():
            if index == predicted:
                output_word = word
                break
        seed_text += " " + output_word
    return seed_text
```

[ ]:
```
def generate_lyrics(seed_text, next_words):
    # Loop until desired length is reached
    for _ in range(next_words):

        # Convert the seed text to a token sequence
            token_list = tokenizer.texts_to_sequences([seed_text])[0]

        # Pad the sequence
            token_list = pad_sequences([token_list], maxlen=max_sequence_len-1,␣
 ↪padding='pre')

        # Feed to the model and get the probabilities for each index
            probabilities = model.predict(token_list, verbose=0)

        # Get the index with the highest probability
            predicted = np.argmax(probabilities, axis=-1)[0]

        # Ignore if index is 0 because that is just the padding.
            if predicted != 0:
```

```
                # Look up the word associated with the index.
                    output_word = tokenizer.index_word[predicted]

                # Combine with the seed text
                    seed_text += " " + output_word

# Print the result
    print(seed_text)
```

[ ]:
```
seed_text = "hello darkness my old friend"
generate_lyrics(seed_text, 10)
```

```
hello darkness my old friend the the the the the the the the the the
```

[ ]:
```

```