Experiment No 5

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Aim: Machine Translation Using Transformer Models.

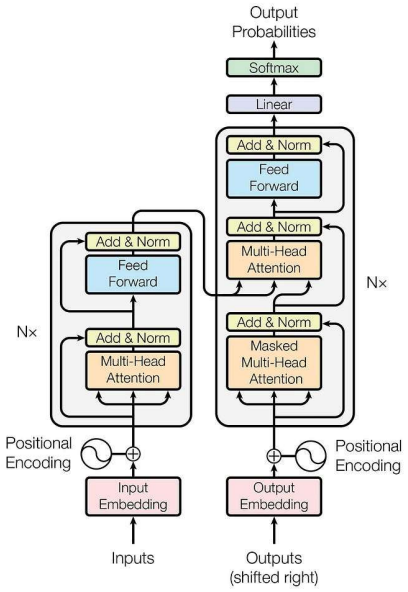
Theory:

Introduction

The Transformer model, introduced in the paper "Attention is All You Need" (Vaswani et al., 2017), revolutionized the field of natural language processing (NLP) by eliminating the need for recurrent neural networks (RNNs) and convolutional networks for sequence modelling tasks. Instead, the Transformer relies entirely on a mechanism called self-attention to process and relate elements in a sequence.

Key Components of the Transformer:

1. **Self-Attention Mechanism:**
   - The self-attention mechanism allows the model to focus on different parts of an input sequence to compute a representation of the sequence. It captures dependencies between tokens, regardless of their position in the sequence.
   - Given an input sentence, self-attention computes the relevance (attention scores) of each word with respect to every other word in the sentence.
   - For example, in the sentence "The cat sat on the mat," self-attention allows the model to understand that "the" relates to both "cat" and "mat," despite being separated by other words.
2. **Multi-Head Attention:**
   - To capture different relationships between words, the Transformer uses **multi-head attention**, where the self-attention mechanism is applied multiple times in parallel, and the outputs are concatenated. This enables the model to focus on different aspects of the sequence simultaneously.
3. **Positional Encoding:**
   - Since the Transformer does not have a built-in notion of word order (unlike RNNs), it uses **positional encodings** to inject information about the position of words in the sequence. These encodings are added to the input embedding, ensuring that the model can differentiate between words based on their position in a sentence.
4. **Encoder-Decoder Structure:**
   - The Transformer consists of an **encoder** and a **decoder**, each composed of several identical layers.
     - **Encoder:** The encoder processes the input sequence by applying self-attention and feed-forward layers. It generates a set of encoded representations.
     - **Decoder:** The decoder takes the encoder's output and the target sequence (shifted by one step) as input. It uses both self-attention and **encoder-decoder attention** (which focuses on the encoder's output) to generate the final translated output.



5. **Feed-Forward Networks:**
   - Each attention mechanism is followed by a **position-wise feed-forward network**, which consists of two fully connected layers applied independently to each position in the sequence. This helps in learning non-linear transformations of the input.
6. **Layer Normalization and Residual Connections:**
   - Each sub-layer in the encoder and decoder has a **residual connection** around it, followed by layer normalization. This helps stabilize training and allows the model to learn more effectively.

Here are the key steps to train a transformer model for **Neural Machine Translation (NMT)** from scratch:

1. Data Collection

The first and most crucial step is to gather a **large parallel dataset** consisting of sentence pairs from the source and target languages (e.g., English-German). A parallel dataset contains text in both languages that are aligned on a sentence level.

- **Open datasets**: Common parallel datasets include Europarl, TED talks, or datasets from the WMT (Workshop on Machine Translation).
- **Custom datasets**: You might also need to create your own dataset, especially if you're working with specialized domains or less common languages.

For example:

- **Source sentence (English)**: "I am learning."
- **Target sentence (German)**: "Ich lerne."

2. Data Pre-processing

Once you have the dataset, the next step is to prepare the data for training. This includes:

- **Cleaning the data**: Remove noisy or corrupted sentences, sentence pairs that are not properly aligned, etc.
- **Tokenization**: Split the sentences into smaller subword tokens. The transformer model works at the subword level rather than whole words. For example:
  - "I am learning" might be tokenized into ["I", "am", "learn", "ing"].
  - "Ich lerne" might be tokenized into ["Ich", "lern", "e"].
- **Create vocabulary**: Build a vocabulary for the source and target languages based on the tokens in your dataset. This vocabulary is used to convert tokens into numerical representations (IDs).
- **Padding and truncation**: Sentences will vary in length, so shorter sentences need to be padded to match the length of the longest sentence in a batch. Longer sentences might be truncated to a maximum length.

3. Model Architecture Setup

Now that your data is ready, you need to build the transformer architecture. The main components include:

- **Encoder**: This part of the model processes the source language sentence (e.g., English) and converts it into a sequence of hidden representations.
  - It uses multiple layers of self-attention and feed-forward networks.
- **Decoder**: The decoder generates the translated sentence (e.g., German) from the hidden representations produced by the encoder.
  - It also uses self-attention and attention mechanisms to focus on the relevant parts of the source sentence.

The transformer model typically consists of multiple layers of encoders and decoders (e.g., 6 layers each), and each layer includes:

- **Multi-head self-attention**: To allow the model to focus on different parts of the sentence.
- **Feed-forward networks**: To transform the attention outputs.

You can initialize the transformer model's weights randomly since you're training from scratch.

4. Training the Model

Once the model is set up, the training process begins. This involves multiple steps:

a) Loss Function

- The model is trained to minimize the **cross-entropy loss**, which measures how well the predicted output matches the actual target sentences. The goal is to increase the probability of correct translations and decrease the probability of incorrect ones.

b) Optimization

- You typically use optimizers like **Adam** or **Adafactor** to update the model's weights during training.
- **Learning rate schedules**: The learning rate is gradually increased in the initial stages (warm-up) and then decreased later.

c) Training Strategy

- You input batches of source sentences (e.g., English) and their corresponding target translations (e.g., German).
- For each batch:
    1. The **encoder** processes the source sentence and generates hidden representations.
    2. The **decoder** uses these hidden representations to predict the target sentence, one token at a time.
    3. The model compares its prediction with the actual target sentence, calculates the loss, and updates the weights accordingly.

d) Teacher Forcing

- During training, **teacher forcing** is used, where the correct previous token is given as input to the decoder rather than the decoder's own previous prediction. This helps the model learn more effectively, especially in the early stages of training.

5. Evaluation Metrics

Once the model is trained, it is essential to evaluate its performance.

- **BLEU Score**: The most common metric for evaluating machine translation models. It compares n-grams (consecutive sequences of tokens) in the machine-generated translation with reference translations.
- **Validation**: You should periodically evaluate the model on a validation set (a part of the dataset not used during training) to ensure it is not overfitting.

6. Hyperparameter Tuning

- **Batch size**: Adjust the number of examples processed at a time.
- **Learning rate**: Fine-tune the learning rate schedule for better performance.
- **Number of layers**: You may adjust the number of encoder and decoder layers based on the complexity of the dataset.

- **Dropout**: Use dropout regularization to avoid overfitting.

7. Model Evaluation and Fine-Tuning

After training the model, you need to test it on unseen data (test set) to evaluate how well it generalizes. You can also fine-tune it on more specific data if needed.

8. Deploying the Model

Once the model has been trained and evaluated, you can deploy it for real-world applications:

- **Batch translation**: Translate large volumes of text efficiently.
- **Real-time translation**: Use the model in applications such as live chat translation or multilingual customer service.

Lab Assignment:

Perform machine translation using Transformers on the following dataset.

cfilt/iitb-english-hindi · Datasets at Hugging Face

```
import pandas as pd
import numpy as np
import string
from string import digits
import matplotlib.pyplot as plt
%matplotlib inline
import re
from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split
from tensorflow.keras.layers import Input, LSTM, Embedding, Dense
from tensorflow.keras.models import Model


lines= pd.read_table('/content/hin.txt', names=['eng', 'hin',' ''])
lines.shape
```

```
(2779, 3)
```

```
# Lowercase all characters
lines.eng=lines.eng.apply(lambda x: x.lower())
lines.hin=lines.hin.apply(lambda x: x.lower())

# Remove quotes
lines.eng=lines.eng.apply(lambda x: re.sub("'", '', x))
lines.hin=lines.hin.apply(lambda x: re.sub("'", '', x))

exclude = set(string.punctuation) # Set of all special characters
# Remove all the special characters
lines.eng=lines.eng.apply(lambda x: ''.join(ch for ch in x if ch not in exclude))
lines.hin=lines.hin.apply(lambda x: ''.join(ch for ch in x if ch not in exclude))


# Remove all numbers from text
remove_digits = str.maketrans('', '', digits)
lines.eng=lines.eng.apply(lambda x: x.translate(remove_digits))
lines.hin = lines.hin.apply(lambda x: re.sub("[२३०८१५७९४६]", "", x))

# Remove extra spaces
lines.eng=lines.eng.apply(lambda x: x.strip())
lines.hin=lines.hin.apply(lambda x: x.strip())
lines.eng=lines.eng.apply(lambda x: re.sub(" +", " ", x))
lines.hin=lines.hin.apply(lambda x: re.sub(" +", " ", x))

lines.hin = lines.hin.apply(lambda x : 'START_ '+ x + ' _END')


lines.sample(10)
```

	eng	hin	
2514	i have lots of work to clear up by the weekend	START_ मुझे इस ह े ब5त सारा काम कर के खतम ...	CC-BY 2.0 (France) Attribution: tatoeba.org #2...
2523	sometimes she tried talking to him about india	START_ वह कभीकभी उससे भारत की बात करने की कोिश...	CC-BY 2.0 (France) Attribution: tatoeba.org #2...
81	how are you	START_ आप कै सी ह _END	CC-BY 2.0 (France) Attribution: tatoeba.org #3...
965	what happened last night	START_ कल रात ◌ T 5आ _END	CC-BY 2.0 (France) Attribution: tatoeba.org
#2... **2353**	during the war we had to do without sugar	START_ जंग के समय म हमे चीनी के िबना ही काम ...	CC-BY 2.0 (France) Attribution: tatoeba.org
#2... **1405**	can you teach me how to steal	START_ ा तुम मुझे चोरी करना िसखा सकते हो _END	CC-BY 2.0 (France) Attribution: tatoeba.org
#3...			
301	he began to shout	START_ वह िचWाने लगा। _END	CC-BY 2.0 (France) Attribution: tatoeba.org #2
1886	i learned french instead of german	START_ म ने जमन की बजाय ◌ानसीसी सीखी । _END	CC-BY 2.0 (France) Attribution: tatoeba.org #2...
305	he is walking now	START_ वह अब चल रहा है। _END	CC-BY 2.0 (France) Attribution: tatoeba.org #2...
60	im coming	START म आ रहा 5। END	CC-BY 2 0 (France) Attribution: tatoeba org #5

```
# Vocabulary of English
all_eng_words=set()
for eng in lines.eng:
    for word in eng.split():
        if word not in all_eng_words:
            all_eng_words.add(word)

# Vocabulary of Hindi
all_hindi_words=set()
for hin in lines.hin:
    for word in hin.split():
        if word not in all_hindi_words:
            all_hindi_words.add(word)


# Max Length of source sequence
lenght_list=[]
for l in lines.eng:
    lenght_list.append(len(l.split(' ')))
max_length_src = np.max(lenght_list)
max_length_src
print(max_length_src)

# Max Length of target sequence
lenght_list=[]
for l in lines.hin:
    lenght_list.append(len(l.split(' ')))
max_length_tar = np.max(lenght_list)
max_length_tar
print(max_length_tar)

input_words = sorted(list(all_eng_words))
target_words = sorted(list(all_hindi_words))
num_encoder_tokens = len(all_eng_words)
num_decoder_tokens = len(all_hindi_words)
num_encoder_tokens, num_decoder_tokens
```

```
num_decoder_tokens += 1 # For zero padding
num_decoder_tokens

input_token_index = dict([(word, i+1) for i, word in enumerate(input_words)])
target_token_index = dict([(word, i+1) for i, word in enumerate(target_words)])

reverse_input_char_index = dict((i, word) for word, i in input_token_index.items())
reverse_target_char_index = dict((i, word) for word, i in target_token_index.items())
print(input_token_index)
print(target_token_index)
print(reverse_input_char_index)
print(reverse_target_char_index)
```

```
22
27
{'a': 1, 'abandoned': 2, 'ability': 3, 'ablaze': 4, 'able': 5, 'about': 6, 'above': 7, 'abroad': 8, 'absence': 9, 'absent': 10, 'absolut
{'START_': 1, '_END': 2, 'a': 3, 'b': 4, 'i': 5, 'अँडे': 6, 'अंकल': 7, 'अंगर': 8, 'अंगूर': 9, 'अं ेज़ी': 10, 'अं ेजी': 11, 'अंडे': 12, 'अं
{1: 'a', 2: 'abandoned', 3: 'ability', 4: 'ablaze', 5: 'able', 6: 'about', 7: 'above', 8: 'abroad', 9: 'absence', 10: 'absent', 11
{1: 'START_', 2: '_END', 3: 'a', 4: 'b', 5: 'i', 6: 'अँडे', 7: 'अंकल', 8: 'अंगर', 9: 'अंगूर', 10: 'अं ेज़ी', 11: 'अं ेजी', 12: 'अंडे', 13
```

```
lines = shuffle(lines)
lines.head(10)
```

```
# Train - Test Split
X, y = lines.eng, lines.hin
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
X_train.shape, X_test.shape
```

```
((2223,), (556,))
```

2534 when did america become independent of england START_ अमेरीका को इं ड से आज़ादी कब िमली _END CC-BY 2.0 (France) Attribution: tatoeba.org #6...

```
def generate_batch(X = X_train, y = y_train, batch_size = 128):
    ''' Generate a batch of data '''
    while True:
        for j in range(0, len(X), batch_size):
            encoder_input_data = np.zeros((batch_size, max_length_src),dtype='float32')
            decoder_input_data = np.zeros((batch_size, max_length_tar),dtype='float32')
            decoder_target_data = np.zeros((batch_size, max_length_tar, num_decoder_tokens),dtype='float32')
            for i, (input_text, target_text) in enumerate(zip(X[j:j+batch_size], y[j:j+batch_size])):
                for t, word in enumerate(input_text.split()):
                    encoder_input_data[i, t] = input_token_index[word] # encoder input seq
                    #  # For the encoder input data, it maps each word to its corresponding index (according to input_token_index) and stores
                for t, word in enumerate(target_text.split()):
                    if t<len(target_text.split())-1:
                        decoder_input_data[i, t] = target_token_index[word] # decoder input seq
                    if t>0:
                        # decoder target sequence (one hot encoded)
                        # does not include the START_ token
                        # Offset by one timestep
                        decoder_target_data[i, t - 1, target_token_index[word]] = 1.
            yield([encoder_input_data, decoder_input_data], decoder_target_data)
            #the yield keyword to perform iteration inside a while True: loop, so each time Keras calls the generator, it gets a batch of dat
```

```
generate_batch(X_train, y_train, batch_size = batch_size)
```

```
<generator object generate_batch at 0x7c7f250800b0>
```

```
latent_dim = 20 #hidden layer dimension
```

```
# Train - Test Split
X, y = lines.eng, lines.hin
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
X_train.shape, X_test.shape
```

```
((2223,), (556,))
```

2534 when did america become independent of england START_ अमेरीका को इं ड से आज़ादी कब िमली _END CC-BY 2.0 (France) Attribution: tatoeba.org #6...

```
def generate_batch(X = X_train, y = y_train, batch_size = 128):
    ''' Generate a batch of data '''
    while True:
        for j in range(0, len(X), batch_size):
            encoder_input_data = np.zeros((batch_size, max_length_src),dtype='float32')
            decoder_input_data = np.zeros((batch_size, max_length_tar),dtype='float32')
            decoder_target_data = np.zeros((batch_size, max_length_tar, num_decoder_tokens),dtype='float32')
            for i, (input_text, target_text) in enumerate(zip(X[j:j+batch_size], y[j:j+batch_size])):
                for t, word in enumerate(input_text.split()):
                    encoder_input_data[i, t] = input_token_index[word] # encoder input seq
                    #  # For the encoder input data, it maps each word to its corresponding index (according to input_token_index) and stores
                for t, word in enumerate(target_text.split()):
                    if t<len(target_text.split())-1:
                        decoder_input_data[i, t] = target_token_index[word] # decoder input seq
                    if t>0:
                        # decoder target sequence (one hot encoded)
                        # does not include the START_ token
                        # Offset by one timestep
                        decoder_target_data[i, t - 1, target_token_index[word]] = 1.
            yield([encoder_input_data, decoder_input_data], decoder_target_data)
            #the yield keyword to perform iteration inside a while True: loop, so each time Keras calls the generator, it gets a batch of dat
```

```
generate_batch(X_train, y_train, batch_size = batch_size)
```

```
<generator object generate_batch at 0x7c7f250800b0>
```

```
latent_dim = 20 #hidden layer dimension
```

```
# Encoder
encoder_inputs = Input(shape=(None,)) #specifies that the input will be sequences of varying lengths (indicated by shape=(None,))
enc_emb =  Embedding(num_encoder_tokens+1, latent_dim, mask_zero = True)(encoder_inputs) #to convert the input sequences into dense vectors
encoder_lstm = LSTM(latent_dim, return_state=True) #LSTM layer should return the internal states along with the output.
encoder_outputs, state_h, state_c = encoder_lstm(enc_emb)
# We discard `encoder_outputs` and only keep the states.
encoder_states = [state_h, state_c] #the hidden state (state_h) and cell state (state_c) of the LSTM at the last time step are retained as th
#These states will be passed to the decoder part of the model to initialize the decoder's internal state.


# Set up the decoder, using `encoder_states` as initial state.
decoder_inputs = Input(shape=(None,))
dec_emb_layer = Embedding(num_decoder_tokens, latent_dim, mask_zero = True)
dec_emb = dec_emb_layer(decoder_inputs)
# We set up our decoder to return full output sequences,
# and to return internal states as well. We don't use the
# return states in the training model, but we will use them in inference.
decoder_lstm = LSTM(latent_dim, return_sequences=True, return_state=True)
decoder_outputs, _, _ = decoder_lstm(dec_emb,
                                     initial_state=encoder_states)
decoder_dense = Dense(num_decoder_tokens, activation='softmax')
decoder_outputs = decoder_dense(decoder_outputs)

# Define the model that will turn
# `encoder_input_data` & `decoder_input_data` into `decoder_target_data`
model = Model([encoder_inputs, decoder_inputs], decoder_outputs)


model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['acc'])


train_samples = len(X_train)
val_samples = len(X_test)
```

```
batch_size = 128
epochs =150



model.fit_generator(generator = generate_batch(X_train, y_train, batch_size = batch_size),
                    steps_per_epoch = train_samples//batch_size,
                    epochs=epochs,
                    validation_data = generate_batch(X_test, y_test, batch_size = batch_size),
                    validation_steps = val_samples//batch_size)

    Epoch 1/150
    <ipython-input-54-b22c3ec5e69e>:1: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Please u
      model.fit_generator(generator = generate_batch(X_train, y_train, batch_size = batch_size),
    17/17 [==============================] - 20s 568ms/step - loss: 7.9862 - acc: 0.1133 - val_loss: 7.9717 - val_acc: 0.1290
    Epoch 2/150
    17/17 [==============================] - 8s 509ms/step - loss: 7.9530 - acc: 0.1279 - val_loss: 7.9235 - val_acc: 0.1308
    Epoch 3/150
    17/17 [==============================] - 6s 375ms/step - loss: 7.8683 - acc: 0.1284 - val_loss: 7.7806 - val_acc: 0.1286
    Epoch 4/150
    17/17 [==============================] - 8s 494ms/step - loss: 7.6607 - acc: 0.1281 - val_loss: 7.5100 - val_acc: 0.1309
    Epoch 5/150
    17/17 [==============================] - 6s 377ms/step - loss: 7.3611 - acc: 0.1282 - val_loss: 7.1958 - val_acc: 0.1307
    Epoch 6/150
    17/17 [==============================] - 8s 494ms/step - loss: 7.0568 - acc: 0.1279 - val_loss: 6.9069 - val_acc: 0.1290
    Epoch 7/150
    17/17 [==============================] - 6s 378ms/step - loss: 6.7786 - acc: 0.1281 - val_loss: 6.6609 - val_acc: 0.1308
    Epoch 8/150
    17/17 [==============================] - 8s 508ms/step - loss: 6.5484 - acc: 0.1284 - val_loss: 6.4505 - val_acc: 0.1286
    Epoch 9/150
    17/17 [==============================] - 7s 390ms/step - loss: 6.3723 - acc: 0.1279 - val_loss: 6.3041 - val_acc: 0.1309
    Epoch 10/150
    17/17 [==============================] - 8s 497ms/step - loss: 6.2378 - acc: 0.1285 - val_loss: 6.1841 - val_acc: 0.1307
    Epoch 11/150
    17/17 [==============================] - 7s 420ms/step - loss: 6.1412 - acc: 0.1278 - val_loss: 6.1227 - val_acc: 0.1290
    Epoch 12/150
    17/17 [==============================] - 8s 506ms/step - loss: 6.0757 - acc: 0.1283 - val_loss: 6.0685 - val_acc: 0.1308
    Epoch 13/150
    17/17 [==============================] - 6s 379ms/step - loss: 6.0241 - acc: 0.1280 - val_loss: 6.0128 - val_acc: 0.1286
    Epoch 14/150
    17/17 [==============================] - 8s 507ms/step - loss: 5.9884 - acc: 0.1279 - val_loss: 5.9873 - val_acc: 0.1309
    Epoch 15/150
    17/17 [==============================] - 7s 391ms/step - loss: 5.9621 - acc: 0.1284 - val_loss: 5.9608 - val_acc: 0.1307
    Epoch 16/150
    17/17 [==============================] - 8s 476ms/step - loss: 5.9453 - acc: 0.1279 - val_loss: 5.9757 - val_acc: 0.1290
    Epoch 17/150
    17/17 [==============================] - 7s 391ms/step - loss: 5.9311 - acc: 0.1282 - val_loss: 5.9677 - val_acc: 0.1308
    Epoch 18/150
    17/17 [==============================] - 8s 483ms/step - loss: 5.9246 - acc: 0.1287 - val_loss: 5.9440 - val_acc: 0.1286
    Epoch 19/150
    17/17 [==============================] - 7s 390ms/step - loss: 5.9197 - acc: 0.1281 - val_loss: 5.9372 - val_acc: 0.1309
    Epoch 20/150
    17/17 [==============================] - 8s 483ms/step - loss: 5.9043 - acc: 0.1279 - val_loss: 5.9245 - val_acc: 0.1307
    Epoch 21/150
    17/17 [==============================] - 8s 469ms/step - loss: 5.8888 - acc: 0.1284 - val_loss: 5.9423 - val_acc: 0.1290
    Epoch 22/150
    17/17 [==============================] - 7s 410ms/step - loss: 5.8843 - acc: 0.1281 - val_loss: 5.9296 - val_acc: 0.1308
    Epoch 23/150
    17/17 [==============================] - 8s 488ms/step - loss: 5.8645 - acc: 0.1282 - val_loss: 5.8961 - val_acc: 0.1286
    Epoch 24/150
```

```
# Encode the input sequence to get the "thought vectors"
encoder_model = Model(encoder_inputs, encoder_states)

# Decoder setup
# Below tensors will hold the states of the previous time step
decoder_state_input_h = Input(shape=(latent_dim,))
decoder_state_input_c = Input(shape=(latent_dim,))
decoder_states_inputs = [decoder_state_input_h, decoder_state_input_c]

dec_emb2= dec_emb_layer(decoder_inputs) # Get the embeddings of the decoder sequence

# To predict the next word in the sequence, set the initial states to the states from the previous time step
decoder_outputs2, state_h2, state_c2 = decoder_lstm(dec_emb2, initial_state=decoder_states_inputs)
decoder_states2 = [state_h2, state_c2]
decoder_outputs2 = decoder_dense(decoder_outputs2) # A dense softmax layer to generate prob dist. over the target vocabulary

# Final decoder model
decoder_model = Model(
    [decoder_inputs] + decoder_states_inputs,
    [decoder_outputs2] + decoder_states2)
```

Decode sample sequeces

```
def decode_sequence(input_seq):
    # Encode the input as state vectors.

    states_value = encoder_model.predict(input_seq)
    # Generate empty target sequence of length 1.
    target_seq = np.zeros((1,1))
    # Populate the first character of target sequence with the start character.
    target_seq[0, 0] = target_token_index['START_']

    # Sampling loop for a batch of sequences
    # (to simplify, here we assume a batch of size 1).
    stop_condition = False
    decoded_sentence = ''
    while not stop_condition:
        output_tokens, h, c = decoder_model.predict([target_seq] + states_value)

        # Sample a token
        sampled_token_index = np.argmax(output_tokens[0, -1, :])
        sampled_char = reverse_target_char_index[sampled_token_index]
        decoded_sentence += ' '+sampled_char

        # Exit condition: either hit max length
        # or find stop character.
        if (sampled_char == '_END' or
           len(decoded_sentence) > 50):
           stop_condition = True

        # Update the target sequence (of length 1).
        target_seq = np.zeros((1,1))
        target_seq[0, 0] = sampled_token_index

        # Update states
        states_value = [h, c]

    return decoded_sentence
```

Evaluation on Train Dataset

```
train_gen = generate_batch(X_train, y_train, batch_size = 1)
k=-1
```

```
(input_seq, actual_output), _ = next(train_gen)
print(input_seq)
print(actual_output)
decoded_sentence = decode_sequence(input_seq)
print(decoded_sentence)
print('Input English sentence:', X_train[k:k+1].values[0])
print('Actual Hindi Translation:', y_train[k:k+1].values[0][6:-4])
print('Predicted Hindi Translation:', decoded_sentence[:-4])

[[2041. 1267. 2237. 1016.  813. 1191.    0.    0.    0.    0.    0.    0.
     0.    0.    0.    0.    0.    0.    0.    0.    0.    0.]]
[[1.000e+00 2.567e+03 1.550e+02 2.610e+03 4.800e+02 2.602e+03 4.220e+02
  1.487e+03 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00
  0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00
  0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00]]
1/1 [==============================] - 1s 1s/step
1/1 [==============================] - 2s 2s/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 44ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 23ms/step
 हम ने ने सारी िलए कम को सकते पर चाहिए। _END
Input English sentence: the men went hunting for lions
Actual Hindi Translation:  वे आदमी शेरों का िशकार करने िनकले।
Predicted Hindi Translation:  हम ने ने सारी िलए कम को सकते पर चाहिए।
```