

In [1]:

```
!gdown --id 1OurDQutbWQacvT32HMqFL7vIUrSM11Op
Downloading...
From: https://drive.google.com/uc?id=1OurDQutbWQacvT32HMqFL7vIUrSM11Op
To: /content/preprocessed_data.csv
100% 300k/300k [00:00<00:00, 2.33MB/s]
```

In [2]:

```
#Importing necessary libraries
import pandas as pd
import numpy as np
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

In [3]:

```
df=pd.read_csv('preprocessed_data.csv')#reading the data into DataFrame
```

In [4]:

```
df.head(4)#displaying top 4 four data
```

Out[4]:

	Unnamed: 0	source	target
0	0	U wan me to "chop" seat 4 u nt?\n	Do you want me to reserve seat for you or not?\n
1	1	Yup. U reaching. We order some durian pastry a...	Yeap. You reaching? We ordered some Durian pas...
2	2	They become more ex oredi... Mine is like 25.....	They become more expensive already. Mine is li...
3	3	I'm thai. what do u do?\n	I'm Thai. What do you do?\n

In [5]:

```
def preprocess(x):#removing the last character
    x=x[:-1]
    return x
```

In [6]:

```
df['source']=df['source'].apply(preprocess)#preprocessing on source data
df['target']=df['target'].apply(preprocess)#perprocessing on target data
```

In [7]:

```
df=df[['source','target']]
df.head()
```

Out[7]:

	source	target
0	U wan me to "chop" seat 4 u nt?	Do you want me to reserve seat for you or not?
1	Yup. U reaching. We order some durian pastry a...	Yeap. You reaching? We ordered some Durian pas...
2	They become more ex oredi... Mine is like 25.....	They become more expensive already. Mine is li...
3	I'm thai. what do u do?	I'm Thai. What do you do?
4	Hi! How did your week go? Haven heard from you...	Hi! How did your week go? Haven't heard from y...

In [8]:

```
df.shape#shape of the data
```

Out[8]:

```
(2000, 2)
```

In [9]:

```
df=df[df['source'].apply(len)<170]#removing source datapoints having length greater than equal to 170
df=df[df['target'].apply(len)<200]#removing target datapoints having length greater than equal to 200
```

In [10]:

```
df.shape#shape of the data
```

Out[10]:

```
(1990, 2)
```

In [151]:

```
from sklearn.model_selection import train_test_split
X=df['source']
y=df['target']
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.01)#splitting the data
print(X_train.shape)
```

```
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(1970,)
(20,)
(1970,)
(20,)
```

Target:

In [152]:

```
target_tokenizer=Tokenizer()#tokenization on target
target_tokenizer.fit_on_texts(y_train)#fitting on ytrain
target_vocab_size= len(target_tokenizer.word_index) + 1#target vocab size
print(len(target_tokenizer.word_index))
```

3034

In [153]:

```
target_encoded_docs_train = target_tokenizer.texts_to_sequences(y_train)#converting text to integers
target_encoded_docs_test = target_tokenizer.texts_to_sequences(y_test)#converting text to integers
```

In [154]:

```
target_padded_docs_train = pad_sequences(target_encoded_docs_train,padding='post')#padding to maxlength
```

In [155]:

```
target_padded_docs_train.shape
```

Out[155]:

```
(1970, 43)
```

In [156]:

```
target_padded_docs_test = pad_sequences(target_encoded_docs_test,maxlen=target_padded_docs_train.shape[1])
```

In [157]:

```
target_padded_docs_test.shape
```

Out[157]:

```
(20, 43)
```

Source:

In [158]:

```
source_tokenizer=Tokenizer()#tokenization on source
source_tokenizer.fit_on_texts(X_train)#fitting to X_train
source_vocab_size= len(source_tokenizer.word_index) + 1#source vocab size
print(len(source_tokenizer.word_index))
```

3702

In [159]:

```
source_encoded_docs_train = source_tokenizer.texts_to_sequences(X_train)#converting text to sequence
source_encoded_docs_test = source_tokenizer.texts_to_sequences(X_test)#converting text to sequence
```

In [160]:

```
source_padded_docs_train = pad_sequences(source_encoded_docs_train,maxlen=target_padded_docs_train.shape[1])
```

In [161]:

```
source_padded_docs_train.shape
```

Out[161]:

```
(1970, 43)
```

In [162]:

```
source_padded_docs_test = pad_sequences(source_encoded_docs_test,maxlen=target_padded_docs_train.shape[1])
```

In [163]:

```
source_padded_docs_test.shape
```

Out[163]:

```
(20, 43)
```

In [164]:

```
#we are reshaping the dataset because the sparse_categorical_crossentropy requires data to be three dimensional
target_padded_docs_train=target_padded_docs_train.reshape((*target_padded_docs_train.shape,1))
target_padded_docs_test=target_padded_docs_test.reshape((*target_padded_docs_test.shape,1))
```

In [165]:

```
print(target_padded_docs_train.shape)
print(target_padded_docs_test.shape)
```

```
(1970, 43, 1)
(20, 43, 1)
```

In [166]:

```
#we are reshaping the dataset because the sparse_categorical_crossentropy requires data to be three dimensional
source_padded_docs_train=source_padded_docs_train.reshape((*source_padded_docs_train.shape,1))
```

```
source_padded_docs_test=source_padded_docs_test.reshape((*source_padded_docs_test.shape,1))
```

In [167]:

```
print(source_padded_docs_train.shape)
print(source_padded_docs_test.shape)

(1970, 43, 1)
(20, 43, 1)
```

Model1:

In [171]:

```
input=tf.keras.layers.Input(shape=(43,))
embed=tf.keras.layers.Embedding(source_vocab_size,512, input_length=source_padded_docs_train.shape[1])(input)
lstm1=tf.keras.layers.LSTM(128, return_sequences=True)(embed)
dense=tf.keras.layers.TimeDistributed(tf.keras.layers.Dense(512, activation='relu'))(lstm1)
drop=tf.keras.layers.Dropout(0.5)(dense)
output=tf.keras.layers.TimeDistributed(tf.keras.layers.Dense(target_vocab_size, activation='softmax'))(drop)
model=tf.keras.models.Model(inputs=input,outputs=output)
model.summary()
```

Model: "model_8"

Layer (type)	Output Shape	Param #
=====		
input_9 (InputLayer)	[(None, 43)]	0
=====		
embedding_8 (Embedding)	(None, 43, 512)	1895936
=====		
lstm_8 (LSTM)	(None, 43, 128)	328192
=====		
time_distributed_16 (TimeDis	(None, 43, 512)	66048
=====		
dropout_8 (Dropout)	(None, 43, 512)	0
=====		
time_distributed_17 (TimeDis	(None, 43, 3035)	1556955
=====		
Total params: 3,847,131		
Trainable params: 3,847,131		
Non-trainable params: 0		

In [172]:

```
# Compile model
model.compile(optimizer=tf.keras.optimizers.Adam(0.01),
              loss='sparse_categorical_crossentropy',metrics=['accuracy'])
```

In [173]:

```
model.fit(source_padded_docs_train,target_padded_docs_train,batch_size=1024,epochs=50,
          validation_data=(source_padded_docs_test,target_padded_docs_test))
```

```
Epoch 1/50
2/2 [=====] - 59s 57s/step - loss: 7.7430 - accuracy: 0.3208 - val_loss: 2.7519
- val_accuracy: 0.7698
Epoch 2/50
2/2 [=====] - 1s 305ms/step - loss: 3.4479 - accuracy: 0.6728 - val_loss:
2.5025 - val_accuracy: 0.7698
Epoch 3/50
2/2 [=====] - 1s 316ms/step - loss: 3.5213 - accuracy: 0.6728 - val_loss:
1.9935 - val_accuracy: 0.7721
Epoch 4/50
2/2 [=====] - 1s 314ms/step - loss: 2.7795 - accuracy: 0.6730 - val_loss:
1.5858 - val_accuracy: 0.7791
Epoch 5/50
2/2 [=====] - 1s 313ms/step - loss: 2.2776 - accuracy: 0.6807 - val_loss:
1.5165 - val_accuracy: 0.7709
Epoch 6/50
2/2 [=====] - 1s 313ms/step - loss: 2.2367 - accuracy: 0.6729 - val_loss:
1.5061 - val_accuracy: 0.7698
Epoch 7/50
2/2 [=====] - 1s 317ms/step - loss: 2.2036 - accuracy: 0.6739 - val_loss:
1.4808 - val_accuracy: 0.7779
Epoch 8/50
2/2 [=====] - 1s 313ms/step - loss: 2.1772 - accuracy: 0.6805 - val_loss:
1.4521 - val_accuracy: 0.7791
Epoch 9/50
2/2 [=====] - 1s 316ms/step - loss: 2.1343 - accuracy: 0.6825 - val_loss:
1.4368 - val_accuracy: 0.7814
Epoch 10/50
2/2 [=====] - 1s 313ms/step - loss: 2.1044 - accuracy: 0.6819 - val_loss:
1.4336 - val accuracy: 0.7791
```

Epoch 11/50
2/2 [=====] - 1s 316ms/step - loss: 2.0708 - accuracy: 0.6837 - val_loss: 1.4310 - val_accuracy: 0.7814
Epoch 12/50
2/2 [=====] - 1s 315ms/step - loss: 2.0483 - accuracy: 0.6863 - val_loss: 1.4018 - val_accuracy: 0.7849
Epoch 13/50
2/2 [=====] - 1s 316ms/step - loss: 2.0173 - accuracy: 0.6879 - val_loss: 1.3817 - val_accuracy: 0.7849
Epoch 14/50
2/2 [=====] - 1s 310ms/step - loss: 1.9866 - accuracy: 0.6885 - val_loss: 1.3591 - val_accuracy: 0.7849
Epoch 15/50
2/2 [=====] - 1s 312ms/step - loss: 1.9527 - accuracy: 0.6894 - val_loss: 1.3418 - val_accuracy: 0.7872
Epoch 16/50
2/2 [=====] - 1s 311ms/step - loss: 1.9202 - accuracy: 0.6916 - val_loss: 1.3293 - val_accuracy: 0.7860
Epoch 17/50
2/2 [=====] - 1s 319ms/step - loss: 1.8916 - accuracy: 0.6921 - val_loss: 1.3174 - val_accuracy: 0.7884
Epoch 18/50
2/2 [=====] - 1s 319ms/step - loss: 1.8620 - accuracy: 0.6944 - val_loss: 1.3016 - val_accuracy: 0.7907
Epoch 19/50
2/2 [=====] - 1s 315ms/step - loss: 1.8346 - accuracy: 0.6972 - val_loss: 1.2932 - val_accuracy: 0.7919
Epoch 20/50
2/2 [=====] - 1s 316ms/step - loss: 1.8075 - accuracy: 0.6993 - val_loss: 1.2764 - val_accuracy: 0.7965
Epoch 21/50
2/2 [=====] - 1s 318ms/step - loss: 1.7780 - accuracy: 0.7020 - val_loss: 1.2680 - val_accuracy: 0.7942
Epoch 22/50
2/2 [=====] - 1s 324ms/step - loss: 1.7495 - accuracy: 0.7045 - val_loss: 1.2495 - val_accuracy: 0.8000
Epoch 23/50
2/2 [=====] - 1s 318ms/step - loss: 1.7181 - accuracy: 0.7080 - val_loss: 1.2368 - val_accuracy: 0.8035
Epoch 24/50
2/2 [=====] - 1s 314ms/step - loss: 1.6881 - accuracy: 0.7115 - val_loss: 1.2230 - val_accuracy: 0.8058
Epoch 25/50
2/2 [=====] - 1s 321ms/step - loss: 1.6586 - accuracy: 0.7140 - val_loss: 1.2126 - val_accuracy: 0.8093
Epoch 26/50
2/2 [=====] - 1s 316ms/step - loss: 1.6247 - accuracy: 0.7168 - val_loss: 1.1898 - val_accuracy: 0.8140
Epoch 27/50
2/2 [=====] - 1s 312ms/step - loss: 1.5962 - accuracy: 0.7213 - val_loss: 1.1732 - val_accuracy: 0.8186
Epoch 28/50
2/2 [=====] - 1s 318ms/step - loss: 1.5594 - accuracy: 0.7254 - val_loss: 1.1697 - val_accuracy: 0.8233
Epoch 29/50
2/2 [=====] - 1s 314ms/step - loss: 1.5303 - accuracy: 0.7302 - val_loss: 1.1395 - val_accuracy: 0.8314
Epoch 30/50
2/2 [=====] - 1s 319ms/step - loss: 1.4953 - accuracy: 0.7371 - val_loss: 1.1235 - val_accuracy: 0.8349
Epoch 31/50
2/2 [=====] - 1s 317ms/step - loss: 1.4593 - accuracy: 0.7407 - val_loss: 1.1209 - val_accuracy: 0.8384
Epoch 32/50
2/2 [=====] - 1s 315ms/step - loss: 1.4236 - accuracy: 0.7477 - val_loss: 1.1059 - val_accuracy: 0.8419
Epoch 33/50
2/2 [=====] - 1s 317ms/step - loss: 1.3867 - accuracy: 0.7514 - val_loss: 1.0881 - val_accuracy: 0.8442
Epoch 34/50
2/2 [=====] - 1s 319ms/step - loss: 1.3504 - accuracy: 0.7583 - val_loss: 1.0822 - val_accuracy: 0.8453
Epoch 35/50
2/2 [=====] - 1s 315ms/step - loss: 1.3140 - accuracy: 0.7633 - val_loss: 1.0658 - val_accuracy: 0.8465
Epoch 36/50
2/2 [=====] - 1s 317ms/step - loss: 1.2742 - accuracy: 0.7691 - val_loss:

```

1.0565 - val_accuracy: 0.8488
Epoch 37/50
2/2 [=====] - 1s 327ms/step - loss: 1.2396 - accuracy: 0.7743 - val_loss:
1.0437 - val_accuracy: 0.8547
Epoch 38/50
2/2 [=====] - 1s 314ms/step - loss: 1.2227 - accuracy: 0.7780 - val_loss:
1.0457 - val_accuracy: 0.8523
Epoch 39/50
2/2 [=====] - 1s 314ms/step - loss: 1.2551 - accuracy: 0.7719 - val_loss:
1.0567 - val_accuracy: 0.8558
Epoch 40/50
2/2 [=====] - 1s 317ms/step - loss: 1.2022 - accuracy: 0.7853 - val_loss:
1.0322 - val_accuracy: 0.8593
Epoch 41/50
2/2 [=====] - 1s 314ms/step - loss: 1.1494 - accuracy: 0.7873 - val_loss:
1.0276 - val_accuracy: 0.8570
Epoch 42/50
2/2 [=====] - 1s 315ms/step - loss: 1.1155 - accuracy: 0.7881 - val_loss:
1.0399 - val_accuracy: 0.8570
Epoch 43/50
2/2 [=====] - 1s 311ms/step - loss: 1.0756 - accuracy: 0.7968 - val_loss:
1.0274 - val_accuracy: 0.8593
Epoch 44/50
2/2 [=====] - 1s 308ms/step - loss: 1.0426 - accuracy: 0.8013 - val_loss:
1.0311 - val_accuracy: 0.8605
Epoch 45/50
2/2 [=====] - 1s 314ms/step - loss: 1.0029 - accuracy: 0.8069 - val_loss:
1.0222 - val_accuracy: 0.8616
Epoch 46/50
2/2 [=====] - 1s 315ms/step - loss: 0.9696 - accuracy: 0.8117 - val_loss:
1.0364 - val_accuracy: 0.8640
Epoch 47/50
2/2 [=====] - 1s 317ms/step - loss: 0.9377 - accuracy: 0.8166 - val_loss:
1.0423 - val_accuracy: 0.8616
Epoch 48/50
2/2 [=====] - 1s 316ms/step - loss: 0.9083 - accuracy: 0.8210 - val_loss:
1.0496 - val_accuracy: 0.8628
Epoch 49/50
2/2 [=====] - 1s 310ms/step - loss: 0.8767 - accuracy: 0.8248 - val_loss:
1.0535 - val_accuracy: 0.8651
Epoch 50/50
2/2 [=====] - 1s 315ms/step - loss: 0.8457 - accuracy: 0.8306 - val_loss:
1.0778 - val_accuracy: 0.8686

```

Out[173]:

```
<tensorflow.python.keras.callbacks.History at 0x7f67c2382550>
```

In [174]:

```

#https://machinelearningmastery.com/beam-search-decoder-natural-language-processing/
#Beam Search
from math import log
from numpy import array
from numpy import argmax
import numpy as np
def beam_search_decoder(data, k):
    sequences = [[list(), 0.0]]
    # walk over each step in sequence
    #print(sequences)
    for row in data:
        all_candidates = list()
        # expand each current candidate
        for i in range(len(sequences)):
            seq, score = sequences[i]
            for j in range(len(row)):
                candidate = [seq + [j], score - np.log(row[j])]
                all_candidates.append(candidate)
        # order all candidates by score
        ordered = sorted(all_candidates, key=lambda tup:tup[1])
        sequences = ordered[:k]
    return sequences

```

In [175]:

```

#prediction
def prediction(x):

    index_to_words = {id: word for word, id in target_tokenizer.word_index.items()}
    index_to_words[0] = '<PAD>'

```


[illegible]

Don't know. Ben just asked. He never say. Why is she like an middle-aged lady like that always play

[illegible]

```
import nltk.translate.bleu_score as bleu
bleu_score1=[]
bleu_score2=[]
bleu_score3=[]

for i in range(20):
    b=list(y_test[i:i+1])
    x=model.predict(source_padded_docs_test[i:i+1])

    res=beam_search_decoder(x[0],3)

    y1=prediction(res[0][0])
    y1=y1.split(' ')
    y_lst1=[]
    for i in y1:
        if i=='<PAD>':
            continue
        else:
            y_lst1.append(i)
    bleu_score1.append(bleu.sentence_bleu([b[0].split(),],y_lst1))

    y2=prediction(res[1][0])
    y2=y2.split(' ')
    y_lst2=[]
    for i in y2:
        if i=='<PAD>':
            continue
        else:
            y_lst2.append(i)
    bleu_score2.append(bleu.sentence_bleu([b[0].split(),],y_lst2))

    y3=prediction(res[2][0])
    y3=y3.split(' ')
    y_lst3=[]
    for i in y3:
        if i=='<PAD>':
            continue
        else:
            y_lst3.append(i)
    bleu_score3.append(bleu.sentence_bleu([b[0].split(),],y_lst3))

print("The Average Bleu Score1 is: ",sum(bleu_score1)/20)
print('> '*180)
print("The Average Bleu Score2 is: ",sum(bleu_score2)/20)
print('> '*180)
print("The Average Bleu Score3 is: ",sum(bleu_score3)/20)
print('> '*180)
```


Epoch 7/50
2/2 [=====] - 1s 286ms/step - loss: 2.2420 - accuracy: 0.6735 - val_loss: 1.4918 - val_accuracy: 0.7756
Epoch 8/50
2/2 [=====] - 1s 285ms/step - loss: 2.1406 - accuracy: 0.6795 - val_loss: 1.4636 - val_accuracy: 0.7756
Epoch 9/50
2/2 [=====] - 1s 290ms/step - loss: 2.1163 - accuracy: 0.6844 - val_loss: 1.4504 - val_accuracy: 0.7791
Epoch 10/50
2/2 [=====] - 1s 286ms/step - loss: 2.1090 - accuracy: 0.6839 - val_loss: 1.4436 - val_accuracy: 0.7791
Epoch 11/50
2/2 [=====] - 1s 284ms/step - loss: 2.0970 - accuracy: 0.6844 - val_loss: 1.4331 - val_accuracy: 0.7779
Epoch 12/50
2/2 [=====] - 1s 287ms/step - loss: 2.0796 - accuracy: 0.6858 - val_loss: 1.4136 - val_accuracy: 0.7767
Epoch 13/50
2/2 [=====] - 1s 293ms/step - loss: 2.0534 - accuracy: 0.6899 - val_loss: 1.3890 - val_accuracy: 0.7826
Epoch 14/50
2/2 [=====] - 1s 285ms/step - loss: 2.0201 - accuracy: 0.6924 - val_loss: 1.3725 - val_accuracy: 0.7849
Epoch 15/50
2/2 [=====] - 1s 284ms/step - loss: 1.9935 - accuracy: 0.6913 - val_loss: 1.3610 - val_accuracy: 0.7826
Epoch 16/50
2/2 [=====] - 1s 288ms/step - loss: 1.9651 - accuracy: 0.6913 - val_loss: 1.3476 - val_accuracy: 0.7837
Epoch 17/50
2/2 [=====] - 1s 286ms/step - loss: 1.9356 - accuracy: 0.6929 - val_loss: 1.3348 - val_accuracy: 0.7826
Epoch 18/50
2/2 [=====] - 1s 289ms/step - loss: 1.9069 - accuracy: 0.6948 - val_loss: 1.3185 - val_accuracy: 0.7849
Epoch 19/50
2/2 [=====] - 1s 289ms/step - loss: 1.8763 - accuracy: 0.6975 - val_loss: 1.2984 - val_accuracy: 0.7860
Epoch 20/50
2/2 [=====] - 1s 290ms/step - loss: 1.8429 - accuracy: 0.6996 - val_loss: 1.2787 - val_accuracy: 0.7872
Epoch 21/50
2/2 [=====] - 1s 290ms/step - loss: 1.8082 - accuracy: 0.7010 - val_loss: 1.2591 - val_accuracy: 0.7895
Epoch 22/50
2/2 [=====] - 1s 290ms/step - loss: 1.7717 - accuracy: 0.7037 - val_loss: 1.2377 - val_accuracy: 0.7919
Epoch 23/50
2/2 [=====] - 1s 285ms/step - loss: 1.7335 - accuracy: 0.7076 - val_loss: 1.2126 - val_accuracy: 0.7942
Epoch 24/50
2/2 [=====] - 1s 286ms/step - loss: 1.6949 - accuracy: 0.7120 - val_loss: 1.1878 - val_accuracy: 0.8000
Epoch 25/50
2/2 [=====] - 1s 289ms/step - loss: 1.6553 - accuracy: 0.7192 - val_loss: 1.1662 - val_accuracy: 0.8081
Epoch 26/50
2/2 [=====] - 1s 291ms/step - loss: 1.6147 - accuracy: 0.7265 - val_loss: 1.1468 - val_accuracy: 0.8186
Epoch 27/50
2/2 [=====] - 1s 288ms/step - loss: 1.5731 - accuracy: 0.7337 - val_loss: 1.1242 - val_accuracy: 0.8209
Epoch 28/50
2/2 [=====] - 1s 291ms/step - loss: 1.5308 - accuracy: 0.7402 - val_loss: 1.1069 - val_accuracy: 0.8291
Epoch 29/50
2/2 [=====] - 1s 289ms/step - loss: 1.4883 - accuracy: 0.7473 - val_loss: 1.0902 - val_accuracy: 0.8337
Epoch 30/50
2/2 [=====] - 1s 292ms/step - loss: 1.4461 - accuracy: 0.7547 - val_loss: 1.0731 - val_accuracy: 0.8372
Epoch 31/50
2/2 [=====] - 1s 288ms/step - loss: 1.4047 - accuracy: 0.7621 - val_loss: 1.0563 - val_accuracy: 0.8442
Epoch 32/50
2/2 [=====] - 1s 284ms/step - loss: 1.3630 - accuracy: 0.7682 - val_loss:

```
1.0421 - val_accuracy: 0.8453
Epoch 33/50
2/2 [=====] - 1s 298ms/step - loss: 1.3218 - accuracy: 0.7750 - val_loss:
1.0275 - val_accuracy: 0.8465
Epoch 34/50
2/2 [=====] - 1s 288ms/step - loss: 1.2818 - accuracy: 0.7815 - val_loss:
1.0125 - val_accuracy: 0.8488
Epoch 35/50
2/2 [=====] - 1s 286ms/step - loss: 1.2420 - accuracy: 0.7883 - val_loss:
1.0010 - val_accuracy: 0.8547
Epoch 36/50
2/2 [=====] - 1s 290ms/step - loss: 1.2037 - accuracy: 0.7944 - val_loss:
0.9922 - val_accuracy: 0.8581
Epoch 37/50
2/2 [=====] - 1s 290ms/step - loss: 1.1664 - accuracy: 0.8007 - val_loss:
0.9795 - val_accuracy: 0.8593
Epoch 38/50
2/2 [=====] - 1s 288ms/step - loss: 1.1290 - accuracy: 0.8070 - val_loss:
0.9709 - val_accuracy: 0.8616
Epoch 39/50
2/2 [=====] - 1s 289ms/step - loss: 1.0930 - accuracy: 0.8132 - val_loss:
0.9617 - val_accuracy: 0.8651
Epoch 40/50
2/2 [=====] - 1s 297ms/step - loss: 1.0571 - accuracy: 0.8190 - val_loss:
0.9520 - val_accuracy: 0.8651
Epoch 41/50
2/2 [=====] - 1s 290ms/step - loss: 1.0230 - accuracy: 0.8241 - val_loss:
0.9453 - val_accuracy: 0.8674
Epoch 42/50
2/2 [=====] - 1s 289ms/step - loss: 0.9890 - accuracy: 0.8287 - val_loss:
0.9389 - val_accuracy: 0.8663
Epoch 43/50
2/2 [=====] - 1s 287ms/step - loss: 0.9561 - accuracy: 0.8329 - val_loss:
0.9338 - val_accuracy: 0.8686
Epoch 44/50
2/2 [=====] - 1s 291ms/step - loss: 0.9242 - accuracy: 0.8370 - val_loss:
0.9315 - val_accuracy: 0.8686
Epoch 45/50
2/2 [=====] - 1s 284ms/step - loss: 0.8932 - accuracy: 0.8409 - val_loss:
0.9264 - val_accuracy: 0.8674
Epoch 46/50
2/2 [=====] - 1s 285ms/step - loss: 0.8641 - accuracy: 0.8442 - val_loss:
0.9248 - val_accuracy: 0.8698
Epoch 47/50
2/2 [=====] - 1s 293ms/step - loss: 0.8352 - accuracy: 0.8474 - val_loss:
0.9221 - val_accuracy: 0.8721
Epoch 48/50
2/2 [=====] - 1s 302ms/step - loss: 0.8082 - accuracy: 0.8498 - val_loss:
0.9187 - val_accuracy: 0.8733
Epoch 49/50
2/2 [=====] - 1s 287ms/step - loss: 0.7807 - accuracy: 0.8527 - val_loss:
0.9172 - val_accuracy: 0.8721
Epoch 50/50
2/2 [=====] - 1s 287ms/step - loss: 0.7557 - accuracy: 0.8551 - val_loss:
0.9166 - val_accuracy: 0.8709
```

<tensorflow.python.keras.callbacks.History at 0x7f67caeca10>

Out[188]:

```
model.fit(source_padded_docs_train,target_padded_docs_train,batch_size=1024,epochs=10,
          validation_data=(source_padded_docs_test,target_padded_docs_test))
```

In [189]:

```

Epoch 1/10
2/2 [=====] - 1s 313ms/step - loss: 0.7306 - accuracy: 0.8575 - val_loss:
0.9117 - val_accuracy: 0.8733
Epoch 2/10
2/2 [=====] - 1s 292ms/step - loss: 0.7071 - accuracy: 0.8601 - val_loss:
0.9130 - val_accuracy: 0.8744
Epoch 3/10
2/2 [=====] - 1s 296ms/step - loss: 0.6841 - accuracy: 0.8626 - val_loss:
0.9143 - val_accuracy: 0.8756
Epoch 4/10
2/2 [=====] - 1s 286ms/step - loss: 0.6617 - accuracy: 0.8648 - val_loss:
0.9150 - val_accuracy: 0.8733
Epoch 5/10
2/2 [=====] - 1s 290ms/step - loss: 0.6407 - accuracy: 0.8671 - val_loss:
0.9149 - val_accuracy: 0.8733
Epoch 6/10
2/2 [=====] - 1s 294ms/step - loss: 0.6204 - accuracy: 0.8699 - val_loss:
0.9132 - val_accuracy: 0.8756
Epoch 7/10
2/2 [=====] - 1s 293ms/step - loss: 0.6007 - accuracy: 0.8718 - val_loss:
0.9126 - val_accuracy: 0.8767
Epoch 8/10
2/2 [=====] - 1s 289ms/step - loss: 0.5823 - accuracy: 0.8743 - val_loss:
0.9142 - val_accuracy: 0.8756
Epoch 9/10
2/2 [=====] - 1s 288ms/step - loss: 0.5641 - accuracy: 0.8775 - val_loss:
0.9143 - val_accuracy: 0.8744
Epoch 10/10
2/2 [=====] - 1s 294ms/step - loss: 0.5471 - accuracy: 0.8793 - val_loss:
0.9148 - val_accuracy: 0.8744

```

Out[189]:

```
<tensorflow.python.keras.callbacks.History at 0x7f67caf1de90>
```

In [190]:

```

#https://machinelearningmastery.com/beam-search-decoder-natural-language-processing/
#Beam Search

```

```

from math import log
from numpy import array
from numpy import argmax
import numpy as np
def beam_search_decoder(data, k):
    sequences = [[list(), 0.0]]
    # walk over each step in sequence
    #print(sequences)
    for row in data:
        all_candidates = list()
        # expand each current candidate
        for i in range(len(sequences)):
            seq, score = sequences[i]
            for j in range(len(row)):
                candidate = [seq + [j], score - np.log(row[j])]
                all_candidates.append(candidate)
            # order all candidates by score
            ordered = sorted(all_candidates, key=lambda tup:tup[1])
            sequences = ordered[:k]
    return sequences

```

In [191]:

```

#prediction
def prediction(x):

    index_to_words = {id: word for word, id in target_tokenizer.word_index.items()}
    index_to_words[0] = '<PAD>'

    y=' '.join([index_to_words[prediction] for prediction in x])
    return y
#calculating bleu score using beam search where K==3
for i in range(20):
    print("Input text: ")
    a=list(X_test[i:i+1])
    print(a[0])

    print("Actual Output: ")
    b=list(y_test[i:i+1])
    print(b[0])

```


[illegible]

[illegible]

[illegible]

```

import nltk.translate.bleu_score as bleu
bleu_score1=[]
bleu_score2=[]
bleu_score3=[]

for i in range(20):
    b=list(y_test[i:i+1])
    x=model.predict(source_padded_docs_test[i:i+1])

    res=beam_search_decoder(x[0],3)

    y1=prediction(res[0][0])
    y1=y1.split(' ')
    y_lst1=[]
    for i in y1:
        if i=='<PAD>':
            continue
        else:
            y_lst1.append(i)
    bleu_score1.append(bleu.sentence_bleu([b[0].split(),],y_lst1))

    y2=prediction(res[1][0])
    y2=y2.split(' ')
    y_lst2=[]
    for i in y2:
        if i=='<PAD>':
            continue
        else:
            y_lst2.append(i)
    bleu_score2.append(bleu.sentence_bleu([b[0].split(),],y_lst2))

    y3=prediction(res[2][0])
    y3=y3.split(' ')
    y_lst3=[]
    for i in y3:
        if i=='<PAD>':
            continue
        else:
            y_lst3.append(i)
    bleu_score3.append(bleu.sentence_bleu([b[0].split(),],y_lst3))

print("The Average Bleu Score1 is: ",sum(bleu_score1)/20)
print('> '*180)
print("The Average Bleu Score2 is: ",sum(bleu_score2)/20)
print('> '*180)
print("The Average Bleu Score3 is: ",sum(bleu_score3)/20)
print('> '*180)

```

```

/usr/local/lib/python3.7/dist-packages/nltk/translate/bleu_score.py:490: UserWarning:
Corpus/Sentence contains 0 counts of 2-gram overlaps.
BLEU scores might be undesirable; use SmoothingFunction().
  warnings.warn(_msg)
/usr/local/lib/python3.7/dist-packages/nltk/translate/bleu_score.py:490: UserWarning:
Corpus/Sentence contains 0 counts of 3-gram overlaps.
BLEU scores might be undesirable; use SmoothingFunction().
  warnings.warn(_msg)
/usr/local/lib/python3.7/dist-packages/nltk/translate/bleu_score.py:490: UserWarning:
Corpus/Sentence contains 0 counts of 4-gram overlaps.
BLEU scores might be undesirable; use SmoothingFunction().
  warnings.warn(_msg)

```

