```
In [5]:
 !gdown --id 10urDQUtbWQacvT32HMqFL7vIUrSMl10p
Downloading ...
From: https://drive.google.com/uc?id=10urDQUtbWQacvT32HMgFL7vIUrSM1lOp
To: /content/preprocessed data.csv
100% 300k/300k [00:00<00:00, 92.3MB/s]
                                                                                                                                                                                                                                          In [6]:
 #Importing the necessary packages
 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 [7]:
 df=pd.read csv('preprocessed data.csv') #reading the file preprocessed data.csv
                                                                                                                                                                                                                                          In [8]:
 df.head(4) #visulazing the DataFrame
                                                                                                                                                                                                                                        Out[8]:
      Unnamed: 0
                                                                                                                                                                      target
                                                                                        source
 0
                      0
                                                 U wan me to "chop" seat 4 u nt?\n
                                                                                                        Do you want me to reserve seat for you or not?\n
                                Yup. U reaching. We order some durian pastry
                                                                                                             Yeap. You reaching? We ordered some Durian
                      1
                      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?\n
                                                                                                                                       I'm Thai. What do you do?\n
                                                                                                                                                                                                                                          In [9]:
 def preprocess(x):#for removing the last character
     x = x[:-1]
     return x
                                                                                                                                                                                                                                       In [10]:
 df['source'] = df['source'].apply(preprocess)
 df['target'] = df['target'].apply(preprocess)
                                                                                                                                                                                                                                       In [11]:
 df=df[['source','target']]
 df.head()
                                                                                                                                                                                                                                     Out[11]:
                                                                      source
                                                                                                                                                     target
                                   U wan me to "chop" seat 4 u nt?
 0
                                                                                          Do you want me to reserve seat for you or not?
                                                                                            Yeap. You reaching? We ordered some Durian
          Yup. U reaching. We order some durian pastry a...
 1
             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?
              Hi! How did your week go? Haven heard from
                                                                                      Hi! How did your week go? Haven't heard from y...
                                                                         you...
                                                                                                                                                                                                                                       In [12]:
 df.shape
                                                                                                                                                                                                                                     Out[12]:
(2000, 2)
                                                                                                                                                                                                                                       In [13]:
 df=df[df['source'].apply(len)<170]#removing sentences where source sentence is greater than 170
 df=df[df['target'].apply(len)<200] #removing snetences where target sentence is greater than 200
                                                                                                                                                                                                                                       In [14]:
 df.shape#printing the shape
                                                                                                                                                                                                                                     Out[14]:
(1990, 2)
                                                                                                                                                                                                                                       In [15]:
 from sklearn.model selection import train test split
 X=df['source']
 y=df['target']
  \texttt{X\_train,X\_test,y\_train,y\_test=train\_test\_split(X,y,test\_size=0.01)} \ \# splitting \ in \ the \ data \ in \ the \ ratio \ of \ an algorithms and the latter of the lat
```

print(X train.shape)

```
print(X test.shape)
print(y_train.shape)
print(y test.shape)
(1970,)
(20,)
(1970,)
(20,)
Target:
                                                                                                                                                                          In [16]:
target tokenizer= Tokenizer(filters=None, char level=True, lower=False) #tokenzing the target in character is
target tokenizer.fit on texts(y train) #fitting on the target train
target vocab size= len(target tokenizer.word index) + 1
print(len(target_tokenizer.word_index)) #printing the vocabulary size
                                                                                                                                                                          In [17]:
target encoded docs train = target tokenizer.texts to sequences(y train) #converting target train into sec
target encoded docs test = target tokenizer.texts to sequences(y test) #converting target test into sequen
 target padded docs train = pad sequences(target encoded docs train,padding='post') #padding target train
target padded_docs_test = pad_sequences(target_encoded_docs_test,maxlen=target_padded_docs_train.shape[1]
Source:
                                                                                                                                                                          In [18]:
source_tokenizer= Tokenizer(char_level=True,lower=False) #tokenzing the source in character level
source tokenizer.fit on texts(X train) #fitting on the source train
source vocab size= len(source tokenizer.word index) + 1
print(len(source tokenizer.word index)) #printing the vocabulary size
                                                                                                                                                                          In [19]:
 source_encoded_docs_train = source_tokenizer.texts_to_sequences(X_train) #converting source train into seq
\verb|source_encoded_docs_test| = \verb|source_tokenizer.texts_to_sequences| (X_test) \#| converting| source| train| into sequences| (X_test) \#| converting| source| train| tr
source padded docs train = pad sequences(source encoded docs train, maxlen=target padded docs train.shape[
source padded docs test = pad sequences (source encoded docs test, maxlen=target padded docs train.shape[1]
                                                                                                                                                                          In [20]:
 #we are reshaping because sparse_categorical_entropy expects 3dimensions
 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 [21]:
print(target padded docs train.shape)
print(target_padded_docs_test.shape)
(1970, 199, 1)
(20, 199, 1)
                                                                                                                                                                          In [22]:
 #we are reshaping because sparse_categorical_entropy expects 3dimensions
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 [23]:
print (source padded docs train.shape)
print(source padded docs test.shape)
(1970, 199, 1)
(20, 199, 1)
                                                                                                                                                                          In [49]:
X train.to csv('X train2.csv')
y_train.to_csv('y_train2.csv')
X_test.to_csv('X_test2.csv')
y_test.to_csv('y_test2.csv')
                                                                                                                                                                          In [50]:
import pandas as pd
pd.DataFrame(source encoded docs train).to csv("source encoded docs train2.csv")
pd.DataFrame(source_encoded_docs_test).to_csv("source_encoded_docs_test2.csv")
pd.DataFrame(target_encoded_docs_train).to_csv("target_encoded_docs_train2.csv")
pd.DataFrame(target encoded docs test).to csv("target encoded docs test2.csv")
Model1:
                                                                                                                                                                          In [24]:
 input=tf.keras.layers.Input(shape=(199,))
embed=tf.keras.layers.Embedding(source_vocab_size,256, input_length=source_padded_docs_train.shape[1])(in
```

```
lstm1=tf.keras.layers.LSTM(128, return sequences=True)(embed)
dense=tf.keras.layers.TimeDistributed(tf.keras.layers.Dense(512, activation='relu'))(lstml)
drop=tf.keras.layers.Dropout(0.5)(dense)
output=tf.keras.layers.TimeDistributed(tf.keras.layers.Dense(target vocab size, activation='softmax'))(dr
model=tf.keras.models.Model(inputs=input,outputs=output)
model.summary()
Model: "model"
Layer (type)
                     Output Shape
                                          Param #
_____
                      [(None, 199)]
input 1 (InputLayer)
                      (None, 199, 256)
embedding (Embedding)
                                          26624
1stm (LSTM)
                      (None, 199, 128)
                                         197120
time distributed (TimeDistri (None, 199, 512)
                                          66048
dropout (Dropout)
                      (None, 199, 512)
time_distributed_1 (TimeDist (None, 199, 91)
                                          46683
______
Total params: 336,475
Trainable params: 336,475
Non-trainable params: 0
                                                                            In [25]:
# Compile model
model.compile(optimizer=tf.keras.optimizers.Adam(0.01),
           loss='sparse categorical crossentropy',metrics=['accuracy'])
                                                                            In [26]:
model.fit(source_padded_docs_train,target_padded_docs_train,batch_size=1024,epochs=100,
        validation data=(source padded docs test, target padded docs test))
Epoch 1/100
3.0509 - val accuracy: 0.6756
Epoch 2/100
2/2 [========== 0.698 - val loss: 2.5630 - accuracy: 0.6698 - val loss:
1.3701 - val accuracy: 0.7176
Epoch 3/100
2/2 [========== 0.6910 - val loss: 1.5293 - accuracy: 0.6910 - val loss:
1.2024 - val accuracy: 0.6879
Epoch 4/100
2/2 [========== 0.641 - 0s 246ms/step - loss: 1.3614 - accuracy: 0.6641 - val loss:
1.0989 - val_accuracy: 0.7291
Epoch 5/100
2/2 [========== 0.6993 - val loss: 1.3344 - accuracy: 0.6993 - val loss:
1.0950 - val accuracy: 0.7302
Epoch 6/100
2/2 [========== 0.6934 - val loss: 1.3359 - accuracy: 0.6934 - val loss:
1.0957 - val_accuracy: 0.7302
Epoch 7/100
2/2 [========== 0.6955 - val loss: 1.3253 - accuracy: 0.6955 - val loss:
1.0986 - val_accuracy: 0.7302
Epoch 8/100
2/2 [========== 0.6998 - val loss: 1.3172 - accuracy: 0.6998 - val loss:
1.0917 - val_accuracy: 0.7302
Epoch 9/100
2/2 [========== 0.6998 - val loss: 1.3089 - accuracy: 0.6998 - val loss:
1.0867 - val accuracy: 0.7302
Epoch 10/100
1.0887 - val accuracy: 0.7302
Epoch 11/100
1.0894 - val accuracy: 0.7302
Epoch 12/100
2/2 [========== 0.6998 - val loss: 1.2725 - accuracy: 0.6998 - val loss:
1.0809 - val accuracy: 0.7307
Epoch 13/100
1.0777 - val_accuracy: 0.7296
Epoch 14/100
2/2 [=========== 0.7006 - val loss: 1.2479 - accuracy: 0.7006 - val loss:
```

1.0753 - val accuracy: 0.7304

```
Epoch 15/100
1.0738 - val accuracy: 0.7302
Epoch 16/100
2/2 [========== 0.7007 - val loss: 1.2272 - accuracy: 0.7007 - val loss:
1.0751 - val accuracy: 0.7302
Epoch 17/100
2/2 [========== 0.7007 - val loss: 1.2200 - accuracy: 0.7007 - val loss:
1.0738 - val accuracy: 0.7302
Epoch 18/100
2/2 [========== 0.7009 - val loss: 1.2142 - accuracy: 0.7009 - val loss:
1.0675 - val accuracy: 0.7302
Epoch 19/100
2/2 [========== 0.7011 - val loss: 1.2095 - accuracy: 0.7011 - val loss:
1.0623 - val accuracy: 0.7302
Epoch 20/100
2/2 [=========== 0.7014 - val loss: 1.2069 - accuracy: 0.7014 - val loss:
1.0578 - val_accuracy: 0.7317
Epoch 21/100
2/2 [=========== 0.7017 - 0s 247ms/step - loss: 1.2027 - accuracy: 0.7017 - val loss:
1.0584 - val accuracy: 0.7317
Epoch 22/100
1.0486 - val accuracy: 0.7319
Epoch 23/100
2/2 [========== 0.7024 - val loss: 1.1965 - accuracy: 0.7024 - val loss:
1.0518 - val_accuracy: 0.7329
Epoch 24/100
1.0409 - val accuracy: 0.7337
Epoch 25/100
2/2 [========== 0.7034 - val loss: 1.2019 - accuracy: 0.7034 - val loss:
1.0625 - val accuracy: 0.7334
Epoch 26/100
2/2 [========== 0.7035 - val loss: 1.1967 - accuracy: 0.7035 - val loss:
1.0441 - val accuracy: 0.7349
Epoch 27/100
2/2 [========== 0.7040 - val loss: 1.1923 - accuracy: 0.7040 - val loss:
1.0488 - val accuracy: 0.7354
Epoch 28/100
2/2 [========== 0.7046 - val loss: 1.1869 - accuracy: 0.7046 - val loss:
1.0453 - val accuracy: 0.7342
Epoch 29/100
2/2 [========== 0.7043 - val loss: 1.1822 - accuracy: 0.7043 - val loss:
1.0379 - val accuracy: 0.7342
Epoch 30/100
2/2 [========== 0.7047 - val loss: 1.1782 - accuracy: 0.7047 - val loss:
1.0412 - val accuracy: 0.7364
Epoch 31/100
2/2 [========= 0.7055 - val loss: 1.1746 - accuracy: 0.7055 - val loss:
1.0311 - val accuracy: 0.7364
Epoch 32/100
2/2 [========== 0.7058 - val loss: 1.1713 - accuracy: 0.7058 - val loss:
1.0314 - val accuracy: 0.7372
Epoch 33/100
2/2 [========== 0.7055 - val_loss: 1.1661 - accuracy: 0.7055 - val_loss:
1.0245 - val accuracy: 0.7374
Epoch 34/100
1.0214 - val accuracy: 0.7369
Epoch 35/100
2/2 [========== 0.7067 - val_loss: 1.1581 - accuracy: 0.7067 - val_loss:
1.0207 - val accuracy: 0.7369
Epoch 36/100
2/2 [========== 0.7073 - val loss: 1.1536 - accuracy: 0.7073 - val loss:
1.0159 - val accuracy: 0.7399
Epoch 37/100
2/2 [========== 0.7084 - val loss: 1.1487 - accuracy: 0.7084 - val loss:
1.0137 - val accuracy: 0.7382
Epoch 38/100
2/2 [========== 0.7090 - val loss: 1.1442 - accuracy: 0.7090 - val loss:
1.0124 - val accuracy: 0.7394
Epoch 39/100
2/2 [========== 0.7095 - val loss: 1.1405 - accuracy: 0.7095 - val loss:
1.0288 - val accuracy: 0.7405
Epoch 40/100
```

2/2 [========== 0.7097 - val loss: 1.1432 - accuracy: 0.7097 - val loss:

```
1.0192 - val accuracy: 0.7389
Epoch 41/100
2/2 [========== 0.7103 - 0.7103 - val loss: 1.1373 - accuracy: 0.7103 - val loss:
1.0044 - val accuracy: 0.7394
Epoch 42/100
2/2 [========== 0.7103 - val loss: 1.1358 - accuracy: 0.7103 - val loss:
1.0054 - val_accuracy: 0.7392
Epoch 43/100
2/2 [=========== 0.7105 - val loss: 1.1307 - accuracy: 0.7105 - val loss:
1.0016 - val accuracy: 0.7397
Epoch 44/100
2/2 [========== 0.7109 - 0s 245ms/step - loss: 1.1280 - accuracy: 0.7109 - val loss:
1.0062 - val_accuracy: 0.7422
Epoch 45/100
2/2 [=========== 0.7114 - val loss: 1.1232 - accuracy: 0.7114 - val loss:
0.9998 - val_accuracy: 0.7440
Epoch 46/100
2/2 [========== 0.7132 - val loss: 1.1171 - accuracy: 0.7132 - val loss:
0.9826 - val accuracy: 0.7412
Epoch 47/100
2/2 [========== 0.7135 - val loss: 1.1198 - accuracy: 0.7135 - val loss:
0.9919 - val accuracy: 0.7435
Epoch 48/100
0.9935 - val accuracy: 0.7425
Epoch 49/100
2/2 [=========== 0.7145 - val loss: 1.1106 - accuracy: 0.7145 - val loss:
0.9842 - val accuracy: 0.7442
Epoch 50/100
2/2 [========== 0.7157 - val loss: 1.1043 - accuracy: 0.7157 - val loss:
0.9851 - val accuracy: 0.7462
Epoch 51/100
2/2 [========== 0.7163 - val loss: 1.1014 - accuracy: 0.7163 - val loss:
0.9794 - val accuracy: 0.7462
Epoch 52/100
2/2 [========== 0.7169 - 0s 253ms/step - loss: 1.0987 - accuracy: 0.7169 - val loss:
0.9742 - val accuracy: 0.7485
Epoch 53/100
2/2 [========== 0.7175 - val loss: 1.0934 - accuracy: 0.7175 - val loss:
0.9830 - val accuracy: 0.7467
Epoch 54/100
2/2 [========== 0.7182 - 0s 250ms/step - loss: 1.0893 - accuracy: 0.7182 - val loss:
0.9660 - val_accuracy: 0.7467
Epoch 55/100
2/2 [========== 0.7173 - val loss: 1.1011 - accuracy: 0.7173 - val loss:
0.9721 - val_accuracy: 0.7467
Epoch 56/100
2/2 [========== 0.7173 - val loss: 1.0963 - accuracy: 0.7173 - val loss:
0.9701 - val_accuracy: 0.7467
Epoch 57/100
2/2 [========== 0.7182 - os 253ms/step - loss: 1.0872 - accuracy: 0.7182 - val loss:
0.9799 - val accuracy: 0.7513
Epoch 58/100
2/2 [========== 0.7199 - 0s 250ms/step - loss: 1.0839 - accuracy: 0.7199 - val loss:
0.9592 - val accuracy: 0.7525
Epoch 59/100
2/2 [========== 0.7203 - 0.7203 - val loss: 1.0823 - accuracy: 0.7203 - val loss:
0.9751 - val accuracy: 0.7427
Epoch 60/100
2/2 [========== 0.7184 - val loss: 1.0905 - accuracy: 0.7184 - val loss:
0.9692 - val accuracy: 0.7490
Epoch 61/100
0.9578 - val_accuracy: 0.7472
Epoch 62/100
2/2 [========== 0.7177 - val loss: 1.0831 - accuracy: 0.7177 - val loss:
0.9674 - val accuracy: 0.7420
Epoch 63/100
2/2 [========== 0.7176 - val loss: 1.0801 - accuracy: 0.7176 - val loss:
0.9701 - val accuracy: 0.7452
Epoch 64/100
2/2 [========== 0.7196 - val loss: 1.0743 - accuracy: 0.7196 - val loss:
0.9506 - val accuracy: 0.7495
Epoch 65/100
2/2 [=========== 0.7207 - val loss: 1.0728 - accuracy: 0.7207 - val loss:
0.9515 - val_accuracy: 0.7500
```

Epoch 66/100

```
2/2 [========== 0.7216 - val loss: 1.0667 - accuracy: 0.7216 - val loss:
0.9716 - val accuracy: 0.7492
Epoch 67/100
2/2 [========== 0.7217 - val loss: 1.0658 - accuracy: 0.7217 - val loss:
0.9490 - val accuracy: 0.7477
Epoch 68/100
2/2 [========== 0.7218 - val loss: 1.0626 - accuracy: 0.7218 - val loss:
0.9500 - val accuracy: 0.7490
Epoch 69/100
2/2 [========== 0.722 - val loss: 1.0592 - accuracy: 0.7222 - val loss:
0.9498 - val accuracy: 0.7490
Epoch 70/100
2/2 [=========== 0.7229 - 0s 253ms/step - loss: 1.0546 - accuracy: 0.7229 - val loss:
0.9418 - val accuracy: 0.7475
Epoch 71/100
2/2 [========== 0.7227 - 0s 251ms/step - loss: 1.0524 - accuracy: 0.7227 - val loss:
0.9459 - val accuracy: 0.7513
Epoch 72/100
0.9371 - val accuracy: 0.7492
Epoch 73/100
2/2 [=========== 0.7232 - val loss: 1.0487 - accuracy: 0.7232 - val loss:
0.9431 - val accuracy: 0.7475
Epoch 74/100
2/2 [========== 0.7230 - val loss: 1.0499 - accuracy: 0.7230 - val loss:
0.9401 - val accuracy: 0.7530
Epoch 75/100
2/2 [=========== 0.7230 - val loss: 1.0455 - accuracy: 0.7230 - val loss:
0.9307 - val accuracy: 0.7503
Epoch 76/100
2/2 [=========== 0.7235 - val loss: 1.0459 - accuracy: 0.7235 - val loss:
0.9465 - val accuracy: 0.7447
Epoch 77/100
2/2 [=========== 0.721 - 0s 251ms/step - loss: 1.0573 - accuracy: 0.7221 - val loss:
0.9366 - val accuracy: 0.7515
Epoch 78/100
2/2 [========== 0.7213 - val loss: 1.0547 - accuracy: 0.7213 - val loss:
0.9283 - val accuracy: 0.7513
Epoch 79/100
2/2 [========== 0.7223 - val loss: 1.0456 - accuracy: 0.7223 - val loss:
0.9419 - val_accuracy: 0.7475
Epoch 80/100
0.9360 - val accuracy: 0.7482
Epoch 81/100
2/2 [========== 0.7237 - 0.7237 - val loss: 1.0387 - accuracy: 0.7237 - val loss:
0.9269 - val accuracy: 0.7540
Epoch 82/100
2/2 [========== 0.7243 - val loss: 1.0357 - accuracy: 0.7243 - val loss:
0.9259 - val accuracy: 0.7505
Epoch 83/100
2/2 [=========== 0.7246 - val loss: 1.0325 - accuracy: 0.7246 - val loss:
0.9286 - val accuracy: 0.7487
Epoch 84/100
2/2 [========== 0 - 0s 256ms/step - loss: 1.0299 - accuracy: 0.7248 - val loss:
0.9287 - val accuracy: 0.7510
Epoch 85/100
2/2 [========== 0.7249 - 0s 253ms/step - loss: 1.0277 - accuracy: 0.7249 - val loss:
0.9232 - val accuracy: 0.7523
Epoch 86/100
2/2 [========== 0.7254 - val loss: 1.0234 - accuracy: 0.7254 - val loss:
0.9224 - val accuracy: 0.7500
Epoch 87/100
2/2 [=========== 0.7256 - val loss: 1.0234 - accuracy: 0.7256 - val loss:
0.9175 - val accuracy: 0.7510
Epoch 88/100
2/2 [=========== 0.7255 - val loss: 1.0246 - accuracy: 0.7255 - val loss:
0.9156 - val accuracy: 0.7535
Epoch 89/100
2/2 [=========== 0.7259 - 0s 249ms/step - loss: 1.0181 - accuracy: 0.7259 - val loss:
0.9307 - val accuracy: 0.7525
Epoch 90/100
2/2 [========== 0.7260 - val loss: 1.0191 - accuracy: 0.7260 - val loss:
0.9194 - val_accuracy: 0.7543
Epoch 91/100
0.9205 - val accuracy: 0.7515
```

```
var accaracy. v.,oro
Epoch 92/100
2/2 [=========== 0.7265 - val loss: 1.0140 - accuracy: 0.7265 - val loss:
0.9084 - val accuracy: 0.7523
Epoch 93/100
2/2 [=========== 0.7263 - val loss: 1.0105 - accuracy: 0.7263 - val loss:
0.9255 - val_accuracy: 0.7503
Epoch 94/100
2/2 [========== 0.7261 - val loss: 1.0168 - accuracy: 0.7261 - val loss:
0.9594 - val_accuracy: 0.7467
Epoch 95/100
2/2 [=========== 0.723 - 0s 255ms/step - loss: 1.0370 - accuracy: 0.7223 - val loss:
0.9110 - val accuracy: 0.7520
Epoch 96/100
2/2 [========== 0.7216 - val_loss: 1.0333 - accuracy: 0.7216 - val_loss:
0.9341 - val accuracy: 0.7500
Epoch 97/100
0.9180 - val accuracy: 0.7455
Epoch 98/100
0.9208 - val accuracy: 0.7503
Epoch 99/100
2/2 [=========== 0.7251 - 1s 252ms/step - loss: 1.0174 - accuracy: 0.7251 - val loss:
0.9145 - val_accuracy: 0.7538
Epoch 100/100
2/2 [========== 0.7265 - val loss: 1.0126 - accuracy: 0.7265 - val loss:
0.9065 - val accuracy: 0.7528
                                                                   Out[26]:
<tensorflow.python.keras.callbacks.History at 0x7f36ee2a7bd0>
                                                                   In [28]:
x=model.predict(source padded docs test[:1])[0]
                                                                   In [29]:
index_to_words = {id: word for word, id in target_tokenizer.word_index.items()}
index to words[0] = '<PAD>'
''.join([index to words[prediction] for prediction in np.argmax(x, 1)])
                                                                   Out[29]:
'Photo page..
                        <PAD><PAD>
                                               <PAD><PAD><PAD><PAD><PAD><PAD>
<PAD><PAD><PAD><PAD><PAD><PAD><PAD>
4
                                                                   In [30]:
print(y test[:1])
     Photo page. You mean the website. OK, I'll go ...
Name: target, dtype: object
                                                                   In [31]:
X test[:1]
                                                                   Out[31]:
    Photo page... U mean e website huh... Kk, i'll...
Name: source, dtype: object
                                                                   In [33]:
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 np.argmax(x, 1)])
 return y
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])
 print("Predicted Output: ")
```

```
x=model.predict(source padded docs test[i:i+1])
y=prediction(x[0])
y=y.split(' ')
y lst=[]
for i in y:
 y_lst.append(i)
print(' '.join(y_lst))
print('>'*180)
Input text:
Photo page... U mean e website huh... Kk, i'll go mail u now...
Actual Output:
Photo page. You mean the website. OK, I'll go to mail you now.
Predicted Output:
          <PAD><PAD> k
                    <PAD><PAD><PAD><PAD><PAD><PAD>
Photo page..
Input text:
Eh. I'm still at the bus stop... Missed the bus. So i might be later than you
Actual Output:
I'm still at the bus stop. I missed the bus. So I might be later than you.
Predicted Output:
Eh. 'm till t tte
       S
        <PAD><PAD>
            SSS
              е
                      t
                         <PAD><PAD><PAD><
Input text:
Tomw depends on wat time si going to meet us lah... If she not so early maybe we meet bugis else meet
orchard lor
Actual Output:
Tomorrow depends on what time Si is going to meet us. If she is not so early, maybe we meet at Bugis,
else meet at Orchard.
Predicted Output:
Tomw deeends on wwt tttm i iiggg
<PAD><PAD><PAD><PAD><PAD>
>>>>>>>
Input text:
Ok. I going soon and also send xyan home at the same time. Call u when reaching k.
Actual Output:
Ok. I am going soon and also send xyan home at the same time. Call you when reaching.
Predicted Output:
Ok. T oinga on nnn
        nd an n
                        <PAD><PAD><PAD><
                mm
<PAD><PAD><PAD><PAD><PAD><PAD><PAD>
Input text:
WHAT NUMBER? MOBILE OR NOT ?
Actual Output:
What number? Mobile or not?
Predicted Output:
What n
   b 1
        е
```

```
Input text:
HI, R U GAL OR BOY
Actual Output:
Hi, are you girl or boy?
Predicted Output:
Hi, Rru
    Input text:
My painting almost done liao. But my house outside havent start vet. Haiz....
Actual Output:
My painting is almost done. But my house outside haven't started yet. Sigh.
Predicted Output:
My paintingg lmo t onn
         veee tt tt tt aaa
            <PAD><PAD><PAD><PAD><PAD
    0.
        sse
>>>>>>>
Input text:
Fine. Gt posted to SAFTI as a medic
Actual Output:
Fine. Got posted to SAFTI as a medic.
Predicted Output:
Fine. Gt po tte tt a ti a a
      <PAD><PAD><PAD><PAD><PAD><PAD><PAD>
Input text:
No la... Not attached... He's always pesterin me, dunno y... Haha, i find him a jerk oso lor...
Actual Output:
No. Not attached. He's always pestering me, I don't know why. Haha, I find him a jerk also.
Predicted Output:
   <PAD><PAD><PAD>
            <PAD><PAD>
<PAD><PAD><PAD><PAD><PAD><PAD><PAD>
Input text:
WHAT TIME U WRKIN?
Actual Output:
What time are you working?
Predicted Output:
What Ttmm
```

```
Input text:
I thk dun wan da glasses lar... Seldom use it anyway... Save some money... Hee...
Actual Output:
I think I don't want the glasses. Seldom use it anyway. Save some money. Hee.
Predicted Output:
                  <PAD>
                    <PAD><PAD><PAD><PAD><PA
I thk d n n
     SSSSSS
Input text:
Hi babe its me thanks for coming even though it didnt go that well! i just wanted my bed! Hope to see you
soon love and kisses
Actual Output:
Hi baby, it's me, thanks for coming, even though it didn't go that well! I just wanted my bed! Hope to s
ee you soon love and kisses.
Predicted Output:
Hi abe its me thanns r oconn
            ddd
        eeeee
<PAD><PAD><PAD><PAD><PAD>
Input text:
Hello.... Are you free later for a chat?
Actual Output:
Hello. Are you free later for a chat?
Predicted Output:
         <PAD><PAD><PAD><PAD>
Me very hungry... Ü come down faster lei...
Actual Output:
Me very hungry. You come down faster.
Predicted Output:
         Me verv vnnnvv
     0 0 0 0
<PAD><PAD><PAD><PAD><PAD>
>>>>>>>
Input text:
Mmm thats better now i got a roast down me! i'd b better if i had a few drinks down me 2! Good indian?
Actual Output:
That's better now, I got a roast down me! I'd be better if I had a few drinks down me too! Good Indian?
Predicted Output:
Mmm mhats etttte
       aat
```

>>>>>>>

<PAD><PAD><PAD><PAD><PAD><PAD><PAD>

```
Input text:
Yup... I will be going with my hall.
Actual Output:
Yes. I will be going with my hall.
Predicted Output:
      Yes. I
  1
Input text:
Huh... oh! Thats the wooden one right? the aluminium one cheaper
Actual Output:
Huh. Oh! That's the wooden one right? The aluminium one is cheaper.
Predicted Output:
Huh. I
       <PAD>
             e<PAD><PAD><PAD><PAD><PAD><P
<PAD><PAD><PAD><PAD><PAD><PAD>
>>>>>>>
Input text:
Yupz...Kk...Den i anyhow wear...Vv hot...Haha
Actual Output:
Yes. Ok. Then I anyhow wear. It's very hot. Haha.
Predicted Output:
Yes.
 k
     <PAD><PAD><PAD>
          <PAD><PAD>
            <PAD><PAD><PAD><PAD><PAD><PAD><PAD><
<PAD><PAD><PAD><PAD>
>>>>>>
Input text:
So how are you spending yr weekend?
Actual Output:
So how are you spending your weekend?
Predicted Output:
Input text:
Hey....I know its rude of me not to do something abt e fone.N i'm sorry it died on u.
Actual Output:
Hey, I know it's rude of me not to do something about the phone. And I'm sorry it died on you.
Predicted Output:
           <PAD>
                 <PAD><PAD><PAD>
Hev. I
<PAD><PAD><PAD><PAD><PAD><PAD><
```

In [34]: import nltk.translate.bleu score as bleu bleu score=[] for i in range(20): b=list(y test[i:i+1]) x=model.predict(source padded docs test[i:i+1]) y=prediction(x[0])y=y.split(' ') y_lst=[] for i in y: if '<' in i:</pre> continue else: y_lst.append(i) bleu score.append(bleu.sentence bleu([b[0].split(),],y lst)) print(bleu score) print("The Average Bleu Score is: ", sum(bleu score)/20) /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) [0.3839817133079349, 0, 0.3375804740497263, 0.15042653060571137, 0.46173663094410267, $0.3138995505196357,\ 0.42728700639623407,\ 0.25650569096216347,\ 0,\ 0.22679164443904004,\ 0.3672056269893592,$ 0.4172261448611506, 0.43012508513132625, 0.3354232998654124] The Average Bleu Score is: 0.32245004727098137 4 Model2: In [35]: input=tf.keras.layers.Input(shape=(199,)) embed=tf.keras.layers.Embedding(source vocab size,256, input length=source padded docs train.shape[1])(in lstm1=tf.keras.layers.Bidirectional(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'))(dr model=tf.keras.models.Model(inputs=input,outputs=output) model.summary() Model: "model 1" Layer (type) Output Shape Param # ______ input 2 (InputLayer) [(None, 199)] embedding 1 (Embedding) (None, 199, 256) bidirectional (Bidirectional (None, 199, 256) 394240 time distributed 2 (TimeDist (None, 199, 512) 131584 dropout 1 (Dropout) (None, 199, 512) time distributed 3 (TimeDist (None, 199, 91) 46683 _____ Total params: 599,131 Trainable params: 599,131 Non-trainable params: 0 In [36]: # Compile model model.compile(optimizer=tf.keras.optimizers.Adam(0.01), loss='sparse categorical crossentropy',metrics=['accuracy']) In [37]: model.fit(source_padded_docs_train,target_padded_docs_train,batch_size=1024,epochs=100, validation_data=(source_padded_docs_test,target_padded_docs_test)) Epoch 1/100

```
4.5931 - val accuracy: 0.6/56
Epoch 2/100
1.9741 - val accuracy: 0.6161
Epoch 3/100
2/2 [=========== 0.5189 - 1s 375ms/step - loss: 1.9752 - accuracy: 0.5189 - val loss:
1.2263 - val accuracy: 0.6955
Epoch 4/100
2/2 [=========== 0.6602 - val loss: 1.4786 - accuracy: 0.6602 - val loss:
1.1741 - val_accuracy: 0.6952
Epoch 5/100
1.1194 - val accuracy: 0.7286
Epoch 6/100
2/2 [=========== 0.6898 - val loss: 1.3858 - accuracy: 0.6898 - val loss:
1.0952 - val accuracy: 0.7281
Epoch 7/100
2/2 [=========== 0.6989 - val loss: 1.3693 - accuracy: 0.6989 - val loss:
1.0850 - val accuracy: 0.7302
Epoch 8/100
1.0940 - val accuracy: 0.7281
Epoch 9/100
2/2 [=========== 0.6948 - val loss: 1.3194 - accuracy: 0.6948 - val loss:
1.1282 - val accuracy: 0.7279
Epoch 10/100
2/2 [=========== 0.6916 - val loss: 1.2980 - accuracy: 0.6916 - val loss:
1.1399 - val accuracy: 0.7279
Epoch 11/100
1.0905 - val accuracy: 0.7302
Epoch 12/100
2/2 [=========== 0.6995 - val loss: 1.2618 - accuracy: 0.6995 - val loss:
1.0764 - val accuracy: 0.7302
Epoch 13/100
2/2 [=========== 0.6998 - val loss: 1.2526 - accuracy: 0.6998 - val loss:
1.0866 - val accuracy: 0.7302
Epoch 14/100
2/2 [============ 0.6998 - val loss: 1.2482 - accuracy: 0.6998 - val loss:
1.0806 - val accuracy: 0.7302
Epoch 15/100
2/2 [=========== 0.6999 - val loss: 1.2394 - accuracy: 0.6999 - val loss:
1.0676 - val_accuracy: 0.7302
Epoch 16/100
2/2 [========== 0.7000 - val loss: 1.2330 - accuracy: 0.7000 - val loss:
1.0748 - val accuracy: 0.7302
Epoch 17/100
2/2 [========== 0.7003 - val loss: 1.2281 - accuracy: 0.7003 - val loss:
1.0798 - val_accuracy: 0.7314
Epoch 18/100
2/2 [=========== 0.7005 - val loss: 1.2261 - accuracy: 0.7005 - val loss:
1.0651 - val accuracy: 0.7314
Epoch 19/100
2/2 [========== 0.7008 - val loss: 1.2241 - accuracy: 0.7008 - val loss:
1.0701 - val accuracy: 0.7314
Epoch 20/100
2/2 [=========== 0.7009 - val loss: 1.2206 - accuracy: 0.7009 - val loss:
1.0672 - val accuracy: 0.7314
Epoch 21/100
2/2 [=========== 0.7010 - val loss: 1.2169 - accuracy: 0.7010 - val loss:
1.0585 - val accuracy: 0.7314
Epoch 22/100
2/2 [=========== 0.7010 - val loss: 1.2145 - accuracy: 0.7010 - val loss:
1.0650 - val accuracy: 0.7314
Epoch 23/100
2/2 [=========== 0.7011 - val loss: 1.2126 - accuracy: 0.7011 - val loss:
1.0647 - val accuracy: 0.7314
Epoch 24/100
2/2 [========== 0.7014 - val loss: 1.2103 - accuracy: 0.7014 - val loss:
1.0580 - val accuracy: 0.7337
Epoch 25/100
2/2 [========== 0.7017 - val loss: 1.2076 - accuracy: 0.7017 - val loss:
1.0624 - val accuracy: 0.7347
Epoch 26/100
2/2 [=========== 0.7018 - usl loss: 1.2054 - accuracy: 0.7018 - val loss:
1.0490 - val accuracy: 0.7344
Epoch 27/100
```

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2/2 [=========== 0.7020 - val loss: 1.2038 - accuracy: 0.7020 - val loss:
1.0628 - val accuracy: 0.7347
Epoch 28/100
2/2 [========== 0.7021 - 1s 375ms/step - loss: 1.2023 - accuracy: 0.7021 - val loss:
1.0416 - val_accuracy: 0.7344
Epoch 29/100
2/2 [========== 0.7024 - accuracy: 0.7022 - val loss:
1.0614 - val accuracy: 0.7344
Epoch 30/100
2/2 [========== 0.702 - 1s 369ms/step - loss: 1.2010 - accuracy: 0.7022 - val loss:
1.0411 - val accuracy: 0.7344
Epoch 31/100
1.0594 - val accuracy: 0.7344
Epoch 32/100
1.0489 - val accuracy: 0.7344
Epoch 33/100
2/2 [========== 0.7023 - val loss: 1.1957 - accuracy: 0.7023 - val loss:
1.0527 - val accuracy: 0.7344
Epoch 34/100
2/2 [=========== 0.7023 - 1.374ms/step - loss: 1.1943 - accuracy: 0.7023 - val loss:
1.0494 - val accuracy: 0.7344
Epoch 35/100
2/2 [========== 0.7024 - val loss: 1.1920 - accuracy: 0.7024 - val loss:
1.0444 - val accuracy: 0.7347
Epoch 36/100
2/2 [========== 0.7025 - val loss: 1.1918 - accuracy: 0.7025 - val loss:
1.0513 - val accuracy: 0.7347
Epoch 37/100
2/2 [========== 0.7025 - val loss: 1.1909 - accuracy: 0.7025 - val loss:
1.0416 - val_accuracy: 0.7347
Epoch 38/100
2/2 [========== 0.7025 - val loss: 1.1890 - accuracy: 0.7025 - val loss:
1.0471 - val_accuracy: 0.7347
Epoch 39/100
2/2 [=========== 0.7027 - 1s 381ms/step - loss: 1.1872 - accuracy: 0.7027 - val loss:
1.0443 - val_accuracy: 0.7347
Epoch 40/100
2/2 [========== 0.7026 - val loss: 1.1869 - accuracy: 0.7026 - val loss:
1.0346 - val accuracy: 0.7347
Epoch 41/100
2/2 [========== 0.7028 - val loss: 1.1870 - accuracy: 0.7028 - val loss:
1.0384 - val accuracy: 0.7352
Epoch 42/100
2/2 [========== 0.7029 - 1s 377ms/step - loss: 1.1830 - accuracy: 0.7029 - val loss:
1.0376 - val accuracy: 0.7357
Epoch 43/100
1.0325 - val accuracy: 0.7362
Epoch 44/100
2/2 [========== 0.7030 - val loss: 1.1833 - accuracy: 0.7030 - val loss:
1.0210 - val accuracy: 0.7359
Epoch 45/100
2/2 [========== 0.7032 - val loss: 1.1918 - accuracy: 0.7032 - val loss:
1.0431 - val accuracy: 0.7367
Epoch 46/100
2/2 [========== 0.7032 - val loss: 1.1848 - accuracy: 0.7032 - val loss:
1.0258 - val accuracy: 0.7367
Epoch 47/100
2/2 [=========== 0.7035 - val loss: 1.1819 - accuracy: 0.7035 - val loss:
1.0475 - val accuracy: 0.7369
Epoch 48/100
2/2 [========== 0.7035 - val loss: 1.1803 - accuracy: 0.7035 - val loss:
1.0222 - val_accuracy: 0.7372
Epoch 49/100
2/2 [========== 0.7036 - val loss: 1.1787 - accuracy: 0.7036 - val loss:
1.0411 - val_accuracy: 0.7367
Epoch 50/100
2/2 [=========== 0.7039 - val loss: 1.1764 - accuracy: 0.7039 - val loss:
1.0273 - val_accuracy: 0.7369
Epoch 51/100
2/2 [========== 0.7040 - val loss: 1.1742 - accuracy: 0.7040 - val loss:
1.0238 - val_accuracy: 0.7372
Epoch 52/100
2/2 [========== 0.7042 - val loss: 1.1717 - accuracy: 0.7042 - val loss:
1.0369 - val accuracy: 0.7377
```

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Epoch 53/100
2/2 [========== 0.7041 - val loss: 1.1716 - accuracy: 0.7041 - val loss:
1.0224 - val_accuracy: 0.7382
Epoch 54/100
2/2 [=========== 0.7041 - val loss: 1.1691 - accuracy: 0.7041 - val loss:
1.0223 - val accuracy: 0.7387
Epoch 55/100
2/2 [=========== 0.7045 - val loss: 1.1671 - accuracy: 0.7045 - val loss:
1.0283 - val accuracy: 0.7387
Epoch 56/100
1.0161 - val accuracy: 0.7387
Epoch 57/100
2/2 [========== 0.7048 - val loss: 1.1644 - accuracy: 0.7048 - val loss:
1.0244 - val accuracy: 0.7389
Epoch 58/100
2/2 [=========== 0.7049 - val loss: 1.1631 - accuracy: 0.7049 - val loss:
1.0152 - val accuracy: 0.7384
Epoch 59/100
2/2 [=========== 0.7051 - 1.1617 - accuracy: 0.7051 - val loss:
1.0216 - val accuracy: 0.7387
Epoch 60/100
2/2 [=========== 0.7052 - val loss: 1.1615 - accuracy: 0.7052 - val loss:
1.0180 - val accuracy: 0.7387
Epoch 61/100
2/2 [========== 0.7054 - val loss: 1.1599 - accuracy: 0.7054 - val loss:
1.0116 - val accuracy: 0.7394
Epoch 62/100
2/2 [========== 0.7056 - val loss: 1.1585 - accuracy: 0.7056 - val loss:
1.0123 - val accuracy: 0.7399
Epoch 63/100
2/2 [========== 0.7060 - val loss: 1.1564 - accuracy: 0.7060 - val loss:
1.0118 - val accuracy: 0.7397
Epoch 64/100
2/2 [========== 0.7060 - val loss: 1.1539 - accuracy: 0.7060 - val loss:
1.0042 - val_accuracy: 0.7399
Epoch 65/100
2/2 [========== 0.7063 - val loss: 1.1532 - accuracy: 0.7063 - val loss:
1.0193 - val accuracy: 0.7389
Epoch 66/100
2/2 [========== 0.7063 - val loss: 1.1575 - accuracy: 0.7063 - val loss:
1.0208 - val accuracy: 0.7392
Epoch 67/100
2/2 [=========== 0.7064 - val loss: 1.1540 - accuracy: 0.7064 - val loss:
1.0026 - val accuracy: 0.7392
Epoch 68/100
1.0180 - val accuracy: 0.7392
Epoch 69/100
2/2 [========== 0.7067 - val loss: 1.1514 - accuracy: 0.7067 - val loss:
0.9968 - val accuracy: 0.7399
Epoch 70/100
2/2 [=========== 0.7071 - val loss: 1.1498 - accuracy: 0.7071 - val loss:
1.0110 - val accuracy: 0.7417
Epoch 71/100
2/2 [=========== 0.7073 - val loss: 1.1470 - accuracy: 0.7073 - val loss:
0.9977 - val_accuracy: 0.7415
Epoch 72/100
2/2 [=========== 0.7074 - val loss: 1.1452 - accuracy: 0.7074 - val loss:
1.0066 - val accuracy: 0.7417
Epoch 73/100
2/2 [=========== 0.7078 - val loss: 1.1435 - accuracy: 0.7078 - val loss:
0.9967 - val accuracy: 0.7420
Epoch 74/100
2/2 [========== 0.7081 - 1s 383ms/step - loss: 1.1420 - accuracy: 0.7081 - val loss:
0.9997 - val_accuracy: 0.7417
Epoch 75/100
2/2 [=========== 0.7085 - val loss: 1.1395 - accuracy: 0.7085 - val loss:
0.9920 - val_accuracy: 0.7425
Epoch 76/100
2/2 [========== 0.7086 - val loss: 1.1381 - accuracy: 0.7086 - val loss:
1.0012 - val accuracy: 0.7415
Epoch 77/100
2/2 [=========== 0.7089 - 1 1 378ms/step - loss: 1.1383 - accuracy: 0.7089 - val loss:
0.9937 - val accuracy: 0.7422
Epoch 78/100
2/2 [========== 0.7091 - 1s 381ms/step - loss: 1.1350 - accuracy: 0.7091 - val loss:
```

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0.9941 - val_accuracy: 0.7427
Epoch 79/100
0.9921 - val accuracy: 0.7420
Epoch 80/100
2/2 [=========== 0.7101 - val loss: 1.1320 - accuracy: 0.7101 - val loss:
0.9889 - val accuracy: 0.7415
2/2 [========== 0.7099 - val loss: 1.1308 - accuracy: 0.7099 - val loss:
0.9850 - val accuracy: 0.7422
Epoch 82/100
2/2 [=========== 0.7104 - val loss: 1.1291 - accuracy: 0.7104 - val loss:
0.9932 - val accuracy: 0.7422
Epoch 83/100
2/2 [=========== 0.7108 - val loss: 1.1287 - accuracy: 0.7108 - val loss:
0.9961 - val accuracy: 0.7405
Epoch 84/100
2/2 [=========== 0.7103 - 1.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.7103 - 2.71
0.9911 - val accuracy: 0.7410
Epoch 85/100
2/2 [=========== 0.7108 - val loss: 1.1256 - accuracy: 0.7108 - val loss:
0.9773 - val accuracy: 0.7432
Epoch 86/100
2/2 [=========== 0.7111 - val loss: 1.1259 - accuracy: 0.7111 - val loss:
0.9859 - val accuracy: 0.7437
Epoch 87/100
2/2 [========== 0.7115 - val loss: 1.1246 - accuracy: 0.7115 - val loss:
0.9888 - val accuracy: 0.7432
Epoch 88/100
2/2 [============ 0.7114 - val loss: 1.1241 - accuracy: 0.7114 - val loss:
0.9881 - val accuracy: 0.7427
Epoch 89/100
2/2 [=========== 0.7124 - val loss: 1.1242 - accuracy: 0.7124 - val loss:
0.9871 - val accuracy: 0.7425
Epoch 90/100
2/2 [=========== 0.7123 - val loss: 1.1215 - accuracy: 0.7123 - val loss:
0.9903 - val accuracy: 0.7420
Epoch 91/100
0.9796 - val accuracy: 0.7435
Epoch 92/100
2/2 [=========== 0.7134 - val loss: 1.1175 - accuracy: 0.7134 - val loss:
0.9733 - val accuracy: 0.7440
Epoch 93/100
2/2 [=========== 0.7136 - val loss: 1.1153 - accuracy: 0.7136 - val loss:
0.9769 - val accuracy: 0.7460
Epoch 94/100
2/2 [=========== 0.7142 - val loss: 1.1149 - accuracy: 0.7142 - val loss:
0.9843 - val accuracy: 0.7442
Epoch 95/100
2/2 [=========== 0.7142 - val loss: 1.1129 - accuracy: 0.7142 - val loss:
0.9785 - val accuracy: 0.7450
Epoch 96/100
2/2 [=========== 0.7145 - val loss: 1.1117 - accuracy: 0.7145 - val loss:
0.9703 - val accuracy: 0.7472
Epoch 97/100
2/2 [========== 0.7149 - val loss: 1.1085 - accuracy: 0.7149 - val loss:
0.9649 - val accuracy: 0.7447
Epoch 98/100
2/2 [========== 0.7145 - val loss: 1.1117 - accuracy: 0.7145 - val loss:
0.9667 - val accuracy: 0.7450
Epoch 99/100
2/2 [=========== 0.7152 - 1s 375ms/step - loss: 1.1093 - accuracy: 0.7152 - val loss:
0.9867 - val accuracy: 0.7445
Epoch 100/100
2/2 [========== 0.7162 - 1s 373ms/step - loss: 1.1069 - accuracy: 0.7162 - val loss:
0.9626 - val_accuracy: 0.7457
                                                                                                                                     Out[37]:
<tensorflow.python.keras.callbacks.History at 0x7f3612e2b9d0>
                                                                                                                                      In [38]:
model.fit(source padded_docs_train,target_padded_docs_train,batch_size=1024,epochs=100,
             validation data=(source padded docs test, target padded docs test))
0.9645 - val accuracy: 0.7460
```

Epoch 2/100

```
2/2 [========== 0.7166 - val loss: 1.1036 - accuracy: 0.7166 - val loss:
0.9765 - val accuracy: 0.7462
Epoch 3/100
2/2 [=========== 0.7174 - val loss: 1.1021 - accuracy: 0.7174 - val loss:
0.9615 - val accuracy: 0.7487
Epoch 4/100
2/2 [========== 0.7174 - val loss: 1.0997 - accuracy: 0.7174 - val loss:
0.9702 - val accuracy: 0.7455
Epoch 5/100
2/2 [=========== 0.7170 - 12 370ms/step - loss: 1.0990 - accuracy: 0.7170 - val loss:
0.9556 - val accuracy: 0.7467
Epoch 6/100
2/2 [========== 0.7182 - val loss: 1.0960 - accuracy: 0.7182 - val loss:
0.9704 - val accuracy: 0.7475
Epoch 7/100
2/2 [========== 0.7189 - 1s 377ms/step - loss: 1.0952 - accuracy: 0.7189 - val loss:
0.9628 - val accuracy: 0.7482
Epoch 8/100
2/2 [=========== 0.7179 - 1.0926 - accuracy: 0.7179 - val loss:
0.9533 - val accuracy: 0.7485
Epoch 9/100
2/2 [========== 0.71ms/step - loss: 1.0898 - accuracy: 0.7189 - val loss:
0.9595 - val_accuracy: 0.7467
Epoch 10/100
2/2 [=========== 0.7192 - 1s 375ms/step - loss: 1.0892 - accuracy: 0.7192 - val loss:
0.9524 - val_accuracy: 0.7472
Epoch 11/100
2/2 [========== 0.7194 - val loss: 1.0863 - accuracy: 0.7194 - val loss:
0.9556 - val_accuracy: 0.7485
Epoch 12/100
2/2 [========== 0.7197 - val loss: 1.0853 - accuracy: 0.7197 - val loss:
0.9575 - val accuracy: 0.7465
Epoch 13/100
2/2 [=========== 0.7201 - val loss: 1.0843 - accuracy: 0.7201 - val loss:
0.9569 - val_accuracy: 0.7487
Epoch 14/100
2/2 [=========== 0.7197 - val loss: 1.0835 - accuracy: 0.7197 - val loss:
0.9476 - val accuracy: 0.7490
Epoch 15/100
2/2 [=========== 0.7203 - val loss: 1.0811 - accuracy: 0.7203 - val loss:
0.9583 - val accuracy: 0.7477
Epoch 16/100
0.9690 - val accuracy: 0.7457
Epoch 17/100
2/2 [========== 0 - 1s 374ms/step - loss: 1.0873 - accuracy: 0.7194 - val loss:
0.9434 - val accuracy: 0.7497
Epoch 18/100
2/2 [========== 0 - 1s 379ms/step - loss: 1.0788 - accuracy: 0.7214 - val loss:
0.9536 - val accuracy: 0.7472
Epoch 19/100
2/2 [=========== 0.7216 - val loss: 1.0771 - accuracy: 0.7216 - val loss:
0.9412 - val accuracy: 0.7477
Epoch 20/100
2/2 [=========== 0.7216 - val loss: 1.0744 - accuracy: 0.7216 - val loss:
0.9445 - val_accuracy: 0.7487
Epoch 21/100
2/2 [=========== 0.722 - accuracy: 0.7225 - val loss:
0.9432 - val_accuracy: 0.7477
Epoch 22/100
0.9419 - val accuracy: 0.7503
Epoch 23/100
2/2 [========== 0.722 - val loss: 1.0680 - accuracy: 0.7222 - val loss:
0.9377 - val accuracy: 0.7487
Epoch 24/100
2/2 [=========== 0.7231 - val loss: 1.0665 - accuracy: 0.7231 - val loss:
0.9395 - val accuracy: 0.7492
Epoch 25/100
0.9435 - val accuracy: 0.7508
Epoch 26/100
2/2 [========== 0.7228 - val loss: 1.0742 - accuracy: 0.7228 - val loss:
0.9871 - val_accuracy: 0.7425
Epoch 27/100
0.9395 - val accuracy: 0.7475
```

```
Epoch 28/100
2/2 [========== 0.7165 - val loss: 1.0921 - accuracy: 0.7165 - val loss:
0.9533 - val accuracy: 0.7435
Epoch 29/100
0.9423 - val accuracy: 0.7480
Epoch 30/100
2/2 [=========== 0.7172 - val loss: 1.0840 - accuracy: 0.7172 - val loss:
0.9477 - val accuracy: 0.7495
Epoch 31/100
2/2 [=========== 0.7185 - val loss: 1.0802 - accuracy: 0.7185 - val loss:
0.9419 - val accuracy: 0.7485
Epoch 32/100
2/2 [=========== 0.7198 - val loss: 1.0756 - accuracy: 0.7198 - val loss:
0.9362 - val accuracy: 0.7497
Epoch 33/100
2/2 [=========== 0.720 - accuracy: 0.7208 - val loss:
0.9390 - val accuracy: 0.7503
Epoch 34/100
0.9332 - val accuracy: 0.7497
Epoch 35/100
2/2 [=========== 0.721 - 1s 384ms/step - loss: 1.0664 - accuracy: 0.7221 - val loss:
0.9315 - val_accuracy: 0.7497
Epoch 36/100
2/2 [========== 0.725 - val loss: 1.0639 - accuracy: 0.7225 - val loss:
0.9280 - val_accuracy: 0.7482
Epoch 37/100
0.9262 - val accuracy: 0.7503
Epoch 38/100
2/2 [=========== 0.7234 - val loss: 1.0598 - accuracy: 0.7234 - val loss:
0.9347 - val accuracy: 0.7508
Epoch 39/100
0.9196 - val accuracy: 0.7495
Epoch 40/100
2/2 [=========== 0.7234 - val loss: 1.0592 - accuracy: 0.7234 - val loss:
0.9217 - val accuracy: 0.7510
Epoch 41/100
2/2 [========== 0.7238 - val loss: 1.0555 - accuracy: 0.7238 - val loss:
0.9255 - val accuracy: 0.7510
Epoch 42/100
2/2 [========== 0.7243 - val loss: 1.0523 - accuracy: 0.7243 - val loss:
0.9183 - val_accuracy: 0.7520
Epoch 43/100
0.9222 - val accuracy: 0.7513
Epoch 44/100
2/2 [=========== 0.7244 - val loss: 1.0479 - accuracy: 0.7244 - val loss:
0.9147 - val accuracy: 0.7508
Epoch 45/100
2/2 [========== 0.7249 - val loss: 1.0466 - accuracy: 0.7249 - val loss:
0.9149 - val_accuracy: 0.7513
Epoch 46/100
2/2 [========== 0.7248 - val loss: 1.0456 - accuracy: 0.7248 - val loss:
0.9176 - val_accuracy: 0.7528
Epoch 47/100
2/2 [========== 0.7252 - val loss: 1.0436 - accuracy: 0.7252 - val loss:
0.9126 - val accuracy: 0.7525
Epoch 48/100
2/2 [=========== 0.7254 - val loss: 1.0409 - accuracy: 0.7254 - val loss:
0.9089 - val_accuracy: 0.7525
Epoch 49/100
0.9087 - val accuracy: 0.7530
Epoch 50/100
2/2 [========== 0.7253 - 1.0383 - accuracy: 0.7253 - val loss:
0.9115 - val accuracy: 0.7540
Epoch 51/100
2/2 [========== 0.7257 - val loss: 1.0401 - accuracy: 0.7257 - val loss:
0.9344 - val accuracy: 0.7543
Epoch 52/100
2/2 [========== 0.7247 - val loss: 1.0507 - accuracy: 0.7247 - val loss:
0.9046 - val accuracy: 0.7533
Epoch 53/100
2/2 [========== 0.7256 - val loss: 1.0391 - accuracy: 0.7256 - val loss:
```

```
0.9121 - val accuracy: 0.7540
Epoch 54/100
2/2 [=========== 0.7260 - val loss: 1.0374 - accuracy: 0.7260 - val loss:
0.9068 - val accuracy: 0.7560
Epoch 55/100
2/2 [========== 0.7254 - val loss: 1.0361 - accuracy: 0.7254 - val loss:
0.9078 - val accuracy: 0.7538
Epoch 56/100
2/2 [========== 0.7269 - 1s 381ms/step - loss: 1.0322 - accuracy: 0.7269 - val loss:
0.9083 - val accuracy: 0.7535
Epoch 57/100
2/2 [=========== 0.7271 - val loss: 1.0303 - accuracy: 0.7271 - val loss:
0.9045 - val accuracy: 0.7513
Epoch 58/100
2/2 [========== 0.7265 - val loss: 1.0318 - accuracy: 0.7265 - val loss:
0.9014 - val accuracy: 0.7550
Epoch 59/100
2/2 [=========== 0.7270 - 1s 380ms/step - loss: 1.0284 - accuracy: 0.7270 - val loss:
0.9016 - val accuracy: 0.7558
Epoch 60/100
2/2 [=========== 0.7272 - 1s 400ms/step - loss: 1.0254 - accuracy: 0.7272 - val loss:
0.9033 - val accuracy: 0.7508
Epoch 61/100
2/2 [=========== 0.727 - 1s 377ms/step - loss: 1.0243 - accuracy: 0.7272 - val loss:
0.9051 - val_accuracy: 0.7560
Epoch 62/100
0.8984 - val accuracy: 0.7508
Epoch 63/100
2/2 [========== 0.727 - val loss: 1.0210 - accuracy: 0.7277 - val loss:
0.8953 - val_accuracy: 0.7530
Epoch 64/100
0.8973 - val accuracy: 0.7555
Epoch 65/100
0.9028 - val accuracy: 0.7500
Epoch 66/100
2/2 [========== 0.7263 - val loss: 1.0255 - accuracy: 0.7263 - val loss:
0.8930 - val accuracy: 0.7550
Epoch 67/100
2/2 [=========== 0.724ms/step - loss: 1.0219 - accuracy: 0.7273 - val loss:
0.9110 - val accuracy: 0.7508
Epoch 68/100
2/2 [========== 0.7278 - 1.0196 - accuracy: 0.7278 - val loss:
0.8932 - val accuracy: 0.7535
Epoch 69/100
2/2 [========== 0.7284 - val loss: 1.0159 - accuracy: 0.7284 - val loss:
0.8991 - val accuracy: 0.7548
Epoch 70/100
2/2 [========== 0.7285 - val loss: 1.0178 - accuracy: 0.7285 - val loss:
0.9049 - val_accuracy: 0.7553
Epoch 71/100
2/2 [=========== 0.7280 - 1.0187 - accuracy: 0.7280 - val loss:
0.8888 - val accuracy: 0.7530
Epoch 72/100
2/2 [=========== 0.7285 - val loss: 1.0146 - accuracy: 0.7285 - val loss:
0.8951 - val_accuracy: 0.7535
Epoch 73/100
2/2 [============ 0.7286 - val loss: 1.0119 - accuracy: 0.7286 - val loss:
0.8888 - val accuracy: 0.7538
Epoch 74/100
2/2 [=========== 0.729z - 1.0066 - accuracy: 0.7292 - val loss:
0.8956 - val accuracy: 0.7528
Epoch 75/100
2/2 [=========== 0.7297 - 1s 378ms/step - loss: 1.0046 - accuracy: 0.7297 - val loss:
0.8897 - val accuracy: 0.7550
Epoch 76/100
2/2 [========== 0.7293 - val loss: 1.0036 - accuracy: 0.7293 - val loss:
0.8830 - val accuracy: 0.7530
Epoch 77/100
2/2 [============ 0.7297 - val loss: 1.0021 - accuracy: 0.7297 - val loss:
0.8853 - val accuracy: 0.7520
Epoch 78/100
2/2 [=========== 0.7299 - 1s 374ms/step - loss: 0.9988 - accuracy: 0.7299 - val loss:
0.8832 - val accuracy: 0.7558
Epoch 79/100
```

```
2/2 [========== 0.7302 - 1s 379ms/step - loss: 0.9983 - accuracy: 0.7302 - val loss:
0.8836 - val accuracy: 0.7560
Epoch 80/100
2/2 [========== 0.7303 - val loss: 0.9967 - accuracy: 0.7303 - val loss:
0.8854 - val accuracy: 0.7518
Epoch 81/100
2/2 [=========== 0.7300 - val loss: 0.9997 - accuracy: 0.7300 - val loss:
0.8771 - val accuracy: 0.7538
Epoch 82/100
2/2 [========== 0.7303 - val loss: 0.9944 - accuracy: 0.7303 - val loss:
0.8817 - val accuracy: 0.7553
Epoch 83/100
2/2 [=========== 0.73ms/step - loss: 0.9918 - accuracy: 0.7312 - val loss:
0.8780 - val_accuracy: 0.7573
Epoch 84/100
2/2 [=========== 0.7311 - val loss: 0.9885 - accuracy: 0.7311 - val loss:
0.8916 - val_accuracy: 0.7520
Epoch 85/100
2/2 [========== 0.7268 - val loss: 1.0144 - accuracy: 0.7268 - val loss:
0.8836 - val accuracy: 0.7533
Epoch 86/100
2/2 [========== 0.7247 - val loss: 1.0202 - accuracy: 0.7247 - val loss:
0.8879 - val accuracy: 0.7530
Epoch 87/100
2/2 [========== 0.7254 - val_loss: 1.0122 - accuracy: 0.7254 - val_loss:
0.8868 - val_accuracy: 0.7487
Epoch 88/100
0.8834 - val accuracy: 0.7550
Epoch 89/100
2/2 [========== 0.7293 - 1s 371ms/step - loss: 0.9998 - accuracy: 0.7293 - val loss:
0.8868 - val accuracy: 0.7530
Epoch 90/100
2/2 [========== 0.73ms/step - loss: 0.9948 - accuracy: 0.7306 - val loss:
0.8951 - val accuracy: 0.7508
Epoch 91/100
2/2 [=========== 0.7309 - val loss: 0.9924 - accuracy: 0.7309 - val loss:
0.8838 - val accuracy: 0.7535
Epoch 92/100
2/2 [========== 0.7308 - val loss: 0.9894 - accuracy: 0.7308 - val loss:
0.8803 - val accuracy: 0.7533
Epoch 93/100
2/2 [============ 0.7307 - val loss: 0.9878 - accuracy: 0.7307 - val loss:
0.8786 - val accuracy: 0.7515
Epoch 94/100
2/2 [=========== 0.7316 - val loss: 0.9830 - accuracy: 0.7316 - val loss:
0.8748 - val_accuracy: 0.7535
Epoch 95/100
2/2 [========== 0.7322 - val loss: 0.9799 - accuracy: 0.7322 - val loss:
0.8824 - val accuracy: 0.7543
Epoch 96/100
2/2 [=========== 0.7319 - 1s 372ms/step - loss: 0.9804 - accuracy: 0.7319 - val loss:
0.8784 - val accuracy: 0.7545
Epoch 97/100
2/2 [========== 0.7323 - val_loss: 0.9781 - accuracy: 0.7323 - val_loss:
0.8754 - val accuracy: 0.7535
Epoch 98/100
2/2 [============ 0.732 - accuracy: 0.7325 - val_loss:
0.8747 - val_accuracy: 0.7553
Epoch 99/100
2/2 [========== 0.7328 - val loss: 0.9747 - accuracy: 0.7328 - val loss:
0.8796 - val accuracy: 0.7563
Epoch 100/100
2/2 [=========== 0.7318 - 1.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.7318 - 2.73
0.8754 - val accuracy: 0.7523
                                                                                                                                          Out[38]:
<tensorflow.python.keras.callbacks.History at 0x7f357deb3290>
                                                                                                                                           In [43]:
model.save weights('model2.h5')
x=model.predict(source padded docs test[:1])[0]
                                                                                                                                           In [44]:
index_to_words = {id: word for word, id in target tokenizer.word index.items()}
 index to words[0] = '<PAD>'
 ''.join([index_to_words[prediction] for prediction in np.argmax(x, 1)])
```

```
Out[44]:
```

```
■
                                   In [45]:
print(y test[:1])
  Photo page. You mean the website. OK, I'll go ...
Name: target, dtype: object
                                   In [46]:
X test[:1]
                                  Out[46]:
1108
  Photo page... U mean e website huh... Kk, i'll...
Name: source, dtype: object
                                   In [47]:
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 np.argmax(x, 1)])
return y
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])
print("Predicted Output: ")
x=model.predict(source padded docs test[i:i+1])
y=prediction(x[0])
y=y.split(' ')
y_lst=[]
for i in y:
  y lst.append(i)
print(' '.join(y_lst))
print('>'*180)
Input text:
Photo page... U mean e website huh... Kk, i'll go mail u now...
Actual Output:
Photo page. You mean the website. OK, I'll go to mail you now.
Predicted Output:
Photo page.
       ee e
                  >>>>>>>
Input text:
Eh. I'm still at the bus stop... Missed the bus. So i might be later than you
Actual Output:
I'm still at the bus stop. I missed the bus. So I might be later than you.
Predicted Output:
 'm till t t e
        ss p
                       e t
                          <PAD><PAD><PAD><PAD><PAD>
```

>>>>>>>

```
Input text:
Tomw depends on wat time si going to meet us lah... If she not so early maybe we meet bugis else meet
orchard lor
Actual Output:
Tomorrow depends on what time Si is going to meet us. If she is not so early, maybe we meet at Bugis,
else meet at Orchard.
Predicted Output:
Tomw depeeds n
                  eeee
                     e ee
<PAD><PAD><PAD><PAD><PAD><PAD>
Input text:
Ok. I going soon and also send xyan home at the same time. Call u when reaching k.
Actual Output:
Ok. I am going soon and also send xyan home at the same time. Call you when reaching.
Predicted Output:
            allll wee eachinn k<PAD><PAD><PAD><PAD>
Ok. I ggingg oon nd also send xyan ome at the same ime
>>>>>>>
Input text:
WHAT NUMBER? MOBILE OR NOT ?
Actual Output:
What number? Mobile or not?
Predicted Output:
     What n er m e
Input text:
HI, R U GAL OR BOY
Actual Output:
Hi, are you girl or boy?
Predicted Output:
Hi, R oo
     Input text:
My painting almost done liao. But my house outside havent start yet. Haiz....
Actual Output:
My painting is almost done. But my house outside haven't started yet. Sigh.
Predicted Output:
My painting lmost one
         u sss
           eee ttttt <PAD><PAD><PAD><PAD><PAD><PAD><PAD>
        SS
<PAD><PAD><PAD><PAD><PAD>
>>>>>>>
```

Input text:

```
Fine. Gt posted to SAFTI as a medic
Actual Output:
Fine. Got posted to SAFTI as a medic.
Predicted Output:
Fine. G
        tte tt
<PAD><PAD><PAD><PAD><PAD><PAD><PAD>
Input text:
No la... Not attached... He's always pesterin me, dunno y... Haha, i find him a jerk oso lor...
Actual Output:
No. Not attached. He's always pestering me, I don't know why. Haha, I find him a jerk also.
Predicted Output:
No. a.
   tt hee
        eeteein
                  <PAD><PAD><PAD>
>>>>>>>
Input text:
WHAT TIME U WRKIN?
Actual Output:
What time are you working?
Predicted Output:
What Ti m
    <PAD><PAD>
>>>>>>>
Input text:
I thk dun wan da glasses lar... Seldom use it anyway... Save some money... Hee...
Actual Output:
I think I don't want the glasses. Seldom use it anyway. Save some money. Hee.
Predicted Output:
I thk n
              m <PAD><PAD><PAD><PAD><PAD><PAD>
     SS
>>>>>>>
Input text:
Hi babe its me thanks for coming even though it didnt go that well!i just wanted my bed! Hope to see you
soon love and kisses
Actual Output:
Hi baby, it's me, thanks for coming, even though it didn't go that well! I just wanted my bed! Hope to s
ee you soon love and kisses.
Predicted Output:
Hi babe its me ttaa
       eee
             t.t.
  00 0
```

Hello.... Are you free later for a chat?

Actual Output:

```
Hello. Are you free later for a chat?
Predicted Output:
    Hello.
<PAD><PAD><PAD><PAD><PAD><PAD><PAD>
Input text:
Me very hungry... Ü come down faster lei...
Actual Output:
Me very hungry. You come down faster.
Predicted Output:
Me very ungry. u u
      <PAD><PAD><PAD><PAD><PAD>
Input text:
Mmm thats better now i got a roast down me! i'd b better if i had a few drinks down me 2! Good indian?
Actual Output:
That's better now, I got a roast down me! I'd be better if I had a few drinks down me too! Good Indian?
Predicted Output:
Mmm hatss etter
<PAD><PAD><PAD><PAD><PAD><PAD><PAD>
Input text:
Yup... I will be going with my hall.
Actual Output:
Yes. I will be going with my hall.
Predicted Output:
   Yes. I
Input text:
Huh... oh! Thats the wooden one right? the aluminium one cheaper
Actual Output:
Huh. Oh! That's the wooden one right? The aluminium one is cheaper.
Predicted Output:
Huh.
           e <PAD><PAD><PAD><PAD><PAD><PAD><PAD
<PAD><PAD><PAD><PAD><PAD><PAD>
Input text:
Yupz...Kk...Den i anyhow wear...Vv hot...Haha
```

Actual Output:

Yes. Ok. Then I anyhow wear. It's very hot. Haha.

```
Predicted Output:
 k.
      Yes..
  n
Input text:
So how are you spending yr weekend?
Actual Output:
So how are you spending your weekend?
Predicted Output:
<PAD><PAD><PAD><PAD><PAD><PAD><PAD>
Input text:
Hey....I know its rude of me not to do something abt e fone.N i'm sorry it died on u.
Actual Output:
Hey, I know it's rude of me not to do something about the phone. And I'm sorry it died on you.
Predicted Output:
Hev. II
         i
               i
                iidd
                 <PAD> <PAD><PAD><PAD>
        Ω
<PAD><PAD><PAD><PAD><PAD><PAD><PAD>
4
                     In [48]:
import nltk.translate.bleu score as bleu
bleu_score=[]
for i in range(20):
b=list(y test[i:i+1])
x=model.predict(source_padded_docs_test[i:i+1])
y=prediction(x[0])
y=y.split(' ')
y_lst=[]
for i in y:
 if '<' in i:</pre>
 continue
```

y lst.append(i)

bleu score.append(bleu.sentence bleu([b[0].split(),],y lst))

print("The Average Bleu Score is: ",sum(bleu score)/20)

```
/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)
/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)
 [0.1942053406068\overline{8}37,\ 0,\ 0.\ 29456425448249246,\ 0.4924790605054523,\ 0.4854917717073234,
0.2086130724305753,\ 0.4428500142691474,\ 0.3508439695638686,\ 0.5266403878479265,\ 0.35782241396102615,
0.31947155212313627,\ 0.5491004867761125,\ 0.25650569096216347,\ 0,\ 0.2928298013714698,
 \texttt{0.36889397323344053, 0, 0.6431870218238024, 0] } \\
The Average Bleu Score is: 0.289174940583241
```

In []: