Diving into the core of LLMs. Coding Attention from scratch.

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CODING ATTENTION FROM SCRATCH FOR LANGUAGE TRANSLATION

Rohan Thoma

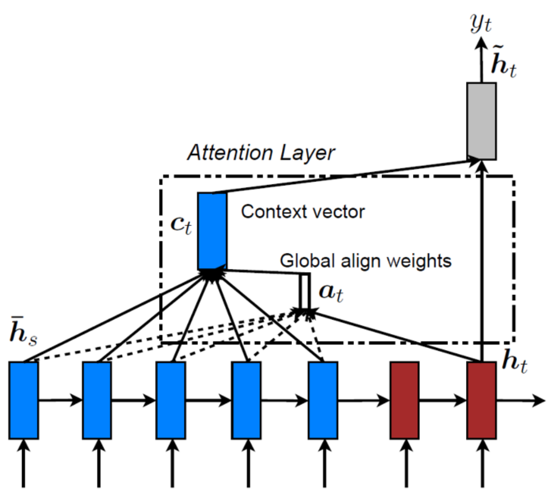


Figure 2: **Global attentional model** – at each time step t, the model infers a *variable-length* alignment weight vector $\boldsymbol{a}_t$ based on the current target state $\boldsymbol{h}_t$ and all source states $\bar{\boldsymbol{h}}_s$. A global context vector $\boldsymbol{c}_t$ is then computed as the weighted average, according to $\boldsymbol{a}_t$, over all the source states.

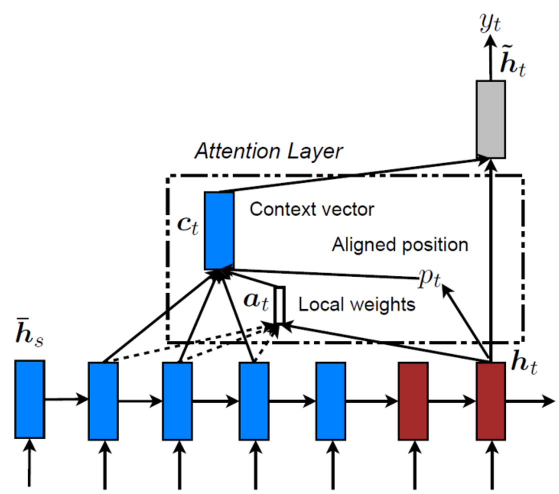


Figure 3: **Local attention model** – the model first predicts a single aligned position p_t for the current target word. A window centered around the source position p_t is then used to compute a context vector $\boldsymbol{c}_t$, a weighted average of the source hidden states in the window. The weights $\boldsymbol{a}_t$ are inferred from the current target state $\boldsymbol{h}_t$ and those source states $\bar{\boldsymbol{h}}_s$ in the window.

Reference papers

Paper 1: Effective approach to attention based neural machine translation: https://arxiv.org/pdf/1409.0473.pdf

Paper 2: Neural Machine Translation by jointly learning to align and translate: https://arxiv.org/pdf/1508.04025.pdf

Downloading required files

> lets download the data which have italian words along with its english translaton

In [ ]:

```
!wget http://www.manythings.org/anki/ita-eng.zip
!unzip ita-eng.zip
```

```
--2020-09-17 17:30:51--  http://www.manythings.org/anki/ita-eng.zip
Resolving www.manythings.org (www.manythings.org)... 172.67.173.198, 104.24.108.196, 10
4.24.109.196, ...
Connecting to www.manythings.org (www.manythings.org)|172.67.173.198|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 7468237 (7.1M) [application/zip]
Saving to: 'ita-eng.zip'

ita-eng.zip         100%[===================>]   7.12M  4.28MB/s    in 1.7s

2020-09-17 17:30:53 (4.28 MB/s) - 'ita-eng.zip' saved [7468237/7468237]

Archive:  ita-eng.zip
  inflating: ita.txt
  inflating: _about.txt
```

> lets download the glove vectors ("vectors for english words"), note that this file will have vectors with 50d, 100d and 300d, you can choose any one of them based on your computing power

Here we will be passing english text to the decoder, so we will be using these vectors in decoder embedding layer

In [ ]:
```
!wget https://www.dropbox.com/s/ddkmtqz01jc024u/glove.6B.100d.txt
```

```
--2020-08-29 17:23:15--  https://www.dropbox.com/s/ddkmtqz01jc024u/glove.6B.100d.txt
Resolving www.dropbox.com (www.dropbox.com)... 162.125.65.1, 2620:100:6021:1::a27d:4101
Connecting to www.dropbox.com (www.dropbox.com)|162.125.65.1|:443... connected.
HTTP request sent, awaiting response... 301 Moved Permanently
Location: /s/raw/ddkmtqz01jc024u/glove.6B.100d.txt [following]
--2020-08-29 17:23:15--  https://www.dropbox.com/s/raw/ddkmtqz01jc024u/glove.6B.100d.txt
Reusing existing connection to www.dropbox.com:443.
HTTP request sent, awaiting response... 302 Found
Location: https://uca40c7c23141e02ee0b88baa137.dl.dropboxusercontent.com/cd/0/inline/A-Z
h8w3W9V509FRBs2Q6z_vIl5GAHk325hebibhDv3NCe7pjEvoG-xT_xgCzmCOenx8fE2dMHRArTYUpSihBcBOjI51
uki4e2K5g35Epb2UQKxc7DmKiP140HbwpUBfvSBM/file# [following]
--2020-08-29 17:23:16--  https://uca40c7c23141e02ee0b88baa137.dl.dropboxusercontent.com/
cd/0/inline/A-Zh8w3W9V509FRBs2Q6z_vIl5GAHk325hebibhDv3NCe7pjEvoG-xT_xgCzmCOenx8fE2dMHRAr
TYUpSihBcBOjI51uki4e2K5g35Epb2UQKxc7DmKiP140HbwpUBfvSBM/file
Resolving uca40c7c23141e02ee0b88baa137.dl.dropboxusercontent.com (uca40c7c23141e02ee0b88
baa137.dl.dropboxusercontent.com)... 162.125.65.15, 2620:100:6021:15::a27d:410f
Connecting to uca40c7c23141e02ee0b88baa137.dl.dropboxusercontent.com (uca40c7c23141e02ee
0b88baa137.dl.dropboxusercontent.com)|162.125.65.15|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 347116733 (331M) [text/plain]
Saving to: 'glove.6B.100d.txt'

glove.6B.100d.txt   100%[===================>] 331.04M  22.1MB/s    in 15s

2020-08-29 17:23:32 (21.7 MB/s) - 'glove.6B.100d.txt' saved [347116733/347116733]
```

Loading data

> if you observe the data file, each feild was seperated by a tab '\t'

In [ ]:
```
import matplotlib.pyplot as plt
%matplotlib inline
# import seaborn as sns
import pandas as pd
```

```
import re
import tensorflow as tf
from tensorflow.keras.layers import Embedding, LSTM, Dense
from tensorflow.keras.models import Model
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
import numpy as np
```

In [ ]:
```
with open('ita.txt', 'r', encoding="utf8") as f:
    eng=[]
    ita=[]
    for i in f.readlines():
        eng.append(i.split("\t")[0])
        ita.append(i.split("\t")[1])
data = pd.DataFrame(data=list(zip(eng, ita)), columns=['english','italian'])
print(data.shape)
data.head()
```

```
(352894, 2)
```

	english	italian
0	Hi.	Ciao!
1	Hi.	Ciao.
2	Run!	Corri!
3	Run!	Corra!
4	Run!	Correte!

In [ ]:
```
data.drop_duplicates(inplace=True)
```

In [ ]:
```
data.shape
```

```
(352894, 2)
```

In [ ]:
```
with open('ita.txt', 'r', encoding="utf8") as f:
    eng=[]
    ita=[]
    for i in f.readlines():
        eng.append(i.split("\t")[0])
        ita.append(i.split("\t")[1])
data = pd.DataFrame(data=list(zip(eng, ita)), columns=['english','italian'])
print(data.shape)
data.head()
```

```
(341554, 2)
```

	english	italian
0	Hi.	Ciao!
1	Run!	Corri!
2	Run!	Corra!
3	Run!	Correte!
4	Who?	Chi?

In [ ]:
```
def decontractions(phrase):
    """decontracted takes text and convert contractions into natural form.
     ref: https://stackoverflow.com/questions/19790188/expanding-english-language-contra
    # specific
    phrase = re.sub(r"won\'t", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)
```

```
    phrase = re.sub(r"won\’t", "will not", phrase)
    phrase = re.sub(r"can\’t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)

    return phrase

def preprocess(text):
    # convert all the text into lower letters
    # use this function to remove the contractions: https://gist.github.com/anandborad/d
    # remove all the spacial characters: except space ' '
    text = text.lower()
    text = decontractions(text)
    text = re.sub('[^A-Za-z0-9 ]+', '', text)
    text = text.strip()
    return text

def preprocess_ita(text):
    # convert all the text into lower letters
    # remove the words betweent brakets ()
    # remove these characters: {'$', ')', '?', '"', '’', '.',  '°', '!', ';', '/', "'",
    # replace these spl characters with space: '\u200b', '\xa0', '-', '/'
    # we have found these characters after observing the data points, feel free to explo
    # you are free to do more proprocessing
    # note that the model will learn better with better preprocessed data

    text = text.lower()
    text = decontractions(text)
    text = re.sub('[$)\?"’.°!;\'€%:,(/]', '', text)
    text = re.sub('\u200b', ' ', text)
    text = re.sub('\xa0', ' ', text)
    text = re.sub('-', ' ', text)
    text = text.strip()
    return text


data['english'] = data['english'].apply(preprocess)
data['italian'] = data['italian'].apply(preprocess_ita)
data.head()
```

	english	italian
0	hi	ciao
1	hi	ciao
2	run	corri
3	run	corra
4	run	correte

In [ ]:
```
ita_lengths = data['italian'].str.split().apply(len)
eng_lengths = data['english'].str.split().apply(len)
```

In [ ]:
```
for i in range(0,101,10):
    print(i,np.percentile(ita_lengths, i))
for i in range(90,101):
```

```
    print(i,np.percentile(ita_lengths, i))
for i in [99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.8,99.9,100]:
    print(i,np.percentile(ita_lengths, i))
```

```
0 1.0
10 3.0
20 4.0
30 4.0
40 5.0
50 5.0
60 6.0
70 6.0
80 7.0
90 8.0
100 92.0
90 8.0
91 8.0
92 8.0
93 9.0
94 9.0
95 9.0
96 9.0
97 10.0
98 11.0
99 12.0
100 92.0
99.1 12.0
99.2 12.0
99.3 13.0
99.4 13.0
99.5 13.0
99.6 14.0
99.7 15.0
99.8 16.0
99.9 22.0
100 92.0
```

In [ ]:

```
for i in range(0,101,10):
    print(i,np.percentile(eng_lengths, i))
for i in range(90,101):
    print(i,np.percentile(eng_lengths, i))
for i in [99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.8,99.9,100]:
    print(i,np.percentile(eng_lengths, i))
```

```
0 1.0
10 4.0
20 4.0
30 5.0
40 5.0
50 6.0
60 6.0
70 7.0
80 7.0
90 8.0
100 101.0
90 8.0
91 9.0
92 9.0
93 9.0
94 9.0
95 9.0
96 10.0
97 10.0
98 11.0
99 12.0
100 101.0
```

```
99.1 12.0
99.2 13.0
99.3 13.0
99.4 13.0
99.5 14.0
99.6 14.0
99.7 15.0
99.8 16.0
99.9 25.0
100 101.0
```

> **If you observe the values, 99.9% of the data points are having length < 20, so select the sentences that have words < 20**
>
> **Inorder to do the teacher forcing while training of seq-seq models, lets create two new columns, one with <start> token at begining of the sentence and other column with <end> token at the end of the sequence**

In [ ]:

```python
data['italian_len'] = data['italian'].str.split().apply(len)
data = data[data['italian_len'] < 20]

data['english_len'] = data['english'].str.split().apply(len)
data = data[data['english_len'] < 20]

data['english_inp'] = '<start> ' + data['english'].astype(str)
data['english_out'] = data['english'].astype(str) + ' <end>'

data = data.drop(['english','italian_len','english_len'], axis=1)
# only for the first sentance add a toke <end> so that we will have <end> in tokenizer
data.head()
```

	italian	english_inp	english_out
0	ciao	<start> hi	hi <end>
1	ciao	<start> hi	hi <end>
2	corri	<start> run	run <end>
3	corra	<start> run	run <end>
4	correte	<start> run	run <end>

In [ ]:

```python
data.sample(10)
```

	italian	english_inp	english_out
30968	tom viveva da solo	<start> tom lived alone	tom lived alone <end>
180934	voi siete mai stati sposati	<start> have you ever been married	have you ever been married <end>
106525	io sono il nuovo partner di tom	<start> i am tom is new partner	i am tom is new partner <end>
295740	ho fatto diversi errori allesame	<start> i made several mistakes in the exam	i made several mistakes in the exam <end>
345465	noi avevamo degli aerei però abbiamo dovuto ve...	<start> we used to have airplanes but we had t...	we used to have airplanes but we had to sell t...
58454	non vada lì ora	<start> do not go there now	do not go there now <end>
20731	è eccellente	<start> it is excellent	it is excellent <end>
215006	ho un problema con la mia macchina	<start> i have a problem with my car	i have a problem with my car <end>

324452	la mia camera è tre volte più grande della sua	<start> my room is three times as large as yours	my room is three times as large as yours <end>
96085	tom vive allestero	<start> tom is living abroad	tom is living abroad <end>

Teacher Forcing

```
Let us consider the example data point

italian: erano occupate
english_inp: <start> they were busy
                |      |     |     |
english_out:  they   were busy <end>

if you observe the sentences, the start token is getting mapped to the
first word in your english sentence, the first word is mapped to 2nd
word, the 2nd word mapped to 3rd word and so on, finall the last one
will is mapped to end token. i.e i the word will be mapped to i+1th
word.

As we will be passing "english_inp" as an input to the decoder and the
outputs(predictions) of the decoder will be compared against the
"english_out"

with this way of mapping, we can ensure that the model will predict the
next word and calculate the loss accordingly.
```

Getting train and test

In [ ]:
```python
from sklearn.model_selection import train_test_split
train, validation = train_test_split(data, test_size=0.2)
print(train.shape, validation.shape)
```

```
(281922, 3) (70481, 3)
```

In [ ]:
```python
print(train.shape, validation.shape)
# for one sentence we will be adding <end> token so that the tokanizer learns the word <
# with this we can use only one tokenizer for both encoder output and decoder output
train.iloc[0]['english_inp']= str(train.iloc[0]['english_inp'])+' <end>'
train.iloc[0]['english_out']= str(train.iloc[0]['english_out'])+' <end>'
```

```
(281922, 3) (70481, 3)
```

In [ ]:
```python
train.head()
```

	italian	english_inp	english_out
1259	scusami	<start> excuse me <end>	excuse me <end> <end>
183812	ho incontrato tom solo tre volte	<start> i only met tom three times	i only met tom three times <end>
43560	dovè la sua chiave	<start> where is your key	where is your key <end>
168566	parlo inglese tutti i giorni	<start> i speak english every day	i speak english every day <end>
29067	mi fa male il collo	<start> my neck is sore	my neck is sore <end>

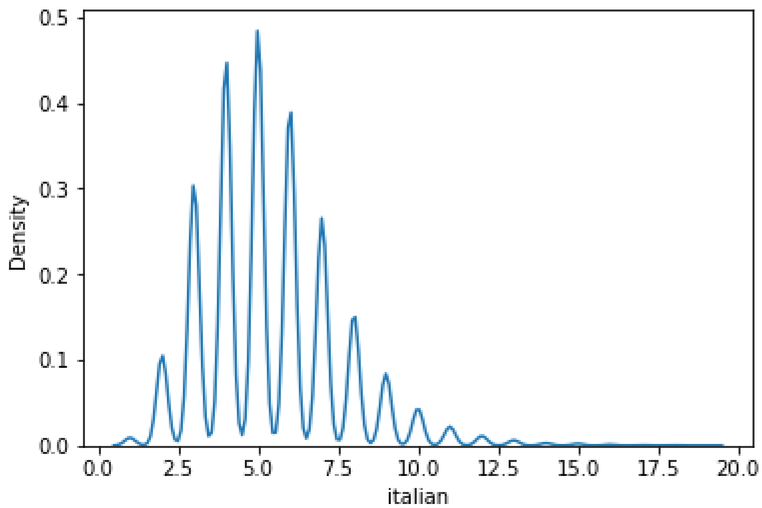
In [ ]:
```python
validation.head()
```

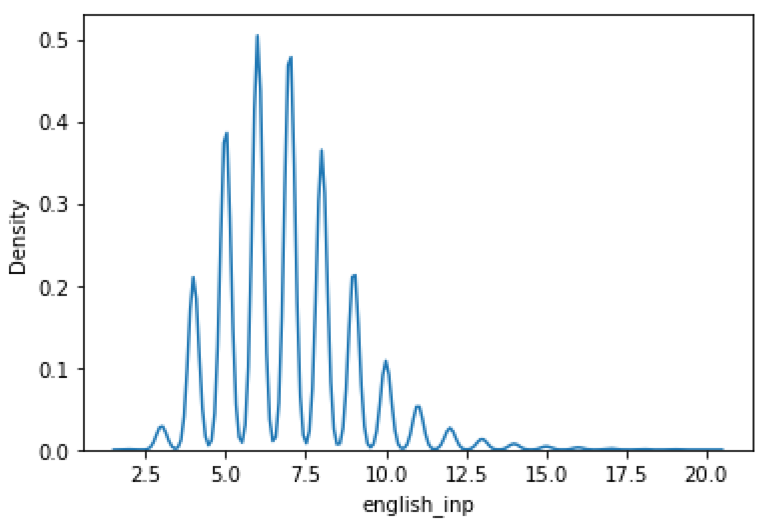
	italian	english_inp	english_out

28746	sono le otto passate	<start> it is past eight	it is past eight <end>
246954	lei sarà in ritardo per la riunione	<start> she will be late for the meeting	she will be late for the meeting <end>
175490	tom dovrebbe lasciarmelo fare	<start> tom should let me do that	tom should let me do that <end>
252681	lei aveva ragione e io avevo torto	<start> you were right and i was wrong	you were right and i was wrong <end>
126342	tom ha avuto un attacco di cuore	<start> tom had a heart attack	tom had a heart attack <end>

In [ ]:

```
ita_lengths = train['italian'].str.split().apply(len)
eng_lengths = train['english_inp'].str.split().apply(len)
import seaborn as sns
sns.kdeplot(ita_lengths)
plt.show()
sns.kdeplot(eng_lengths)
plt.show()
```





Creating Tokenizer on the train data and learning vocabulary

In [ ]:

```
tknizer_ita = Tokenizer(filters='',oov_token='<UNK>')
tknizer_ita.fit_on_texts(train['italian'].values)
tknizer_eng = Tokenizer(filters='',oov_token='<UNK>')
tknizer_eng.fit_on_texts(train['english_inp'].values)
```

In [ ]:

```
vocab_size_eng=len(tknizer_eng.word_index.keys())
print(vocab_size_eng)
vocab_size_ita=len(tknizer_ita.word_index.keys())
print(vocab_size_ita)
```

```
13046
26605
```

In [ ]:
```
tknizer_eng.word_index['<start>'], tknizer_eng.word_index['<end>']
```

```
(2, 10338)
```

Creating embeddings for english sentences

In [ ]:
```
embeddings_index = dict()
f = open('glove.6B.100d.txt',encoding='utf-8')
for line in f:
    values = line.split()
    word = values[0]
    coefs = np.asarray(values[1:], dtype='float32')
    embeddings_index[word] = coefs
f.close()

embedding_matrix = np.zeros((vocab_size_eng+1, 100))
for word, i in tknizer_eng.word_index.items():
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
```

Creating data pipeline

In [ ]:
```
class Dataset:
    def __init__(self, data, tknizer_ita, tknizer_eng, max_len):
        self.encoder_inps = data['italian'].values
        self.decoder_inps = data['english_inp'].values
        self.decoder_outs = data['english_out'].values
        self.tknizer_eng = tknizer_eng
        self.tknizer_ita = tknizer_ita
        self.max_len = max_len

    def __getitem__(self, i):
        self.encoder_seq = self.tknizer_ita.texts_to_sequences([self.encoder_inps[i]]) #
        self.decoder_inp_seq = self.tknizer_eng.texts_to_sequences([self.decoder_inps[i]
        self.decoder_out_seq = self.tknizer_eng.texts_to_sequences([self.decoder_outs[i]

        self.encoder_seq = pad_sequences(self.encoder_seq, maxlen=self.max_len, dtype='i
        self.decoder_inp_seq = pad_sequences(self.decoder_inp_seq, maxlen=self.max_len,
        self.decoder_out_seq = pad_sequences(self.decoder_out_seq, maxlen=self.max_len,
        return self.encoder_seq, self.decoder_inp_seq, self.decoder_out_seq

    def __len__(self): # your model.fit_gen requires this function
        return len(self.encoder_inps)


class Dataloder(tf.keras.utils.Sequence):
    def __init__(self, dataset, batch_size=1):
        self.dataset = dataset
        self.batch_size = batch_size
        self.indexes = np.arange(len(self.dataset.encoder_inps))


    def __getitem__(self, i):
        start = i * self.batch_size
        stop = (i + 1) * self.batch_size
        data = []
        for j in range(start, stop):
            data.append(self.dataset[j])
```

```
        batch = [np.squeeze(np.stack(samples, axis=1), axis=0) for samples in zip(*data)]
        # we are creating data like ([italian, english_inp], english_out) these are alre
        return tuple([[batch[0],batch[1]],batch[2]])

    def __len__(self):  #model.fit_gen requires this function
        return len(self.indexes) // self.batch_size

    def on_epoch_end(self):
        self.indexes = np.random.permutation(self.indexes)
```

In [ ]:

```
train_dataset = Dataset(train, tknizer_ita, tknizer_eng, 20)
test_dataset  = Dataset(validation, tknizer_ita, tknizer_eng, 20)

train_dataloader = Dataloder(train_dataset, batch_size=512)
test_dataloader = Dataloder(test_dataset, batch_size=512)

print(train_dataloader[0][0][0].shape, train_dataloader[0][0][1].shape, train_dataloader
```

```
(512, 20) (512, 20) (512, 20)
```

Task-1 Implementing a custom encoder decoder

Encoder

In [ ]:

```
class Encoder(tf.keras.Model):
  '''
    Encoder model -- That takes a input sequence and returns encoder-outputs,encoder_fin
  '''

  def __init__(self,inp_vocab_size,embedding_size,lstm_size,input_length):
    super().__init__()
    #Initialize Embedding layer
    #Intialize Encoder LSTM layer
    self.inp_vocab_size=inp_vocab_size
    self.embedding_size=embedding_size
    self.lstm_size=lstm_size
    self.input_length=input_length
    self.lstm_output = 0
    self.lstm_state_h = 0
    self.lstm_state_c = 0
    self.embedding = Embedding(input_dim=self.inp_vocab_size+1, output_dim=self.embeddin
                          mask_zero=True, name="embedding_layer_encoder")
    self.lstm = LSTM(self.lstm_size, return_state=True, return_sequences=True, name="Enc

  def call(self,input_sequence,states,training=True):
    '''
    This function takes a sequence input and the initial states of the encoder.
    Pass the input_sequence input to the Embedding layer, Pass the embedding layer ouput
    returns -- encoder_output, last time step's hidden and cell state
    '''
    input_embedd = self.embedding(input_sequence)
    self.lstm_output, self.lstm_state_h,self.lstm_state_c = self.lstm(input_embedd, init

    return self.lstm_output, self.lstm_state_h,self.lstm_state_c

  def initialize_states(self,batch_size):
      '''
      Given a batch size it will return intial hidden state and intial cell state.
      If batch size is 32- Hidden state is zeros of size [32,lstm_units], cell state zer
      '''
      self.lstm_state_h = tf.zeros(shape=(batch_size,self.lstm_size))
      self.lstm_state_c = tf.zeros(shape=(batch_size,self.lstm_size))
```

```
        return [self.lstm_state_h,self.lstm_state_c]
```

Decoder

In [ ]:
```
class Decoder(tf.keras.Model):
  '''
    Decoder model -- That takes a input sequence, encoder states and returns output sequ
  '''

  def __init__(self,out_vocab_size,embedding_size,lstm_size,input_length,emb_matrix=None
    super().__init__()
    #Initialize Embedding layer
    #Intialize Decoder LSTM layer
    self.out_vocab_size=out_vocab_size
    self.embedding_size= embedding_size
    self.lstm_size=lstm_size
    self.input_length=input_length

    if type(emb_matrix)==np.ndarray:
      self.emb_matrix= emb_matrix
      self.embedding=Embedding(input_dim=self.out_vocab_size+1, output_dim=self.embeddin
                           mask_zero=True, name="embedding_layer_decoder",weights=[self.
    else:
      self.embedding=Embedding(input_dim=self.out_vocab_size, output_dim=self.embedding_
                           mask_zero=True, name="embedding_layer_decoder")

    self.lstm= LSTM(self.lstm_size,return_sequences=True,return_state=True,name='Decoder

  def call(self,input_sequence,initial_states):
    '''
    This function takes a sequence input and the initial states of the encoder.
    Pass the input_sequence input to the Embedding layer, Pass the embedding layer ouput

    returns -- decoder_output,decoder_final_state_h,decoder_final_state_c
    '''

    input_embedd = self.embedding(input_sequence)
    self.lstm_output, self.lstm_state_h,self.lstm_state_c = self.lstm(input_embedd, init

    return self.lstm_output, self.lstm_state_h,self.lstm_state_c
```

Encoder-Decoder Combined

In [ ]:
```
class Encoder_decoder(tf.keras.Model):

    def __init__(self,enc_embedding_size,dec_embedding_size,encoder_input_length,\
                 decoder_input_length, output_vocab_size,batch_size,embed_matrix=None
        super().__init__()
        self.batch_size=batch_size
        #Create encoder object
        #Create decoder object
        #Intialize Dense layer(out_vocab_size) with activation='softmax'
        self.encoder=Encoder(inp_vocab_size=vocab_size_ita,embedding_size=enc_embedding_
        self.decoder=Decoder(out_vocab_size=vocab_size_eng,embedding_size=dec_embedding_
        self.dense=Dense(units=output_vocab_size,activation='softmax')

    def call(self,data):
        '''
        A. Pass the input sequence to Encoder layer -- Return encoder_output,encoder_fin
        B. Pass the target sequence to Decoder layer with intial states as encoder_final
        C. Pass the decoder_outputs into Dense layer
```

```
        Return decoder_outputs
        '''
        initial_states=self.encoder.initialize_states(self.batch_size)
        input_data=data[0]
        output_data=data[1]
        encoder_output, encoder_final_state_h, encoderfinal_state_c = self.encoder(input
        decoder_output, decoder_h, decoder_c  = self.decoder(output_data, [encoder_final
        output_dense=self.dense(decoder_output)

        return output_dense
```

Training the simple encoder decoder model

In [ ]:

```
#Create an object of encoder_decoder Model class,
# Compile the model and fit the model
from tensorflow.keras.callbacks import ModelCheckpoint,TensorBoard
import os
import datetime
optimizer = tf.keras.optimizers.Adam()

model_1=Encoder_decoder(enc_embedding_size=100,dec_embedding_size=100,encoder_input_leng
                        decoder_input_length=20,output_vocab_size=vocab_size_eng,batch_s

model_1.compile(loss='sparse_categorical_crossentropy',optimizer=optimizer)

train_steps=train.shape[0]//512
valid_steps=validation.shape[0]//512

log_dir = os.path.join("logs",'fits', datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
tensorboard_callback = TensorBoard(log_dir=log_dir,histogram_freq=1,write_graph=True)
checkpt = ModelCheckpoint(monitor="val_loss",mode="auto",filepath='model_1_weights.h5',v
callback_list = [tensorboard_callback,checkpt]

model_1.fit(train_dataloader, steps_per_epoch=train_steps, epochs=25, validation_data=tr
                validation_steps=valid_steps,callbacks=callback_list)

model_1.summary()
```

```
Epoch 1/25
550/550 [==============================] - ETA: 0s - loss: 1.8852
Epoch 00001: val_loss improved from inf to 1.64469, saving model to model_1_weights.h5
550/550 [==============================] - 39s 63ms/step - loss: 1.8852 - val_loss: 1.64
47
Epoch 2/25
550/550 [==============================] - ETA: 0s - loss: 1.5285
Epoch 00002: val_loss improved from 1.64469 to 1.37994, saving model to model_1_weights.
h5
550/550 [==============================] - 32s 58ms/step - loss: 1.5285 - val_loss: 1.37
99
Epoch 3/25
549/550 [============================>.] - ETA: 0s - loss: 1.2617
Epoch 00003: val_loss improved from 1.37994 to 1.14684, saving model to model_1_weights.
h5
550/550 [==============================] - 32s 57ms/step - loss: 1.2615 - val_loss: 1.14
68
Epoch 4/25
549/550 [============================>.] - ETA: 0s - loss: 1.0718
Epoch 00004: val_loss improved from 1.14684 to 0.98744, saving model to model_1_weights.
h5
550/550 [==============================] - 32s 57ms/step - loss: 1.0717 - val_loss: 0.98
74
Epoch 5/25
550/550 [==============================] - ETA: 0s - loss: 0.9346
Epoch 00005: val_loss improved from 0.98744 to 0.86874, saving model to model_1_weights.
```

```
h5
550/550 [==============================] - 33s 59ms/step - loss: 0.9346 - val_loss: 0.86
87
Epoch 6/25
549/550 [============================>.] - ETA: 0s - loss: 0.8291
Epoch 00006: val_loss improved from 0.86874 to 0.77252, saving model to model_1_weights.
h5
550/550 [==============================] - 33s 59ms/step - loss: 0.8290 - val_loss: 0.77
25
Epoch 7/25
549/550 [============================>.] - ETA: 0s - loss: 0.7437
Epoch 00007: val_loss improved from 0.77252 to 0.69456, saving model to model_1_weights.
h5
550/550 [==============================] - 33s 59ms/step - loss: 0.7437 - val_loss: 0.69
46
Epoch 8/25
549/550 [============================>.] - ETA: 0s - loss: 0.6726
Epoch 00008: val_loss improved from 0.69456 to 0.62876, saving model to model_1_weights.
h5
550/550 [==============================] - 32s 58ms/step - loss: 0.6725 - val_loss: 0.62
88
Epoch 9/25
549/550 [============================>.] - ETA: 0s - loss: 0.6117
Epoch 00009: val_loss improved from 0.62876 to 0.57115, saving model to model_1_weights.
h5
550/550 [==============================] - 32s 58ms/step - loss: 0.6116 - val_loss: 0.57
11
Epoch 10/25
550/550 [==============================] - ETA: 0s - loss: 0.5591
Epoch 00010: val_loss improved from 0.57115 to 0.52292, saving model to model_1_weights.
h5
550/550 [==============================] - 32s 57ms/step - loss: 0.5591 - val_loss: 0.52
29
Epoch 11/25
550/550 [==============================] - ETA: 0s - loss: 0.5135
Epoch 00011: val_loss improved from 0.52292 to 0.47980, saving model to model_1_weights.
h5
550/550 [==============================] - 32s 58ms/step - loss: 0.5135 - val_loss: 0.47
98
Epoch 12/25
550/550 [==============================] - ETA: 0s - loss: 0.4730
Epoch 00012: val_loss improved from 0.47980 to 0.44218, saving model to model_1_weights.
h5
550/550 [==============================] - 32s 58ms/step - loss: 0.4730 - val_loss: 0.44
22
Epoch 13/25
550/550 [==============================] - ETA: 0s - loss: 0.4373
Epoch 00013: val_loss improved from 0.44218 to 0.40870, saving model to model_1_weights.
h5
550/550 [==============================] - 33s 59ms/step - loss: 0.4373 - val_loss: 0.40
87
Epoch 14/25
549/550 [============================>.] - ETA: 0s - loss: 0.4056
Epoch 00014: val_loss improved from 0.40870 to 0.37907, saving model to model_1_weights.
h5
550/550 [==============================] - 31s 57ms/step - loss: 0.4056 - val_loss: 0.37
91
Epoch 15/25
550/550 [==============================] - ETA: 0s - loss: 0.3777
Epoch 00015: val_loss improved from 0.37907 to 0.35236, saving model to model_1_weights.
h5
550/550 [==============================] - 31s 57ms/step - loss: 0.3777 - val_loss: 0.35
24
Epoch 16/25
550/550 [==============================] - ETA: 0s - loss: 0.3532
Epoch 00016: val_loss improved from 0.35236 to 0.33012, saving model to model_1_weights.
```

```
h5
550/550 [==============================] - 31s 57ms/step - loss: 0.3532 - val_loss: 0.33
01
Epoch 17/25
549/550 [============================>.] - ETA: 0s - loss: 0.3318
Epoch 00017: val_loss improved from 0.33012 to 0.31113, saving model to model_1_weights.
h5
550/550 [==============================] - 31s 57ms/step - loss: 0.3317 - val_loss: 0.31
11
Epoch 18/25
550/550 [==============================] - ETA: 0s - loss: 0.3128
Epoch 00018: val_loss improved from 0.31113 to 0.29238, saving model to model_1_weights.
h5
550/550 [==============================] - 32s 57ms/step - loss: 0.3128 - val_loss: 0.29
24
Epoch 19/25
550/550 [==============================] - ETA: 0s - loss: 0.2957
Epoch 00019: val_loss improved from 0.29238 to 0.27702, saving model to model_1_weights.
h5
550/550 [==============================] - 32s 58ms/step - loss: 0.2957 - val_loss: 0.27
70
Epoch 20/25
550/550 [==============================] - ETA: 0s - loss: 0.2807
Epoch 00020: val_loss improved from 0.27702 to 0.26221, saving model to model_1_weights.
h5
550/550 [==============================] - 31s 57ms/step - loss: 0.2807 - val_loss: 0.26
22
Epoch 21/25
549/550 [============================>.] - ETA: 0s - loss: 0.2670
Epoch 00021: val_loss improved from 0.26221 to 0.25053, saving model to model_1_weights.
h5
550/550 [==============================] - 31s 57ms/step - loss: 0.2670 - val_loss: 0.25
05
Epoch 22/25
550/550 [==============================] - ETA: 0s - loss: 0.2547
Epoch 00022: val_loss improved from 0.25053 to 0.23751, saving model to model_1_weights.
h5
550/550 [==============================] - 31s 57ms/step - loss: 0.2547 - val_loss: 0.23
75
Epoch 23/25
549/550 [============================>.] - ETA: 0s - loss: 0.2434
Epoch 00023: val_loss improved from 0.23751 to 0.22730, saving model to model_1_weights.
h5
550/550 [==============================] - 32s 58ms/step - loss: 0.2434 - val_loss: 0.22
73
Epoch 24/25
550/550 [==============================] - ETA: 0s - loss: 0.2332
Epoch 00024: val_loss improved from 0.22730 to 0.21699, saving model to model_1_weights.
h5
550/550 [==============================] - 32s 58ms/step - loss: 0.2332 - val_loss: 0.21
70
Epoch 25/25
550/550 [==============================] - ETA: 0s - loss: 0.2239
Epoch 00025: val_loss improved from 0.21699 to 0.20905, saving model to model_1_weights.
h5
550/550 [==============================] - 32s 58ms/step - loss: 0.2239 - val_loss: 0.20
90
Model: "encoder_decoder_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 encoder_5 (Encoder)         multiple                  2705140

 decoder_5 (Decoder)         multiple                  1350340

 dense_3 (Dense)             multiple                  850265
```

```
=================================================================
Total params: 4,905,745
Trainable params: 4,905,745
Non-trainable params: 0
_________________________________________________________________
```

Testing the model with the help of BLEU scores

In [ ]:
```
def predict(input_sentence,model):

  '''
  A. Given input sentence, convert the sentence into integers using tokenizer used earli
  B. Pass the input_sequence to encoder. we get encoder_outputs, last time step hidden a
  C. Initialize index of <start> as input to decoder. and encoder final states as input_
  D. till we reach max_length of decoder or till the model predicted word <end>:
         predicted_out,state_h,state_c=model.layers[1](dec_input,states)
         pass the predicted_out to the dense layer
         update the states=[state_h,state_c]
         And get the index of the word with maximum probability of the dense layer outpu
         Update the input_to_decoder with current predictions
  F. Return the predicted sentence
  '''

  encoder_seq = tknizer_ita.texts_to_sequences([input_sentence])
  encoder_seq = pad_sequences([encoder_seq[0]], maxlen=20, dtype='int32', padding='post'
  encoder_seq = tf.convert_to_tensor(encoder_seq)
  initial_state = model.layers[0].initialize_states(1)
  enc_output, enc_state_h, enc_state_c = model.layers[0](encoder_seq, initial_state)

  decoder_input_states=[enc_state_h,enc_state_c]
  decoder_seq=tknizer_eng.word_index['<start>']
  decoder_seq=tf.expand_dims([decoder_seq], 0)

  pred_words_indices=[]

  for i in range(20):

         dec_output, dec_state_h, dec_state_c =model.layers[1](decoder_seq,decoder_input

         dense_output=model.layers[2](dec_output)
         decoder_input_states=[dec_state_h,dec_state_c]

         pred_index=np.argmax(dense_output)
         decoder_seq = np.reshape(pred_index, (1, 1))
         stop_index=tknizer_eng.word_index['<end>']

         if pred_index == stop_index:
                break
         if pred_index!=0:
              pred_words_indices.append(pred_index)

  return pred_words_indices
```

In [ ]:
```
# Predict on 1000 random sentences on test data and calculate the average BLEU score of
# https://www.nltk.org/_modules/nltk/translate/bleu_score.html

import nltk.translate.bleu_score as bleu
from tqdm import tqdm

import warnings
warnings.filterwarnings('ignore')

BLEU_scores=[]
```

```python
model_1.load_weights('model_1_weights.h5')

for i in tqdm(range(5)):
    index= np.random.randint(low=0,high=validation.shape[0])

    italian_sentence=validation['italian'].values[index]
    english_sentence=validation['english_out'].values[index]

    predicted_words_indices=predict(italian_sentence,model_1)
    predicted_sentence=''
    for index in predicted_words_indices:
        predicted_sentence+= tknizer_eng.index_word[index]+' '

    reference=english_sentence.split()[:-1]
    translation=predicted_sentence.split()

    BLEU_scores.append(bleu.sentence_bleu([reference],translation,weights=[1]))
    print("italian sentence --> ",italian_sentence)
    print("true english translation --> ",english_sentence)
    print("predicted english translation --> ",predicted_sentence)
    print(BLEU_scores[i])
    print('#'*20)

print('Average_BLEU_score for 5 random sentences is :',np.mean(BLEU_scores))
```

```
 40%|████      | 2/5 [00:00<00:00, 15.04it/s]
italian sentence -->  vedi qualcosa di interessante
true english translation -->  do you see something interesting <end>
predicted english translation -->  do you see what you deserve a lot
0.375
####################
italian sentence -->  io so molto sugli animali
true english translation -->  i know a lot about animals <end>
predicted english translation -->  i know about a lot of animals
0.8571428571428571
####################
italian sentence -->  spero che tom non lo farà
true english translation -->  i hope tom will not do that <end>
predicted english translation -->  i hope tom will not do that
1.0
####################
italian sentence -->  odio quel rumore
true english translation -->  i hate that noise <end>
predicted english translation -->  i hate it matter
0.5
####################
italian sentence -->  tom disse che sembravi un robot
true english translation -->  tom said you sounded like a robot <end>
predicted english translation -->  tom said you appeared very much
0.423240862445307
####################
100%|██████████| 5/5 [00:00<00:00, 18.25it/s]
Average_BLEU_score for 5 random sentences is : 0.6310767439176328
```

In [ ]:

```python
# Predict on 1000 random sentences on test data and calculate the average BLEU score of
# https://www.nltk.org/_modules/nltk/translate/bleu_score.html

import nltk.translate.bleu_score as bleu
from tqdm import tqdm

import warnings
warnings.filterwarnings('ignore')
```

```
BLEU_scores=[]

#model_1.load_weights('model_1_weights.h5')

for i in tqdm(range(1000)):
    index= np.random.randint(low=0,high=validation.shape[0])

    italian_sentence=validation['italian'].values[index]
    english_sentence=validation['english_out'].values[index]

    predicted_words_indices=predict(italian_sentence,model_1)
    predicted_sentence=''
    for index in predicted_words_indices:
        predicted_sentence+= tknizer_eng.index_word[index]+' '

    reference=english_sentence.split()[:-1]
    translation=predicted_sentence.split()

    BLEU_scores.append(bleu.sentence_bleu([reference],translation,weights=[1]))

print('Average_BLEU_score for 1000 random sentences is :',np.mean(BLEU_scores))
```

```
100%|██████████| 1000/1000 [00:49<00:00, 20.01it/s]
Average_BLEU_score for 1000 random sentences is : 0.711568344352006
```

Task -2: Including Attention mechanism

1. Here we use the preprocessed data from Task-1
2. We implement an Encoder and Decoder architecture with attention.
    - Encoder - with 1 layer LSTM
    - Decoder - with 1 layer LSTM
    - Attention
3. In Global attention, we have 3 types of scoring functions(as discussed in the reference research paper). **Here we create 3 models for each scoring function**

    Here, score is referred as a *content-based* function for which we consider three different alternatives:

$$\text{score}(\boldsymbol{h}_t, \bar{\boldsymbol{h}}_s) = \begin{cases} \boldsymbol{h}_t^\top \bar{\boldsymbol{h}}_s & \textit{dot} \\ \boldsymbol{h}_t^\top \boldsymbol{W_a} \bar{\boldsymbol{h}}_s & \textit{general} \\ \boldsymbol{v}_a^\top \tanh\left(\boldsymbol{W_a}[\boldsymbol{h}_t; \bar{\boldsymbol{h}}_s]\right) & \textit{concat} \end{cases}$$

    - In model 1 you need to implemnt "dot" score function
    - In model 2 you need to implemnt "general" score function
    - In model 3 you need to implemnt "concat" score function.
4. Resources: a. Resource 1 b. Resource 2 c. Resource 3

Implement custom encoder decoder and attention layers

Encoder

In [ ]:
```
class Encoder(tf.keras.Model):
    '''
    Encoder model -- That takes a input sequence and returns output sequence
    '''

    def __init__(self,inp_vocab_size,embedding_size,lstm_size,input_length):
      super().__init__()
      #Initialize Embedding layer
      #Intialize Encoder LSTM layer
      self.inp_vocab_size=inp_vocab_size
      self.embedding_size=embedding_size
      self.lstm_size=lstm_size
      self.input_length=input_length
      self.lstm_output = 0
      self.lstm_state_h = 0
      self.lstm_state_c = 0
      self.embedding = Embedding(input_dim=self.inp_vocab_size+1, output_dim=self.embedd
                                 name="embedding_layer_encoder")
      self.lstm = LSTM(self.lstm_size, return_state=True, return_sequences=True, name="E

    def call(self,input_sequence,states):
      '''
        This function takes a sequence input and the initial states of the encoder.
        Pass the input_sequence input to the Embedding layer, Pass the embedding layer o
        returns -- All encoder_outputs, last time steps hidden and cell state
      '''
      input_embedd = self.embedding(input_sequence)
      self.lstm_output, self.lstm_state_h,self.lstm_state_c = self.lstm(input_embedd, in

      return self.lstm_output, self.lstm_state_h,self.lstm_state_c


    def initialize_states(self,batch_size):
      '''
      Given a batch size it will return intial hidden state and intial cell state.
      If batch size is 32- Hidden state is zeros of size [32,lstm_units], cell state zer
      '''
      self.lstm_state_h = tf.zeros(shape=(batch_size,self.lstm_size))
      self.lstm_state_c = tf.zeros(shape=(batch_size,self.lstm_size))

      return [self.lstm_state_h,self.lstm_state_c]
```

Attention using Bahdanu attention mechanism

In [ ]:
```
class Attention(tf.keras.layers.Layer):
  '''
    Class the calculates score based on the scoring_function using Bahdanu attention mec
  '''
  def __init__(self,scoring_function, att_units):
    super().__init__()
    self.scoring_function=scoring_function
    self.att_units=att_units


  #Here the shape of the weights depends on the last dimension of the input given , so w
  #so we need to initialize them in the build method.
  def build(self,input_shape):
    if self.scoring_function=='dot':
      # Intialize variables needed for Dot score function here
      pass
    if self.scoring_function == 'general':
```

```
        # Intialize variables needed for General score function here
        self.W = self.add_weight(shape=(input_shape[-1], self.att_units), initializer='glo
        pass
      elif self.scoring_function == 'concat':
        # Intialize variables needed for Concat score function here
        self.W1 = self.add_weight(shape=(input_shape[-1], self.att_units), initializer='gl
        self.W2 = self.add_weight(shape=(input_shape[-1], self.att_units), initializer='gl
        self.V = self.add_weight(shape=(input_shape[-1], 1), initializer='glorot_uniform',
        pass

    def call(self,decoder_hidden_state,encoder_output):
      '''
      Attention mechanism takes two inputs current step -- decoder_hidden_state and all th
      * Based on the scoring function we will find the score or similarity between decoder
        Multiply the score function with your encoder_outputs to get the context vector.
        Function returns context vector and attention weights(softmax - scores)
      '''
      decoder_hidden_state = tf.expand_dims(decoder_hidden_state, axis = 1)

      if self.scoring_function == 'dot':
        # Implement Dot score function here
        sim_scores = tf.matmul(encoder_output, decoder_hidden_state, transpose_b = True)
        pass
      elif self.scoring_function == 'general':
        # Implement General score function here
        temp = tf.matmul(encoder_output, self.W, transpose_b = True)
        sim_scores = tf.matmul(temp, decoder_hidden_state, transpose_b = True)
        pass
      elif self.scoring_function == 'concat':
        # Implement General score function here
        temp1 = tf.matmul(decoder_hidden_state, self.W1, transpose_b = True)
        temp2 = tf.matmul(encoder_output, self.W2, transpose_b = True)
        temp = tf.nn.tanh(temp1+temp2)
        sim_scores = tf.matmul(temp, self.V)
        pass

      #pass the scores through the softmax to get the attention weights between 0 and 1
      attention_weights = tf.nn.softmax(sim_scores, axis = 1)

      #compute the weighted average of the encoder outputs
      context_vector = tf.reduce_sum((attention_weights * encoder_output), axis=1)

      return context_vector, attention_weights
```

One-step decoder

In [ ]:

```
class One_Step_Decoder(tf.keras.Model):
    def __init__(self,tar_vocab_size, embedding_dim, input_length,dec_units ,score_fun ,at
      super().__init__()
      # Initialize decoder embedding layer, LSTM and any other objects needed
      if type(emb_matrix)==np.ndarray:
        self.embedding = Embedding(input_dim = tar_vocab_size + 1, output_dim = embedding_
                                   input_length = input_length, weights=[emb_matrix], trainable
      else:
        self.embedding = Embedding(input_dim = tar_vocab_size + 1, output_dim = embedding_
                                   input_length = input_length)

      self.attention = Attention(score_fun, att_units)
      self.lstm = LSTM(units = dec_units, return_sequences = True,return_state = True)
      self.dense = Dense(units = tar_vocab_size, activation = 'softmax')
```

```
    def call(self,input_to_decoder, encoder_output, state_h,state_c):
      '''
        One step decoder mechanisim step by step:
      A. Pass the input_to_decoder to the embedding layer and then get the output(batch_
      B. Using the encoder_output and decoder hidden state, compute the context vector.
      C. Concat the context vector with the step A output
      D. Pass the Step-C output to LSTM/GRU and get the decoder output and states(hidden
      E. Pass the decoder output to dense layer(vocab size) and store the result into ou
      F. Return the states from step D, output from Step E, attention weights from Step
      '''
      embeddings = self.embedding(input_to_decoder)

      context_vector, attention_weights = self.attention(state_h, encoder_output)

      context_mod = tf.expand_dims(context_vector, axis = 1)
      final_vector = tf.concat([embeddings, context_mod], axis=-1)

      decoder_output, decoder_state_h, decoder_state_c = self.lstm(final_vector)

      decoder_output = tf.squeeze(decoder_output, axis = 1)

      dense_output = self.dense(decoder_output)

      return dense_output, decoder_state_h, decoder_state_c, attention_weights, context_ve
```

Decoder

In [ ]:
```
class Decoder(tf.keras.Model):
    def __init__(self,out_vocab_size, embedding_dim, input_length, dec_units ,score_fun ,a
      super().__init__()
      #Intialize necessary variables and create an object from the class onestepdecoder
      if type(emb_matrix)==np.ndarray:
        self.onestepdecoder = One_Step_Decoder(out_vocab_size, embedding_dim, input_length
      else:
        self.onestepdecoder = One_Step_Decoder(out_vocab_size, embedding_dim, input_length
      self.input_length = input_length

    def call(self, input_to_decoder,encoder_output,decoder_hidden_state,decoder_cell_state

      #Initialize an empty Tensor array, that will store the outputs at each and every tim
      #Create a tensor array as shown in the reference notebook

      #Iterate till the length of the decoder input
          # Call onestepdecoder for each token in decoder_input
          # Store the output in tensorarray
      # Return the tensor array

      Output = tf.TensorArray(tf.float32, size = self.input_length)

      for step in range(self.input_length):
        output, decoder_hidden_state, decoder_cell_state, att_weights, context_vec = self.
                                                              decoder_hidden_state, decoder_ce
        Output = Output.write(step, output)

      Output = tf.transpose(Output.stack(), perm=[1, 0, 2])
      return Output
```

Encoder-decoder model

In [ ]:
```
class encoder_decoder(tf.keras.Model):
```

```
  def __init__(self,ip_vocab_size,ip_embed_size,lstm_units,att_units,input_len,op_vocab_
    #Intialize objects from encoder decoder
    super().__init__()
    self.batch_size = batch_size
    self.encoder = Encoder(ip_vocab_size, ip_embed_size, lstm_units, input_len)
    if type(emb_matrix)==np.ndarray:
      self.decoder = Decoder(op_vocab_size, op_embed_size, output_len, lstm_units ,score
    else:
      self.decoder = Decoder(op_vocab_size, op_embed_size, output_len, lstm_units ,score

  def call(self,data):
    #Intialize encoder states, Pass the encoder_sequence to the embedding layer
    # Decoder initial states are encoder final states, Initialize it accordingly
    # Pass the decoder sequence,encoder_output,decoder states to Decoder
    # return the decoder output

    initial_states=self.encoder.initialize_states(self.batch_size)
    input_data=data[0]
    output_data=data[1]
    encoder_output, encoder_final_state_h, encoder_final_state_c = self.encoder(input_da

    decoder_output = self.decoder(output_data, encoder_output, encoder_final_state_h, en

    return decoder_output
```

Custom loss function

In [ ]:

```
#https://www.tensorflow.org/tutorials/text/image_captioning#model
loss_object = tf.keras.losses.SparseCategoricalCrossentropy(reduction='none')

def loss_function(real, pred):
    """
    Custom loss function that will not consider the loss for padded zeros.
    why are we using this, can't we use simple sparse categorical crossentropy?
    Yes, you can use simple sparse categorical crossentropy as loss like we did in task-
    for the padded zeros. i.e when the input is zero then we do not need to worry what t
    during preprocessing to make equal length for all the sentences.
    """
    mask = tf.math.logical_not(tf.math.equal(real, 0))
    loss_ = loss_object(real, pred)

    mask = tf.cast(mask, dtype=loss_.dtype)
    loss_ *= mask

    return tf.reduce_mean(loss_)
```

Training the model

Model 2.1 Implementation with dot scoring function.

In [ ]:

```
# Implement teacher forcing while training your model. You can do it two ways.
# Prepare your data, encoder_input,decoder_input and decoder_output
# if decoder input is
# <start> Hi how are you
# decoder output should be
# Hi How are you <end>
# i.e when you have send <start>-- decoder predicted Hi, 'Hi' decoder predicted 'How' ..

# or

# model.fit([train_ita,train_eng],train_eng[:,1:]..)
```

```
from tensorflow.keras.callbacks import ModelCheckpoint,TensorBoard,EarlyStopping
import os
import datetime
optimizer = tf.keras.optimizers.Adam()

model_2=encoder_decoder(ip_vocab_size=vocab_size_ita,ip_embed_size=100,op_embed_size=100
                        att_units=64,output_len=20,op_vocab_size=vocab_size_eng,batch_si

model_2.compile(loss=[loss_function],optimizer=optimizer)

train_steps=train.shape[0]//512
valid_steps=validation.shape[0]//512

log_dir = os.path.join("logs",'fits', datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
tensorboard_callback = TensorBoard(log_dir=log_dir,histogram_freq=1,write_graph=True)
earlystop = EarlyStopping(monitor="val_loss",mode="auto",patience=7,verbose=1)
checkpt = ModelCheckpoint(monitor="val_loss",mode="auto",filepath='model_2_weights.h5',v
callback_list = [tensorboard_callback,checkpt,earlystop]

model_2.fit(train_dataloader, steps_per_epoch=train_steps, epochs=25, validation_data=tr
                validation_steps=valid_steps,callbacks=callback_list)

model_2.summary()
```

```
Epoch 1/25
550/550 [==============================] - ETA: 0s - loss: 1.9485
Epoch 00001: val_loss improved from inf to 1.81599, saving model to model_2_weights.h5
550/550 [==============================] - 144s 219ms/step - loss: 1.9485 - val_loss: 1.
8160
Epoch 2/25
550/550 [==============================] - ETA: 0s - loss: 1.7586
Epoch 00002: val_loss improved from 1.81599 to 1.64940, saving model to model_2_weights.
h5
550/550 [==============================] - 114s 208ms/step - loss: 1.7586 - val_loss: 1.
6494
Epoch 3/25
550/550 [==============================] - ETA: 0s - loss: 1.5284
Epoch 00003: val_loss improved from 1.64940 to 1.41194, saving model to model_2_weights.
h5
550/550 [==============================] - 111s 202ms/step - loss: 1.5284 - val_loss: 1.
4119
Epoch 4/25
550/550 [==============================] - ETA: 0s - loss: 1.3235
Epoch 00004: val_loss improved from 1.41194 to 1.23524, saving model to model_2_weights.
h5
550/550 [==============================] - 112s 204ms/step - loss: 1.3235 - val_loss: 1.
2352
Epoch 5/25
550/550 [==============================] - ETA: 0s - loss: 1.1765
Epoch 00005: val_loss improved from 1.23524 to 1.10988, saving model to model_2_weights.
h5
550/550 [==============================] - 101s 183ms/step - loss: 1.1765 - val_loss: 1.
1099
Epoch 6/25
550/550 [==============================] - ETA: 0s - loss: 1.0677
Epoch 00006: val_loss improved from 1.10988 to 1.01291, saving model to model_2_weights.
h5
550/550 [==============================] - 96s 175ms/step - loss: 1.0677 - val_loss: 1.0
129
Epoch 7/25
550/550 [==============================] - ETA: 0s - loss: 0.9800
Epoch 00007: val_loss improved from 1.01291 to 0.93231, saving model to model_2_weights.
h5
550/550 [==============================] - 97s 176ms/step - loss: 0.9800 - val_loss: 0.9
323
Epoch 8/25
```

```
550/550 [==============================] - ETA: 0s - loss: 0.9056
Epoch 00008: val_loss improved from 0.93231 to 0.86284, saving model to model_2_weights.
h5
550/550 [==============================] - 96s 174ms/step - loss: 0.9056 - val_loss: 0.8
628
Epoch 9/25
550/550 [==============================] - ETA: 0s - loss: 0.8392
Epoch 00009: val_loss improved from 0.86284 to 0.79833, saving model to model_2_weights.
h5
550/550 [==============================] - 93s 169ms/step - loss: 0.8392 - val_loss: 0.7
983
Epoch 10/25
550/550 [==============================] - ETA: 0s - loss: 0.7779
Epoch 00010: val_loss improved from 0.79833 to 0.73740, saving model to model_2_weights.
h5
550/550 [==============================] - 92s 168ms/step - loss: 0.7779 - val_loss: 0.7
374
Epoch 11/25
550/550 [==============================] - ETA: 0s - loss: 0.7201
Epoch 00011: val_loss improved from 0.73740 to 0.68010, saving model to model_2_weights.
h5
550/550 [==============================] - 92s 168ms/step - loss: 0.7201 - val_loss: 0.6
801
Epoch 12/25
550/550 [==============================] - ETA: 0s - loss: 0.6653
Epoch 00012: val_loss improved from 0.68010 to 0.62631, saving model to model_2_weights.
h5
550/550 [==============================] - 93s 169ms/step - loss: 0.6653 - val_loss: 0.6
263
Epoch 13/25
550/550 [==============================] - ETA: 0s - loss: 0.6139
Epoch 00013: val_loss improved from 0.62631 to 0.57797, saving model to model_2_weights.
h5
550/550 [==============================] - 93s 168ms/step - loss: 0.6139 - val_loss: 0.5
780
Epoch 14/25
550/550 [==============================] - ETA: 0s - loss: 0.5668
Epoch 00014: val_loss improved from 0.57797 to 0.53389, saving model to model_2_weights.
h5
550/550 [==============================] - 93s 169ms/step - loss: 0.5668 - val_loss: 0.5
339
Epoch 15/25
550/550 [==============================] - ETA: 0s - loss: 0.5249
Epoch 00015: val_loss improved from 0.53389 to 0.49277, saving model to model_2_weights.
h5
550/550 [==============================] - 95s 173ms/step - loss: 0.5249 - val_loss: 0.4
928
Epoch 16/25
550/550 [==============================] - ETA: 0s - loss: 0.4870
Epoch 00016: val_loss improved from 0.49277 to 0.46355, saving model to model_2_weights.
h5
550/550 [==============================] - 96s 175ms/step - loss: 0.4870 - val_loss: 0.4
636
Epoch 17/25
550/550 [==============================] - ETA: 0s - loss: 0.4544
Epoch 00017: val_loss improved from 0.46355 to 0.42797, saving model to model_2_weights.
h5
550/550 [==============================] - 96s 175ms/step - loss: 0.4544 - val_loss: 0.4
280
Epoch 18/25
550/550 [==============================] - ETA: 0s - loss: 0.4251
Epoch 00018: val_loss improved from 0.42797 to 0.39894, saving model to model_2_weights.
h5
550/550 [==============================] - 96s 175ms/step - loss: 0.4251 - val_loss: 0.3
989
Epoch 19/25
```

```
550/550 [==============================] - ETA: 0s - loss: 0.3994
Epoch 00019: val_loss improved from 0.39894 to 0.37812, saving model to model_2_weights.
h5
550/550 [==============================] - 96s 175ms/step - loss: 0.3994 - val_loss: 0.3
781
Epoch 20/25
550/550 [==============================] - ETA: 0s - loss: 0.3764
Epoch 00020: val_loss improved from 0.37812 to 0.35449, saving model to model_2_weights.
h5
550/550 [==============================] - 96s 175ms/step - loss: 0.3764 - val_loss: 0.3
545
Epoch 21/25
550/550 [==============================] - ETA: 0s - loss: 0.3555
Epoch 00021: val_loss improved from 0.35449 to 0.33437, saving model to model_2_weights.
h5
550/550 [==============================] - 96s 174ms/step - loss: 0.3555 - val_loss: 0.3
344
Epoch 22/25
550/550 [==============================] - ETA: 0s - loss: 0.3374
Epoch 00022: val_loss improved from 0.33437 to 0.31789, saving model to model_2_weights.
h5
550/550 [==============================] - 94s 170ms/step - loss: 0.3374 - val_loss: 0.3
179
Epoch 23/25
550/550 [==============================] - ETA: 0s - loss: 0.3211
Epoch 00023: val_loss improved from 0.31789 to 0.30198, saving model to model_2_weights.
h5
550/550 [==============================] - 93s 170ms/step - loss: 0.3211 - val_loss: 0.3
020
Epoch 24/25
550/550 [==============================] - ETA: 0s - loss: 0.3068
Epoch 00024: val_loss improved from 0.30198 to 0.29136, saving model to model_2_weights.
h5
550/550 [==============================] - 94s 170ms/step - loss: 0.3068 - val_loss: 0.2
914
Epoch 25/25
550/550 [==============================] - ETA: 0s - loss: 0.2941
Epoch 00025: val_loss improved from 0.29136 to 0.28001, saving model to model_2_weights.
h5
550/550 [==============================] - 94s 171ms/step - loss: 0.2941 - val_loss: 0.2
800
Model: "encoder_decoder_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 encoder_7 (Encoder)         multiple                  2702840

 decoder_17 (Decoder)        multiple                  2211314

=================================================================
Total params: 4,914,154
Trainable params: 3,609,454
Non-trainable params: 1,304,700
_________________________________________________________________
```

Testing

Plot attention weights

In [ ]:

```
import matplotlib.ticker as ticker

def plot_attention(attention, sentence, predicted_sentence):
  #Refer: https://www.tensorflow.org/tutorials/text/nmt_with_attention#translate
  sentence = sentence.split()
```

```python
    predicted_sentence = predicted_sentence.split()
    fig = plt.figure(figsize=(10, 10))
    ax = fig.add_subplot(1, 1, 1)

    attention = attention[:len(predicted_sentence), :len(sentence)]

    ax.matshow(attention, cmap='viridis', vmin=0.0)

    fontdict = {'fontsize': 14}

    ax.set_xticklabels([''] + sentence, fontdict=fontdict, rotation=90)
    ax.set_yticklabels([''] + predicted_sentence, fontdict=fontdict)

    ax.xaxis.set_major_locator(ticker.MultipleLocator(1))
    ax.yaxis.set_major_locator(ticker.MultipleLocator(1))

    ax.set_xlabel('Input text')
    ax.set_ylabel('Output text')
    plt.suptitle('Attention weights')
```

Predict the sentence translation

In [ ]:

```python
def predict(input_sentence,model):

    '''
    A. Given input sentence, convert the sentence into integers using tokenizer used earli
    B. Pass the input_sequence to encoder. we get encoder_outputs, last time step hidden a
    C. Initialize index of <start> as input to decoder. and encoder final states as input_
    D. till we reach max_length of decoder or till the model predicted word <end>:
           predictions, input_states, attention_weights = model.layers[1].onestepdecoder(i
           Save the attention weights
           And get the word using the tokenizer(word index) and then store it in a string.
    E. Call plot_attention(#params)
    F. Return the predicted sentence
    '''
    encoder_seq = tknizer_ita.texts_to_sequences([input_sentence])
    encoder_seq = pad_sequences([encoder_seq[0]], maxlen=20, dtype='int32', padding='post'
    encoder_seq = tf.convert_to_tensor(encoder_seq)
    initial_state = model.layers[0].initialize_states(1)
    enc_output, enc_state_h, enc_state_c = model.layers[0](encoder_seq, initial_state)

    dec_state_h = enc_state_h
    dec_state_c = enc_state_c
    decoder_seq=tknizer_eng.word_index['<start>']
    decoder_seq=tf.expand_dims([decoder_seq], 0)

    pred_words_indices=[]
    attention_matrix=[]

    for i in range(20):

           dec_output, dec_state_h, dec_state_c, attention_weights, context_vector =model.

           pred_index=np.argmax(dec_output)
           decoder_seq = np.reshape(pred_index, (1, 1))
           stop_index=tknizer_eng.word_index['<end>']

           attention_weights = tf.reshape(attention_weights, (-1, ))
           attention_matrix.append(attention_weights)

           if pred_index == stop_index:
                  break
           if pred_index!=0:
                pred_words_indices.append(pred_index)
```

```
    predicted_sentence=''
    for index in pred_words_indices:
        predicted_sentence+= tknizer_eng.index_word[index]+' '

    return pred_words_indices,np.array(attention_matrix),predicted_sentence
```

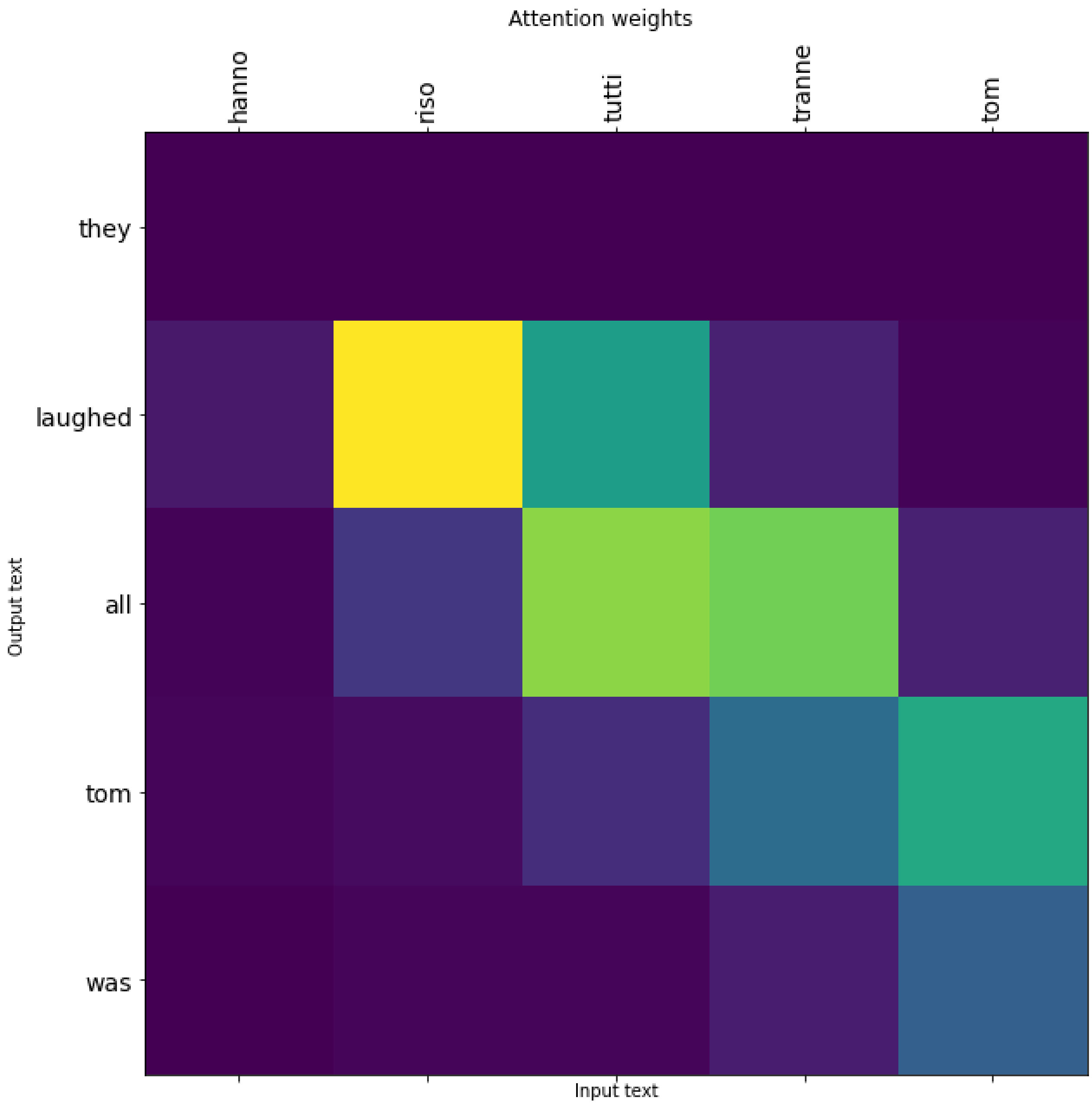
Calculate BLEU score

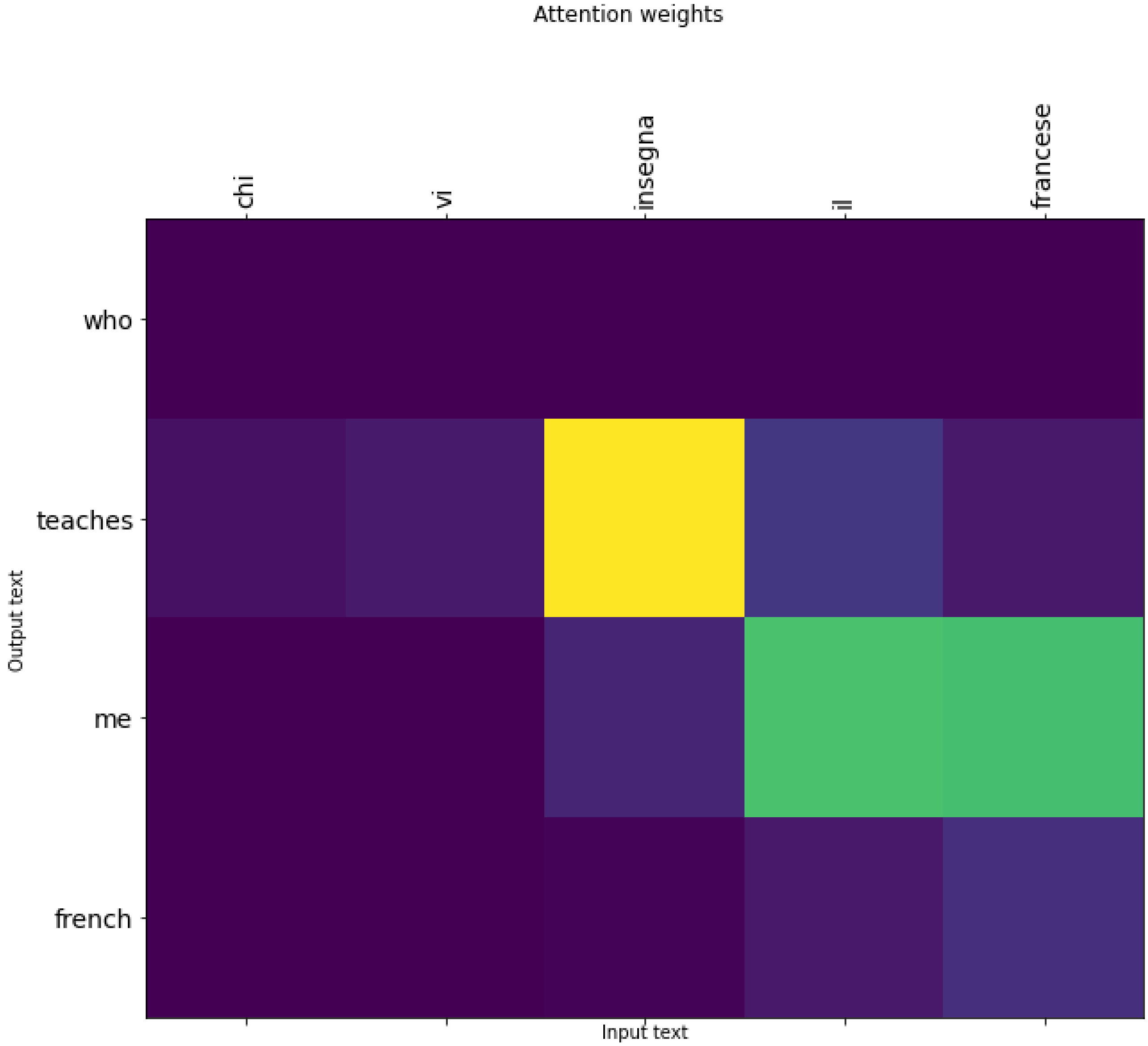
In [ ]:

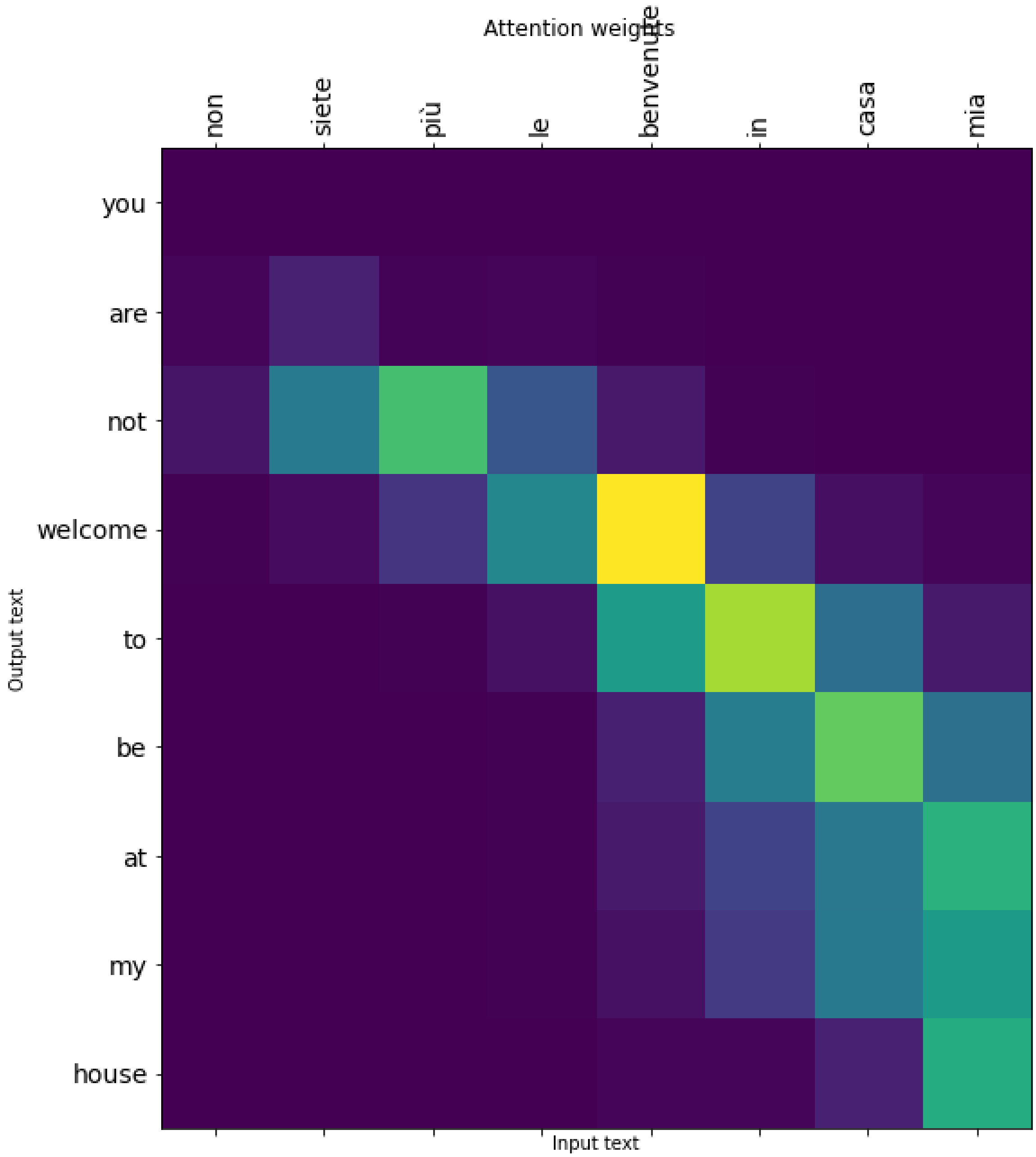
```
# Create an object of your custom model.
# Compile and train your model on dot scoring function.
# Visualize few sentences randomly in Test data
# Predict on 1000 random sentences on test data and calculate the average BLEU score of
# https://www.nltk.org/_modules/nltk/translate/bleu_score.html

import nltk.translate.bleu_score as bleu
from tqdm import tqdm

import warnings
warnings.filterwarnings('ignore')

BLEU_scores=[]

#model_2.load_weights('model_1_weights.h5')

for i in tqdm(range(5)):
    index= np.random.randint(low=0,high=validation.shape[0])

    italian_sentence=validation['italian'].values[index]
    english_sentence=validation['english_out'].values[index]

    predicted_words_indices,att_weights,predicted_sentence=predict(italian_sentence,mode

    reference=english_sentence.split()[:-1]
    translation=predicted_sentence.split()

    BLEU_scores.append(bleu.sentence_bleu([reference],translation,weights=[1]))
    print("italian sentence --> ",italian_sentence)
    print("true english translation --> ",english_sentence)
    print("predicted english translation --> ",predicted_sentence)
    print("BLEU Score is : ",BLEU_scores[i])

    plot_attention(att_weights,italian_sentence,predicted_sentence)
    print('#'*20)
```

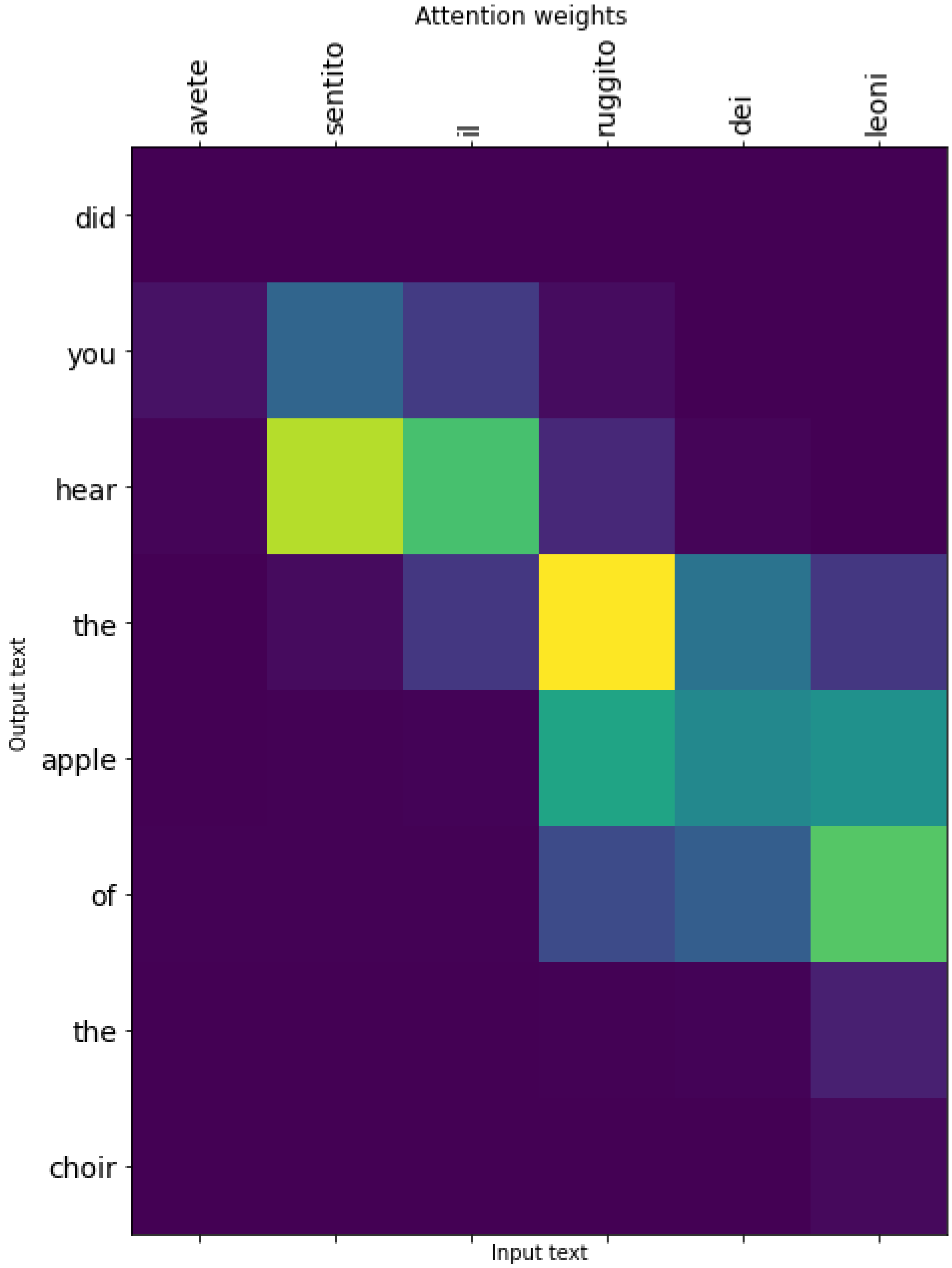
```
 60%|██████    | 3/5 [00:00<00:00,  7.80it/s]
italian sentence -->  hanno riso tutti tranne tom
true english translation -->  everyone laughed except tom <end>
predicted english translation -->  they laughed all tom was
BLEU Score is :  0.4
####################
italian sentence -->  chi vi insegna il francese
true english translation -->  who teaches you french <end>
predicted english translation -->  who teaches me french
BLEU Score is :  0.75
####################
italian sentence -->  non siete più le benvenute in casa mia
true english translation -->  you are not welcome in my home anymore <end>
predicted english translation -->  you are not welcome to be at my house
BLEU Score is :  0.5555555555555556
####################
100%|██████████| 5/5 [00:00<00:00,  8.71it/s]
italian sentence -->  avete sentito il ruggito dei leoni
```

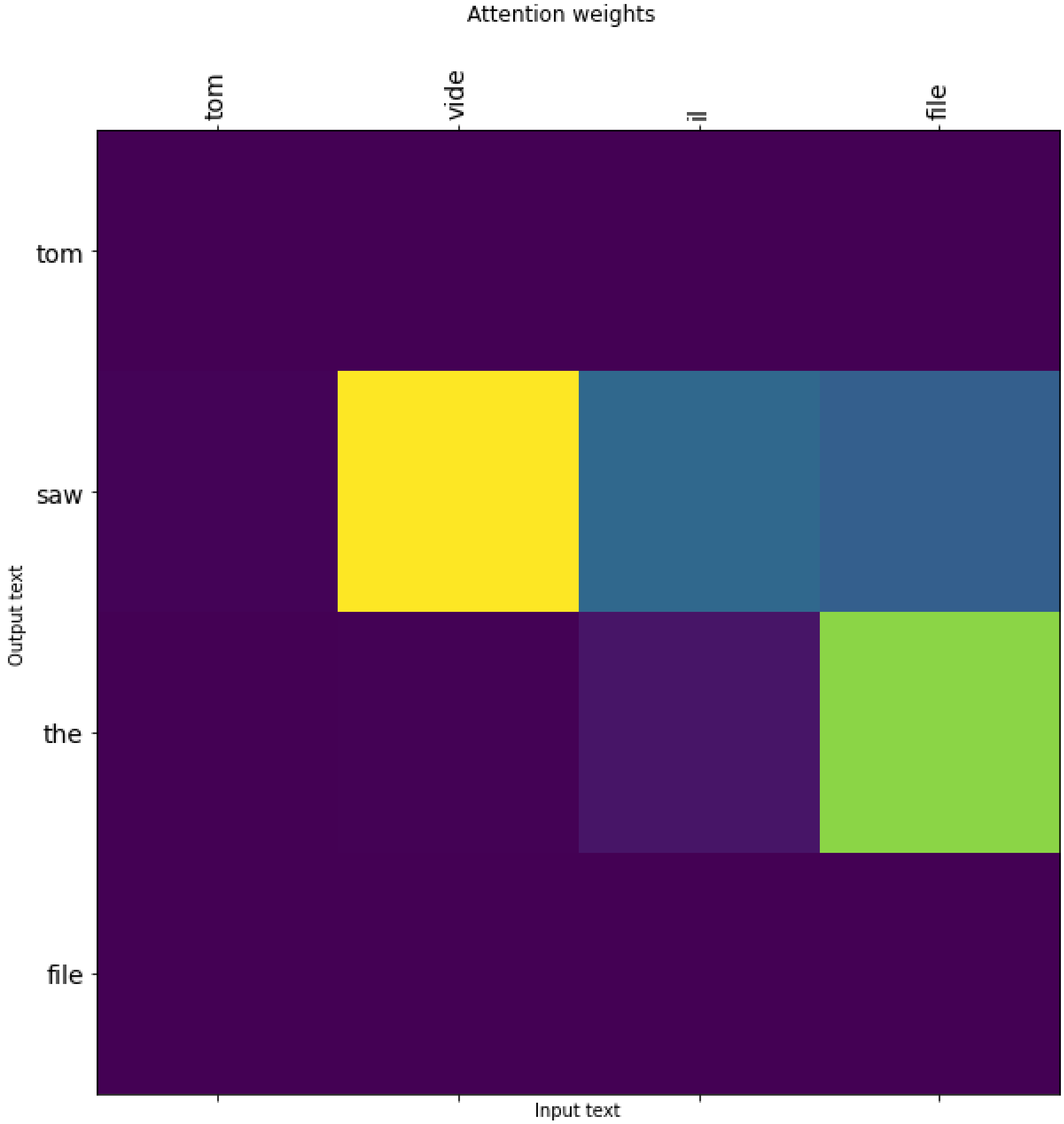
```
true english translation -->  did you hear the roar of the lions <end>
predicted english translation -->  did you hear the apple of the choir
BLEU Score is :  0.75
####################
italian sentence -->  tom vide il file
true english translation -->  tom saw the file <end>
predicted english translation -->  tom saw the file
BLEU Score is :  1.0
####################
```




Attention weights
chi
vi
insegna
il
francese
who
teaches
me
french
Output text
Input text


Attention weights
non
siete
più
le
benvenute
in
casa
mia
you
are
not
welcome
to
be
at
my
house
Output text
Input text


Attention weights
avete
sentito
il
ruggito
dei
leoni
did
you
hear
the
apple
of
the
choir
Output text
Input text



In [ ]:
```
# Predict on 1000 random sentences on test data and calculate the average BLEU score of
# https://www.nltk.org/_modules/nltk/translate/bleu_score.html

import nltk.translate.bleu_score as bleu
from tqdm import tqdm

import warnings
warnings.filterwarnings('ignore')

BLEU_scores=[]

#model_1.load_weights('model_1_weights.h5')

for i in tqdm(range(1000)):
    index= np.random.randint(low=0,high=validation.shape[0])

    italian_sentence=validation['italian'].values[index]
    english_sentence=validation['english_out'].values[index]

    predicted_words_indices,att_weights,predicted_sentence=predict(italian_sentence,mode

    reference=english_sentence.split()[:-1]
    translation=predicted_sentence.split()
```

```
    BLEU_scores.append(bleu.sentence_bleu([reference],translation,weights=[1]))

print('Average_BLEU_score for 1000 random sentences is :',np.mean(BLEU_scores))
```

```
100%|██████████| 1000/1000 [00:45<00:00, 22.07it/s]
Average_BLEU_score for 1000 random sentences is : 0.7265969438011216
```

Model 2.2 Implementation with General scoring function

In [ ]:

```
# Implement teacher forcing while training your model. You can do it two ways.
# Prepare your data, encoder_input,decoder_input and decoder_output
# if decoder input is
# <start> Hi how are you
# decoder output should be
# Hi How are you <end>
# i.e when you have send <start>-- decoder predicted Hi, 'Hi' decoder predicted 'How' ..

# or

# model.fit([train_ita,train_eng],train_eng[:,1:]..)
# Note: If you follow this approach some grader functions might return false and this is

from tensorflow.keras.callbacks import ModelCheckpoint,TensorBoard,EarlyStopping
import os
import datetime
optimizer = tf.keras.optimizers.Adam()

model_2=encoder_decoder(ip_vocab_size=vocab_size_ita,ip_embed_size=100,op_embed_size=100
                        att_units=64,output_len=20,op_vocab_size=vocab_size_eng,batch_si

model_2.compile(loss=[loss_function],optimizer=optimizer)

train_steps=train.shape[0]//512
valid_steps=validation.shape[0]//512

log_dir = os.path.join("logs",'fits', datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
tensorboard_callback = TensorBoard(log_dir=log_dir,histogram_freq=1,write_graph=True)
earlystop = EarlyStopping(monitor="val_loss",mode="auto",patience=7,verbose=1)
checkpt = ModelCheckpoint(monitor="val_loss",mode="auto",filepath='model_2_2_weights.h5'
callback_list = [tensorboard_callback,checkpt,earlystop]

model_2.fit(train_dataloader, steps_per_epoch=train_steps, epochs=25, validation_data=tr
                validation_steps=valid_steps,callbacks=callback_list)

model_2.summary()
```

```
Epoch 1/25
550/550 [==============================] - ETA: 0s - loss: 1.9661
Epoch 00001: val_loss improved from inf to 1.84727, saving model to model_2_2_weights.h5
550/550 [==============================] - 127s 191ms/step - loss: 1.9661 - val_loss: 1.
8473
Epoch 2/25
550/550 [==============================] - ETA: 0s - loss: 1.7988
Epoch 00002: val_loss improved from 1.84727 to 1.72969, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 99s 180ms/step - loss: 1.7988 - val_loss: 1.7
297
Epoch 3/25
550/550 [==============================] - ETA: 0s - loss: 1.6551
Epoch 00003: val_loss improved from 1.72969 to 1.56945, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 99s 180ms/step - loss: 1.6551 - val_loss: 1.5
695
Epoch 4/25
```

```
550/550 [==============================] - ETA: 0s - loss: 1.4491
Epoch 00004: val_loss improved from 1.56945 to 1.33011, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 181ms/step - loss: 1.4491 - val_loss: 1.
3301
Epoch 5/25
550/550 [==============================] - ETA: 0s - loss: 1.2485
Epoch 00005: val_loss improved from 1.33011 to 1.15618, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 181ms/step - loss: 1.2485 - val_loss: 1.
1562
Epoch 6/25
550/550 [==============================] - ETA: 0s - loss: 1.0859
Epoch 00006: val_loss improved from 1.15618 to 1.00362, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 1.0859 - val_loss: 1.
0036
Epoch 7/25
550/550 [==============================] - ETA: 0s - loss: 0.9499
Epoch 00007: val_loss improved from 1.00362 to 0.88055, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 101s 183ms/step - loss: 0.9499 - val_loss: 0.
8805
Epoch 8/25
550/550 [==============================] - ETA: 0s - loss: 0.8406
Epoch 00008: val_loss improved from 0.88055 to 0.78474, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 0.8406 - val_loss: 0.
7847
Epoch 9/25
550/550 [==============================] - ETA: 0s - loss: 0.7526
Epoch 00009: val_loss improved from 0.78474 to 0.70136, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 0.7526 - val_loss: 0.
7014
Epoch 10/25
550/550 [==============================] - ETA: 0s - loss: 0.6781
Epoch 00010: val_loss improved from 0.70136 to 0.63353, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 183ms/step - loss: 0.6781 - val_loss: 0.
6335
Epoch 11/25
550/550 [==============================] - ETA: 0s - loss: 0.6146
Epoch 00011: val_loss improved from 0.63353 to 0.57229, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 101s 183ms/step - loss: 0.6146 - val_loss: 0.
5723
Epoch 12/25
550/550 [==============================] - ETA: 0s - loss: 0.5587
Epoch 00012: val_loss improved from 0.57229 to 0.52699, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 101s 183ms/step - loss: 0.5587 - val_loss: 0.
5270
Epoch 13/25
550/550 [==============================] - ETA: 0s - loss: 0.5114
Epoch 00013: val_loss improved from 0.52699 to 0.48024, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 0.5114 - val_loss: 0.
4802
Epoch 14/25
550/550 [==============================] - ETA: 0s - loss: 0.4719
Epoch 00014: val_loss improved from 0.48024 to 0.44107, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 0.4719 - val_loss: 0.
4411
Epoch 15/25
```

```
550/550 [==============================] - ETA: 0s - loss: 0.4374
Epoch 00015: val_loss improved from 0.44107 to 0.40985, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 183ms/step - loss: 0.4374 - val_loss: 0.
4099
Epoch 16/25
550/550 [==============================] - ETA: 0s - loss: 0.4065
Epoch 00016: val_loss improved from 0.40985 to 0.38212, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 0.4065 - val_loss: 0.
3821
Epoch 17/25
550/550 [==============================] - ETA: 0s - loss: 0.3818
Epoch 00017: val_loss improved from 0.38212 to 0.36059, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 0.3818 - val_loss: 0.
3606
Epoch 18/25
550/550 [==============================] - ETA: 0s - loss: 0.3585
Epoch 00018: val_loss improved from 0.36059 to 0.33693, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 0.3585 - val_loss: 0.
3369
Epoch 19/25
550/550 [==============================] - ETA: 0s - loss: 0.3389
Epoch 00019: val_loss improved from 0.33693 to 0.31890, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 0.3389 - val_loss: 0.
3189
Epoch 20/25
550/550 [==============================] - ETA: 0s - loss: 0.3215
Epoch 00020: val_loss improved from 0.31890 to 0.30101, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 0.3215 - val_loss: 0.
3010
Epoch 21/25
550/550 [==============================] - ETA: 0s - loss: 0.3065
Epoch 00021: val_loss improved from 0.30101 to 0.28786, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 0.3065 - val_loss: 0.
2879
Epoch 22/25
550/550 [==============================] - ETA: 0s - loss: 0.2929
Epoch 00022: val_loss improved from 0.28786 to 0.27735, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 0.2929 - val_loss: 0.
2774
Epoch 23/25
550/550 [==============================] - ETA: 0s - loss: 0.2798
Epoch 00023: val_loss improved from 0.27735 to 0.26400, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 101s 183ms/step - loss: 0.2798 - val_loss: 0.
2640
Epoch 24/25
550/550 [==============================] - ETA: 0s - loss: 0.2690
Epoch 00024: val_loss improved from 0.26400 to 0.25458, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 0.2690 - val_loss: 0.
2546
Epoch 25/25
550/550 [==============================] - ETA: 0s - loss: 0.2591
Epoch 00025: val_loss improved from 0.25458 to 0.24753, saving model to model_2_2_weight
s.h5
550/550 [==============================] - 100s 182ms/step - loss: 0.2591 - val_loss: 0.
2475
Model: "encoder_decoder_6"
```

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 encoder_8 (Encoder)         multiple                  2702840

 decoder_18 (Decoder)        multiple                  2215410

=================================================================
Total params: 4,918,250
Trainable params: 3,613,550
Non-trainable params: 1,304,700
_________________________________________________________________
```

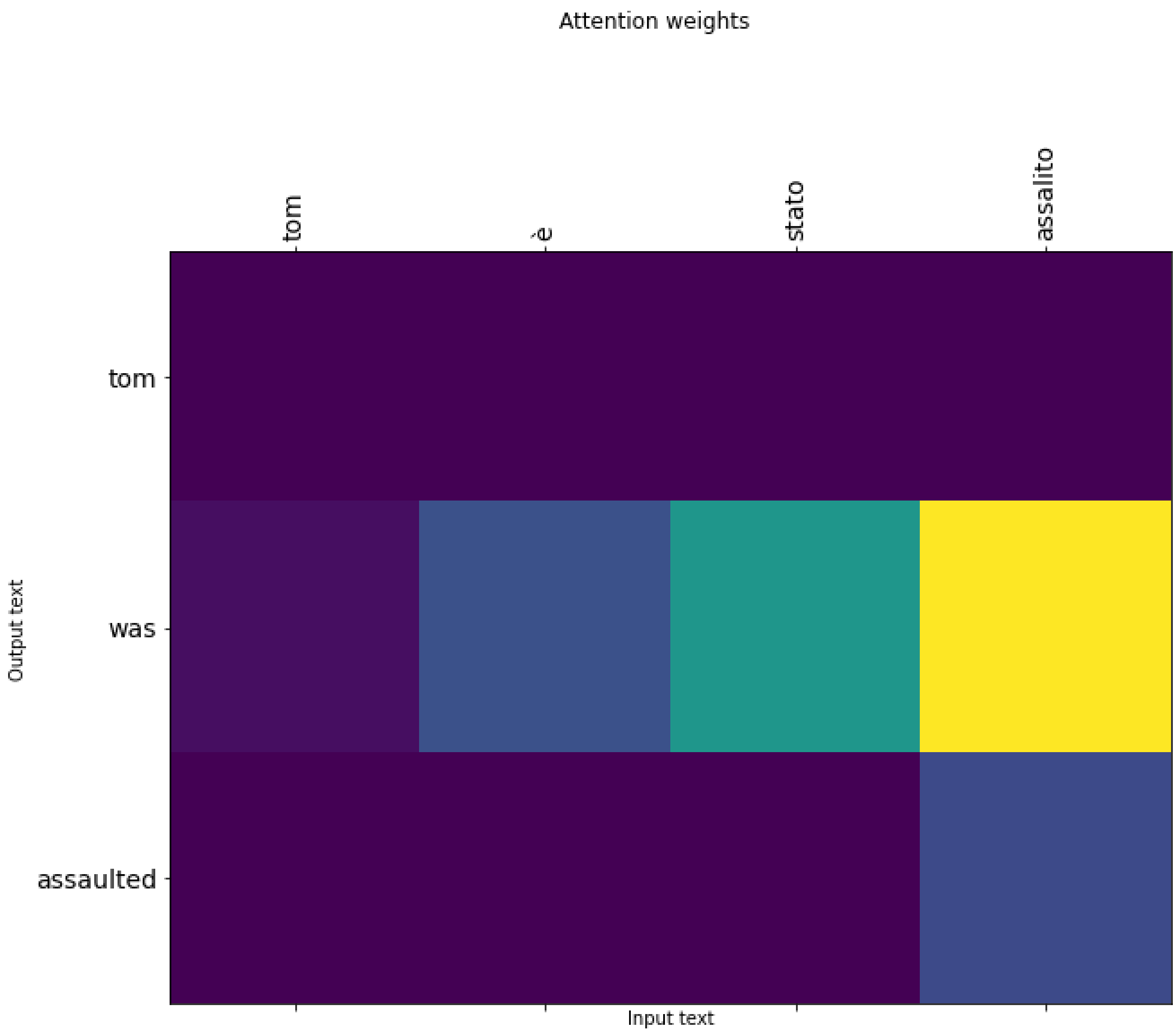
Testing

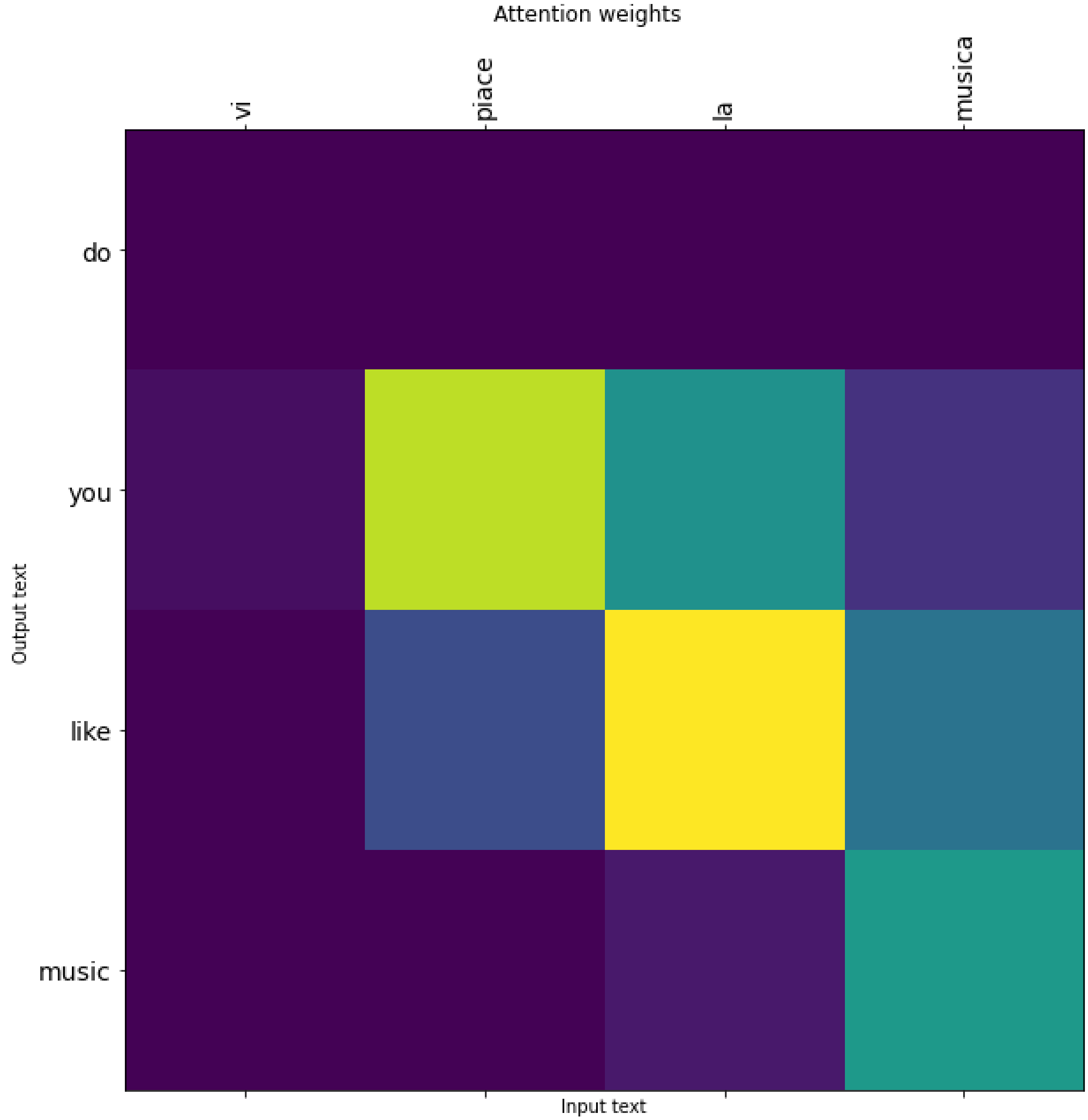
Calculate BLEU score

In [ ]:
```
#Create an object of your custom model.
#Compile and train your model on dot scoring function.
# Visualize few sentences randomly in Test data
# Predict on 1000 random sentences on test data and calculate the average BLEU score of
# https://www.nltk.org/_modules/nltk/translate/bleu_score.html

import nltk.translate.bleu_score as bleu
from tqdm import tqdm

import warnings
warnings.filterwarnings('ignore')

BLEU_scores=[]

#model_2.load_weights('model_1_weights.h5')

for i in tqdm(range(5)):
    index= np.random.randint(low=0,high=validation.shape[0])

    italian_sentence=validation['italian'].values[index]
    english_sentence=validation['english_out'].values[index]

    predicted_words_indices,att_weights,predicted_sentence=predict(italian_sentence,mode

    reference=english_sentence.split()[:-1]
    translation=predicted_sentence.split()

    BLEU_scores.append(bleu.sentence_bleu([reference],translation,weights=[1]))
    print("italian sentence --> ",italian_sentence)
    print("true english translation --> ",english_sentence)
    print("predicted english translation --> ",predicted_sentence)
    print("BLEU Score is : ",BLEU_scores[i])

    plot_attention(att_weights,italian_sentence,predicted_sentence)
    print('#'*20)
```

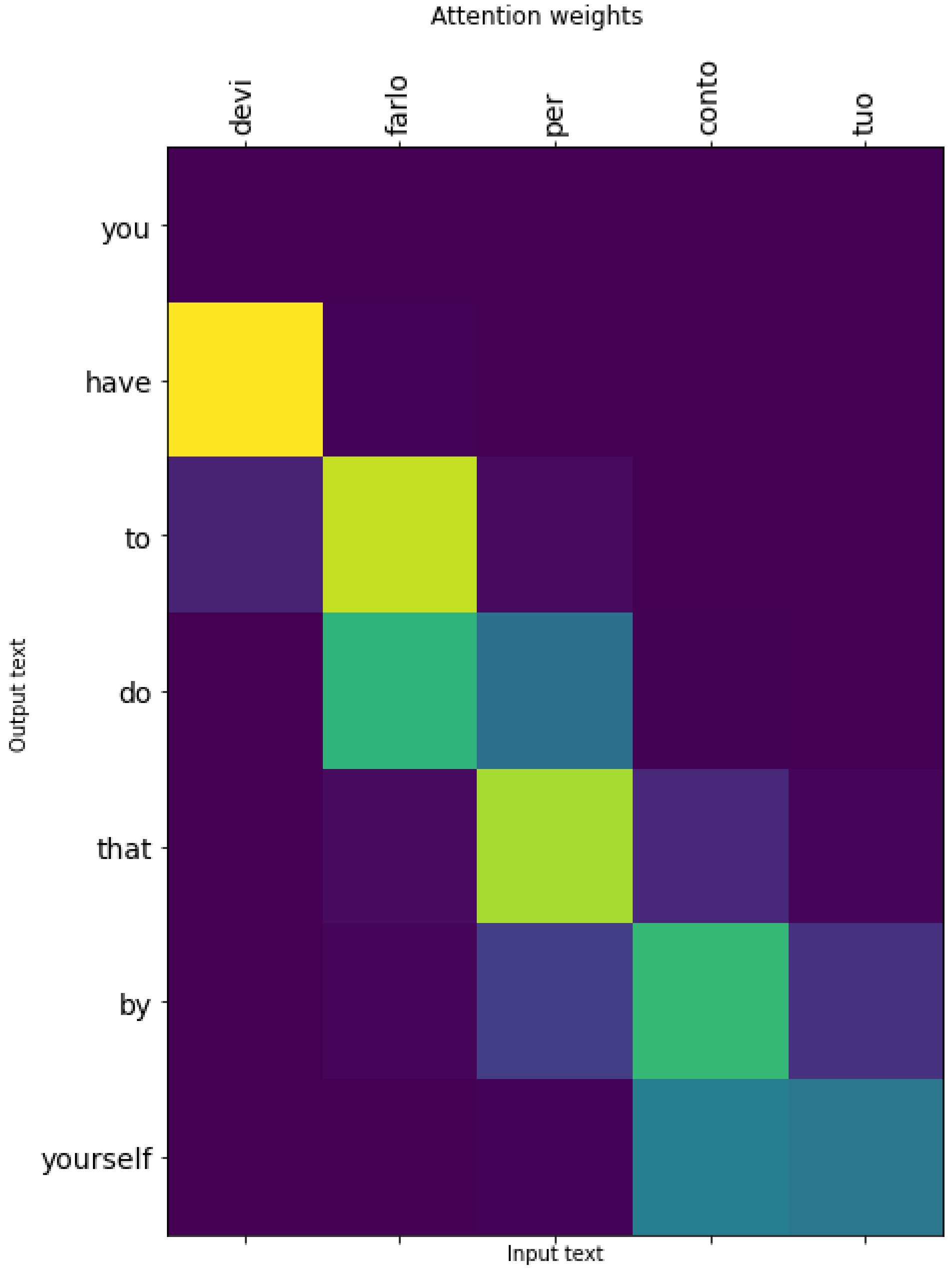
```
 60%|██████    | 3/5 [00:00<00:00,  7.12it/s]
italian sentence -->  tom è stato assalito
true english translation -->  tom was assaulted <end>
predicted english translation -->  tom was assaulted
BLEU Score is :  1.0
####################
italian sentence -->  vi piace la musica
true english translation -->  do you like music <end>
predicted english translation -->  do you like music
BLEU Score is :  1.0
```

```
####################
italian sentence -->  devi farlo per conto tuo
true english translation -->  you have to do it by yourself <end>
predicted english translation -->  you have to do that by yourself
BLEU Score is :  0.8571428571428571
####################
italian sentence -->  perché le interessa
true english translation -->  why does that interest you <end>
predicted english translation -->  why do you care
BLEU Score is :  0.38940039153570244
100%|██████████| 5/5 [00:00<00:00,  8.15it/s]
####################
italian sentence -->  penso che tom sia amico di mary
true english translation -->  i think tom is acquainted with mary <end>
predicted english translation -->  i think tom is friend
BLEU Score is :  0.5362560368285115
####################
```

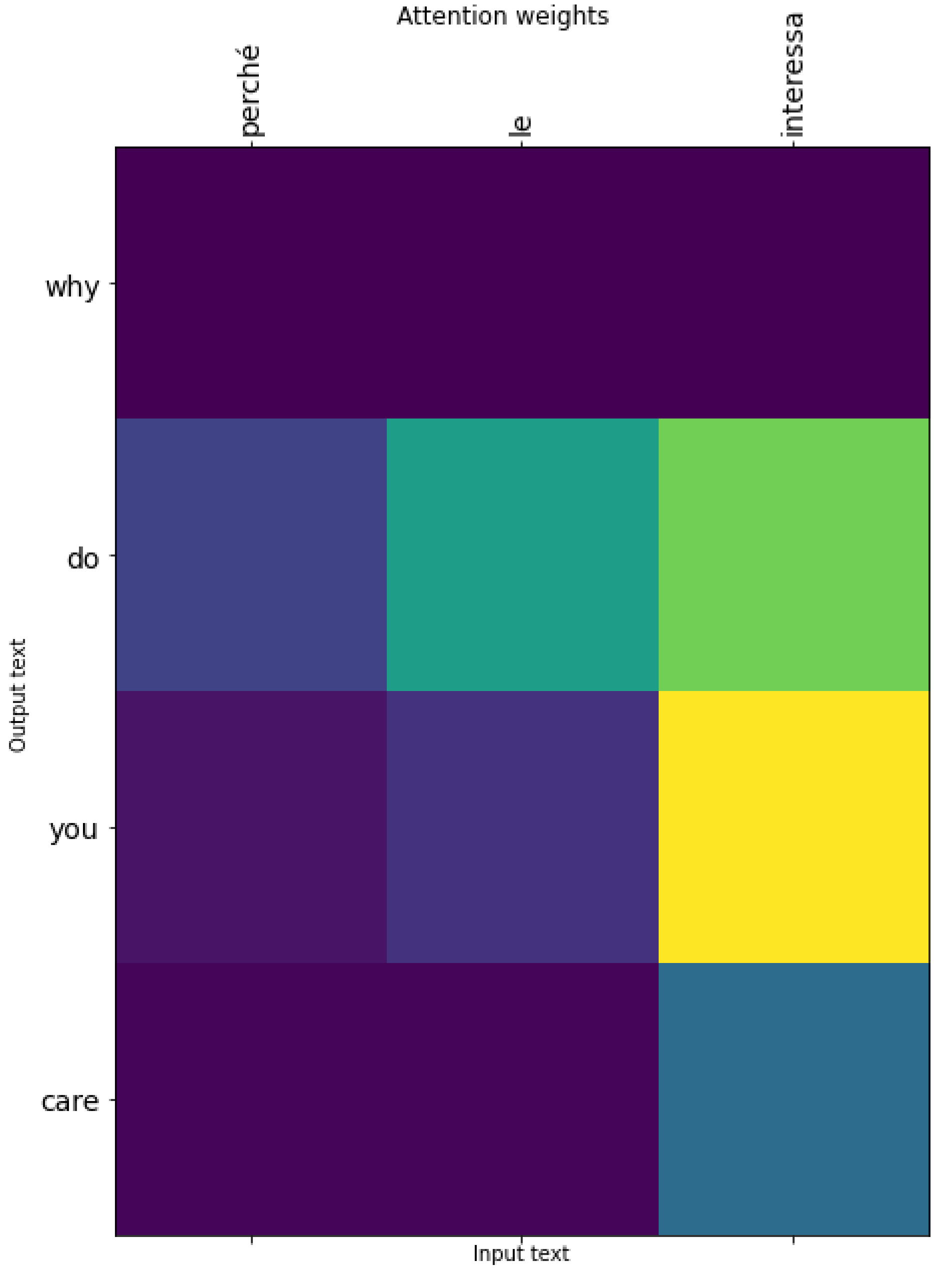


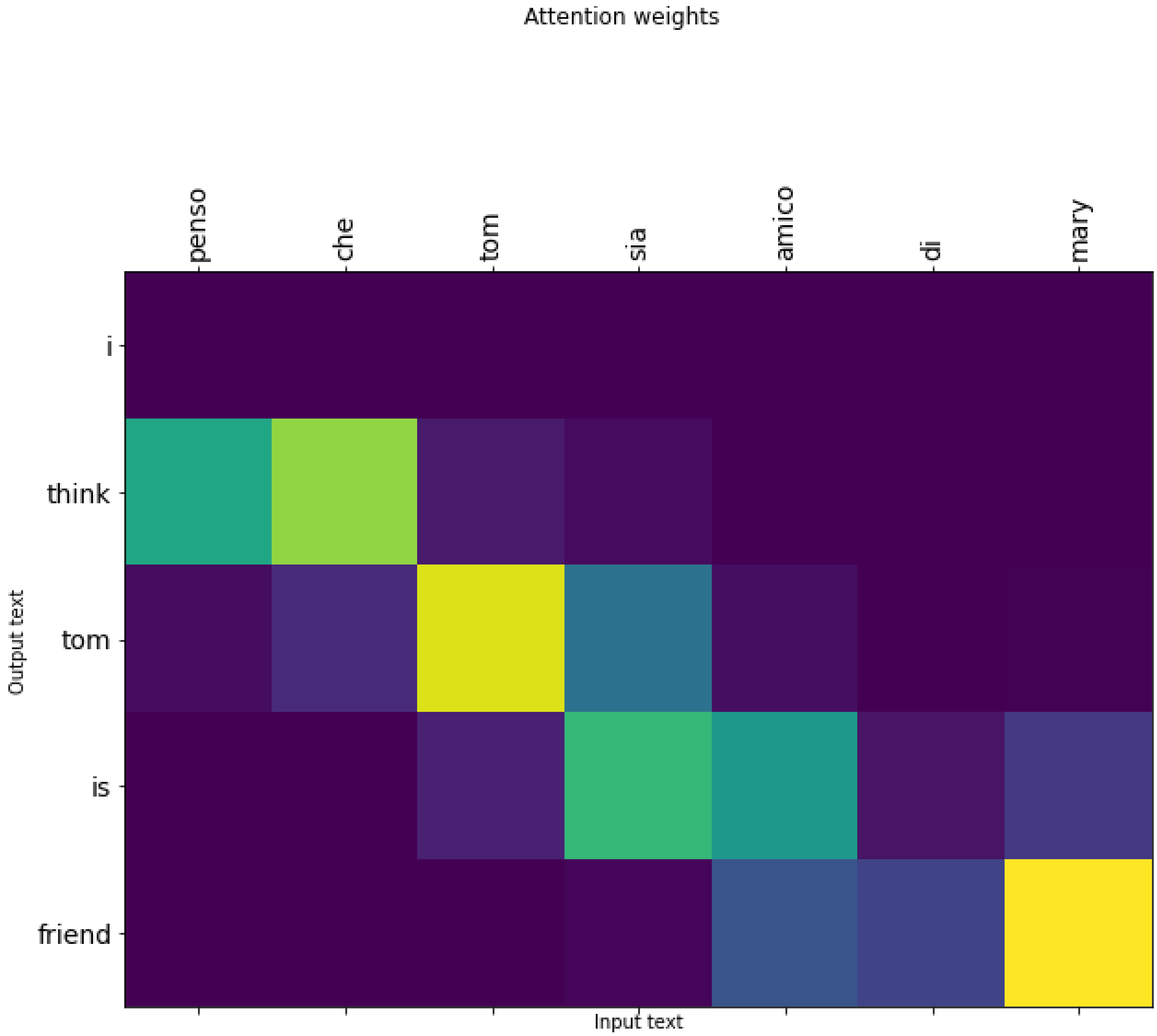


Attention weights
vi
piace
la
musica
do
you
like
music
Output text
Input text



Attention weights
devi
farlo
per
conto
tuo
you
have
to
do
that
by
yourself
Output text
Input text


Attention weights
perché
le
interessa
why
do
you
care
Output text
Input text



In [ ]:

```
# Predict on 1000 random sentences on test data and calculate the average BLEU score of
# https://www.nltk.org/_modules/nltk/translate/bleu_score.html

import nltk.translate.bleu_score as bleu
from tqdm import tqdm

import warnings
warnings.filterwarnings('ignore')

BLEU_scores=[]

#model_1.load_weights('model_1_weights.h5')

for i in tqdm(range(1000)):
    index= np.random.randint(low=0,high=validation.shape[0])

    italian_sentence=validation['italian'].values[index]
    english_sentence=validation['english_out'].values[index]

    predicted_words_indices,att_weights,predicted_sentence=predict(italian_sentence,mode

    reference=english_sentence.split()[:-1]
    translation=predicted_sentence.split()

    BLEU_scores.append(bleu.sentence_bleu([reference],translation,weights=[1]))

print('Average_BLEU_score for 1000 random sentences is :',np.mean(BLEU_scores))
```

```
100%|██████████| 1000/1000 [00:47<00:00, 20.94it/s]
```

```
Average_BLEU_score for 1000 random sentences is : 0.7394842381177127
```

Model 2.3 Implementation with Concat scoring function

In [ ]:
```
# Implement teacher forcing while training your model. You can do it two ways.
# Prepare your data, encoder_input,decoder_input and decoder_output
# if decoder input is
# <start> Hi how are you
# decoder output should be
# Hi How are you <end>
# i.e when you have send <start>-- decoder predicted Hi, 'Hi' decoder predicted 'How' ..

# or

# model.fit([train_ita,train_eng],train_eng[:,1:]..)

from tensorflow.keras.callbacks import ModelCheckpoint,TensorBoard,EarlyStopping
import os
import datetime
optimizer = tf.keras.optimizers.Adam()

model_2=encoder_decoder(ip_vocab_size=vocab_size_ita,ip_embed_size=100,op_embed_size=100
                        att_units=64,output_len=20,op_vocab_size=vocab_size_eng,batch_si

model_2.compile(loss=[loss_function],optimizer=optimizer)

train_steps=train.shape[0]//512
valid_steps=validation.shape[0]//512

log_dir = os.path.join("logs",'fits', datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
tensorboard_callback = TensorBoard(log_dir=log_dir,histogram_freq=1,write_graph=True)
earlystop = EarlyStopping(monitor="val_loss",mode="auto",patience=7,verbose=1)
checkpt = ModelCheckpoint(monitor="val_loss",mode="auto",filepath='model_2_3_weights.h5'
callback_list = [tensorboard_callback,earlystop,checkpt]

model_2.fit(train_dataloader, steps_per_epoch=train_steps, epochs=25, validation_data=tr
                validation_steps=valid_steps,callbacks=callback_list)

model_2.summary()
```

```
Epoch 1/25
550/550 [==============================] - 133s 198ms/step - loss: 1.9670 - val_loss: 1.
8470
Epoch 2/25
550/550 [==============================] - 103s 187ms/step - loss: 1.7979 - val_loss: 1.
6935
Epoch 3/25
550/550 [==============================] - 103s 188ms/step - loss: 1.5288 - val_loss: 1.
3790
Epoch 4/25
550/550 [==============================] - 104s 189ms/step - loss: 1.2756 - val_loss: 1.
1698
Epoch 5/25
550/550 [==============================] - 104s 190ms/step - loss: 1.0917 - val_loss: 1.
0038
Epoch 6/25
550/550 [==============================] - 104s 189ms/step - loss: 0.9411 - val_loss: 0.
8658
Epoch 7/25
550/550 [==============================] - 104s 190ms/step - loss: 0.8203 - val_loss: 0.
7577
Epoch 8/25
550/550 [==============================] - 104s 189ms/step - loss: 0.7225 - val_loss: 0.
6705
```

```
Epoch 9/25
550/550 [==============================] - 105s 190ms/step - loss: 0.6431 - val_loss: 0.
5967
Epoch 10/25
550/550 [==============================] - 105s 190ms/step - loss: 0.5773 - val_loss: 0.
5365
Epoch 11/25
550/550 [==============================] - 104s 190ms/step - loss: 0.5233 - val_loss: 0.
4884
Epoch 12/25
550/550 [==============================] - 105s 190ms/step - loss: 0.4778 - val_loss: 0.
4470
Epoch 13/25
550/550 [==============================] - 105s 191ms/step - loss: 0.4425 - val_loss: 0.
4112
Epoch 14/25
550/550 [==============================] - 105s 191ms/step - loss: 0.4078 - val_loss: 0.
3825
Epoch 15/25
550/550 [==============================] - 105s 190ms/step - loss: 0.3792 - val_loss: 0.
3548
Epoch 16/25
550/550 [==============================] - 104s 190ms/step - loss: 0.3576 - val_loss: 0.
3338
Epoch 17/25
550/550 [==============================] - 104s 190ms/step - loss: 0.3355 - val_loss: 0.
3136
Epoch 18/25
550/550 [==============================] - 104s 190ms/step - loss: 0.3168 - val_loss: 0.
2981
Epoch 19/25
550/550 [==============================] - 105s 190ms/step - loss: 0.3006 - val_loss: 0.
2821
Epoch 20/25
550/550 [==============================] - 105s 190ms/step - loss: 0.2871 - val_loss: 0.
2696
Epoch 21/25
550/550 [==============================] - 105s 190ms/step - loss: 0.2750 - val_loss: 0.
2561
Epoch 22/25
550/550 [==============================] - 105s 190ms/step - loss: 0.2640 - val_loss: 0.
2465
Epoch 23/25
550/550 [==============================] - 104s 190ms/step - loss: 0.2513 - val_loss: 0.
2371
Epoch 24/25
550/550 [==============================] - 104s 190ms/step - loss: 0.2425 - val_loss: 0.
2274
Epoch 25/25
550/550 [==============================] - 105s 190ms/step - loss: 0.2347 - val_loss: 0.
2209
Model: "encoder_decoder_10"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 encoder_12 (Encoder)        multiple                  2702840

 decoder_22 (Decoder)        multiple                  2219570

=================================================================
Total params: 4,922,410
Trainable params: 3,617,710
Non-trainable params: 1,304,700
_________________________________________________________________
```

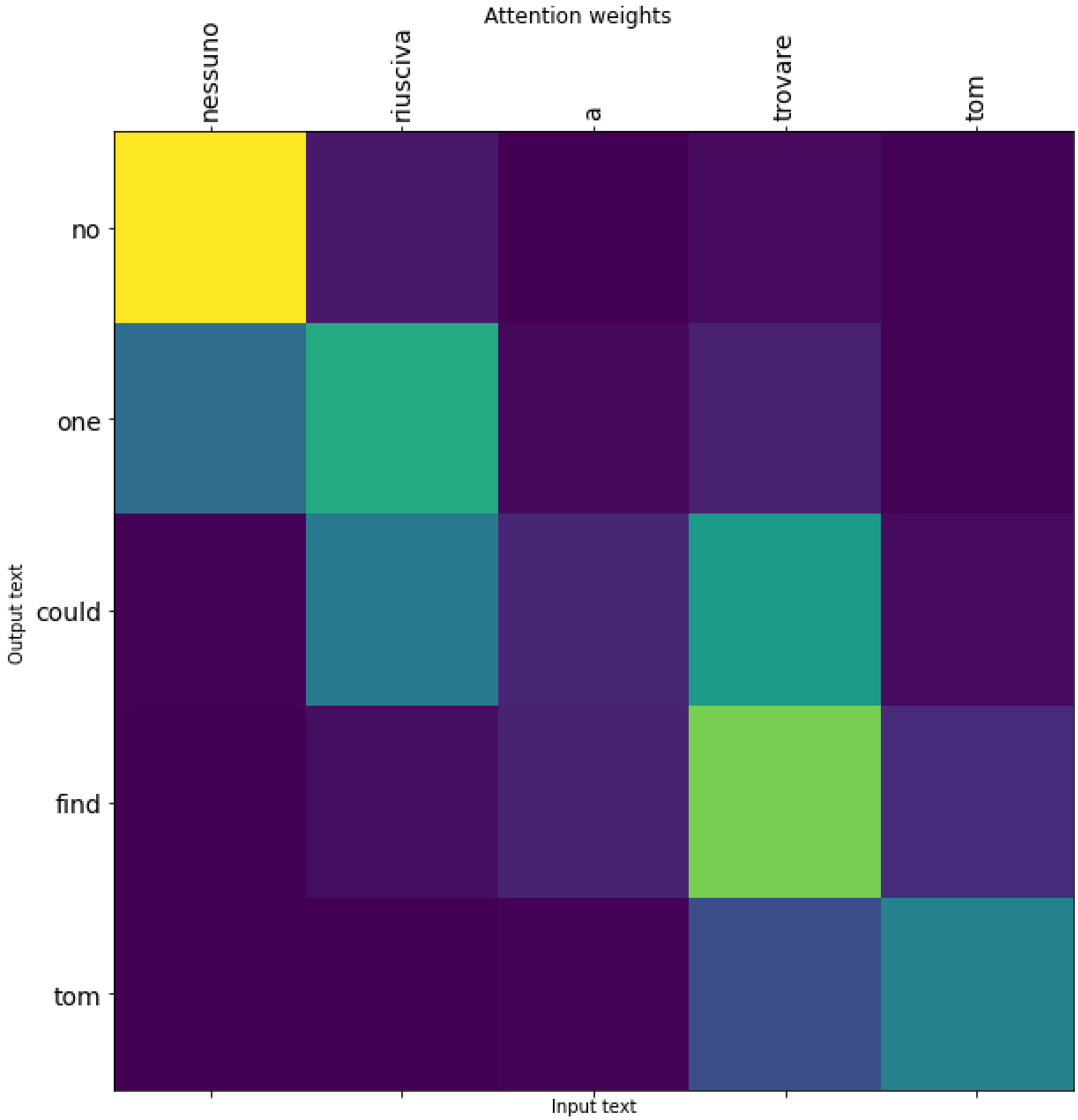
Testing

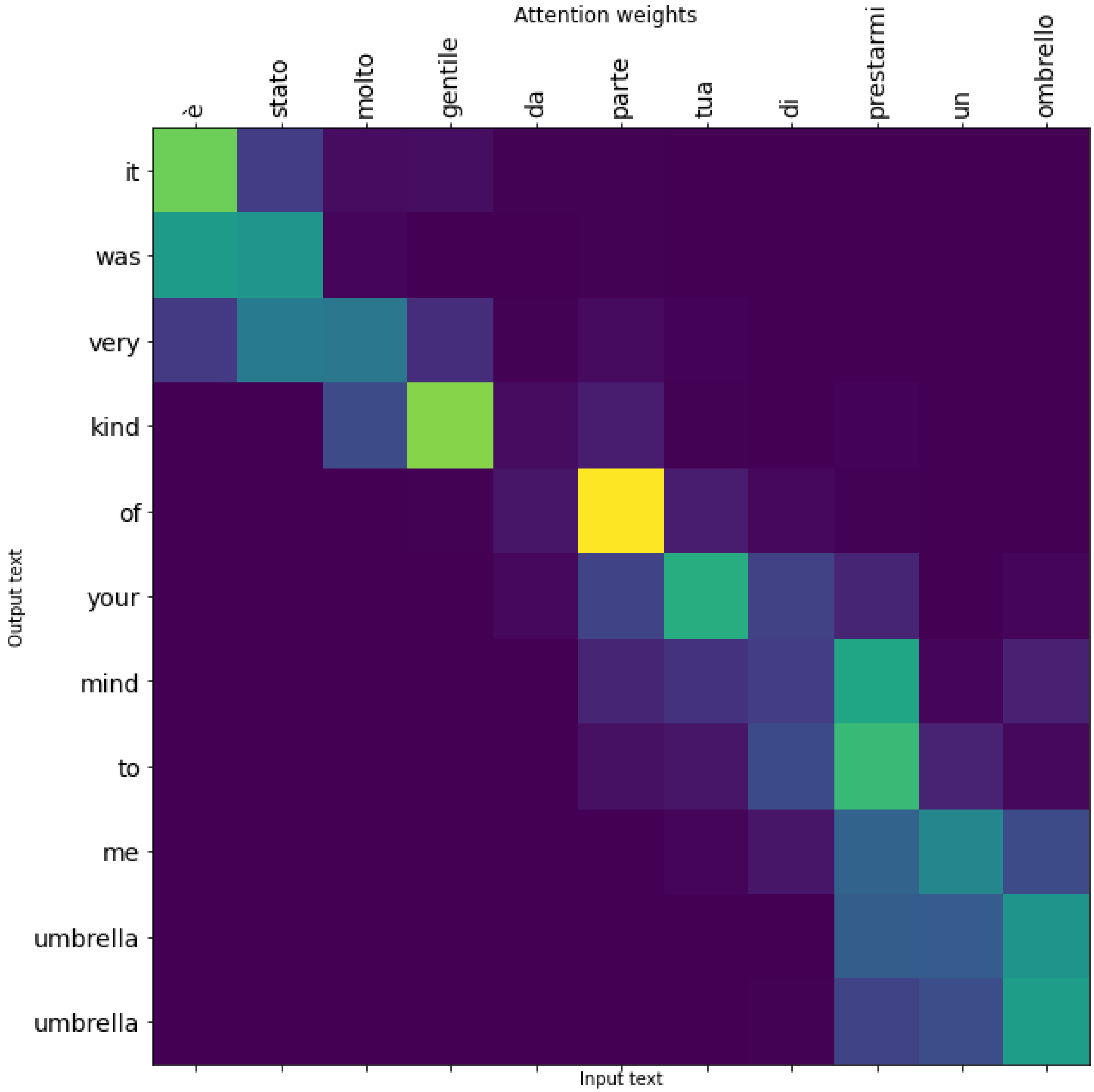
Calculate BLEU score

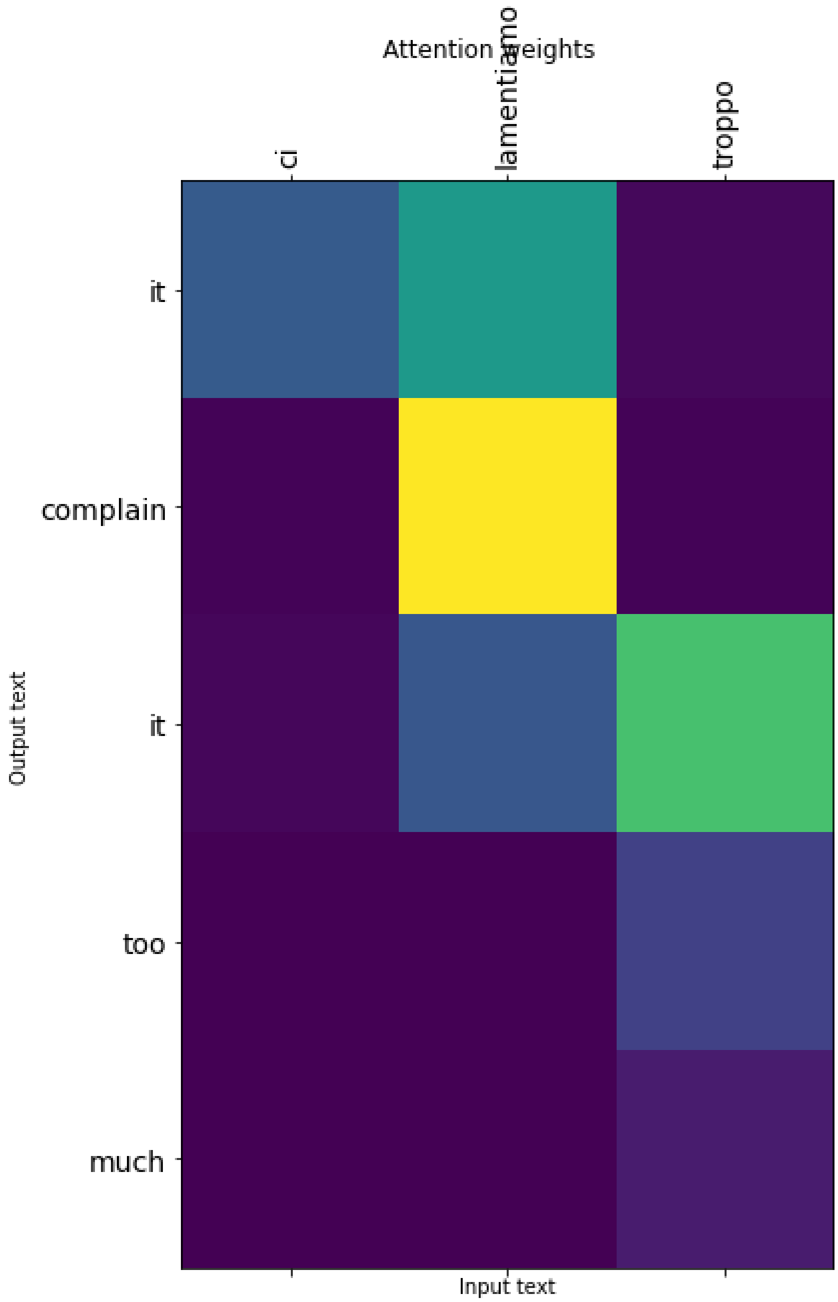
In [ ]:
```python
#Create an object of your custom model.
#Compile and train your model on dot scoring function.
# Visualize few sentences randomly in Test data
# Predict on 1000 random sentences on test data and calculate the average BLEU score of
# https://www.nltk.org/_modules/nltk/translate/bleu_score.html

import nltk.translate.bleu_score as bleu
from tqdm import tqdm

import warnings
warnings.filterwarnings('ignore')

BLEU_scores=[]

#model_2.load_weights('model_1_weights.h5')

for i in tqdm(range(5)):
    index= np.random.randint(low=0,high=validation.shape[0])

    italian_sentence=validation['italian'].values[index]
    english_sentence=validation['english_out'].values[index]

    predicted_words_indices,att_weights,predicted_sentence=predict(italian_sentence,mode

    reference=english_sentence.split()[:-1]
    translation=predicted_sentence.split()

    BLEU_scores.append(bleu.sentence_bleu([reference],translation,weights=[1]))
    print("italian sentence --> ",italian_sentence)
    print("true english translation --> ",english_sentence)
    print("predicted english translation --> ",predicted_sentence)
    print("BLEU Score is : ",BLEU_scores[i])

    plot_attention(att_weights,italian_sentence,predicted_sentence)
    print('#'*20)
```

```
 40%|████      | 2/5 [00:00<00:00,  7.98it/s]
italian sentence -->  nessuno riusciva a trovare tom
true english translation -->  no one could find tom <end>
predicted english translation -->  no one could find tom
BLEU Score is :  1.0
####################
italian sentence -->  è stato molto gentile da parte tua di prestarmi un ombrello
true english translation -->  it was very kind of you to lend me an umbrella <end>
predicted english translation -->  it was very kind of your mind to me umbrella umbrella

BLEU Score is :  0.7272727272727273
####################
italian sentence -->  ci lamentiamo troppo
true english translation -->  we complain too much <end>
predicted english translation -->  it complain it too much
BLEU Score is :  0.6
100%|██████████| 5/5 [00:00<00:00, 11.61it/s]
####################
italian sentence -->  amo davvero allenarmi
true english translation -->  i really love working out <end>
predicted english translation -->  i really love working out
BLEU Score is :  1.0
####################
```

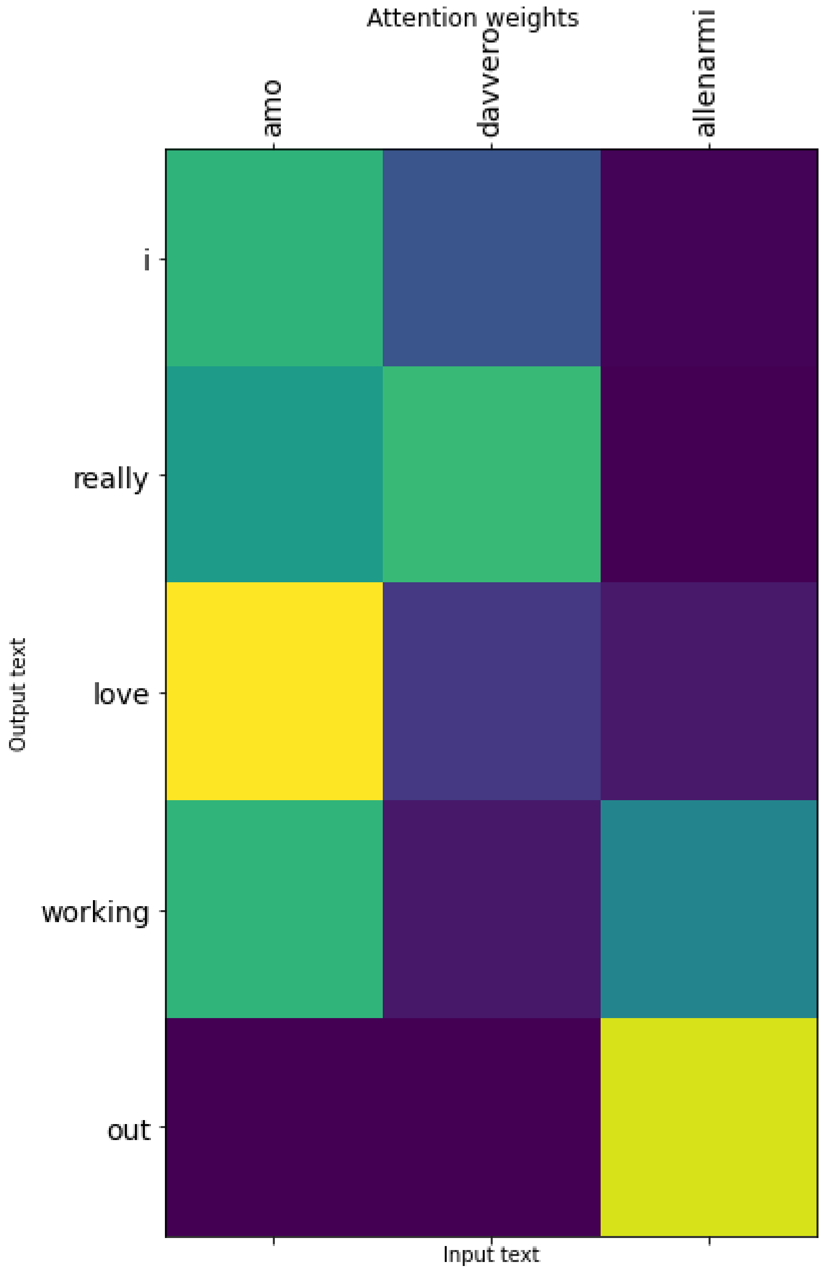
```
italian sentence -->  silenzio per piacere
true english translation -->  quiet please <end>
predicted english translation -->  they please
BLEU Score is :  0.5
####################
```



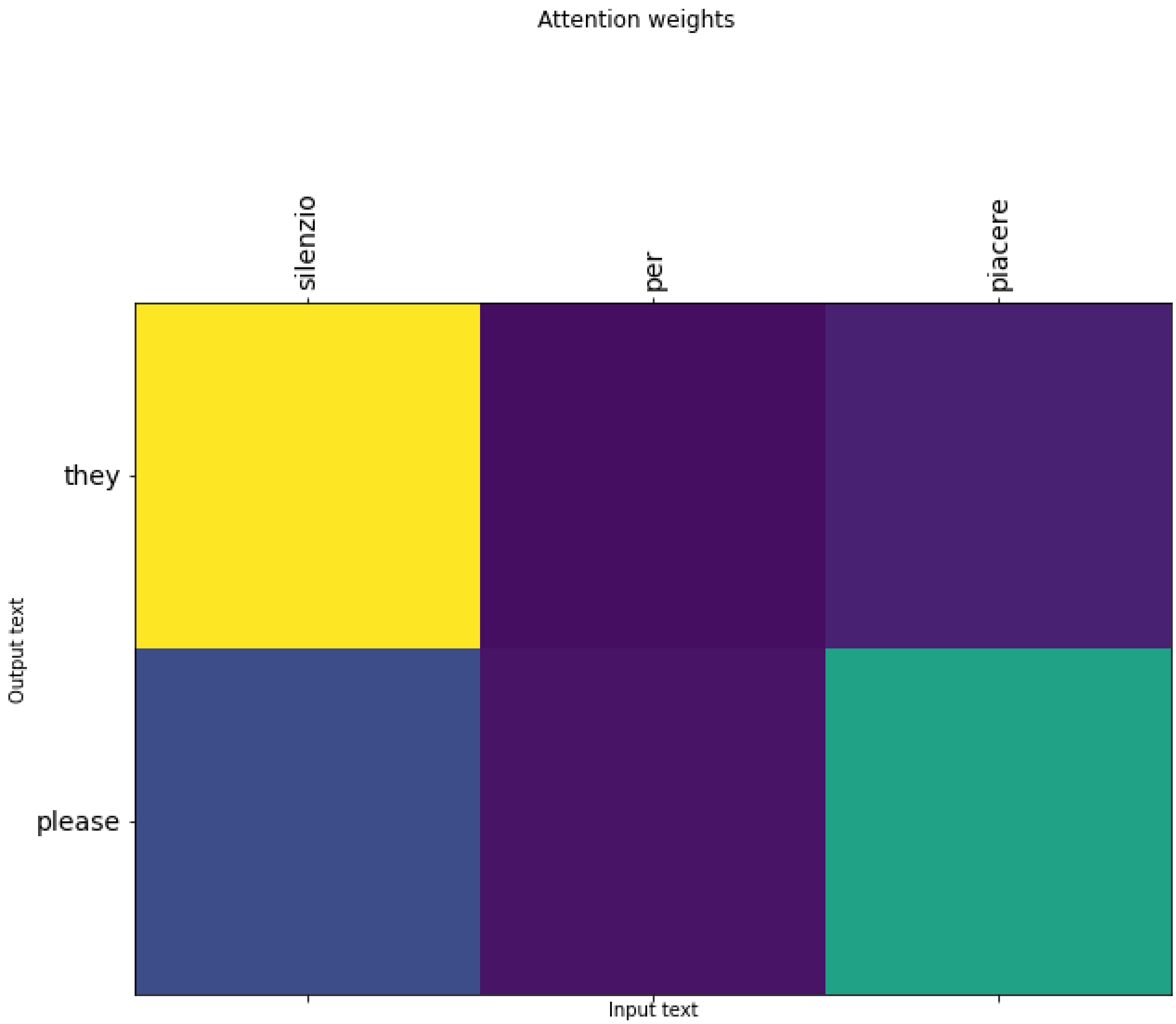

Attention weights
è
stato
molto
gentile
da
parte
tua
di
prestarmi
un
ombrello
it
was
very
kind
of
your
mind
to
me
umbrella
umbrella
Output text
Input text



Attention weights
ci
lamentiamo
troppo
it
complain
it
too
much
Output text
Input text



Attention weights
amo
davvero
allenarmi
i
really
love
working
out
Output text
Input text




```
In [ ]: # Predict on 1000 random sentences on test data and calculate the average BLEU score of
        # https://www.nltk.org/_modules/nltk/translate/bleu_score.html

        import nltk.translate.bleu_score as bleu
        from tqdm import tqdm

        import warnings
        warnings.filterwarnings('ignore')

        BLEU_scores=[]

        #model_1.load_weights('model_1_weights.h5')

        for i in tqdm(range(1000)):
            index= np.random.randint(low=0,high=validation.shape[0])

            italian_sentence=validation['italian'].values[index]
            english_sentence=validation['english_out'].values[index]

            predicted_words_indices,att_weights,predicted_sentence=predict(italian_sentence,mode

            reference=english_sentence.split()[:-1]
            translation=predicted_sentence.split()

            BLEU_scores.append(bleu.sentence_bleu([reference],translation,weights=[1]))

        print('Average_BLEU_score for 1000 random sentences is :',np.mean(BLEU_scores))
```

```
100%|██████████| 1000/1000 [00:48<00:00, 20.53it/s]
```

```
Average_BLEU_score for 1000 random sentences is : 0.7789334684572429
```

Observations

In [ ]:

```python
# Write your observations on each of the scoring function
from  prettytable import PrettyTable

x=PrettyTable()
x.field_names = ["Model","similarity scoring function", "Average BLEU score for 1000 ran
x.add_row(["Simple encoder-decoder","None", 0.7115])
x.add_row(["Encoder-decoder with attention ","Dot" ,0.7265])
x.add_row(["Encoder-decoder with attention ","General", 0.7394])
x.add_row(["Encoder-decoder with attention ","Concat", 0.7789])
print(x)
```

```
+----------------------------------+-----------------------------+-----------------------
-------------------------+
|              Model               | similarity scoring function | Average BLEU score for
1000 random data points |
+----------------------------------+-----------------------------+-----------------------
-------------------------+
|      Simple encoder-decoder      |             None            |                     0.
7115                     |
| Encoder-decoder with attention  |             Dot             |                     0.
7265                     |
| Encoder-decoder with attention  |           General           |                     0.
7394                     |
| Encoder-decoder with attention  |            Concat           |                     0.
7789                     |
+----------------------------------+-----------------------------+-----------------------
-------------------------+
```