Sequence to sequence implementation

There will be some functions that start with the word "grader" ex: grader_check_encoder(), grader_check_attention(), grader_onestepdecoder() etc, you should not change those function definition.

Every Grader function has to return True.

Note 1: There are many blogs on the attention mechanisum which might be misleading you, so do read the references completly and after that only please check the internet. The best things is to read the research papers and try to implement it on your own.

Note 2: To complete this assignment, the reference that are mentioned will be enough.

Note 3: If you are starting this assignment, you might have completed minimum of 20 assignment. If you are still not able to implement this algorithm you might have rushed in the previous assignments with out learning much and didn't spend your time productively.

Task -1: Simple Encoder and Decoder

Implement simple Encoder-Decoder model

1. Download the **Italian** to **English** translation dataset from here
2. You will find **ita.txt** file in that ZIP, you can read that data using python and preprocess that data this way only:

```
Encoder input: "<start> vado a scuola <end>"
Decoder input: "<start> i am going school"
Decoder output: "i am going school <end>"
```

3. You have to implement a simple Encoder and Decoder architecture
4. Use BLEU score as metric to evaluate your model. You can use any loss function you need.
5. You have to use Tensorboard to plot the Graph, Scores and histograms of gradients.
6. a. Check the reference notebook
   b. Resource 2

In [1]:

```
%%bash
rm -r *
mkdir -p raw_data
wget -qO raw_data/ita-eng.zip http://www.manythings.org/anki/ita-eng.zip
wget -qO raw_data/glove.6B.100d.txt https://www.dropbox.com/s/ddkmtqz01jc024u/glove.6B.100d.txt
unzip -q raw_data/ita-eng.zip -d raw_data/

tree
```

```
.
└── raw_data
    ├── _about.txt
    ├── glove.6B.100d.txt
    ├── ita-eng.zip
    └── ita.txt

1 directory, 4 files
```

Load the data

In [2]:

```
import os
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
import re
import shutil

import numpy as np
import pandas as pd
import seaborn as sns
from tqdm import tqdm
from datetime import datetime
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
```

```
from sklearn.model_selection import train_test_split

import tensorflow as tf
from tensorflow.keras.layers import Embedding
from tensorflow.keras.layers import LSTM
from tensorflow.keras.layers import Dense
from tensorflow.keras.callbacks import TensorBoard
from tensorflow.keras.callbacks import ModelCheckpoint
from keras.preprocessing.sequence import pad_sequences

from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.text import Tokenizer

from tensorflow.nn import tanh
from tensorflow import reduce_sum
from tensorflow.nn import softmax
from tensorflow import expand_dims
from tensorflow.keras.layers import Dot

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

tqdm.pandas()
plt.style.use('fivethirtyeight')

import logging
logging.getLogger("tensorflow").setLevel(logging.WARNING)

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

In [3]:

```
with open('raw_data/ita.txt', 'r') as file:

    eng, ita = [], []

    for line in file.readlines():
        eng.append(line.split('\t')[0].strip())
        ita.append(line.split('\t')[1].strip())

data = pd.DataFrame({'english' : eng, 'italian' : ita})
print(f'Shape of data frame :: {data.shape}')
data.head()
```

```
Shape of data frame :: (358373, 2)
```

Out[3]:

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

In [4]:

```
data.tail()
```

Out[4]:

	english	italian
358368	I know that adding sentences only in your nati...	So che aggiungere frasi soltanto nella sua lin...
358369	I know that adding sentences only in your nati...	So che aggiungere frasi solamente nella sua li...
358370	I know that adding sentences only in your nati...	So che aggiungere frasi solamente nella sua li...
358371	Doubtless there exists in this world precisely...	Senza dubbio esiste in questo mondo proprio la...
358372	Doubtless there exists in this world precisely...	Senza dubbio esiste in questo mondo proprio la...

Preprocess data

In [5]:

```
def decontractions(phrase):

    # https://stackoverflow.com/questions/19790188/expanding-english-language-contractions-in-python/47091490#47
    # decontracted takes text and convert contractions into natural form.

    # 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)

    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):

    # https://gist.github.com/anandborad/d410a49a493b56dace4f814ab5325bbd
    # convert all the text into lower letters
    # remove all the spacial characters: except space ' '

    text = text.lower()
    text = decontractions(text)
    text = re.sub('[^A-Za-z0-9 ]+', '', text)
    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 explore more and see if you ca
    # 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)
    return text


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

```
100%|██████████| 358373/358373 [00:08<00:00, 42862.03it/s]
100%|██████████| 358373/358373 [00:09<00:00, 38626.95it/s]
```

Out[5]:

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

In [6]:

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

```
100%|██████████| 358373/358373 [00:00<00:00, 919873.24it/s]
100%|██████████| 358373/358373 [00:00<00:00, 933077.48it/s]
```

Analysis on Ennglish sentence length

In [7]:

```
print('Percentile : 0 - 100'); print('-' * 20)
```

```python
for i in range(0,101,10):
    print(f'{i:3d} : {np.percentile(eng_lengths, i)}')

print('\nPercentile : 90 - 100'); print('-' * 20)
for i in range(90,101):
    print(f'{i:3d} : {np.percentile(eng_lengths, i)}')

print('\nPercentile : 99 - 100'); print('-' * 20)
for i in [99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.8,99.9,100]:
    print(f'{i} : {np.percentile(eng_lengths, i)}')
```

```
Percentile : 0 - 100
--------------------
  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

Percentile : 90 - 100
--------------------
 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

Percentile : 99 - 100
--------------------
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
```

Analysis on Italian sentence length

In [8]:

```python
print('Percentile : 0 - 100'); print('-' * 20)
for i in range(0,101,10):
    print(f'{i:3d} : {np.percentile(ita_lengths, i)}')

print('\nPercentile : 90 - 100'); print('-' * 20)
for i in range(90,101):
    print(f'{i:3d} : {np.percentile(ita_lengths, i)}')

print('\nPercentile : 99 - 100'); print('-' * 20)
for i in [99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.8,99.9,100]:
    print(f'{i} : {np.percentile(ita_lengths, i)}')
```

```
Percentile : 0 - 100
--------------------
  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

Percentile : 90 - 100
--------------------
 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

Percentile : 99 - 100
--------------------
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
```

> **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 [9]:

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

data['english_len'] = data['english'].str.split().progress_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()
```

```
100%|██████████| 358373/358373 [00:00<00:00, 916978.18it/s]
100%|██████████| 357956/357956 [00:00<00:00, 751496.38it/s]
```

Out[9]:

	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 [10]:

```python
train, validation = train_test_split(data, test_size = 0.2, random_state = 45)
```

In [11]:

```python
train.head()
```

Out[11]:

	italian	english_inp	english_out
291747	ho bisogno di scoprire dove vive tom	<start> i need to find out where tom lives	i need to find out where tom lives <end>
340581	puoi permetterti di prendere le ferie questestate	<start> can you afford to take a holiday this ...	can you afford to take a holiday this summer <...
59340	non mi dare quella	<start> do not give me that	do not give me that <end>
13685	io non danzerò	<start> i will not dance	i will not dance <end>
348676	tom ha iniziato a trascorrere molto tempo con ...	<start> tom has started spending a lot of time...	tom has started spending a lot of time with ma...

In [12]:

```python
print(f'Train Shape : {train.shape}\nValidation Shape : {validation.shape}')
```

```
# for one sentence we will be adding <end> token so that the tokanizer learns the word <end>
# 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>'
```

```
Train Shape : (286329, 3)
Validation Shape : (71583, 3)
```

In [13]:

```
train.head()
```

Out[13]:

	italian	english_inp	english_out
291747	ho bisogno di scoprire dove vive tom	<start> i need to find out where tom lives <end>	i need to find out where tom lives <end> <end>
340581	puoi permetterti di prendere le ferie questestate	<start> can you afford to take a holiday this ...	can you afford to take a holiday this summer <...
59340	non mi dare quella	<start> do not give me that	do not give me that <end>
13685	io non danzerò	<start> i will not dance	i will not dance <end>
348676	tom ha iniziato a trascorrere molto tempo con ...	<start> tom has started spending a lot of time...	tom has started spending a lot of time with ma...

In [14]:

```
tknizer_ita = Tokenizer()
tknizer_ita.fit_on_texts(train['italian'].values)
tknizer_eng = Tokenizer(filters='!"#$%&()*+,-./:;=?@[\\]^_`{|}~\t\n')
tknizer_eng.fit_on_texts(train['english_inp'].values)
```

In [15]:

```
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)
```

```
13206
26862
```

In [16]:

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

Out[16]:

```
(1, 10389)
```

Implement custom encoder decoder

Encoder

In [17]:

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

    def __init__(self, inp_vocab_size, embedding_size, lstm_size, input_length):
        super().__init__()

        self.inp_vocab_size = inp_vocab_size
        self.embedding_size = embedding_size
        self.input_length = input_length
        self.lstm_size = lstm_size

        # Initialize Embedding layer
        self.embeding = Embedding(input_dim = self.inp_vocab_size, output_dim = self.embedding_size, input_length

        # Intialize Encoder LSTM layer
        self.lstm = LSTM(units = self.lstm_size, return_state = True, return_sequences = True,  name = 'LSTM_Enco

    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 ouput to encoder_lstm
        returns -- encoder_output, last time step's hidden and cell state
        '''

        input_embeddings = self.embeding(input_sequence)
```

```
        self.encoder_output, self.encoder_last_state_h, self.encoder_last_state_c = self.lstm(input_embeddings) #
        return self.encoder_output, self.encoder_last_state_h, self.encoder_last_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 zeros is of size [32,lstm_
        '''

        self.st_h = tf.zeros((batch_size, self.lstm_size))
        self.st_i = tf.zeros((batch_size, self.lstm_size))

        return self.st_h, self.st_i
```

Grader function - 1

In [18]:
```
def grader_check_encoder():

    '''
        vocab-size: Unique words of the input language,
        embedding_size: output embedding dimension for each word after embedding layer,
        lstm_size: Number of lstm units,
        input_length: Length of the input sentence,
        batch_size
    '''

    vocab_size = 10
    embedding_size = 20
    lstm_size = 32
    input_length = 10
    batch_size = 16

    #Intialzing encoder
    encoder = Encoder(vocab_size, embedding_size, lstm_size, input_length)
    input_sequence = tf.random.uniform(shape = [batch_size, input_length], maxval = vocab_size, minval = 0, dtype

    #Intializing encoder initial states
    initial_state=encoder.initialize_states(batch_size)

    encoder_output,state_h,state_c=encoder(input_sequence,initial_state)

    assert(encoder_output.shape==(batch_size,input_length,lstm_size) and state_h.shape==(batch_size,lstm_size) an
    return True

print(grader_check_encoder())
```

```
True
```

In [19]:
```
class Decoder(tf.keras.Model):
    '''
    Encoder model -- That takes a input sequence and returns output sequence
    '''

    def __init__(self, out_vocab_size, embedding_size, lstm_size, input_length):
        super().__init__()


        self.out_vocab_size = out_vocab_size
        self.embedding_size = embedding_size
        self.input_length = input_length
        self.lstm_size = lstm_size

        # Initialize Embedding layer
        self.embeding = Embedding(input_dim = self.out_vocab_size, output_dim = self.embedding_size, input_length

        # Intialize Decoder LSTM layer
        self.lstm = LSTM(units = self.lstm_size, return_state = True, return_sequences = True, name = 'LSTM_Decod

    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 to decoder_lstm

          returns -- decoder_output, decoder_final_state_h, decoder_final_state_c
        '''

        input_embed = self.embeding(input_sequence)
        self.decoder_output, self.decoder_final_state_h, self.decoder_final_state_c = self.lstm(input_embed, init

        return self.decoder_output, self.decoder_final_state_h, self.decoder_final_state_c
```

Grader function - 2

In [20]:

```
def grader_decoder():

    '''
    out_vocab_size: Unique words of the target language,
    embedding_size: output embedding dimension for each word after embedding layer,
    dec_units: Number of lstm units in decoder,
    input_length: Length of the input sentence,
    batch_size
    '''

    out_vocab_size = 13
    embedding_dim = 12
    input_length = 10
    dec_units = 16
    batch_size = 32

    target_sentences = tf.random.uniform(shape = (batch_size, input_length), maxval = 10, minval = 0, dtype = tf.
    encoder_output = tf.random.uniform(shape = [batch_size, input_length, dec_units])
    state_h = tf.random.uniform(shape = [batch_size, dec_units])
    state_c = tf.random.uniform(shape = [batch_size, dec_units])
    states = [state_h, state_c]
    decoder = Decoder(out_vocab_size, embedding_dim, dec_units,input_length )
    output, _ ,_ = decoder(target_sentences, states)

    assert(output.shape == (batch_size, input_length, dec_units))
    return True

print(grader_decoder())
```

```
True
```

In [21]:

```
class Encoder_decoder(tf.keras.Model):

    def __init__(self, en_vocab_size, en_embed_size, en_inputs_length, en_units,
                    de_vocab_size, de_embed_size, de_inputs_length, de_units, batch_size):

        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 = en_vocab_size, embedding_size = en_embed_size,
                               lstm_size = en_inputs_length, input_length = en_units)

        self.decoder = Decoder(out_vocab_size = de_vocab_size, embedding_size = de_embed_size,
                               lstm_size = de_inputs_length, input_length = de_units)

        self.dense = Dense(de_vocab_size, activation = 'softmax')

    def call(self, data):

        '''
        A. Pass the input sequence to Encoder layer -- Return encoder_output,encoder_final_state_h,encoder_final_
        B. Pass the target sequence to Decoder layer with intial states as encoder_final_state_h,encoder_final_st
        C. Pass the decoder_outputs into Dense layer

        Return decoder_outputs
        '''

        encoder_in_eng, target_in_ita = data[0], data[1]

        # Intializing encoder initial states

        initial_state = self.encoder.initialize_states(self.batch_size)
        encoder_out, en_state_h, en_state_c = self.encoder(encoder_in_eng, initial_state)
        decoder_out, de_state_h, de_state_c = self.decoder(target_in_ita, [en_state_h, en_state_c])
        output = self.dense(decoder_out)

        return output
```

In [22]:

```
EPOCH = 71
BATCH_SIZE = 1024
MAX_INPUT_LEN = 20

if os.path.isdir('results'):
    shutil.rmtree('results')
```

In [23]:

```
# Create an object of encoder decoder Model class.
```

```
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]]) # need to pass list of va
        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='int32', padding='post')
        self.decoder_inp_seq = pad_sequences(self.decoder_inp_seq, maxlen=self.max_len, dtype='int32', padding='p
        self.decoder_out_seq = pad_sequences(self.decoder_out_seq, maxlen=self.max_len, dtype='int32', padding='p
        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 already converted into seq
        return tuple([[batch[0],batch[1]],batch[2]])

    def __len__(self):  # your 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 [24]:

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

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


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

```
(1024, 20) (1024, 20) (1024, 20)
```

In [25]:

```
model_1 = Encoder_decoder(en_vocab_size = vocab_size_ita + 1, en_embed_size = 100, en_inputs_length = MAX_INPUT_L
                de_vocab_size = vocab_size_eng + 1, de_embed_size = 100, de_inputs_length = MAX_INPUT_LEN, de_uni
```

In [26]:

```
def call_back_tBoard(model):

    log_dir = f'results/{model}/' + datetime.now().strftime('%y_%b%d_%H%M')
    return TensorBoard(log_dir = log_dir, histogram_freq = 1, write_graph = True)
```

In [27]:

```
print(f'GPU Available :: {tf.test.is_gpu_available()}\n')
!nvidia-smi
```

```
GPU Available :: True

Thu Dec  1 23:05:19 2022
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 470.82.01    Driver Version: 470.82.01    CUDA Version: 11.4     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
```

```
|   0  Tesla P100-PCIE...  Off  | 00000000:00:04.0 Off |                    0 |
| N/A   35C    P0    33W / 250W |  15849MiB / 16280MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
+-----------------------------------------------------------------------------+
```

In [28]:

```
# Compile the model and fit the model

optimizer_ = Adam(learning_rate = 0.0001)

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

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

tensorBord = call_back_tBoard('logs_1')

task_1 = model_1.fit(x = train_dataloader, validation_data = test_dataloader, epochs = EPOCH, steps_per_epoch = t
                     callbacks = [tensorBord])
```

```
Epoch 1/71
279/279 [==============================] - 56s 175ms/step - loss: 3.1840 - val_loss: 2.9625
Epoch 2/71
279/279 [==============================] - 46s 164ms/step - loss: 2.7014 - val_loss: 2.4943
Epoch 3/71
279/279 [==============================] - 46s 165ms/step - loss: 2.3594 - val_loss: 2.2435
Epoch 4/71
279/279 [==============================] - 46s 164ms/step - loss: 2.1624 - val_loss: 2.0902
Epoch 5/71
279/279 [==============================] - 47s 167ms/step - loss: 2.0401 - val_loss: 1.9944
Epoch 6/71
279/279 [==============================] - 49s 175ms/step - loss: 1.9641 - val_loss: 1.9355
Epoch 7/71
279/279 [==============================] - 46s 164ms/step - loss: 1.9178 - val_loss: 1.8998
Epoch 8/71
279/279 [==============================] - 46s 166ms/step - loss: 1.8893 - val_loss: 1.8772
Epoch 9/71
279/279 [==============================] - 46s 166ms/step - loss: 1.8699 - val_loss: 1.8604
Epoch 10/71
279/279 [==============================] - 46s 163ms/step - loss: 1.8558 - val_loss: 1.8496
Epoch 11/71
279/279 [==============================] - 46s 164ms/step - loss: 1.8473 - val_loss: 1.8428
Epoch 12/71
279/279 [==============================] - 45s 162ms/step - loss: 1.8413 - val_loss: 1.8374
Epoch 13/71
279/279 [==============================] - 46s 164ms/step - loss: 1.8359 - val_loss: 1.8320
Epoch 14/71
279/279 [==============================] - 47s 167ms/step - loss: 1.8299 - val_loss: 1.8256
Epoch 15/71
279/279 [==============================] - 46s 164ms/step - loss: 1.8236 - val_loss: 1.8199
Epoch 16/71
279/279 [==============================] - 46s 166ms/step - loss: 1.8181 - val_loss: 1.8145
Epoch 17/71
279/279 [==============================] - 46s 164ms/step - loss: 1.8123 - val_loss: 1.8084
Epoch 18/71
279/279 [==============================] - 46s 166ms/step - loss: 1.8055 - val_loss: 1.8013
Epoch 19/71
279/279 [==============================] - 46s 165ms/step - loss: 1.7984 - val_loss: 1.7945
Epoch 20/71
279/279 [==============================] - 47s 168ms/step - loss: 1.7914 - val_loss: 1.7874
Epoch 21/71
279/279 [==============================] - 47s 167ms/step - loss: 1.7822 - val_loss: 1.7754
Epoch 22/71
279/279 [==============================] - 46s 166ms/step - loss: 1.7677 - val_loss: 1.7596
Epoch 23/71
279/279 [==============================] - 45s 162ms/step - loss: 1.7514 - val_loss: 1.7436
Epoch 24/71
279/279 [==============================] - 47s 167ms/step - loss: 1.7354 - val_loss: 1.7278
Epoch 25/71
279/279 [==============================] - 46s 165ms/step - loss: 1.7189 - val_loss: 1.7108
Epoch 26/71
279/279 [==============================] - 47s 167ms/step - loss: 1.7003 - val_loss: 1.6910
Epoch 27/71
279/279 [==============================] - 49s 175ms/step - loss: 1.6793 - val_loss: 1.6698
Epoch 28/71
279/279 [==============================] - 46s 166ms/step - loss: 1.6575 - val_loss: 1.6483
Epoch 29/71
279/279 [==============================] - 46s 166ms/step - loss: 1.6360 - val_loss: 1.6274
Epoch 30/71
```

```
279/279 [==============================] - 46s 166ms/step - loss: 1.6152 - val_loss: 1.6072
Epoch 31/71
279/279 [==============================] - 45s 162ms/step - loss: 1.5951 - val_loss: 1.5877
Epoch 32/71
279/279 [==============================] - 46s 164ms/step - loss: 1.5759 - val_loss: 1.5696
Epoch 33/71
279/279 [==============================] - 46s 164ms/step - loss: 1.5579 - val_loss: 1.5523
Epoch 34/71
279/279 [==============================] - 46s 165ms/step - loss: 1.5404 - val_loss: 1.5353
Epoch 35/71
279/279 [==============================] - 47s 168ms/step - loss: 1.5231 - val_loss: 1.5185
Epoch 36/71
279/279 [==============================] - 47s 167ms/step - loss: 1.5060 - val_loss: 1.5019
Epoch 37/71
279/279 [==============================] - 46s 164ms/step - loss: 1.4891 - val_loss: 1.4854
Epoch 38/71
279/279 [==============================] - 46s 165ms/step - loss: 1.4722 - val_loss: 1.4687
Epoch 39/71
279/279 [==============================] - 46s 165ms/step - loss: 1.4553 - val_loss: 1.4525
Epoch 40/71
279/279 [==============================] - 47s 168ms/step - loss: 1.4389 - val_loss: 1.4367
Epoch 41/71
279/279 [==============================] - 46s 164ms/step - loss: 1.4229 - val_loss: 1.4213
Epoch 42/71
279/279 [==============================] - 48s 171ms/step - loss: 1.4073 - val_loss: 1.4064
Epoch 43/71
279/279 [==============================] - 46s 166ms/step - loss: 1.3922 - val_loss: 1.3919
Epoch 44/71
279/279 [==============================] - 46s 165ms/step - loss: 1.3773 - val_loss: 1.3776
Epoch 45/71
279/279 [==============================] - 46s 163ms/step - loss: 1.3631 - val_loss: 1.3641
Epoch 46/71
279/279 [==============================] - 46s 166ms/step - loss: 1.3496 - val_loss: 1.3514
Epoch 47/71
279/279 [==============================] - 46s 164ms/step - loss: 1.3368 - val_loss: 1.3394
Epoch 48/71
279/279 [==============================] - 46s 166ms/step - loss: 1.3247 - val_loss: 1.3280
Epoch 49/71
279/279 [==============================] - 47s 167ms/step - loss: 1.3130 - val_loss: 1.3170
Epoch 50/71
279/279 [==============================] - 46s 166ms/step - loss: 1.3019 - val_loss: 1.3066
Epoch 51/71
279/279 [==============================] - 47s 167ms/step - loss: 1.2911 - val_loss: 1.2966
Epoch 52/71
279/279 [==============================] - 46s 164ms/step - loss: 1.2807 - val_loss: 1.2870
Epoch 53/71
279/279 [==============================] - 46s 164ms/step - loss: 1.2707 - val_loss: 1.2776
Epoch 54/71
279/279 [==============================] - 46s 166ms/step - loss: 1.2610 - val_loss: 1.2686
Epoch 55/71
279/279 [==============================] - 46s 163ms/step - loss: 1.2515 - val_loss: 1.2598
Epoch 56/71
279/279 [==============================] - 47s 168ms/step - loss: 1.2424 - val_loss: 1.2513
Epoch 57/71
279/279 [==============================] - 46s 165ms/step - loss: 1.2334 - val_loss: 1.2429
Epoch 58/71
279/279 [==============================] - 46s 166ms/step - loss: 1.2247 - val_loss: 1.2348
Epoch 59/71
279/279 [==============================] - 48s 170ms/step - loss: 1.2161 - val_loss: 1.2269
Epoch 60/71
279/279 [==============================] - 47s 167ms/step - loss: 1.2078 - val_loss: 1.2193
Epoch 61/71
279/279 [==============================] - 47s 167ms/step - loss: 1.1996 - val_loss: 1.2116
Epoch 62/71
279/279 [==============================] - 46s 166ms/step - loss: 1.1915 - val_loss: 1.2042
Epoch 63/71
279/279 [==============================] - 47s 168ms/step - loss: 1.1837 - val_loss: 1.1970
Epoch 64/71
279/279 [==============================] - 47s 168ms/step - loss: 1.1761 - val_loss: 1.1898
Epoch 65/71
279/279 [==============================] - 47s 167ms/step - loss: 1.1686 - val_loss: 1.1829
Epoch 66/71
279/279 [==============================] - 47s 169ms/step - loss: 1.1611 - val_loss: 1.1761
Epoch 67/71
279/279 [==============================] - 48s 171ms/step - loss: 1.1539 - val_loss: 1.1693
Epoch 68/71
279/279 [==============================] - 47s 167ms/step - loss: 1.1467 - val_loss: 1.1627
Epoch 69/71
279/279 [==============================] - 46s 166ms/step - loss: 1.1397 - val_loss: 1.1562
Epoch 70/71
279/279 [==============================] - 47s 170ms/step - loss: 1.1328 - val_loss: 1.1499
Epoch 71/71
279/279 [==============================] - 46s 167ms/step - loss: 1.1261 - val_loss: 1.1437
```

In [29]:

```
model_1.summary()
```

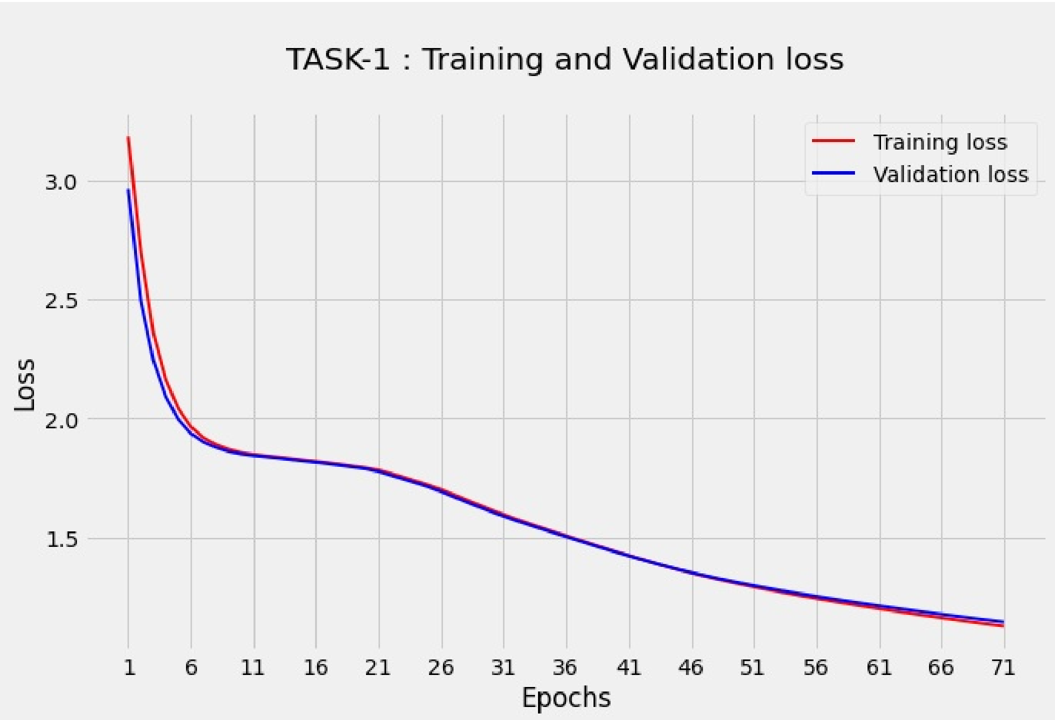
```
Model: "encoder_decoder"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
encoder_1 (Encoder)          multiple                  2695980   
_________________________________________________________________
decoder_1 (Decoder)          multiple                  1330380   
_________________________________________________________________
dense (Dense)                multiple                  277347    
=================================================================
Total params: 4,303,707
Trainable params: 4,303,707
Non-trainable params: 0
_________________________________________________________________
```

In [30]:

```
def save_nd_plot_curve(task, Task, steps, model, model_name):

    model.save_weights(f'results/{model_name}.h5')

    task_train_loss = task.history['loss']
    task_valid_loss = task.history['val_loss']

    plt.figure(figsize = (10, 6))
    epochs = range(1, len(task_train_loss) + 1 )
    plt.plot(epochs, task_train_loss, 'r', lw = 2, label = 'Training loss')
    plt.plot(epochs, task_valid_loss, 'b', lw = 2, label = 'Validation loss')
    plt.title(f'\n{Task} : Training and Validation loss\n')
    plt.xticks(range(1, len(epochs) + 1, steps))
    plt.xlabel('Epochs'); plt.ylabel('Loss')
    plt.legend()
    plt.show()
```

In [31]:

```
save_nd_plot_curve(task_1, 'TASK-1', 5, model_1, 'model_1')
```



In [32]:

```
def predict(input_sentence, model):

    '''
    A. Given input sentence, convert the sentence into integers using tokenizer used earlier
    B. Pass the input_sequence to encoder. we get encoder_outputs, last time step hidden and cell state
    C. Initialize index of <start> as input to decoder. and encoder final states as input_states to decoder
    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 output, using the tokenizer(wor
         Update the input_to_decoder with current predictions
    F. Return the predicted sentence
    '''
#     A. Given input sentence, convert the sentence into integers using tokenizer used earlier
    encoder_inp = tknizer_ita.texts_to_sequences([input_sentence])
    encoder_inp_pad_seq = pad_sequences(encoder_inp, maxlen = 20, dtype = 'int32', padding = 'post')
```

```
#     B. Pass the input_sequence to encoder. we get encoder_outputs, last time step hidden and cell state
    initial_stat = model.layers[0].initialize_states(1) # Batch size is 1, because we are only giving one at a ti
    encoder_output, encoder_h, encoder_c  = model.layers[0](encoder_inp_pad_seq, initial_stat) # Encoder Layer

#     C. Initialize index of <start> as input to decoder. and encoder final states as input_states to decoder
    start_idx = tknizer_eng.word_index['<start>']
    end_idx = tknizer_eng.word_index['<end>']
    curr_vec = np.ones((1, 1))
    init_states = [encoder_h, encoder_c]

#     D. till we reach max_length of decoder or till the model predicted word <end>:

    predicted_string = []

    for idx in range(MAX_INPUT_LEN):

        predicted_out, state_h, state_c = model.layers[1](curr_vec, init_states) # Decoder Layer
        init_states = [state_h, state_c]
        predicted = model.layers[2](predicted_out) # Denes Layer
        predicted_index = np.argmax(predicted)

        if predicted_index == end_idx or predicted_index == 0:
            break

        predicted_string.append(tknizer_eng.index_word[predicted_index])

        curr_vec = np.reshape(predicted_index, (1, 1))

#     F. Return the predicted sentence
    return ' '.join(predicted_string)
```

In [33]:

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

validation_sampled = validation.sample(1000, random_state = 43)

def generate_predictoins(valid):

    g_truth, predicted_ressult = [], []

    for value in tqdm(valid.values):
        g_truth.append(re.sub(r'<\w*>', '', value[1]).strip())
        predicted_ressult.append(predict(value[0], model_1).strip())

    return g_truth, predicted_ressult

g_truth, predicted_ressult = generate_predictoins(validation_sampled)
```

```
100%|██████████| 1000/1000 [00:53<00:00, 18.86it/s]
```

In [34]:

```
avg_bleu_score = []
for g_t, p_r in zip(g_truth, predicted_ressult):
    avg_bleu_score.append(sentence_bleu([g_t], p_r))

print(f'Average Bleu Score :: {np.mean(avg_bleu_score)}')
```

```
Average Bleu Score :: 0.20797411217743747
```

Task -2: Including Attention mechanisum

1. Use the preprocessed data from Task-1

2. You have to implement an Encoder and Decoder architecture with attention as discussed in the reference notebook.

   - Encoder - with 1 layer LSTM
   - Decoder - with 1 layer LSTM
   - attention - (Please refer the **reference notebook** to know more about the attention mechanism.)

3. In Global attention, we have 3 types of scoring functions(as discussed in the reference notebook). As a part of this assignment **you need**

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

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

to create 3 models for each scoring function

- 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.

Please do add the markdown titles for each model so that we can have a better look at the code and verify.

4. It is mandatory to train the model with simple model.fit() only, Donot train the model with custom GradientTape()
5. Using attention weights, you can plot the attention plots, please plot those for 2-3 examples. You can check about those in this
6. The attention layer has to be written by yourself only. The main objective of this assignment is to read and implement a paper on yourself so please do it yourself.
7. Please implement the class **onestepdecoder** as mentioned in the assignment instructions.
8. You can use any tf.Keras highlevel API's to build and train the models. Check the reference notebook for better understanding.
9. Use BLEU score as metric to evaluate your model. You can use any loss function you need.
10. You have to use Tensorboard to plot the Graph, Scores and histograms of gradients.
11. Resources: a. Check the reference notebook b. Resource 1 c. Resource 2 d. Resource 3

Implement custom encoder decoder and attention layers

Encoder

In [35]:

```
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__()

        self.inp_vocab_size = inp_vocab_size
        self.embedding_size = embedding_size
        self.input_length = input_length
        self.lstm_size = lstm_size

        # Initialize Embedding layer
        self.embeding = Embedding(input_dim = self.inp_vocab_size, output_dim = self.embedding_size, input_length

        # Intialize Encoder LSTM layer
        self.lstm = LSTM(units = self.lstm_size, return_state = True, return_sequences = True,  name = 'LSTM_Enco


    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 ouput to encoder_lstm
        returns -- All encoder_outputs, last time steps hidden and cell state
        '''

        input_embeddings = self.embeding(input_sequence)
        self.encoder_output, self.encoder_last_state_h, self.encoder_last_state_c = self.lstm(input_embeddings) #
        return self.encoder_output, self.encoder_last_state_h, self.encoder_last_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 zeros is of size [32,lstm_
        '''

        self.st_h = tf.zeros((batch_size, self.lstm_size))
        self.st_i = tf.zeros((batch_size, self.lstm_size))
```

```
        return self.st_h, self.st_i
```

Grader function - 1

In [36]:

```
def grader_check_encoder():

    '''
        vocab-size: Unique words of the input language,
        embedding_size: output embedding dimension for each word after embedding layer,
        lstm_size: Number of lstm units in encoder,
        input_length: Length of the input sentence,
        batch_size
    '''

    vocab_size=10
    embedding_size=20
    lstm_size=32
    input_length=10
    batch_size=16
    encoder=Encoder(vocab_size,embedding_size,lstm_size,input_length)
    input_sequence=tf.random.uniform(shape=[batch_size,input_length],maxval=vocab_size,minval=0,dtype=tf.int32)
    initial_state=encoder.initialize_states(batch_size)
    encoder_output,state_h,state_c=encoder(input_sequence,initial_state)

    assert(encoder_output.shape==(batch_size,input_length,lstm_size) and state_h.shape==(batch_size,lstm_size) ar
    return True

print(grader_check_encoder())
```

```
True
```

Attention

In [37]:

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

#     Please go through the reference notebook and research paper to complete the scoring functions
        self.scoring_function = scoring_function
        self.att_units = att_units

        if self.scoring_function == 'dot':
          # Intialize variables needed for Dot score function here
          pass

        if scoring_function == 'general':
            # Intialize variables needed for General score function here
            self.fc = Dense(units = self.att_units)

        elif scoring_function == 'concat':
            self.WE = Dense(units = self.att_units)
            self.WD = Dense(units = self.att_units)
            self.v = Dense(units = 1)
            # Intialize variables needed for Concat score function here


    def call(self, decoder_hidden_state, encoder_output):
        '''
        Attention mechanism takes two inputs current step -- decoder_hidden_state and all the encoder_outputs.
        * Based on the scoring function we will find the score or similarity between decoder_hidden_state and enc
        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 = expand_dims(decoder_hidden_state, axis = 1)

        if self.scoring_function == 'dot':
            # Implement Dot score function here

            similarity_ =  Dot(axes = (2, 2))([encoder_output, decoder_hidden_state])

        elif self.scoring_function == 'general':
            # Implement General score function here

            weighted_encoder_out =  self.fc(encoder_output)
            similarity_ = Dot(axes = (2, 2))([weighted_encoder_out, decoder_hidden_state])

        elif self.scoring_function == 'concat':
            # Implement General score function here
```

```
            weighted_encoder = self.WE(encoder_output)
            weighted_decoder = self.WD(decoder_hidden_state)
            tan_h_act = tanh(weighted_decoder + weighted_encoder)
            similarity_ = self.v(tan_h_act)


#         attention_weights = Softmax(axis=1)(similarity)
        attention_wt = softmax(similarity_, axis = 1)
        context_v =  attention_wt * encoder_output
        context_v = reduce_sum(context_v, axis = 1)
        return context_v, attention_wt
```

Grader function - 2

In [38]:

```
def grader_check_attention(scoring_fun):

    '''
    att_units: Used in matrix multiplications for scoring functions,
    input_length: Length of the input sentence,
    batch_size
    '''

    input_length=10
    batch_size=16
    att_units=32

    state_h = tf.random.uniform(shape = [batch_size, att_units])
    encoder_output = tf.random.uniform(shape = [batch_size, input_length, att_units])
    attention = Attention(scoring_fun, att_units)
    context_vector,attention_weights = attention(state_h, encoder_output)
    assert(context_vector.shape == (batch_size, att_units) and attention_weights.shape == (batch_size, input_leng

    return True

print(f"'dot'\t\t: {grader_check_attention('dot')}")
print(f"'general'\t: {grader_check_attention('general')}")
print(f"'concat'\t: {grader_check_attention('concat')}")
```

```
'dot'           : True
'general'       : True
'concat'        : True
```

OneStepDecoder

In [39]:

```
class OneStepDecoder(tf.keras.Model):

    def __init__(self,tar_vocab_size, embedding_dim, input_length, dec_units ,score_fun ,att_units):
        #         Initialize decoder embedding layer, LSTM and any other objects needed

        super().__init__()
        self.tar_vocab_size = tar_vocab_size
        self.embedding_dim = embedding_dim
        self.input_length = input_length
        self.dec_units = dec_units
        self.score_fun = score_fun
        self.att_units = att_units

        self.embedding_layer = Embedding(input_dim = self.tar_vocab_size, output_dim = self.embedding_dim, mask_z
        self.lstm_1 = LSTM(units = self.dec_units, return_sequences = True, return_state = True, name = 'LSTM_One
        self.lstm_2 = LSTM(units = self.dec_units, return_sequences = True, return_state = True, name = 'LSTM_One

        self.attention = Attention(self.score_fun, self.att_units)

        self.fc = Dense(units = self.tar_vocab_size)

    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_size,1,embedding_dim)
        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 and cell state)
        E. Pass the decoder output to dense layer(vocab size) and store the result into output.
        F. Return the states from step D, output from Step E, attention weights from Step -B
        '''
#         A. Pass the input_to_decoder to the embedding layer and then get the output(batch_size, 1, embedding_di
        output_embedding = self.embedding_layer(input_to_decoder)
        decoder_out, decoder_state_h, decoder_state_c = self.lstm_1(encoder_output, initial_state = [state_h, sta

#         B. Using the encoder_output and decoder hidden state, compute the context vector.
        context_vec, attention_wt = self.attention(decoder_state_h, encoder_output)

#         C. Concat the context vector with the step A output
```

```
        combined_vec = tf.concat([expand_dims(context_vec, axis = 1), output_embedding], axis = -1)

#         D. Pass the Step-C output to LSTM/GRU and get the decoder output and states(hidden and cell state)
        decoder_out, decoder_h, decoder_c = self.lstm_2(combined_vec)

#         E. Pass the decoder output to dense layer(vocab size) and store the result into output.
        decoder_out = tf.reshape(decoder_out, (-1, decoder_out.shape[2]))
        output = self.fc(decoder_out)

#         F. Return the states from step D, output from Step E, attention weights from Step -B
        return output, decoder_h, decoder_c, attention_wt, context_vec
```

Grader function - 3

In [40]:

```
def grader_onestepdecoder(score_fun):

    '''
    tar_vocab_size: Unique words of the target language,
    embedding_dim: output embedding dimension for each word after embedding layer,
    dec_units: Number of lstm units in decoder,
    att_units: Used in matrix multiplications for scoring functions in attention class,
    input_length: Length of the target sentence,
    batch_size
    '''

    tar_vocab_size=13
    embedding_dim=12
    input_length=10
    dec_units=16
    att_units=16
    batch_size=32

    onestepdecoder = OneStepDecoder(tar_vocab_size, embedding_dim, input_length, dec_units ,score_fun ,att_units)
    input_to_decoder = tf.random.uniform(shape = (batch_size, 1), maxval = 10, minval = 0, dtype = tf.int32)
    encoder_output = tf.random.uniform(shape = [batch_size, input_length, dec_units])
    state_h = tf.random.uniform(shape = [batch_size, dec_units])
    state_c = tf.random.uniform(shape = [batch_size, dec_units])
    output, state_h, state_c, attention_weights, context_vector = onestepdecoder(input_to_decoder, encoder_output
    assert(output.shape == (batch_size, tar_vocab_size))
    assert(state_h.shape == (batch_size, dec_units))
    assert(state_c.shape == (batch_size, dec_units))
    assert(attention_weights.shape == (batch_size, input_length,1))
    assert(context_vector.shape == (batch_size, dec_units))

    return True

print(f"'dot'\t\t: {grader_onestepdecoder('dot')}")
print(f"'general'\t: {grader_onestepdecoder('general')}")
print(f"'concat'\t: {grader_onestepdecoder('concat')}")
```

```
'dot'           : True
'general'       : True
'concat'        : True
```

Decoder

In [41]:

```
class Decoder(tf.keras.Model):
    def __init__(self, out_vocab_size, embedding_dim, input_length, dec_units ,score_fun ,att_units):
        super().__init__()
#       Intialize necessary variables and create an object from the class onestepdecoder

        self.out_vocab_size = out_vocab_size
        self.embedding_dim = embedding_dim
        self.input_length = input_length
        self.dec_units = dec_units
        self.score_fun = score_fun
        self.att_units = att_units

        self.onestepdecoder = OneStepDecoder(tar_vocab_size = self.out_vocab_size, embedding_dim = self.embedding
                                             input_length = self.input_length, dec_units = self.dec_units,
                                             score_fun = self.score_fun, att_units = self.att_units)

    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 time step
#         Create a tensor array as shown in the reference notebook

        output_tf_arr = tf.TensorArray(tf.float32, size = self.input_length, name = 'Output_tf_array')

#         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
```

```
        for length in range(self.input_length):

            output, _, _, _, _ = self.onestepdecoder(input_to_decoder[:, length:length+1], encoder_output, decode
            output_tf_arr = output_tf_arr.write(length, output)

        output_tf_arr = tf.transpose(output_tf_arr.stack(),[1,0,2])

        return output_tf_arr
```

Grader function - 4

In [42]:
```
def grader_decoder(score_fun):

    '''
    out_vocab_size: Unique words of the target language,
    embedding_dim: output embedding dimension for each word after embedding layer,
    dec_units: Number of lstm units in decoder,
    att_units: Used in matrix multiplications for scoring functions in attention class,
    input_length: Length of the target sentence,
    batch_size
    '''

    out_vocab_size = 13
    embedding_dim = 12
    input_length = 11
    dec_units = 16
    att_units = 16
    batch_size = 32

    target_sentences = tf.random.uniform(shape = (batch_size, input_length), maxval = 10, minval = 0, dtype = tf.
    encoder_output = tf.random.uniform(shape = [batch_size, input_length, dec_units])
    state_h = tf.random.uniform(shape = [batch_size, dec_units])
    state_c = tf.random.uniform(shape = [batch_size, dec_units])

    decoder = Decoder(out_vocab_size, embedding_dim, input_length, dec_units ,score_fun ,att_units)
    output = decoder(target_sentences, encoder_output, state_h, state_c)
    assert(output.shape == (batch_size, input_length, out_vocab_size))

    return True

print(f"'dot'\t\t: {grader_decoder('dot')}")
print(f"'general'\t: {grader_decoder('general')}")
print(f"'concat'\t: {grader_decoder('concat')}")
```

```
'dot'           : True
'general'       : True
'concat'        : True
```

Encoder Decoder model

In [43]:
```
class encoder_decoder(tf.keras.Model):

    def __init__(self, enc_vocab_size, dec_vocab_size, en_embedding_size, dec_embedding_size, en_lstm_size, de_ls

        super().__init__()
        self.batch_size = batch_size

#     Intialize objects from encoder decoder

        self.encoder = Encoder(inp_vocab_size = enc_vocab_size, embedding_size = en_embedding_size, lstm_size = e

        self.decoder = Decoder(out_vocab_size = dec_vocab_size, embedding_dim = dec_embedding_size, input_length

    def call(self, data):

#     Intialize encoder states, Pass the encoder_sequence to the embedding layer
        encoder_input, decoder_input = data[0], data[1]
        en_out, en_h, en_c = self.encoder(encoder_input, self.encoder.initialize_states(self.batch_size))

#     Decoder initial states are encoder final states, Initialize it accordingly
        dec_h = en_h
        dec_c = en_c
        decoder_out = self.decoder(decoder_input, en_out, dec_h, dec_c)

#     return the decoder output
        return decoder_out
```

Custom loss function

In [44]:

```
In [44]:
# https://www.tensorflow.org/tutorials/text/image_captioning#model

loss_object = tf.keras.losses.SparseCategoricalCrossentropy(from_logits = True, 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-1. But in this loss funct
    for the padded zeros. i.e when the input is zero then we donot need to worry what the output is. This padded
    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

Implement dot function here.

```
In [45]:
# 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' .. e.t.c

# 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 fine.


EPOCH = 51
BATCH_SIZE = 512
MAX_INPUT_LEN = 20

train_dataset = Dataset(train, tknizer_ita, tknizer_eng, MAX_INPUT_LEN)

test_dataset  = Dataset(validation, tknizer_ita, tknizer_eng, MAX_INPUT_LEN)

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

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

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

```
In [46]:
tf.keras.backend.clear_session()

model_2_dot = encoder_decoder(enc_vocab_size = vocab_size_ita + 1, dec_vocab_size = vocab_size_eng + 1,
                en_embedding_size = 100, dec_embedding_size = 100,
                en_lstm_size = 256, de_lstm_size = 256,
                en_input_length = MAX_INPUT_LEN, de_input_length = MAX_INPUT_LEN,
                score_fun = 'dot', att_units = 256, batch_size = BATCH_SIZE)
```

```
In [47]:
# Compile the model and fit the model

model_2_dot.compile(optimizer_, loss = loss_function)

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

tensorBord = call_back_tBoard('logs_dot')

task_2_dot = model_2_dot.fit(x = train_dataloader, validation_data = test_dataloader, epochs = EPOCH, steps_per_e
                     callbacks = [tensorBord])
```

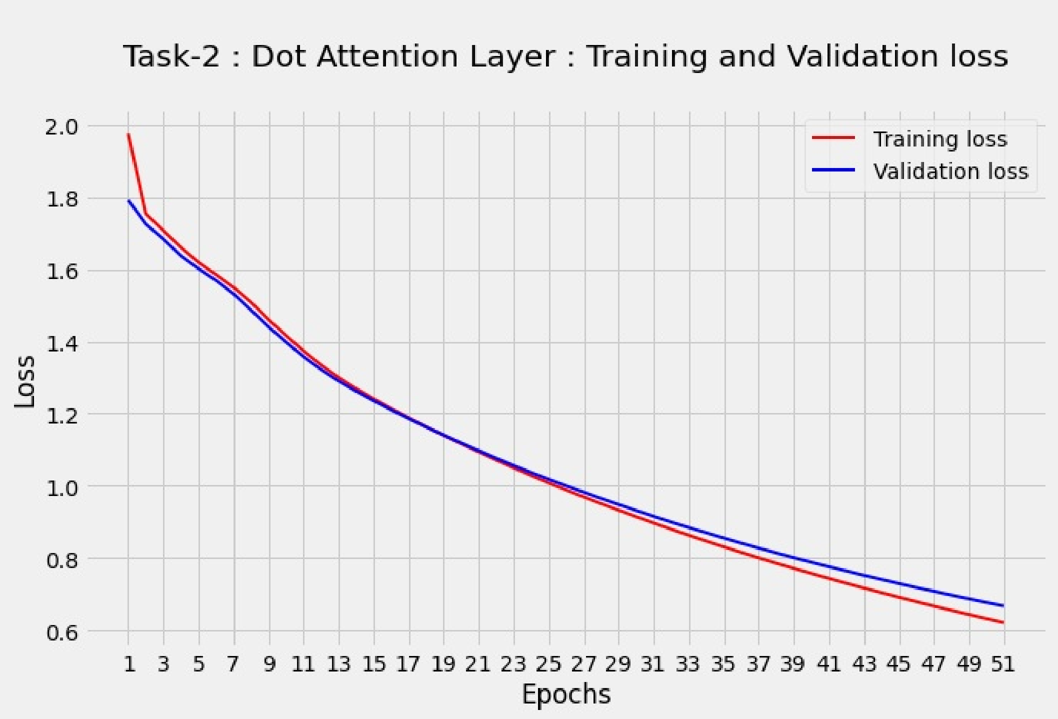
```
Epoch 1/51
559/559 [==============================] - 277s 336ms/step - loss: 1.9764 - val_loss: 1.7917
Epoch 2/51
559/559 [==============================] - 155s 277ms/step - loss: 1.7538 - val_loss: 1.7251
Epoch 3/51
559/559 [==============================] - 154s 275ms/step - loss: 1.7070 - val_loss: 1.6835
```

```
Epoch 4/51
559/559 [==============================] - 154s 275ms/step - loss: 1.6605 - val_loss: 1.6372
Epoch 5/51
559/559 [==============================] - 154s 275ms/step - loss: 1.6192 - val_loss: 1.6016
Epoch 6/51
559/559 [==============================] - 153s 274ms/step - loss: 1.5851 - val_loss: 1.5691
Epoch 7/51
559/559 [==============================] - 154s 276ms/step - loss: 1.5501 - val_loss: 1.5322
Epoch 8/51
559/559 [==============================] - 153s 274ms/step - loss: 1.5089 - val_loss: 1.4870
Epoch 9/51
559/559 [==============================] - 154s 276ms/step - loss: 1.4605 - val_loss: 1.4405
Epoch 10/51
559/559 [==============================] - 154s 276ms/step - loss: 1.4164 - val_loss: 1.3982
Epoch 11/51
559/559 [==============================] - 155s 277ms/step - loss: 1.3737 - val_loss: 1.3577
Epoch 12/51
559/559 [==============================] - 154s 276ms/step - loss: 1.3346 - val_loss: 1.3221
Epoch 13/51
559/559 [==============================] - 154s 276ms/step - loss: 1.3001 - val_loss: 1.2904
Epoch 14/51
559/559 [==============================] - 154s 276ms/step - loss: 1.2693 - val_loss: 1.2621
Epoch 15/51
559/559 [==============================] - 154s 275ms/step - loss: 1.2410 - val_loss: 1.2357
Epoch 16/51
559/559 [==============================] - 154s 276ms/step - loss: 1.2143 - val_loss: 1.2104
Epoch 17/51
559/559 [==============================] - 156s 279ms/step - loss: 1.1885 - val_loss: 1.1863
Epoch 18/51
559/559 [==============================] - 154s 276ms/step - loss: 1.1637 - val_loss: 1.1628
Epoch 19/51
559/559 [==============================] - 155s 276ms/step - loss: 1.1396 - val_loss: 1.1401
Epoch 20/51
559/559 [==============================] - 154s 276ms/step - loss: 1.1164 - val_loss: 1.1184
Epoch 21/51
559/559 [==============================] - 155s 277ms/step - loss: 1.0937 - val_loss: 1.0973
Epoch 22/51
559/559 [==============================] - 154s 276ms/step - loss: 1.0714 - val_loss: 1.0764
Epoch 23/51
559/559 [==============================] - 154s 275ms/step - loss: 1.0495 - val_loss: 1.0562
Epoch 24/51
559/559 [==============================] - 154s 276ms/step - loss: 1.0284 - val_loss: 1.0365
Epoch 25/51
559/559 [==============================] - 154s 275ms/step - loss: 1.0079 - val_loss: 1.0179
Epoch 26/51
559/559 [==============================] - 154s 276ms/step - loss: 0.9881 - val_loss: 0.9996
Epoch 27/51
559/559 [==============================] - 154s 275ms/step - loss: 0.9690 - val_loss: 0.9822
Epoch 28/51
559/559 [==============================] - 155s 277ms/step - loss: 0.9503 - val_loss: 0.9647
Epoch 29/51
559/559 [==============================] - 157s 281ms/step - loss: 0.9321 - val_loss: 0.9481
Epoch 30/51
559/559 [==============================] - 154s 275ms/step - loss: 0.9142 - val_loss: 0.9314
Epoch 31/51
559/559 [==============================] - 154s 276ms/step - loss: 0.8967 - val_loss: 0.9152
Epoch 32/51
559/559 [==============================] - 154s 276ms/step - loss: 0.8794 - val_loss: 0.8994
Epoch 33/51
559/559 [==============================] - 155s 276ms/step - loss: 0.8627 - val_loss: 0.8842
Epoch 34/51
559/559 [==============================] - 155s 277ms/step - loss: 0.8465 - val_loss: 0.8696
Epoch 35/51
559/559 [==============================] - 155s 277ms/step - loss: 0.8307 - val_loss: 0.8550
Epoch 36/51
559/559 [==============================] - 155s 277ms/step - loss: 0.8151 - val_loss: 0.8408
Epoch 37/51
559/559 [==============================] - 155s 277ms/step - loss: 0.8000 - val_loss: 0.8271
Epoch 38/51
559/559 [==============================] - 155s 277ms/step - loss: 0.7853 - val_loss: 0.8136
Epoch 39/51
559/559 [==============================] - 155s 277ms/step - loss: 0.7709 - val_loss: 0.8005
Epoch 40/51
559/559 [==============================] - 155s 278ms/step - loss: 0.7569 - val_loss: 0.7880
Epoch 41/51
559/559 [==============================] - 155s 277ms/step - loss: 0.7432 - val_loss: 0.7756
Epoch 42/51
559/559 [==============================] - 155s 278ms/step - loss: 0.7298 - val_loss: 0.7638
Epoch 43/51
559/559 [==============================] - 155s 278ms/step - loss: 0.7166 - val_loss: 0.7517
Epoch 44/51
559/559 [==============================] - 155s 277ms/step - loss: 0.7037 - val_loss: 0.7405
Epoch 45/51
559/559 [==============================] - 155s 278ms/step - loss: 0.6910 - val_loss: 0.7292
Epoch 46/51
559/559 [==============================] - 157s 281ms/step - loss: 0.6787 - val_loss: 0.7179
Epoch 47/51
559/559 [==============================] - 155s 277ms/step - loss: 0.6664 - val_loss: 0.7075
Epoch 48/51
```

```
559/559 [==============================] - 154s 275ms/step - loss: 0.6546 - val_loss: 0.6967
Epoch 49/51
559/559 [==============================] - 153s 274ms/step - loss: 0.6430 - val_loss: 0.6866
Epoch 50/51
559/559 [==============================] - 154s 275ms/step - loss: 0.6316 - val_loss: 0.6765
Epoch 51/51
559/559 [==============================] - 154s 275ms/step - loss: 0.6205 - val_loss: 0.6667
```

In [48]:

```
save_nd_plot_curve(task_2_dot, 'Task-2 : Dot Attention Layer', 2, model_2_dot, 'model_2_dot')
```



Inference

Plot attention weights

In [49]:

```
# Refer: https://www.tensorflow.org/tutorials/text/nmt_with_attention#translate

def plot_attention(sentence, model):

    pred_, input_sentence, attention_wt = predict(sentence, model)
    print(f'Input :: {input_sentence:>50}')
    print(f'Predicted translation :: {pred_:>16}\n')

    attention_wt = attention_wt[:len(pred_.split()), :len(input_sentence.split())]

    fig = plt.figure(figsize = (10, 10))
    ax = fig.add_subplot(1, 1, 1)
    cax = ax.matshow(attention_wt, cmap = 'viridis')
    fig.colorbar(cax)
    fontdict = {'fontsize': 12}

    imputs = input_sentence.split()
    preds_ = pred_.split()

    ax.set_xticklabels([''] + imputs, fontdict = fontdict, rotation = 90)
    ax.set_yticklabels([''] + preds_, 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.show()
```

Predict the sentence translation

In [50]:

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

```
    '''
    A. Given input sentence, convert the sentence into integers using tokenizer used earlier
    B. Pass the input_sequence to encoder. we get encoder_outputs, last time step hidden and cell state
    C. Initialize index of <start> as input to decoder. and encoder final states as input_states to onestepdecode
    D. till we reach max_length of decoder or till the model predicted word <end>:
         predictions, input_states, attention_weights = model.layers[1].onestepdecoder(input_to_decoder, encoder_
         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
    '''
#     A. Given input sentence, convert the sentence into integers using tokenizer used earlier
    encoder_inp = tknizer_ita.texts_to_sequences([input_sentence])
    encoder_inp_pad_seq = pad_sequences(encoder_inp, maxlen = 20, dtype = 'int32', padding = 'post')

#     B. Pass the input_sequence to encoder. we get encoder_outputs, last time step hidden and cell state
    initial_stat = model.layers[0].initialize_states(1) # Batch size is 1, because we are only giving one at a t
    encoder_output, encoder_h, encoder_c  = model.layers[0](encoder_inp_pad_seq, initial_stat) # Encoder Layer

#     C. Initialize index of <start> as input to decoder. and encoder final states as input_states to onestepdec
    curr_vec = np.array(tknizer_eng.word_index['<start>']).reshape(1,1)
    end_idx = tknizer_eng.word_index['<end>']

    attention_plot = np.zeros((20, 20))

#     D. till we reach max_length of decoder or till the model predicted word <end>:

    predicted_string = []

    for idx in range(MAX_INPUT_LEN):

        output, state_h, state_c, attention_weights, context_vector = model.layers[1].onestepdecoder(curr_vec, en

        attention_weights = tf.reshape(attention_weights, (-1, ))
        attention_plot[idx] = attention_weights.numpy()

        predicted_index = np.argmax(output)
        predicted_string.append(tknizer_eng.index_word[predicted_index])

        if predicted_index == end_idx or predicted_index == 0:
            break

        curr_vec = np.reshape(predicted_index, (1, 1))

#     F. Return the predicted sentence
    return ' '.join(predicted_string), input_sentence, attention_plot
```

In [51]:

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

# validation_sampled = validation.sample(1000, random_state = 43)

def generate_attention_predictoins(valid, model):

    g_truth, predicted_ressult = [], []

    for value in tqdm(valid.values):
        g_truth.append(re.sub(r'<\w*>', '', value[1]).strip())
        pred_, input_sentence, attention_wt = predict(value[0], model)

        predicted_ressult.append(pred_)

    return g_truth, predicted_ressult

g_truth, predicted_ressult = generate_attention_predictoins(validation_sampled, model_2_dot)
```

```
100%|██████████| 1000/1000 [01:40<00:00,  9.92it/s]
```

Calculate BLEU score

In [52]:

```
## 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 these sentences.
## https://www.nltk.org/_modules/nltk/translate/bleu_score.html

## Sample example
# import nltk.translate.bleu_score as bleu
# reference = ['i am groot'.split(),] # the original
# translation = 'it is ship'.split() # trasilated using model
# print('BLEU score: {}'.format(bleu.sentence_bleu(reference, translation)))
```

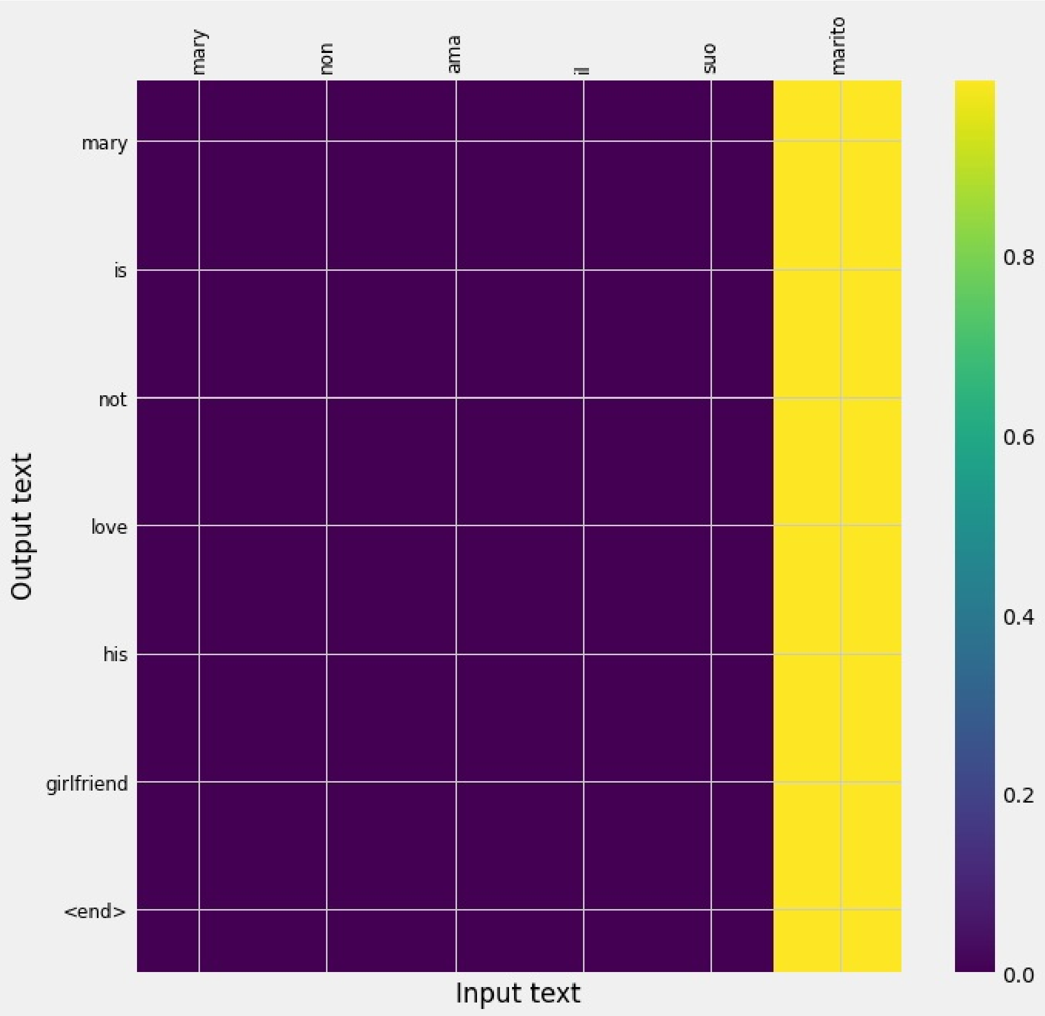
```
avg_bleu_score_att = []
for g_t, p_r in zip(g_truth, predicted_ressult):
    avg_bleu_score_att.append(sentence_bleu([g_t], p_r))

print(f'Average Bleu Score :: {np.mean(avg_bleu_score_att)}')
```

```
Average Bleu Score :: 0.33556081287880274
```

In [54]:

```
plot_attention('mary non ama il suo marito', model_2_dot)
```

```
Input ::                         mary non ama il suo marito
Predicted translation :: mary is not love his girlfriend <end>
```



Repeat the same steps for General scoring function

In [56]:

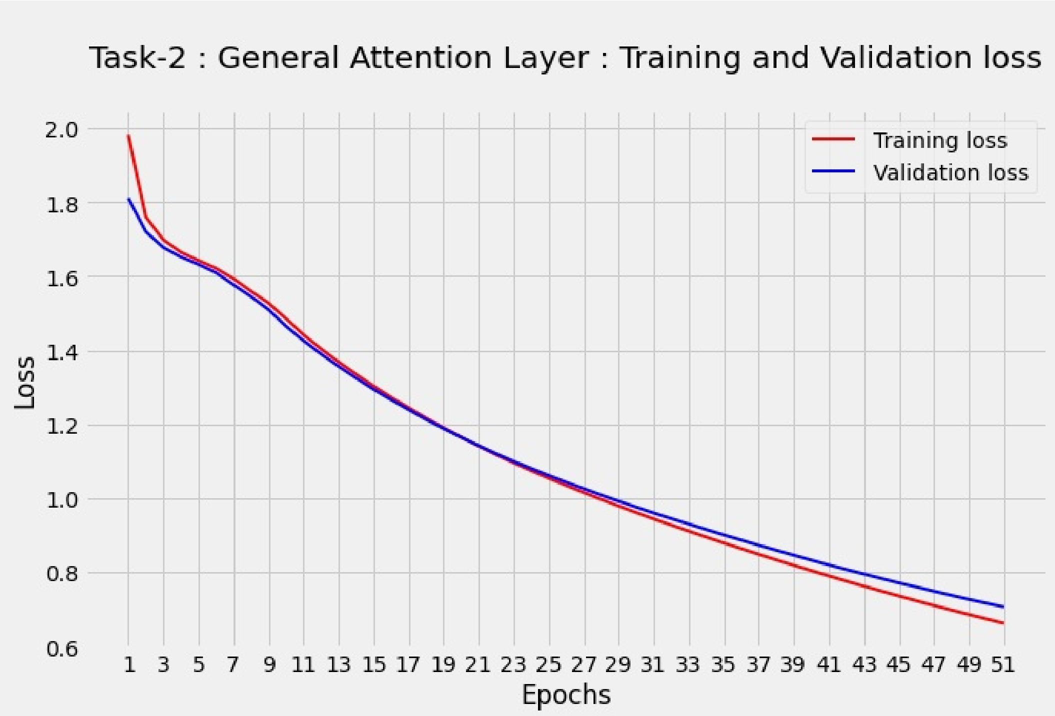
```
#Compile and train your model on general scoring function.
# Visualize few sentences randomly in Test data
# Predict on 1000 random sentences on test data and calculate the average BLEU score of these sentences.
# https://www.nltk.org/_modules/nltk/translate/bleu_score.html


model_2_general = encoder_decoder(enc_vocab_size = vocab_size_ita + 1, dec_vocab_size = vocab_size_eng + 1,
                en_embedding_size = 100, dec_embedding_size = 100,
                en_lstm_size = 256, de_lstm_size = 256,
                en_input_length = MAX_INPUT_LEN, de_input_length = MAX_INPUT_LEN,
                score_fun = 'general', att_units = 256, batch_size = BATCH_SIZE)

# Compile the model and fit the model

model_2_general.compile(optimizer_, loss = loss_function)

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

tensorBord = call_back_tBoard('logs_general')

task_2_general = model_2_general.fit(x = train_dataloader, validation_data = test_dataloader, epochs = EPOCH, ste
                    callbacks = [tensorBord])
```

```
Epoch 1/51
559/559 [==============================] - 292s 355ms/step - loss: 1.9827 - val_loss: 1.8112
Epoch 2/51
559/559 [==============================] - 162s 290ms/step - loss: 1.7601 - val_loss: 1.7205
Epoch 3/51
559/559 [==============================] - 162s 289ms/step - loss: 1.6983 - val_loss: 1.6776
Epoch 4/51
559/559 [==============================] - 163s 291ms/step - loss: 1.6650 - val_loss: 1.6521
Epoch 5/51
559/559 [==============================] - 162s 290ms/step - loss: 1.6424 - val_loss: 1.6321
Epoch 6/51
559/559 [==============================] - 162s 291ms/step - loss: 1.6215 - val_loss: 1.6097
Epoch 7/51
559/559 [==============================] - 163s 292ms/step - loss: 1.5935 - val_loss: 1.5771
Epoch 8/51
559/559 [==============================] - 163s 291ms/step - loss: 1.5597 - val_loss: 1.5452
Epoch 9/51
559/559 [==============================] - 163s 291ms/step - loss: 1.5276 - val_loss: 1.5099
Epoch 10/51
559/559 [==============================] - 163s 292ms/step - loss: 1.4857 - val_loss: 1.4651
Epoch 11/51
559/559 [==============================] - 163s 291ms/step - loss: 1.4419 - val_loss: 1.4258
Epoch 12/51
559/559 [==============================] - 163s 292ms/step - loss: 1.4038 - val_loss: 1.3901
Epoch 13/51
559/559 [==============================] - 163s 292ms/step - loss: 1.3683 - val_loss: 1.3565
Epoch 14/51
559/559 [==============================] - 163s 291ms/step - loss: 1.3352 - val_loss: 1.3249
Epoch 15/51
559/559 [==============================] - 164s 294ms/step - loss: 1.3030 - val_loss: 1.2943
Epoch 16/51
559/559 [==============================] - 163s 291ms/step - loss: 1.2729 - val_loss: 1.2663
Epoch 17/51
559/559 [==============================] - 163s 291ms/step - loss: 1.2446 - val_loss: 1.2394
Epoch 18/51
559/559 [==============================] - 163s 292ms/step - loss: 1.2169 - val_loss: 1.2129
Epoch 19/51
559/559 [==============================] - 164s 293ms/step - loss: 1.1903 - val_loss: 1.1883
Epoch 20/51
559/559 [==============================] - 162s 290ms/step - loss: 1.1653 - val_loss: 1.1648
Epoch 21/51
559/559 [==============================] - 162s 290ms/step - loss: 1.1410 - val_loss: 1.1419
Epoch 22/51
559/559 [==============================] - 163s 291ms/step - loss: 1.1177 - val_loss: 1.1203
Epoch 23/51
559/559 [==============================] - 163s 291ms/step - loss: 1.0955 - val_loss: 1.0998
Epoch 24/51
559/559 [==============================] - 163s 292ms/step - loss: 1.0745 - val_loss: 1.0803
Epoch 25/51
559/559 [==============================] - 162s 290ms/step - loss: 1.0541 - val_loss: 1.0615
Epoch 26/51
559/559 [==============================] - 162s 289ms/step - loss: 1.0345 - val_loss: 1.0432
Epoch 27/51
559/559 [==============================] - 162s 290ms/step - loss: 1.0154 - val_loss: 1.0257
Epoch 28/51
559/559 [==============================] - 163s 292ms/step - loss: 0.9968 - val_loss: 1.0085
Epoch 29/51
559/559 [==============================] - 162s 291ms/step - loss: 0.9788 - val_loss: 0.9920
Epoch 30/51
559/559 [==============================] - 162s 291ms/step - loss: 0.9612 - val_loss: 0.9757
Epoch 31/51
559/559 [==============================] - 164s 293ms/step - loss: 0.9440 - val_loss: 0.9600
Epoch 32/51
559/559 [==============================] - 163s 292ms/step - loss: 0.9274 - val_loss: 0.9451
Epoch 33/51
559/559 [==============================] - 163s 292ms/step - loss: 0.9110 - val_loss: 0.9302
Epoch 34/51
559/559 [==============================] - 161s 289ms/step - loss: 0.8948 - val_loss: 0.9152
Epoch 35/51
559/559 [==============================] - 162s 291ms/step - loss: 0.8790 - val_loss: 0.9006
Epoch 36/51
559/559 [==============================] - 162s 290ms/step - loss: 0.8635 - val_loss: 0.8868
Epoch 37/51
559/559 [==============================] - 162s 290ms/step - loss: 0.8482 - val_loss: 0.8727
Epoch 38/51
559/559 [==============================] - 161s 288ms/step - loss: 0.8332 - val_loss: 0.8591
Epoch 39/51
559/559 [==============================] - 161s 288ms/step - loss: 0.8185 - val_loss: 0.8459
Epoch 40/51
559/559 [==============================] - 163s 291ms/step - loss: 0.8041 - val_loss: 0.8326
Epoch 41/51
559/559 [==============================] - 161s 288ms/step - loss: 0.7899 - val_loss: 0.8196
Epoch 42/51
559/559 [==============================] - 161s 289ms/step - loss: 0.7759 - val_loss: 0.8070
Epoch 43/51
559/559 [==============================] - 163s 291ms/step - loss: 0.7621 - val_loss: 0.7950
Epoch 44/51
559/559 [==============================] - 164s 293ms/step - loss: 0.7487 - val_loss: 0.7830
```

```
Epoch 45/51
559/559 [==============================] - 162s 289ms/step - loss: 0.7356 - val_loss: 0.7711
Epoch 46/51
559/559 [==============================] - 161s 289ms/step - loss: 0.7226 - val_loss: 0.7599
Epoch 47/51
559/559 [==============================] - 162s 289ms/step - loss: 0.7099 - val_loss: 0.7482
Epoch 48/51
559/559 [==============================] - 162s 289ms/step - loss: 0.6975 - val_loss: 0.7373
Epoch 49/51
559/559 [==============================] - 161s 288ms/step - loss: 0.6853 - val_loss: 0.7264
Epoch 50/51
559/559 [==============================] - 162s 290ms/step - loss: 0.6734 - val_loss: 0.7162
Epoch 51/51
559/559 [==============================] - 163s 291ms/step - loss: 0.6617 - val_loss: 0.7061
```

In [57]:

```python
save_nd_plot_curve(task_2_general, 'Task-2 : General Attention Layer', 2, model_2_general, 'model_2_general')
```



In [58]:

```python
g_truth, predicted_ressult = generate_attention_predictoins(validation_sampled, model_2_general)
```

```
100%|██████████| 1000/1000 [01:53<00:00,  8.77it/s]
```

In [59]:

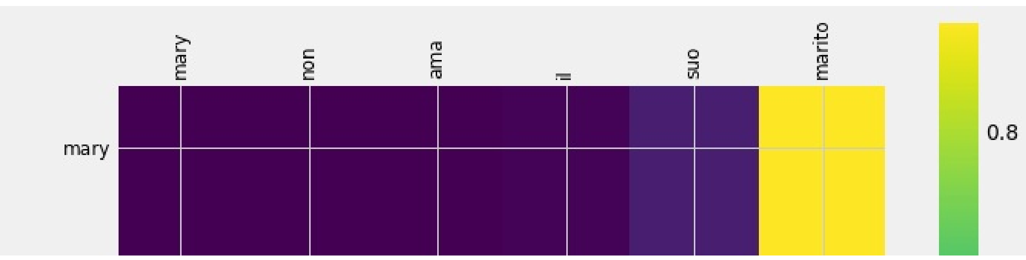
```python
avg_bleu_score_att = []
for g_t, p_r in zip(g_truth, predicted_ressult):
    avg_bleu_score_att.append(sentence_bleu([g_t], p_r))

print(f'Average Bleu Score :: {np.mean(avg_bleu_score_att)}')
```

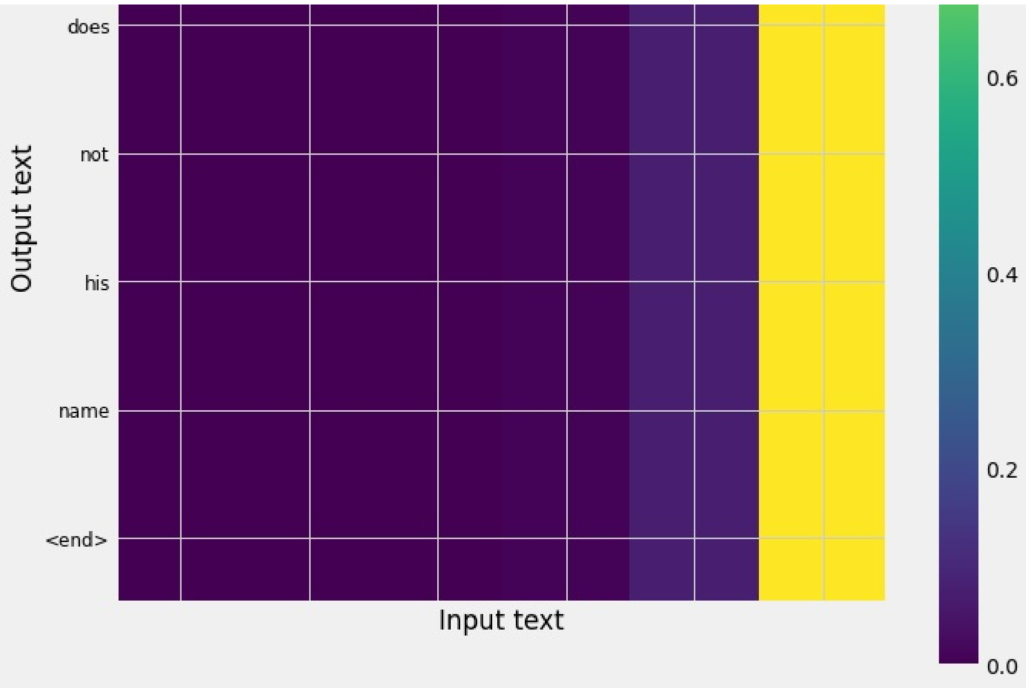
```
Average Bleu Score :: 0.3088731001455924
```

In [61]:

```python
plot_attention('mary non ama il suo marito', model_2_general)
```

```
Input ::                                 mary non ama il suo marito
Predicted translation :: mary does not his name <end>
```





Repeat the same steps for Concat scoring function

In [63]:

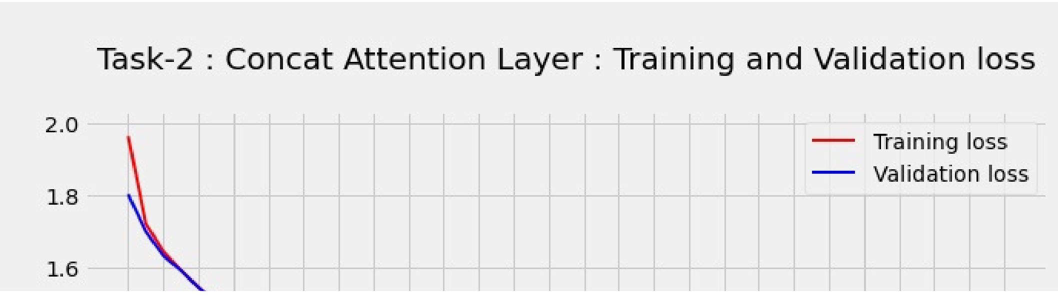
```
#Compile and train your model on concat scoring function.
# Visualize few sentences randomly in Test data
# Predict on 1000 random sentences on test data and calculate the average BLEU score of these sentences.
# https://www.nltk.org/_modules/nltk/translate/bleu_score.html

model_2_concat = encoder_decoder(enc_vocab_size = vocab_size_ita + 1, dec_vocab_size = vocab_size_eng + 1,
                en_embedding_size = 100, dec_embedding_size = 100,
                en_lstm_size = 256, de_lstm_size = 256,
                en_input_length = MAX_INPUT_LEN, de_input_length = MAX_INPUT_LEN,
                score_fun = 'concat', att_units = 256, batch_size = BATCH_SIZE)

# Compile the model and fit the model

model_2_concat.compile(optimizer_, loss = loss_function)

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

tensorBord = call_back_tBoard('logs_concat')

task_2_concat = model_2_concat.fit(x = train_dataloader, validation_data = test_dataloader, epochs = EPOCH, steps
                    callbacks = [tensorBord])
```

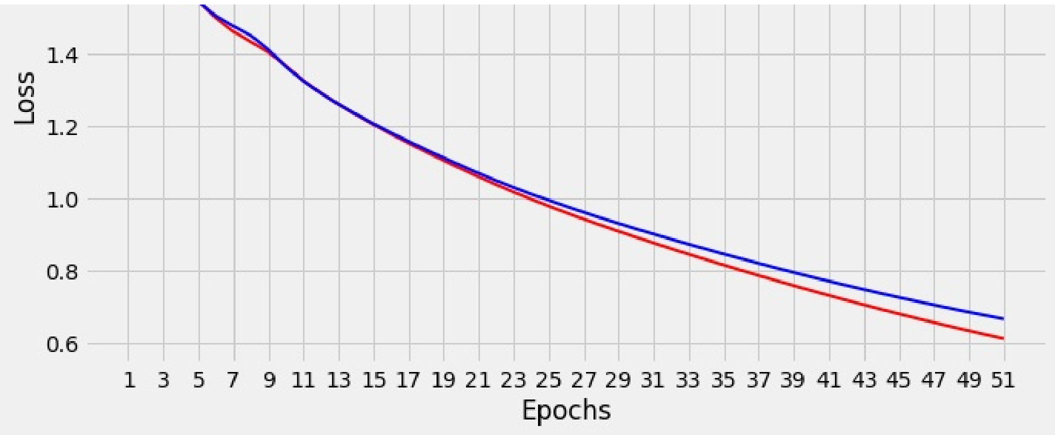
```
Epoch 1/51
559/559 [==============================] - 305s 378ms/step - loss: 1.9638 - val_loss: 1.8018
Epoch 2/51
559/559 [==============================] - 173s 310ms/step - loss: 1.7209 - val_loss: 1.6993
Epoch 3/51
559/559 [==============================] - 172s 307ms/step - loss: 1.6443 - val_loss: 1.6320
Epoch 4/51
559/559 [==============================] - 172s 308ms/step - loss: 1.5920 - val_loss: 1.5914
Epoch 5/51
559/559 [==============================] - 171s 307ms/step - loss: 1.5455 - val_loss: 1.5439
Epoch 6/51
559/559 [==============================] - 172s 307ms/step - loss: 1.4979 - val_loss: 1.5036
Epoch 7/51
559/559 [==============================] - 172s 308ms/step - loss: 1.4608 - val_loss: 1.4757
Epoch 8/51
559/559 [==============================] - 172s 308ms/step - loss: 1.4323 - val_loss: 1.4495
Epoch 9/51
559/559 [==============================] - 172s 308ms/step - loss: 1.4034 - val_loss: 1.4106
Epoch 10/51
559/559 [==============================] - 174s 311ms/step - loss: 1.3660 - val_loss: 1.3636
Epoch 11/51
559/559 [==============================] - 172s 307ms/step - loss: 1.3244 - val_loss: 1.3234
Epoch 12/51
559/559 [==============================] - 172s 308ms/step - loss: 1.2905 - val_loss: 1.2899
Epoch 13/51
559/559 [==============================] - 172s 308ms/step - loss: 1.2595 - val_loss: 1.2597
Epoch 14/51
559/559 [==============================] - 173s 310ms/step - loss: 1.2306 - val_loss: 1.2322
Epoch 15/51
559/559 [==============================] - 172s 308ms/step - loss: 1.2033 - val_loss: 1.2053
Epoch 16/51
```

```
559/559 [==============================] - 174s 312ms/step - loss: 1.1770 - val_loss: 1.1807
Epoch 17/51
559/559 [==============================] - 173s 310ms/step - loss: 1.1518 - val_loss: 1.1568
Epoch 18/51
559/559 [==============================] - 174s 311ms/step - loss: 1.1275 - val_loss: 1.1337
Epoch 19/51
559/559 [==============================] - 172s 308ms/step - loss: 1.1040 - val_loss: 1.1115
Epoch 20/51
559/559 [==============================] - 175s 312ms/step - loss: 1.0812 - val_loss: 1.0898
Epoch 21/51
559/559 [==============================] - 173s 309ms/step - loss: 1.0589 - val_loss: 1.0687
Epoch 22/51
559/559 [==============================] - 172s 308ms/step - loss: 1.0373 - val_loss: 1.0484
Epoch 23/51
559/559 [==============================] - 174s 312ms/step - loss: 1.0166 - val_loss: 1.0295
Epoch 24/51
559/559 [==============================] - 172s 308ms/step - loss: 0.9968 - val_loss: 1.0108
Epoch 25/51
559/559 [==============================] - 173s 309ms/step - loss: 0.9778 - val_loss: 0.9941
Epoch 26/51
559/559 [==============================] - 175s 313ms/step - loss: 0.9594 - val_loss: 0.9770
Epoch 27/51
559/559 [==============================] - 172s 308ms/step - loss: 0.9417 - val_loss: 0.9607
Epoch 28/51
559/559 [==============================] - 175s 313ms/step - loss: 0.9245 - val_loss: 0.9448
Epoch 29/51
559/559 [==============================] - 172s 308ms/step - loss: 0.9079 - val_loss: 0.9296
Epoch 30/51
559/559 [==============================] - 173s 309ms/step - loss: 0.8916 - val_loss: 0.9146
Epoch 31/51
559/559 [==============================] - 172s 308ms/step - loss: 0.8756 - val_loss: 0.9005
Epoch 32/51
559/559 [==============================] - 173s 309ms/step - loss: 0.8599 - val_loss: 0.8861
Epoch 33/51
559/559 [==============================] - 173s 309ms/step - loss: 0.8444 - val_loss: 0.8720
Epoch 34/51
559/559 [==============================] - 173s 309ms/step - loss: 0.8294 - val_loss: 0.8586
Epoch 35/51
559/559 [==============================] - 174s 312ms/step - loss: 0.8145 - val_loss: 0.8449
Epoch 36/51
559/559 [==============================] - 173s 310ms/step - loss: 0.7998 - val_loss: 0.8322
Epoch 37/51
559/559 [==============================] - 174s 311ms/step - loss: 0.7856 - val_loss: 0.8192
Epoch 38/51
559/559 [==============================] - 174s 311ms/step - loss: 0.7715 - val_loss: 0.8063
Epoch 39/51
559/559 [==============================] - 173s 309ms/step - loss: 0.7576 - val_loss: 0.7940
Epoch 40/51
559/559 [==============================] - 173s 309ms/step - loss: 0.7439 - val_loss: 0.7818
Epoch 41/51
559/559 [==============================] - 173s 310ms/step - loss: 0.7305 - val_loss: 0.7699
Epoch 42/51
559/559 [==============================] - 173s 310ms/step - loss: 0.7174 - val_loss: 0.7583
Epoch 43/51
559/559 [==============================] - 175s 313ms/step - loss: 0.7045 - val_loss: 0.7471
Epoch 44/51
559/559 [==============================] - 173s 309ms/step - loss: 0.6918 - val_loss: 0.7358
Epoch 45/51
559/559 [==============================] - 175s 313ms/step - loss: 0.6795 - val_loss: 0.7251
Epoch 46/51
559/559 [==============================] - 171s 306ms/step - loss: 0.6674 - val_loss: 0.7145
Epoch 47/51
559/559 [==============================] - 171s 307ms/step - loss: 0.6556 - val_loss: 0.7042
Epoch 48/51
559/559 [==============================] - 173s 309ms/step - loss: 0.6439 - val_loss: 0.6940
Epoch 49/51
559/559 [==============================] - 173s 309ms/step - loss: 0.6326 - val_loss: 0.6841
Epoch 50/51
559/559 [==============================] - 170s 305ms/step - loss: 0.6214 - val_loss: 0.6748
Epoch 51/51
559/559 [==============================] - 173s 309ms/step - loss: 0.6106 - val_loss: 0.6653
```

In [64]:

```
save_nd_plot_curve(task_2_concat, 'Task-2 : Concat Attention Layer', 2, model_2_concat, 'model_2_concat')
```

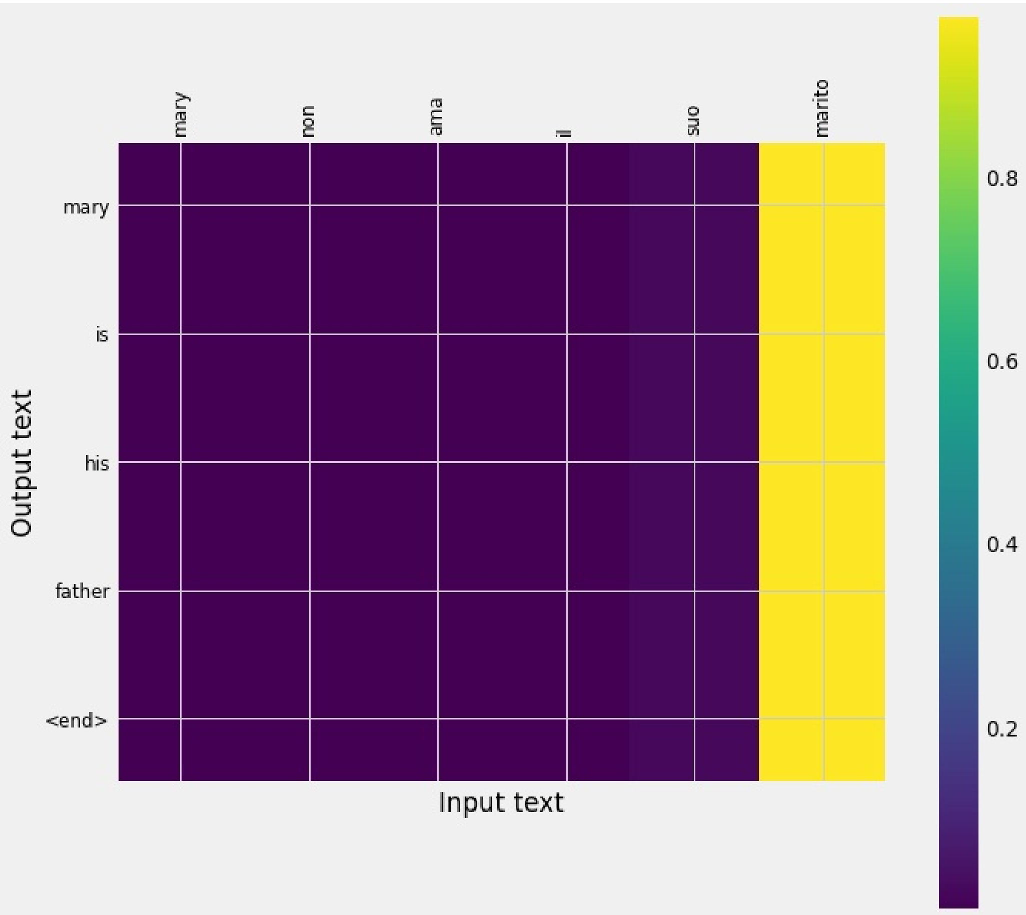




In [65]:
```
g_truth, predicted_ressult = generate_attention_predictoins(validation_sampled, model_2_concat)
```
```
100%|██████████| 1000/1000 [01:48<00:00,  9.25it/s]
```

In [66]:
```
avg_bleu_score_att = []
for g_t, p_r in zip(g_truth, predicted_ressult):
    avg_bleu_score_att.append(sentence_bleu([g_t], p_r))

print(f'Average Bleu Score :: {np.mean(avg_bleu_score_att)}')
```
```
Average Bleu Score :: 0.33176164376840245
```

In [68]:
```
plot_attention('mary non ama il suo marito', model_2_concat)
```
```
Input ::                          mary non ama il suo marito
Predicted translation :: mary is his father <end>
```



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