

## ▼ Sequence to sequence implementation

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. Implement a simple Encoder and Decoder architecture
4. BLEU score as metric to evaluate your model.
5. Use Tensorboard to plot the Graph, Scores and histograms of gradients.

### Load the data

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

```
--2022-01-24 19:51:40-- http://www.manythings.org/anki/ita-eng.zip
Resolving www.manythings.org (www.manythings.org)... 104.21.92.44, 172.67.186.54, 2606:2800:200:100:100:100:100:100
Connecting to www.manythings.org (www.manythings.org)|104.21.92.44|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 7757958 (7.4M) [application/zip]
Saving to: 'ita-eng.zip'
```

```
ita-eng.zip          100%[=====>]    7.40M  40.3MB/s   in 0.2s
```

```
2022-01-24 19:51:41 (40.3 MB/s) - 'ita-eng.zip' saved [7757958/7757958]
```

```
!unzip ita-eng.zip
```

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

### Preprocess data

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

```
--2022-01-24 19:52:10-- https://www.dropbox.com/s/ddkmtqz01jc024u/glove.6B.100d.txt
Resolving www.dropbox.com (www.dropbox.com)... 162.125.3.18, 2620:100:601b:18::a27d:f8
Connecting to www.dropbox.com (www.dropbox.com)|162.125.3.18|:443... connected.
```

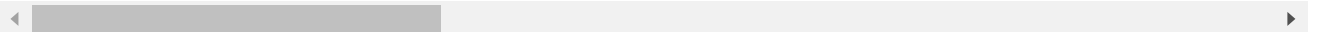
```

HTTP request sent, awaiting response... 301 Moved Permanently
Location: /s/raw/ddkmtqz01jc024u/glove.6B.100d.txt [following]
--2022-01-24 19:52:10-- https://www.dropbox.com/s/raw/ddkmtqz01jc024u/glove.6B.100d
Reusing existing connection to www.dropbox.com:443.
HTTP request sent, awaiting response... 302 Found
Location: https://uc20ceb1fdda04cf0b28c6f4b3b0.dl.dropboxusercontent.com/cd/0/inline
--2022-01-24 19:52:10-- https://uc20ceb1fdda04cf0b28c6f4b3b0.dl.dropboxusercontent.com/cd/0/inline
Resolving uc20ceb1fdda04cf0b28c6f4b3b0.dl.dropboxusercontent.com (uc20ceb1fdda04cf0b28c6f4b3b0.dl.dropboxusercontent.com)
Connecting to uc20ceb1fdda04cf0b28c6f4b3b0.dl.dropboxusercontent.com (uc20ceb1fdda04cf0b28c6f4b3b0.dl.dropboxusercontent.com)
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 69.1MB/s in 4.8s
```

```
2022-01-24 19:52:16 (69.0 MB/s) - 'glove.6B.100d.txt' saved [347116733/347116733]
```



```

import matplotlib.pyplot as plt
%matplotlib inline
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
from tensorflow.keras.callbacks import ModelCheckpoint, TensorBoard, ReduceLROnPlateau, EarlyStopping
import nltk.translate.bleu_score as bleu
from tqdm import tqdm
import random
from nltk.translate import bleu_score

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()

```

(353281, 2)

▲ ▲

```
def decontractions(phrase):
    """decontracted takes text and convert contractions into natural form.
    ref: https://stackoverflow.com/questions/19790188/expanding-english-language-contract
    # 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):
    # convert all the text into lower letters
    # use this function to remove the contractions: https://gist.github.com/anandborad/d41
    # 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 between brackets ( )
    # remove these characters: {'$', ')', '?', '"', '\'', '.', '°', '!', ';', '/', '"', '€'
    # replace these spl characters with space: '\u200b', '\xa0', '-', '/'
    # I have found these characters after observing the data points, feel free to explore
    # you are free to do more preprocessing
    # 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'].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 |

```
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 sentence add a token <end> so that we will have <end> in tokenizer
data.head()
```

/usr/local/lib/python3.7/dist-packages/ipykernel\_launcher.py:7: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: <https://pandas.pydata.org/pandas-docs/stable/10min.html#copy-on-write>

|   | 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>   |

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

|               | italian  | english_inp  | english_out  |
|---------------|--|--|--|
| <b>289143</b> | non è facile parlare bene in<br>francese             | <start> it is not easy to<br>speak french well       | it is not easy to speak french<br>well <end>         |
| <b>352481</b> | linsegnante ha affermato<br>che ci avrebbe fatto ... | <start> the teacher claimed<br>that he would have... | the teacher claimed that he<br>would have us all ... |
| <b>94461</b>  | i ragazzi hanno sete                                 | <start> the boys are thirsty                         | the boys are thirsty <end>                           |
| <b>21748</b>  | le due si sono baciato                               | <start> the two kissed                               | the two kissed <end>                                 |
| <b>349746</b> | che tipo di birra vuoi coshai<br>alla spina          | <start> what kind of beer do<br>you want what do ... | what kind of beer do you want<br>what do you have... |
| <b>106694</b> | io mi prenderò cura di te                            | <start> i will take care of you                      | i will take care of you <end>                        |
| <b>174771</b> | tom è un battitore molto<br>basso                    | <start> tom is a very good<br>batter                 | tom is a very good batter<br>batter                  |

```
data.to_csv('preprocessed_seq', index=False)
```

```
data2=pd.read_csv('preprocessed_seq')
```

```
from sklearn.model_selection import train_test_split
train, validation = train_test_split(data2, test_size=0.2)
```

```
print(train.shape, validation.shape)
```

```
(282230, 3) (70558, 3)
```

```
# for one sentence I will be adding <end> token so that the tokenizer learns the word <end>
# with this I 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.head(10)
```

**italian****english\_inp****english\_out****51527**

lei ha una foto

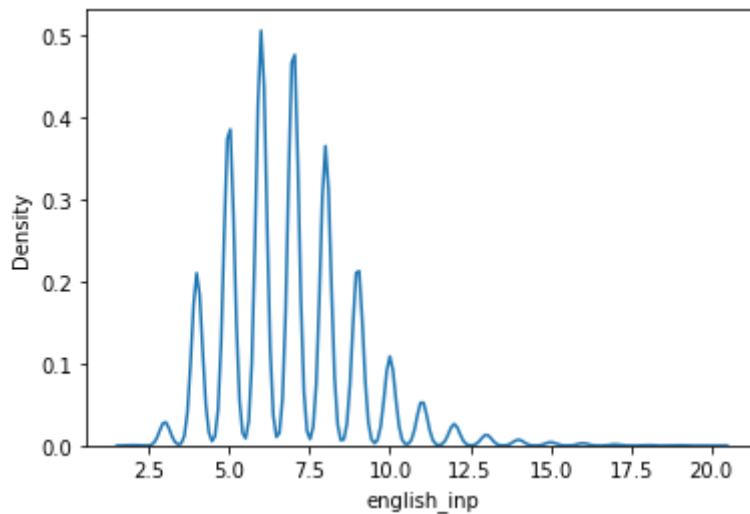
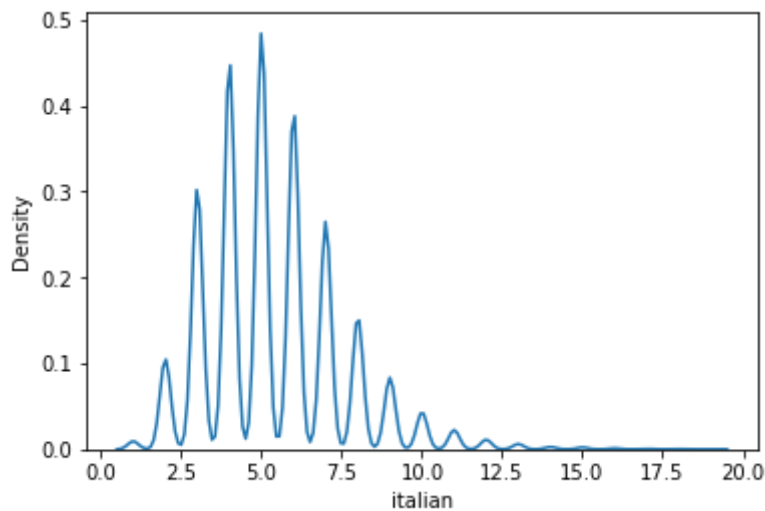
&lt;start&gt; she has a picture

she has a picture &lt;end&gt;

```

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()

```



## ▼ Implement custom encoder decoder

### Encoder

```

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)

```

```

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)
```

```
13121
26649
```

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

```
(1, 10365)
```

```
embeddings_index = dict()
f = open('glove.6B.100d.txt')
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
```

```
class Encoder(tf.keras.layers.Layer):
    def __init__(self, enc_vocab_size, embedding_dim, enc_lstm_size, input_length):
        super().__init__()
        self.enc_vocab_size = enc_vocab_size
        self.embedding_dim = embedding_dim
        self.input_length = input_length
        self.encoder_output=0
        self.lstm_size=enc_lstm_size
        self.lstm_output = 0
        self.enc_state_h=0
        self.enc_state_c=0

    def build(self, input_shape):
        self.embedding = Embedding(input_dim=self.enc_vocab_size, output_dim=self.embedding_dim,
                                   mask_zero=True, name="embedding_layer_encoder")
        self.lstm = LSTM(self.lstm_size, return_state=True, return_sequences=True, name="LSTM")

    def call(self, input_sentences, training=True):
        input_embedded= self.embedding(input_sentences)
        self.encoder_output, self.enc_state_h,self.enc_state_c = self.lstm(input_embedded)
        return self.encoder_output, self.enc_state_h,self.enc_state_c

    def initialize_states(self, batch_size):
        lstm_h=tf.zeros(shape=[batch_size,self.lstm_size])
```

```
lstm_c=tf.zeros(shape=[batch_size,self.lstm_size])

return [lstm_h,lstm_c]
```

## Grader function - 1

```
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,min
    #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==(b
    return True
print(grader_check_encoder())

True

class Decoder(tf.keras.layers.Layer):
    def __init__(self, dec_vocab_size, embedding_dim, dec_lstm_size,input_length):
        super().__init__()
        self.vocab_size = dec_vocab_size
        self.embedding_dim = 100
        #self.dec_units = dec_units
        self.lstm_size=dec_lstm_size
        self.input_length = input_length
        # we are using embedding_matrix and not training the embedding layer
        self.embedding = Embedding(input_dim=self.vocab_size, output_dim=self.embedding_di
                                mask_zero=True, name="embedding_layer_decoder")
        self.lstm = LSTM(self.lstm_size, return_sequences=True, return_state=True, name="D

    def call(self, target_sentences, initial_state):
        target_embedd = self.embedding(target_sentences)
        decoder_output,lstm_h,lstm_c = self.lstm(target_embedd, initial_state)
        return decoder_output,lstm_h,lstm_c
```



```
# initial_hidden_state=np.zeros((batch_size,self.lstm_size))
# initial_cell_state=np.zeros((batch_size,self.lstm_size))
```

## Grader function - 2

```
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,
    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

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

```
def __init__(self, enc_inputs_len,dec_inputs_len, ed_vocab_size,batch_size):
```

```
    #Create encoder object
    #Create decoder object
    #Initialize Dense layer(out_vocab_size) with activation='softmax'

    super().__init__()
```

```
    self.enc=Encoder(enc_vocab_size=vocab_size_ita+1,embedding_dim=50,enc_lstm_size=25
    self.dec=Decoder(dec_vocab_size=vocab_size_eng+1,embedding_dim=100,dec_lstm_size=2
    self.dense_ed=Dense(ed_vocab_size, activation='softmax')
    self.enc_states=self.enc.initialize_states(batch_size)
```

```
def call(self,input_ed):
```

```
    data_enc=input_ed[0]
```

```

data_dec=input_ed[1]
encoder_output,final_state_h,final_state_c=self.enc(data_enc,self.enc_states)
decoder_output,state_h,state_c=self.dec(data_dec,[final_state_h,final_state_c])
dense_ed=self.dense_ed(decoder_output)

return dense_ed

```

```
class Data_en:
```

```

    def __init__(self, data2, tknizer_ita, tknizer_eng, len_data):
        self.in_encoder = data2['italian'].values
        self.in_decoder = data2['english_inp'].values
        self.out_decoder = data2['english_out'].values
        self.tknizer_eng = tknizer_eng
        self.tknizer_ita = tknizer_ita
        self.len_data = len_data

    def __getitem__(self, i):
        self.encoder_seq = self.tknizer_ita.texts_to_sequences([self.in_encoder[i]]) # nee
        self.decoder_inp_seq = self.tknizer_eng.texts_to_sequences([self.in_decoder[i]])
        self.decoder_out_seq = self.tknizer_eng.texts_to_sequences([self.out_decoder[i]])

        self.encoder_seq = pad_sequences(self.encoder_seq, maxlen=self.len_data, dtype='in
        self.decoder_inp_seq = pad_sequences(self.decoder_inp_seq, maxlen=self.len_data, d
        self.decoder_out_seq = pad_sequences(self.decoder_out_seq, maxlen=self.len_data, d
        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.in_encoder)

```

```
class LoadData(tf.keras.utils.Sequence):
```

```

    def __init__(self, data_lan, batch_size=1):
        self.data_lan = data_lan
        self.batch_size = batch_size
        self.index_data = np.arange(len(self.data_lan.in_encoder))

    def __getitem__(self, i):
        a = i * self.batch_size
        b = (i + 1) * self.batch_size
        data_val = []
        for j in range(a, b):
            data_val.append(self.data_lan[j])

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

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

    def on_epoch_end(self):
        self.index_data = np.random.permutation(self.index_data)

```

```

train_enc1 = Data_en(train, tknizer_ita, tknizer_eng, 20)
test_ecn1 = Data_en(validation, tknizer_ita, tknizer_eng, 20)

train_load = LoadData(train_enc1, batch_size=1024)
test_load = LoadData(test_ecn1, batch_size=1024)

print(train_load[0][0][0].shape, train_load[0][0][1].shape, train_load[0][1].shape)

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

import os
import datetime
%load_ext tensorboard
logdir1 = os.path.join("logs1", datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
tensorboard_callback1= tf.keras.callbacks.TensorBoard(logdir1, histogram_freq=1)

model1=Encoder_decoder(enc_inputs_len=20,dec_inputs_len=20,ed_vocab_size=vocab_size_eng,ba
model1.compile(optimizer=tf.keras.optimizers.Adam(),loss='sparse_categorical_crossentropy'
train_steps1=train.shape[0]//1024
valid_steps1=validation.shape[0]//1024
model1.fit(train_load, steps_per_epoch=train_steps1, epochs=35, validation_data=train_load

274/274 [=====] - 71s 260ms/step - loss: 0.8336 - val_loss: 0.8336
Epoch 8/35
274/274 [=====] - 71s 259ms/step - loss: 0.7548 - val_loss: 0.7548
Epoch 9/35
274/274 [=====] - 82s 298ms/step - loss: 0.6850 - val_loss: 0.6850
Epoch 10/35
274/274 [=====] - 72s 261ms/step - loss: 0.6234 - val_loss: 0.6234
Epoch 11/35
274/274 [=====] - 71s 259ms/step - loss: 0.5681 - val_loss: 0.5681
Epoch 12/35
274/274 [=====] - 71s 259ms/step - loss: 0.5192 - val_loss: 0.5192
Epoch 13/35
274/274 [=====] - 82s 298ms/step - loss: 0.4747 - val_loss: 0.4747
Epoch 14/35
274/274 [=====] - 72s 262ms/step - loss: 0.4353 - val_loss: 0.4353
Epoch 15/35
274/274 [=====] - 82s 298ms/step - loss: 0.4000 - val_loss: 0.4000
Epoch 16/35
274/274 [=====] - 72s 261ms/step - loss: 0.3689 - val_loss: 0.3689
Epoch 17/35
274/274 [=====] - 71s 258ms/step - loss: 0.3408 - val_loss: 0.3408
Epoch 18/35
274/274 [=====] - 71s 260ms/step - loss: 0.3161 - val_loss: 0.3161
Epoch 19/35
274/274 [=====] - 71s 260ms/step - loss: 0.2938 - val_loss: 0.2938
Epoch 20/35
274/274 [=====] - 71s 259ms/step - loss: 0.2740 - val_loss: 0.2740
Epoch 21/35
274/274 [=====] - 71s 260ms/step - loss: 0.2560 - val_loss: 0.2560
Epoch 22/35
274/274 [=====] - 72s 263ms/step - loss: 0.2398 - val_loss: 0.2398
Epoch 23/35
274/274 [=====] - 71s 260ms/step - loss: 0.2252 - val_loss: 0.2252
Epoch 24/35
274/274 [=====] - 71s 260ms/step - loss: 0.2104 - val_loss: 0.2104
Epoch 25/35
274/274 [=====] - 71s 260ms/step - loss: 0.1956 - val_loss: 0.1956
Epoch 26/35
274/274 [=====] - 71s 260ms/step - loss: 0.1808 - val_loss: 0.1808
Epoch 27/35
274/274 [=====] - 71s 260ms/step - loss: 0.1660 - val_loss: 0.1660
Epoch 28/35
274/274 [=====] - 71s 260ms/step - loss: 0.1512 - val_loss: 0.1512
Epoch 29/35
274/274 [=====] - 71s 260ms/step - loss: 0.1364 - val_loss: 0.1364
Epoch 30/35
274/274 [=====] - 71s 260ms/step - loss: 0.1216 - val_loss: 0.1216
Epoch 31/35
274/274 [=====] - 71s 260ms/step - loss: 0.1068 - val_loss: 0.1068
Epoch 32/35
274/274 [=====] - 71s 260ms/step - loss: 0.0920 - val_loss: 0.0920
Epoch 33/35
274/274 [=====] - 71s 260ms/step - loss: 0.0772 - val_loss: 0.0772
Epoch 34/35
274/274 [=====] - 71s 260ms/step - loss: 0.0624 - val_loss: 0.0624
Epoch 35/35
274/274 [=====] - 71s 260ms/step - loss: 0.0476 - val_loss: 0.0476

```

```

274/274 [=====] - 71s 260ms/step - loss: 0.2253 - val_loss
Epoch 24/35
274/274 [=====] - 71s 259ms/step - loss: 0.2118 - val_loss
Epoch 25/35
274/274 [=====] - 71s 260ms/step - loss: 0.2002 - val_loss
Epoch 26/35
274/274 [=====] - 71s 260ms/step - loss: 0.1894 - val_loss
Epoch 27/35
274/274 [=====] - 72s 262ms/step - loss: 0.1792 - val_loss
Epoch 28/35
274/274 [=====] - 82s 298ms/step - loss: 0.1700 - val_loss
Epoch 29/35
274/274 [=====] - 72s 262ms/step - loss: 0.1617 - val_loss
Epoch 30/35
274/274 [=====] - 71s 259ms/step - loss: 0.1538 - val_loss
Epoch 31/35
274/274 [=====] - 82s 298ms/step - loss: 0.1470 - val_loss
Epoch 32/35
274/274 [=====] - 72s 262ms/step - loss: 0.1402 - val_loss
Epoch 33/35
274/274 [=====] - 71s 260ms/step - loss: 0.1339 - val_loss
Epoch 34/35
274/274 [=====] - 71s 260ms/step - loss: 0.1279 - val_loss
Epoch 35/35
274/274 [=====] - 82s 298ms/step - loss: 0.1225 - val_loss

```

```
model1.summary()
```

Model: "encoder\_decoder"

| Layer (type)                | Output Shape | Param # |
|-----------------------------|--------------|---------|
| encoder_1 (Encoder)         | multiple     | 1643268 |
| decoder_1 (Decoder)         | multiple     | 1673368 |
| dense (Dense)               | multiple     | 3360789 |
| Total params: 6,677,425     |              |         |
| Trainable params: 6,677,425 |              |         |
| Non-trainable params: 0     |              |         |

```
model1.save_weights('encoder_decoder_task1.h5')
```

```
def predict(input_sentence):
```

```

    in_enc_ita=tknizer_ita.texts_to_sequences([input_sentence])
    in_pad_seq_ita=pad_sequences(in_enc_ita,maxlen=20,padding='post',truncating='post',dtype
    embed_pred=model1.layers[0].embedding(in_pad_seq_ita)
    enc_output1,enc_state_h1,enc_state_c1=model1.layers[0].lstm(embed_pred)
    in_indexs_2d=tknizer_eng.word_index['<start>']
    in_indexs_2d=np.reshape(in_indexs_2d,(1,1))
    att=np.zeros((20,20))
    input_list=[]
    for j in range(20):
        out_pred,dec_state_h1,dec_state_c1=model1.layers[1](in_indexs_2d,[enc_state_h1,enc_sta

```

```

dense_out1=model1.layers[2](out_pred)
enc_state_h1=dec_state_h1
enc_state_c1=dec_state_c1
out_index=np.argmax(dense_out1)
in_indexs_2d=np.reshape(out_index,(1,1))
input_list.append(tknizer_eng.index_word[out_index])
if tknizer_eng.index_word[out_index]=='<end>':
    break
return ' '.join(input_list)

```

```

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

```

```

ita=validation['italian'].values[:1000]
eng=validation['english_out'].values[:1000]
blue=[]
for i in range(1000):
    pred_bl=predict(ita[i])
    blue.append(bleu_score.sentence_bleu(eng[i],pred_bl))

```

```

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

```

```

print(f'Bleu_score: {np.average(blue)}')

```

```

Bleu_score: 0.8361471092114097

```

Double-click (or enter) to edit

## ▼ Task -2: Including Attention mechanism

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 to create 3 models for each scoring**

**function**

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

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

- In model 1 you need to implement "dot" score function
- In model 2 you need to implement "general" score function
- In model 3 you need to implement "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, Do not 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

```
class Encoder(tf.keras.layers.Layer):
    def __init__(self, enc_vocab_size, embedding_dim, enc_lstm_size, input_length):
        super().__init__()
        self.enc_vocab_size = enc_vocab_size
        self.embedding_dim = embedding_dim
        self.input_length = input_length
        self.encoder_output=0
        self.lstm_size=enc_lstm_size
```

```

self.lstm_output = 0
self.enc_state_h=0
self.enc_state_c=0

def build(self, input_shape):
    self.embedding = Embedding(input_dim=self.enc_vocab_size, output_dim=self.embeddin
                                mask_zero=True, name="embedding_layer_encoder")
    self.lstm = LSTM(self.lstm_size, return_state=True, return_sequences=True, name="E

def call(self, input_sentences, training=True):
    input_embedd= self.embedding(input_sentences)
    self.encoder_output, self.enc_state_h,self.enc_state_c = self.lstm(input_embedd)
    return self.encoder_output, self.enc_state_h,self.enc_state_c

def initialize_states(self, batch_size):

    lstm_h=tf.zeros(shape=[batch_size,self.lstm_size])
    lstm_c=tf.zeros(shape=[batch_size,self.lstm_size])

    return [lstm_h,lstm_c]

```

## Grader function - 1

```

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,min
    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==(b
    return True
print(grader_check_encoder())

True

```

## Attention

```

class Attention(tf.keras.layers.Layer):
    ...

    Class the calculates score based on the scoring_function using Bahdanu attention mecha
    ...

def __init__(self,scoring_function, att_units):
    super().__init__()
    self.scoring_function=scoring_function
    # Please go through the reference notebook and research paper to complete the scoring
    if self.scoring_function=='dot':
        # Intialize variables needed for Dot score function here
        self.att_units=att_units
        self.softmax1=tf.keras.layers.Softmax(axis=1)
    if scoring_function == 'general':
        # Intialize variables needed for General score function here
        # Initializing the weights
        self.dense1=tf.keras.layers.Dense(self.att_units)
        self.softmax1=tf.keras.layers.Softmax(axis=1)
    elif scoring_function == 'concat':
        # Intialize variables needed for Concat score function here
        self.dense2=tf.keras.layers.Dense(self.att_units,activation='tanh')
        self.dense_att=tf.keras.layers.Dense(1)
        self.softmax1=tf.keras.layers.Softmax(axis=1)

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)
    ...

    if self.scoring_function == 'dot':

        # Implement Dot score function here
        d1=tf.keras.layers.Dot(axes=(2,1))([encoder_output,tf.reshape(decoder_hidden_state
                                                                    [decoder_hidden_state.shape[0],decoder_h

        d1_softmax=self.softmax1(d1)

        #Find the context vector
        d2=tf.keras.layers.Dot(axes=(1,2))([d1_softmax,
                                                                    tf.reshape(encoder_output,shape=[encoder

        dt_dot=tf.reshape(d2,shape=[d2.shape[0],d2.shape[2]])
        return dt_dot,d1_softmax

    elif self.scoring_function == 'general':
        # Implement General score function here
        d1=self.dense1(decoder_hidden_state)
        dt3=tf.reshape(d1,[d1.shape[0],d1.shape[1],1])
        dt_general=tf.keras.layers.Dot(axes=(2,1))([encoder_output,dt3])
        weights_general=self.softmax1(tf.cast(dt_general,dtype='float32'))

        # Find the context vector
        d2=tf.keras.layers.Dot(axes=(1,2))([weights_general,tf.reshape(encoder_output,shap

```



```
vector_general=tf.reshape(d2,shape=[d2.shape[0],d2.shape[2]])
return vector_general,weights_general
```

```
elif self.scoring_function == 'concat':
```

```
# Implementing concat function
dense_concat=self.dense_att(self.dense2(encoder_output)+tf.expand_dims(self.dense2
softmax_concat=self.softmax1(tf.cast(dense_concat,dtype='float32'))#Finding the at

#Finding the context vector

d2=tf.keras.layers.Dot(axes=(1,2))([softmax_concat,
                                     tf.reshape(encoder_output,shape=[encoder.
vector_concat=tf.reshape(d2,shape=[d2.shape[0],d2.shape[2]])
return vector_concat,softmax_concat
```

## Grader function - 2

```
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_length,att_units))
return True
```

```
print(grader_check_attention('dot'))
print(grader_check_attention('general'))
print(grader_check_attention('concat'))
```

```
True
True
True
```

## OneStepDecoder

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

```
    def __init__(self,tar_vocab_size, embedding_dim, input_length, dec_units ,score_fun ,att
```

```

    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.embed_osd=Embedding(input_dim = self.tar_vocab_size, output_dim = self.embedding_dim,
                             input_length = self.input_length, name="embedding_layer")
    self.lst_osd= LSTM(self.dec_units, return_sequences=True,return_state=True,name="lstm_decoder")

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

    self.dense_osd = Dense(self.tar_vocab_size)

def call(self,input_to_decoder, encoder_output, state_h,state_c):

    vec_osd,wgt=self.att_osd(state_h,encoder_output)
    embed_target=self.embed_osd(input_to_decoder)
    t=tf.expand_dims(vec_osd,1)
    cnct=tf.concat([embed_target,t],axis=2)
    output_osd, hid_osd, cell_osd=self.lst_osd(cnct)
    output_osd=tf.reshape(output_osd, (-1,output_osd.shape[2]))
    output_osd=self.dense_osd(output_osd)
    return output_osd, hid_osd, cell_osd, wgt, vec_osd

```

### Grader function - 3

```

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 ,
    input_to_decoder=tf.random.uniform(shape=(batch_size,1),maxval=10,minval=0,dtype=tf.float32),
    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_decode)
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(grader_onestepdecoder('dot'))
print(grader_onestepdecoder('general'))
print(grader_onestepdecoder('concat'))

```

```

True
True
True

```

## Decoder

```

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

    def call(self, input_to_decoder,encoder_output,decoder_hidden_state,decoder_cell_state
        var=tf.TensorArray(tf.float32,size=len(input_to_decoder[0]),name='tensor_deocoder')
        for i in range(len(input_to_decoder[0])):
            out1,hid_dec,cell_dec,wgt_dec,cnv_vec=self.onestep_decoder(input_to_decoder[:,i:i+
            var=var.write(i,out1)
        var=tf.transpose(var.stack(),[1,0,2])
        return var

```

## Grader function - 4

```

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,
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
output=decoder(target_sentences,encoder_output, state_h, state_c)
assert(output.shape==(batch_size,input_length,out_vocab_size))
return True
print(grader_decoder('dot'))
print(grader_decoder('general'))
print(grader_decoder('concat'))

True
True
True

```

## Encoder Decoder model

```

class encoder_decoder(tf.keras.Model):

    def __init__(self, input_len,output_len, score_ecm,att_units,batch_size):

        #Create encoder object
        #Create decoder object
        #Intialize Dense layer(out_vocab_size) with activation='softmax'

        super().__init__()
        self.input_len=input_len
        self.output_len=output_len
        self.score_ecm=score_ecm
        self.batch_size=batch_size
        self.att_units=att_units
        self.enc=Encoder(enc_vocab_size=vocab_size_ita+1,embedding_dim=50,input_length=inp
        self.dec=Decoder(out_vocab_size=vocab_size_eng+1,embedding_dim=100,dec_units=256,i
        self.enc_state1,self.encoder_state2=self.enc.initialize_states(self.batch_size)

    def call(self,input_ed):
        enc_output,enc_hid,enc_cell=self.enc(input_ed[0],[self.enc_state1,self.encoder_state
        decoder_output=self.dec(input_ed[1],enc_output,enc_hid,enc_cell)

```

```
return decoder_output
```

## Custom loss function

```
loss1= tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True, reduction='none')
def custom_lossfunction(targets, logits):

    # Custom loss function that will not consider the loss for padded zeros.
    # Refer https://www.tensorflow.org/tutorials/text/nmt_with_attention#define_the_optimize

    target=tf.math.logical_not(tf.math.equal(targets,0))
    loss2=loss1(targets,logits)
    #masking loss for padding

    target=tf.cast(target,dtype=loss2.dtype)
    loss2*=target

    return tf.reduce_mean(loss2)
```

## Training

Implement dot function here.

```
class Data_en:
    def __init__(self, data2, tknizer_ita, tknizer_eng, len_data):
        self.in_encoder = data2['italian'].values
        self.in_decoder = data2['english_inp'].values
        self.out_decoder = data2['english_out'].values
        self.tknizer_eng = tknizer_eng
        self.tknizer_ita = tknizer_ita
        self.len_data = len_data

    def __getitem__(self, i):
        self.encoder_seq = self.tknizer_ita.texts_to_sequences([self.in_encoder[i]]) # nee
        self.decoder_inp_seq = self.tknizer_eng.texts_to_sequences([self.in_decoder[i]])
        self.decoder_out_seq = self.tknizer_eng.texts_to_sequences([self.out_decoder[i]])

        self.encoder_seq = pad_sequences(self.encoder_seq, maxlen=self.len_data, dtype='in
        self.decoder_inp_seq = pad_sequences(self.decoder_inp_seq, maxlen=self.len_data, d
        self.decoder_out_seq = pad_sequences(self.decoder_out_seq, maxlen=self.len_data, d
        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.in_encoder)

class LoadData(tf.keras.utils.Sequence):
    def __init__(self, data_lan, batch_size=1):
        self.data_lan = data_lan
        self.batch_size = batch_size
        self.index_data = np.arange(len(self.data_lan.in_encoder))
```

```

def __getitem__(self, i):
    a = i * self.batch_size
    b = (i + 1) * self.batch_size
    data_val = []
    for j in range(a, b):
        data_val.append(self.data_lan[j])

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

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

def on_epoch_end(self):
    self.index_data = np.random.permutation(self.index_data)

train_enc1 = Data_en(train, tknizer_ita, tknizer_eng, 20)
test_ecn1 = Data_en(validation, tknizer_ita, tknizer_eng, 20)

train_load = LoadData(train_enc1, batch_size=1024)
test_load = LoadData(test_ecn1, batch_size=1024)

print(train_load[0][0][0].shape, train_load[0][0][1].shape, train_load[0][1].shape)

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

tf.config.run_functions_eagerly(False)

%load_ext tensorboard

The tensorboard extension is already loaded. To reload it, use:
%reload_ext tensorboard

import os
import datetime
logdir2 = os.path.join("logs2", datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
tensorboard_callback2= tf.keras.callbacks.TensorBoard(logdir1, histogram_freq=1)

model2 = encoder_decoder(input_len=20,output_len=20,score_ecm='dot',att_units=64,batch_size=1024)
model2.compile(optimizer=tf.keras.optimizers.Adam(),loss='sparse_categorical_crossentropy')
train_steps2=train.shape[0]//1024
valid_steps2=validation.shape[0]//1024

model2.fit(train_load, steps_per_epoch=train_steps2, epochs=20, validation_data=train_load)

Epoch 1/20
274/274 [=====] - 180s 634ms/step - loss: 2.2795 - val_loss

```

```

Epoch 2/20
274/274 [=====] - 161s 588ms/step - loss: 2.0567 - val_loss
Epoch 3/20
274/274 [=====] - 168s 615ms/step - loss: 1.9903 - val_loss
Epoch 4/20
274/274 [=====] - 161s 588ms/step - loss: 1.9337 - val_loss
Epoch 5/20
274/274 [=====] - 170s 620ms/step - loss: 1.9559 - val_loss
Epoch 6/20
274/274 [=====] - 161s 588ms/step - loss: 1.9167 - val_loss
Epoch 7/20
274/274 [=====] - 169s 616ms/step - loss: 1.8669 - val_loss
Epoch 8/20
274/274 [=====] - 169s 618ms/step - loss: 1.8785 - val_loss
Epoch 9/20
274/274 [=====] - 169s 616ms/step - loss: 2.0188 - val_loss
Epoch 10/20
274/274 [=====] - 169s 617ms/step - loss: 1.8769 - val_loss
Epoch 11/20
274/274 [=====] - 169s 617ms/step - loss: 1.8726 - val_loss
Epoch 12/20
274/274 [=====] - 162s 591ms/step - loss: 1.9173 - val_loss
Epoch 13/20
274/274 [=====] - 169s 617ms/step - loss: 1.8898 - val_loss
Epoch 14/20
274/274 [=====] - 169s 615ms/step - loss: 1.8776 - val_loss
Epoch 15/20
274/274 [=====] - 160s 584ms/step - loss: 1.8333 - val_loss
Epoch 16/20
274/274 [=====] - 161s 587ms/step - loss: 1.8258 - val_loss
Epoch 17/20
274/274 [=====] - 159s 580ms/step - loss: 1.8800 - val_loss
Epoch 18/20
274/274 [=====] - 169s 618ms/step - loss: 1.9721 - val_loss
Epoch 19/20
274/274 [=====] - 160s 584ms/step - loss: 1.8712 - val_loss
Epoch 20/20
274/274 [=====] - 161s 585ms/step - loss: 1.9660 - val_loss
<tensorflow.python.keras.callbacks.History at 0x7f22ba618b90>

```

```
model2.summary()
```

```
Model: "encoder_decoder_1"
```

| Layer (type)                | Output Shape | Param # |
|-----------------------------|--------------|---------|
| encoder_3 (Encoder)         | multiple     | 1643268 |
| decoder_5 (Decoder)         | multiple     | 5296558 |
| Total params: 6,939,826     |              |         |
| Trainable params: 6,939,826 |              |         |
| Non-trainable params: 0     |              |         |

```
model2.save_weights('seq_dot_model2.h5')
```

## ▼ Inference

### Plot attention weights

#Refer: [https://www.tensorflow.org/tutorials/text/nmt\\_with\\_attention#translate](https://www.tensorflow.org/tutorials/text/nmt_with_attention#translate)

```
import matplotlib.ticker as ticker
def plot_attention(attention,act,pred):

    pred,_=predict(act,plot_t2='dot')
    plot_att=attention[:len(pred.split(' ')),len(act.split(' '))]
    fig,ax = plt.subplots(figsize=(8,6))
    ax.matshow(attention,cmap='Blues')
    ax.set_xticklabels([''] + act.split(' '), rotation=90)
    ax.set_yticklabels([''] + pred.split(' '))
    plt.show()
```

### Predict the sentence translation

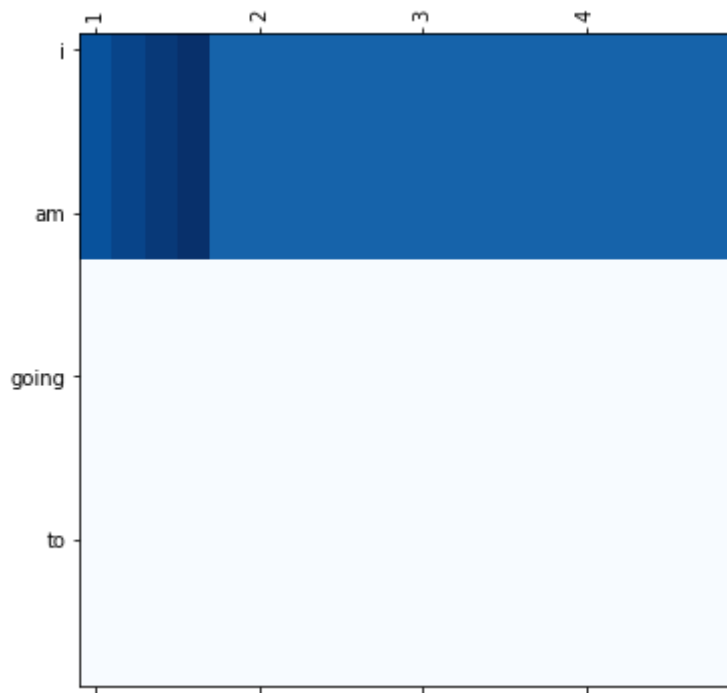
```
def predict(input_sentence,plot_t2):

    sentences=[]
    in_enc_ita=tnkizer_ita.texts_to_sequences([input_sentence])
    in_pad_seq_ita=pad_sequences(in_enc_ita,maxlen=20,padding='post',truncating='post',dtype
    state_enc1=model2.layers[0].initialize_states(in_pad_seq_ita.shape[0])
    enc_output1,enc_state_h1,enc_state_c1=model2.layers[0](in_pad_seq_ita,state_enc1)
    in_indexes=tnkizer_eng.word_index['<start>']
    in_indexes=tf.expand_dims([in_indexes],0)
    att=np.zeros((20,20))
    input_list=[]
    for j in range(in_pad_seq_ita.shape[1]):
        out_pred,dec_state_h1,dec_state_c1,w,cv=model2.layers[1].onestep_decoder(in_indexes,enc
        dense_out1=model2.layers[1](in_indexes,enc_output1,enc_state_h1,enc_state_c1)
        out_index=np.argmax(dense_out1)
        wt=tf.reshape(w,(-1, ))
        att[j]=wt.numpy()
        in_indexes=np.reshape(out_index,(1,1))
        input_list.append(tnkizer_eng.index_word[out_index])
        if tnkizer_eng.index_word[out_index]=='<end>':
            break
    return ' '.join(input_list),att
```

### ATTENTION PLOTS

```
pred,attention=predict('1 2 3 4','dot')
plot_attention(attention,'1 2 3 4',pred)
```





### Calculate BLEU score

```
# #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
```

```
# #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)))
```

```
ita=validation['italian'].values[:1000]
eng=validation['english_out'].values[:1000]
blue=[]
for i in range(1000):
    pred_bl,att_bl=predict(ita[i],'dot')
    blue.append(bleu_score.sentence_bleu(eng[i],pred_bl))
print(f'Bleu_score: {np.average(blue)}')
```

```
/usr/local/lib/python3.7/dist-packages/nltk/translate/bleu_score.py:490: UserWarning
Corpus/Sentence contains 0 counts of 2-gram overlaps.
BLEU scores might be undesirable; use SmoothingFunction().
  warnings.warn(_msg)
Bleu_score: 0.8246226835237551
```

```
print(f'Bleu Score: {np.average(blue)}')
```

```
Bleu Score: 0.8246226835237551
```

## Repeat the same steps for General scoring function

```
#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 th
# https://www.nltk.org/\_modules/nltk/translate/bleu\_score.html
```

```
logdir3 = os.path.join("logs3", datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
tensorboard_callback3= tf.keras.callbacks.TensorBoard(logdir1, histogram_freq=1)
```

```
model3 = encoder_decoder(input_len=20,output_len=20,score_ecm='general',att_units=64,batch
model3.compile(optimizer=tf.keras.optimizers.Adam(),loss='sparse_categorical_crossentropy'
train_steps3=train.shape[0]//1024
valid_steps3=validation.shape[0]//1024
```

```
model3.fit(train_load, steps_per_epoch=train_steps3, epochs=20, validation_data=train_load
```

```
Epoch 1/20
274/274 [=====] - 170s 602ms/step - loss: 2.3031 - val_loss
Epoch 2/20
274/274 [=====] - 161s 587ms/step - loss: 2.0556 - val_loss
Epoch 3/20
274/274 [=====] - 169s 616ms/step - loss: 1.9527 - val_loss
Epoch 4/20
274/274 [=====] - 161s 588ms/step - loss: 1.9027 - val_loss
Epoch 5/20
274/274 [=====] - 169s 618ms/step - loss: 1.8735 - val_loss
Epoch 6/20
274/274 [=====] - 163s 593ms/step - loss: 1.9859 - val_loss
Epoch 7/20
274/274 [=====] - 161s 588ms/step - loss: 2.0781 - val_loss
Epoch 8/20
274/274 [=====] - 169s 616ms/step - loss: 1.9704 - val_loss
Epoch 9/20
274/274 [=====] - 169s 618ms/step - loss: 1.8394 - val_loss
Epoch 10/20
274/274 [=====] - 172s 627ms/step - loss: 1.8451 - val_loss
Epoch 11/20
274/274 [=====] - 162s 591ms/step - loss: 1.8470 - val_loss
Epoch 12/20
274/274 [=====] - 161s 588ms/step - loss: 1.8629 - val_loss
Epoch 13/20
274/274 [=====] - 162s 593ms/step - loss: 1.7991 - val_loss
Epoch 14/20
274/274 [=====] - 171s 624ms/step - loss: 1.8351 - val_loss
Epoch 15/20
274/274 [=====] - 162s 590ms/step - loss: 1.7662 - val_loss
Epoch 16/20
274/274 [=====] - 171s 623ms/step - loss: 1.7702 - val_loss
Epoch 17/20
274/274 [=====] - 162s 590ms/step - loss: 1.8164 - val_loss
Epoch 18/20
274/274 [=====] - 163s 593ms/step - loss: 1.7527 - val_loss
Epoch 19/20
```

```
274/274 [=====] - 171s 623ms/step - loss: 1.7108 - val_loss
Epoch 20/20
274/274 [=====] - 170s 620ms/step - loss: 1.7891 - val_loss
<tensorflow.python.keras.callbacks.History at 0x7f22ccba2c90>
```

```
model3.summary()
```

```
Model: "encoder_decoder_2"
```

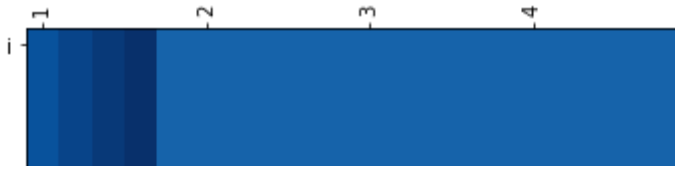
| Layer (type)                | Output Shape | Param # |
|-----------------------------|--------------|---------|
| encoder_4 (Encoder)         | multiple     | 1643268 |
| decoder_6 (Decoder)         | multiple     | 5296558 |
| Total params: 6,939,826     |              |         |
| Trainable params: 6,939,826 |              |         |
| Non-trainable params: 0     |              |         |

```
%tensorboard --logdir logs3
```

```
import matplotlib.ticker as ticker
def plot_attention(attention,act,pred):
    #Refer: https://www.tensorflow.org/tutorials/text/nmt_with_attention#translate

    pred,_=predict(act,plot_t2='general')
    plot_att=attention[:len(pred.split(' ')),len(act.split(' '))]
    fig,ax = plt.subplots(figsize=(8,6))
    ax.matshow(attention,cmap='Blues')
    ax.set_xticklabels([''] + act.split(' '), rotation=90)
    ax.set_yticklabels([''] + pred.split(' '))
    plt.show()

pred,attention=predict('1 2 3 4','general')
plot_attention(attention,'1 2 3 4',pred)
```



```
def predict(input_sentence,plot_t2):
```

```
    sentences=[]
    in_enc_ita=tknizer_ita.texts_to_sequences([input_sentence])
    in_pad_seq_ita=pad_sequences(in_enc_ita,maxlen=20,padding='post',truncating='post',dtype
    state_enc1=model3.layers[0].initialize_states(in_pad_seq_ita.shape[0])
    enc_output1,enc_state_h1,enc_state_c1=model3.layers[0](in_pad_seq_ita,state_enc1)
    in_indexs=tknizer_eng.word_index['<start>']
    in_indexs=tf.expand_dims([in_indexs],0)
    att=np.zeros((20,20))
    input_list=[]
    for j in range(in_pad_seq_ita.shape[1]):
        out_pred,dec_state_h1,dec_state_c1,w,cv=model3.layers[1].onestep_decoder(in_indexs,enc
        dense_out1=model3.layers[1](in_indexs,enc_output1,enc_state_h1,enc_state_c1)
        out_index=np.argmax(dense_out1)
        wt=tf.reshape(w,(-1, ))
        att[j]=wt.numpy()
        in_indexs=np.reshape(out_index,(1,1))
        input_list.append(tknizer_eng.index_word[out_index])
        if tknizer_eng.index_word[out_index]=='<end>':
            break
    return ' '.join(input_list),att
```

```
ita=validation['italian'].values[:1000]
eng=validation['english_out'].values[:1000]
blue=[]
for i in range(1000):
    pred_bl,att_bl=predict(ita[i],'general')
    blue.append(bleu_score.sentence_bleu(eng[i],pred_bl))
```

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

```
print(f'Bleu_score: {np.average(blue)}')
```

```
Bleu_score: 0.8705149732218294
```

### Repeat the same steps for Concat scoring function

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

```
logdir4 = os.path.join("logs4", datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
tensorboard_callback4= tf.keras.callbacks.TensorBoard(logdir1, histogram_freq=1)
```

```
model4 = encoder_decoder(input_len=20,output_len=20,score_ecm='concat',att_units=64,batch_
model4.compile(optimizer=tf.keras.optimizers.Adam(),loss='sparse_categorical_crossentropy'
train_steps3=train.shape[0]//1024
valid_steps3=validation.shape[0]//1024
```

```
model4.fit(train_load, steps_per_epoch=train_steps3, epochs=20, validation_data=train_load
```

```
Epoch 1/20
274/274 [=====] - 187s 659ms/step - loss: 2.3358 - val_loss
Epoch 2/20
274/274 [=====] - 184s 671ms/step - loss: 1.9897 - val_loss
Epoch 3/20
274/274 [=====] - 183s 669ms/step - loss: 1.9982 - val_loss
Epoch 4/20
274/274 [=====] - 183s 669ms/step - loss: 1.9786 - val_loss
Epoch 5/20
274/274 [=====] - 184s 672ms/step - loss: 1.8858 - val_loss
Epoch 6/20
274/274 [=====] - 177s 647ms/step - loss: 1.8964 - val_loss
Epoch 7/20
274/274 [=====] - 176s 644ms/step - loss: 1.9157 - val_loss
Epoch 8/20
274/274 [=====] - 176s 644ms/step - loss: 1.9690 - val_loss
Epoch 9/20
274/274 [=====] - 182s 664ms/step - loss: 1.8564 - val_loss
Epoch 10/20
274/274 [=====] - 184s 672ms/step - loss: 1.8450 - val_loss
Epoch 11/20
274/274 [=====] - 183s 669ms/step - loss: 1.9960 - val_loss
Epoch 12/20
274/274 [=====] - 182s 666ms/step - loss: 1.9400 - val_loss
Epoch 13/20
274/274 [=====] - 183s 666ms/step - loss: 1.8545 - val_loss
Epoch 14/20
274/274 [=====] - 183s 667ms/step - loss: 1.9415 - val_loss
Epoch 15/20
274/274 [=====] - 183s 666ms/step - loss: 1.8513 - val_loss
Epoch 16/20
274/274 [=====] - 176s 642ms/step - loss: 1.8114 - val_loss
Epoch 17/20
274/274 [=====] - 183s 668ms/step - loss: 1.7609 - val_loss
Epoch 18/20
274/274 [=====] - 176s 643ms/step - loss: 1.8445 - val_loss
Epoch 19/20
274/274 [=====] - 181s 661ms/step - loss: 1.9178 - val_loss
Epoch 20/20
274/274 [=====] - 183s 667ms/step - loss: 1.8762 - val_loss
<tensorflow.python.keras.callbacks.History at 0x7f225cbfa790>
```

```
model4.summary()
```

Model: "encoder\_decoder\_3"

| Layer (type)                | Output Shape | Param # |
|-----------------------------|--------------|---------|
| encoder_5 (Encoder)         | multiple     | 1643268 |
| decoder_7 (Decoder)         | multiple     | 5329519 |
| Total params: 6,972,787     |              |         |
| Trainable params: 6,972,787 |              |         |
| Non-trainable params: 0     |              |         |

```
model4.save_weights('concat_model4.h5')
```

```
!kill 1690
```

```
def predict(input_sentence,plot_t2):
```

```

    sentences=[]
    in_enc_ita=tnkizer_ita.texts_to_sequences([input_sentence])
    in_pad_seq_ita=pad_sequences(in_enc_ita,maxlen=20,padding='post',truncating='post',dtype
    state_enc1=model4.layers[0].initialize_states(in_pad_seq_ita.shape[0])
    enc_output1,enc_state_h1,enc_state_c1=model4.layers[0](in_pad_seq_ita,state_enc1)
    in_indexs=tnkizer_eng.word_index['<start>']
    in_indexs=tf.expand_dims([in_indexs],0)
    att=np.zeros((20,20))
    input_list=[]
    for j in range(in_pad_seq_ita.shape[1]):
        out_pred,dec_state_h1,dec_state_c1,w,cv=model4.layers[1].onestep_decoder(in_indexs,enc
        dense_out1=model4.layers[1](in_indexs,enc_output1,enc_state_h1,enc_state_c1)
        out_index=np.argmax(dense_out1)
        wt=tf.reshape(w,(-1, ))
        att[j]=wt.numpy()
        in_indexs=np.reshape(out_index,(1,1))
        input_list.append(tnkizer_eng.index_word[out_index])
        if tnkizer_eng.index_word[out_index]=='<end>':
            break
    return ' '.join(input_list),att
```

```
import matplotlib.ticker as ticker
```

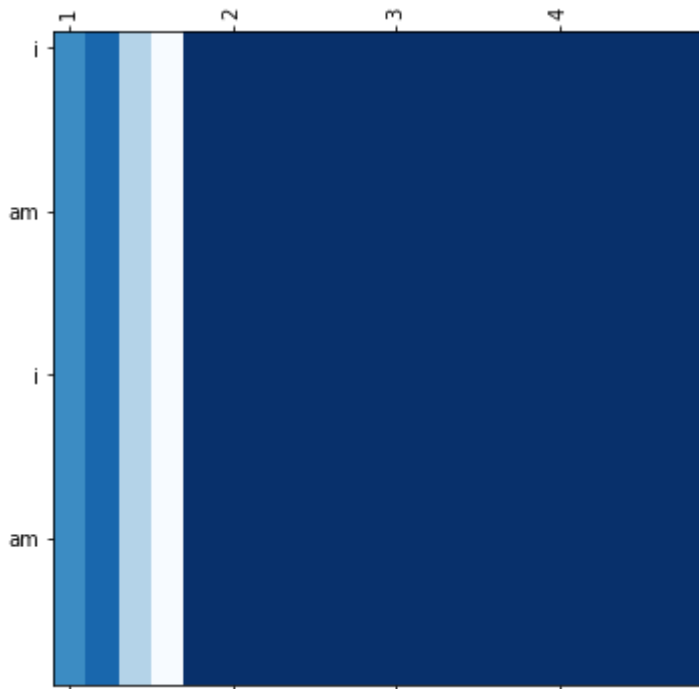
```
def plot_attention(attention,act,pred):
```

```
    #Refer: https://www.tensorflow.org/tutorials/text/nmt\_with\_attention#translate
```

```

    pred,_=predict(act,plot_t2='concat')
    plot_att=attention[:len(pred.split(' ')),len(act.split(' '))]
    fig,ax = plt.subplots(figsize=(8,6))
    ax.matshow(attention,cmap='Blues')
    ax.set_xticklabels([''] + act.split(' '), rotation=90)
    ax.set_yticklabels([''] + pred.split(' '))
    plt.show()
```

```
pred,attention=predict('1 2 3 4','concat')
plot_attention(attention,'1 2 3 4',pred)
```



```
ita=validation['italian'].values[:1000]
eng=validation['english_out'].values[:1000]
blue=[]
for i in range(1000):
    pred_bl,att_bl=predict(ita[i],'concat')
    blue.append(bleu_score.sentence_bleu(eng[i],pred_bl))
```

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

```
print(f'Bleu_score: {np.average(blue)}')
```

```
Bleu_score: 0.5097968335141377
```


```
# Write your observations on each of the scoring function
```

## OBSERVATIONS OF ATTENTION MECHANISM

```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["No","Scoring Function", "Bleu Score"]

x.add_row(["1","Dot",0.8325 ])
x.add_row(["2","General", 0.8614])
x.add_row(["3","Concat ", 0.510])
```

```
print(x)
```



| +-----+                            |         |        |  |
|------------------------------------|---------|--------|--|
| No   Scoring Function   Bleu Score |         |        |  |
| +-----+                            |         |        |  |
| 1                                  | Dot     | 0.8325 |  |
| 2                                  | General | 0.8614 |  |
| 3                                  | Concat  | 0.51   |  |
| +-----+                            |         |        |  |

 0s completed at 1:29 AM