overview_EDA_pipeline_model_Final

February 4, 2021

Problem Overview: Spelling error correction is the task of automatically correcting spelling errors in text; e.g. [I followed his advcie -> I followed his advice]. It can be used to not only help language learners improve their writing errors, but also alert native speakers to accidental mistakes or typos. The aim of the task is to produce a correctly spelled sentence given a incorrectly spelled sentence.

Business Problem: By building the automated spelling error correction. We can create automated tools for writing English scientific texts, Filtering out sentences that need spelling improvements, evaluating articles, etc. These all mentioned tasks are done manually so, by automating this process we can save both time and money for the company.

ML formulation: Building a model using techniques like Encoder-Decoder architecture, Bidirectional LSTM with attention mechanism, etc. can be used.

Performance metric: BLEU Score Bilingual Evaluation Understudy(BLEU) is a metric for comparing machine translated sentence to one or more reference setences. The metric ranges on scale of 0 to 1, in an attempt to measure the adequacy and fluency of the MT output. the more overlap there is with their human reference translations and thus, the better the translation. The BLEU is programming task to compare n-grams of the translated sentences with the reference sentence and count the number of matches. The more the matches the better the performance.

```
[1]: import os
   import re
   import numpy as np
   import pandas as pd
   import warnings
   import matplotlib.pyplot as plt
   import seaborn as sns
   import tensorflow as tf

from tqdm import tqdm
   from sklearn.model_selection import train_test_split
   from tensorflow.keras.layers.experimental.preprocessing import TextVectorization
   from tensorflow.keras.layers import Embedding, LSTM, Dense
   from tensorflow.keras.layers import *
   from tensorflow.keras.callbacks import*
   from nltk.translate.bleu_score import sentence_bleu
```

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

EDA1

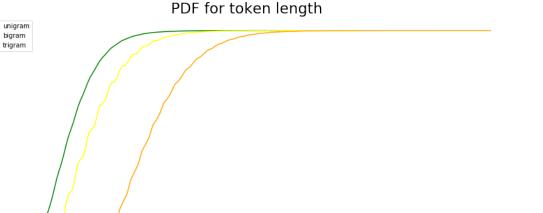
Preprocessing data: Text files which we need to combine to introduce spelling errors in the dataset.

```
So, that we can train model for spelling error correction.
[2]: text_files = os.listdir('data')
     text_files
[2]: ['nietzsche.txt',
      'pride and prejudice.txt',
      'shakespeare.txt',
      'war_and_peace.txt',
      'wonderland.txt']
[3]: REMOVE_CHARS = '[#$%"\+@<=>!&,-.?:;()*\[\]\'^_`{|}~/\d\t\r\x0b\x0c]'
     train_text = ''
     for filename in text_files[:-1]:
         file = open('data/'+filename).read().split()
         train_text += ' '.join([re.sub(REMOVE_CHARS, '', token) for token in_

file])+' '
[4]: from nltk import ngrams
     unigram_train_data = set([token for token in train_text.split()])
     unigram_train_data = list(filter(None, set(unigram_train_data)))
     bigram_train_data = list(ngrams(train_text.split(), 2))
     bigram_train_data = [' '.join(x) for x in bigram_train_data]
     trigram_train_data = list(ngrams(train_text.split(), 3))
     trigram_train_data = [' '.join(x) for x in trigram_train_data]
     print('Size of unigram train data:', len(unigram_train_data))
     print('Size of bigram train data:', len(bigram_train_data))
     print('Size of trigram train data:', len(trigram_train_data))
    Size of unigram train data: 36821
    Size of bigram train data: 983848
    Size of trigram train data: 983847
[5]: file = open('data/'+text_files[-1]).read().split()
     test_text = ' '.join([re.sub(REMOVE_CHARS, '', token) for token in file])
[6]: from nltk import ngrams
     unigram_test_data = set([token for token in test_text.split()])
```

```
unigram_test_data = list(filter(None, set(unigram_test_data)))
     bigram_test_data = list(ngrams(test_text.split(), 2))
     bigram_test_data = [' '.join(x) for x in bigram_test_data]
     trigram_test_data = list(ngrams(test_text.split(), 3))
     trigram_test_data = [' '.join(x) for x in trigram_test_data]
     print('Size of unigram test data:', len(unigram_test_data))
     print('Size of bigram test data:', len(bigram_test_data))
     print('Size of trigram test data:', len(trigram_test_data))
    Size of unigram test data: 3152
    Size of bigram test data: 26387
    Size of trigram test data: 26386
[7]: unigram_length = []
     for i in unigram_train_data:
         unigram_length.append(len(i))
     bigram_length = []
     for i in bigram_train_data:
         bigram_length.append(len(i))
     trigram_length = []
     for i in trigram_train_data:
         trigram_length.append(len(i))
[8]: for i in range(0,101,10):
         print(i,np.percentile(unigram_length, i), np.percentile(bigram_length, i), u
     →np.percentile(trigram_length, i))
     for i in range (90,101):
         print(i,np.percentile(unigram_length, i), np.percentile(bigram_length, i),
     →np.percentile(trigram_length, i))
     for i in [99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.8,99.9,100]:
         print(i,np.percentile(unigram_length, i), np.percentile(bigram_length, i), u
     →np.percentile(trigram_length, i))
    0 1.0 3.0 5.0
    10 5.0 6.0 11.0
    20 6.0 7.0 12.0
    30 6.0 8.0 13.0
    40 7.0 9.0 14.0
    50 8.0 9.0 15.0
    60 8.0 10.0 16.0
    70 9.0 11.0 17.0
    80 10.0 12.0 18.0
    90 12.0 14.0 21.0
```

```
100 27.0 35.0 47.0
    90 12.0 14.0 21.0
    91 12.0 14.0 21.0
    92 12.0 15.0 21.0
    93 12.0 15.0 22.0
    94 12.0 15.0 22.0
    95 13.0 16.0 22.0
    96 13.0 16.0 23.0
    97 14.0 17.0 24.0
    98 14.0 18.0 25.0
    99 16.0 19.0 26.0
    100 27.0 35.0 47.0
    99.1 16.0 20.0 27.0
    99.2 16.0 20.0 27.0
    99.3 16.0 20.0 27.0
    99.4 17.0 20.0 28.0
    99.5 17.0 21.0 28.0
    99.6 17.0 21.0 28.0
    99.7 18.0 22.0 29.0
    99.8 19.0 22.0 30.0
    99.9 20.0 24.0 32.0
    100 27.0 35.0 47.0
[9]: plt.figure(figsize = (15,8))
     ax = sns.kdeplot(data = unigram_length, color='green', cumulative = True, label_
     →= 'unigram')
     sns.kdeplot(data = bigram_length, color='yellow', cumulative = True, ax = ax, __
     →label = 'bigram')
     sns.kdeplot(data = trigram_length, color='orange', cumulative = True, ax = ax, __
     →label = 'trigram')
     plt.xlabel('token length', fontdict = {'fontsize':15})
     plt.title('PDF for token length', fontdict = {'fontsize': 23})
     ax.legend()
     plt.xlim(0, 50)
     ax.spines['right'].set_visible(False)
     ax.spines['top'].set_visible(False)
```



1.0

0.8

0.6

0.4

0.2

Aim: Plot for determining the distribution token length of unigram, bigram, and trigram dataset.

token length

Conclusion: 1. 99.9% of unigram token have length less than 20 characters. 2. 99.9% of biigram token have length less than 24 characters. 3. 99.9% of trigram token have length less than 32 characters.

```
[10]: def add_speling_errors(token, error_rate, VOCAB):
          """Add some artificial spelling mistakes."""
          assert(0.0 <= error_rate < 1.0)</pre>
          if len(token) < 3:
              return token
          rand = np.random.rand()
          # Here are 4 different ways spelling mistakes can occur,
          # each of which has equal chance.
          prob = error_rate / 4.0
          if rand < prob:</pre>
              # Replace a character with a random character.
              random_char_index = np.random.randint(len(token))
              token = token[:random_char_index] + np.random.choice(VOCAB) \
                       + token[random_char_index + 1:]
          elif prob < rand < prob * 2:</pre>
              # Delete a character.
              random_char_index = np.random.randint(len(token))
              token = token[:random_char_index] + token[random_char_index + 1:]
          elif prob * 2 < rand < prob * 3:
              # Add a random character.
```

```
random_char_index = np.random.randint(len(token))
              token = token[:random_char_index] + np.random.choice(VOCAB) \
                       + token[random_char_index:]
          elif prob * 3 < rand < prob * 4:
              # Transpose 2 characters.
              random_char_index = np.random.randint(len(token) - 1)
              token = token[:random_char_index] + token[random_char_index + 1] \
                       + token[random_char_index] + token[random_char_index + 2:]
          else:
              # No spelling errors.
              pass
          return token
 [2]: UNIGRAM_VOCAB = ['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h', 'i', 'j', 'k', 'l', '
       \hookrightarrow 'm', 'n', 'o', 'p', 'q', 'r', 's', 't', 'u', 'v', 'w', 'x', 'y', 'z', \
                        'A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J', 'K', 'L', "
       \hookrightarrow 'M', 'N', 'O', 'P', 'Q', 'R', 'S', 'T', 'U', 'V', 'W', 'X', 'Y', 'Z', \
                        '<SOW>', '<EOW>']
      NGRAM_VOCAB = ['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h', 'i', 'j', 'k', 'l', 'm', '
       \neg'n', 'o', 'p', 'q', 'r', 's', 't', 'u', 'v', 'w', 'x', 'y', 'z', \
                      'A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J', 'K', 'L', 'M', "
       \hookrightarrow 'N', 'O', 'P', 'Q', 'R', 'S', 'T', 'U', 'V', 'W', 'X', 'Y', 'Z', \
                      '', '<SOW>', '<EOW>']
[12]: unigram_maxlen = 20
      unigram_train = []
      for token in unigram_train_data:
          if len(token) < unigram_maxlen:</pre>
              point = [token, add_speling_errors(token, 0.5, UNIGRAM_VOCAB)]
              unigram_train.append(point)
      unigram_train = pd.DataFrame(unigram_train, columns = ['output', 'input'])
      unigram_train.head()
[12]:
               output
                              input
          magistrates magistratse
      0
      1
            Cookshops
                          Cookshops
      2 aristocratic arstocratic
      3
               graced
                             graced
              wagging
                            wagigng
[13]: bigram_maxlen = 24
      bigram_train = []
      for token in bigram_train_data:
          if len(token) < bigram_maxlen:</pre>
              point = [token, add_speling_errors(token, 0.5, NGRAM_VOCAB)]
              bigram_train.append(point)
```

```
bigram_train = pd.DataFrame(bigram_train, columns = ['output', 'input'])
     bigram_train.head()
[13]:
                   output
                                       input
     O PREFACE SUPPOSING PREFACE SUPPOSING
           SUPPOSING that
     1
                              SUPPOSINGt hat
     2
               that Truth
                                  that TruEh
     3
                 Truth is
                                    Truth is
                     is a
                                        si a
[14]: trigram_maxlen = 32
     trigram_train = []
     for token in trigram_train_data:
          if len(token) < trigram maxlen:</pre>
             point = [token, add_speling_errors(token, 0.5, NGRAM_VOCAB)]
             trigram train.append(point)
     trigram_train = pd.DataFrame(trigram_train, columns = ['output', 'input'])
     trigram_train.head()
「14]:
                        output
                                                input
     O PREFACE SUPPOSING that PREFACE SUPPOSIN that
     1
          SUPPOSING that Truth SUPPOSSING that Truth
     2
                 that Truth is
                                        that Truth is
     3
                    Truth is a
                                          Truth si a
                is a womanwhat
                                       is a womanwhat
[15]: unigram_train['enc_inp'] = unigram_train['input'].astype(str).apply(lambda x:___
      unigram_train['dec_inp'] = unigram_train['output'].astype(str).apply(lambda x:__
      \hookrightarrow '<SOW> '+' '.join(list(x)))
     unigram_train['dec_out'] = unigram_train['output'].astype(str).apply(lambda x:__

        ' '.join(list(x))+' <EOW>')
     bigram_train['enc_inp'] = bigram_train['input'].astype(str).apply(lambda x:
      bigram_train['dec_inp'] = bigram_train['output'].astype(str).apply(lambda x:u
      \hookrightarrow '<SOW>*'+'*'.join(list(x)))
     bigram_train['dec_out'] = bigram_train['output'].astype(str).apply(lambda x:
      \rightarrow'*'.join(list(x))+'*<EOW>')
     trigram_train['enc_inp'] = trigram_train['input'].astype(str).apply(lambda x:u
      trigram_train['dec_inp'] = trigram_train['output'].astype(str).apply(lambda x:
      \hookrightarrow '<SOW>*'+'*'.join(list(x)))
     trigram_train['dec_out'] = trigram_train['output'].astype(str).apply(lambda x:__
      →'*'.join(list(x))+'*<EOW>')
```

```
[16]: unigram_train, unigram_val = train_test_split(unigram_train, test_size = 0.1,
       \rightarrowrandom_state = 0)
      bigram_train, bigram_val = train_test_split(bigram_train, test_size = 0.1,__
       \rightarrowrandom state = 0)
      trigram_train, trigram_val = train_test_split(trigram_train, test_size = 0.1, __
       \rightarrowrandom state = 0)
[17]: unigram_test = []
      for token in unigram_test_data:
          if len(token) < unigram_maxlen:</pre>
              point = [token, add_speling_errors(token, 0.5, UNIGRAM_VOCAB)]
              unigram_test.append(point)
      unigram_test = pd.DataFrame(unigram_test, columns = ['output', 'input'])
      unigram_test.head()
[17]:
             output
                           input
           slatesll
                       slatesll
      0
      1
           rumbling
                       rmubling
      2
             chance
                          chacne
      3
             bright
                         brnight
      4 ridiculous ridiculous
[18]: bigram_test = []
      for token in bigram_test_data:
          if len(token) < bigram_maxlen:</pre>
              point = [token, add_speling_errors(token, 0.5, NGRAM_VOCAB)]
              bigram_test.append(point)
      bigram_test = pd.DataFrame(bigram_test, columns = ['output', 'input'])
      bigram_test.head()
[18]:
                        output
                                                input
      O i»; ALICES ADVENTURES i»; ALIECS ADVENTURES
      1
                ADVENTURES IN
                                        ADVENTURES IN
      2
                IN WONDERLAND
                                        IN WONDEtLAND
      3
                                    WONDERLAND Lewis
             WONDERLAND Lewis
                Lewis Carroll
                                       Lewis Carrlol
[19]: trigram_test = []
      for token in trigram_test_data:
          if len(token) < unigram_maxlen:</pre>
              point = [token, add_speling_errors(token, 0.5, NGRAM_VOCAB)]
              trigram_test.append(point)
      trigram_test = pd.DataFrame(trigram_test, columns = ['output', 'input'])
      trigram_test.head()
[19]:
                       output
                                               input
      O IN WONDERLAND Lewis IN WONDEROLAND Lewis
```

```
1
           Lewis Carroll THE
                                 Lewis Carroll THE
      2
           EDITION CHAPTER I
                                  EDITION CHATPER I
      3
              CHAPTER I Down
                                     CHAPTRE I Down
      4
                   I Down the
                                         I Down the
[100]: unigram train.to csv('unigram train.csv')
      unigram test.to csv('unigram test.csv')
      unigram_val.to_csv('unigram_val.csv')
      bigram_train.to_csv('bigram_train.csv')
      bigram_test.to_csv('bigram_test.csv')
      bigram_val.to_csv('bigram_val.csv')
      trigram_train.to_csv('trigram_train.csv')
      trigram_test.to_csv('trigram_test.csv')
      trigram_val.to_csv('trigram_val.csv')
[20]: print('Shape of unigram train set:',unigram_train.shape)
      print('Shape of unigram test set :',unigram_test.shape)
      print('Shape of unigram validation set :', unigram_val.shape)
      print('\nShape of bigram train set :',bigram_train.shape)
      print('Shape of bigram test set :',bigram_test.shape)
      print('Shape of bigram validation set :', bigram_val.shape)
      print('\nShape of trigram train set :',trigram_train.shape)
      print('Shape of trigram test set :',trigram_test.shape)
      print('Shape of trigram validation set :', trigram_val.shape)
      Shape of unigram train set: (33101, 5)
      Shape of unigram test set : (3150, 2)
      Shape of unigram validation set: (3678, 5)
      Shape of bigram train set: (884533, 5)
      Shape of bigram test set: (26377, 2)
      Shape of bigram validation set: (98282, 5)
      Shape of trigram train set: (884550, 5)
      Shape of trigram test set: (24586, 2)
      Shape of trigram validation set: (98284, 5)
[21]: print(unigram_train.isnull().sum(), unigram_val.isnull().sum(), unigram_test.
       →isnull().sum())
      print(bigram_train.isnull().sum(), bigram_val.isnull().sum(), bigram_test.
       →isnull().sum())
      print(trigram_train.isnull().sum(), trigram_val.isnull().sum(), trigram_test.
        →isnull().sum())
```

```
output
           0
input
           0
           0
enc_inp
dec_inp
           0
dec_out
           0
dtype: int64 output
input
           0
enc_inp
dec_inp
           0
dec_out
           0
dtype: int64 output
                        0
input
          0
dtype: int64
output
input
enc_inp
dec_inp
           0
           0
dec_out
dtype: int64 output
                         0
input
           0
enc_inp
           0
dec_inp
           0
dec_out
           0
dtype: int64 output
input
dtype: int64
output
input
           0
           0
enc_inp
dec_inp
dec_out
           0
dtype: int64 output
input
enc_inp
           0
dec_inp
dec_out
           0
dtype: int64 output
input
dtype: int64
```

2 Modeling

```
[14]: unigram_train = pd.read_csv('unigram_train.csv', index_col = 0)
unigram_test = pd.read_csv('unigram_test.csv', index_col = 0)
unigram_val = pd.read_csv('unigram_val.csv', index_col = 0)
bigram_train = pd.read_csv('bigram_train.csv', index_col = 0)
```

```
bigram_test = pd.read_csv('bigram_test.csv', index_col = 0)
      bigram_val = pd.read_csv('bigram_val.csv', index_col = 0)
      trigram_train = pd.read_csv('trigram_train.csv', index_col = 0)
      trigram_test = pd.read_csv('trigram_test.csv', index_col = 0)
      trigram_val = pd.read_csv('trigram_val.csv', index_col = 0)
[16]: def split_on_star(input_data):
          return tf.strings.split(input data, sep = '*')
[15]: batch_size = 128
[11]: unigram_maxlen = 20
      bigram_maxlen = 24
      trigram_maxlen = 32
[17]: unigram_vec = TextVectorization(output_sequence_length= unigram_maxlen+2,__
       ⇒standardize = None, split='whitespace', max_tokens = len(UNIGRAM_VOCAB)+2, __
      →output mode='int')
      unigram_vec.adapt(UNIGRAM_VOCAB)
      bigram_vec = TextVectorization(output_sequence_length= bigram_maxlen+2,__
       →standardize = None, split = split_on_star, max_tokens = len(NGRAM_VOCAB)+2, __
       →output_mode='int')
      bigram_vec.adapt(NGRAM_VOCAB)
      trigram vec = TextVectorization(output sequence length= trigram maxlen+2,,,
      ⇒standardize = None, split = split_on_star, max_tokens = len(NGRAM_VOCAB)+2, __
      →output mode='int')
      trigram_vec.adapt(NGRAM_VOCAB)
      unigram_index_to_word = {idx: word for idx, word in enumerate(unigram_vec.
      →get_vocabulary())}
      unigram word to index = {word: idx for idx, word in enumerate(unigram vec.
      →get_vocabulary())}
      bigram_index_to_word = {idx: word for idx, word in enumerate(bigram_vec.
       →get_vocabulary())}
      bigram_word_to_index = {word: idx for idx, word in enumerate(bigram_vec.
      →get vocabulary())}
      trigram_index_to_word = {idx: word for idx, word in enumerate(trigram_vec.
       →get_vocabulary())}
      trigram_word_to_index = {word: idx for idx, word in enumerate(trigram_vec.
       →get_vocabulary())}
```

```
enc_inp = unigram_vec(x[:, 2])
          dec_inp = unigram_vec(x[:, 3])
          dec_out = unigram_vec(x[:, 4])
          return (enc_inp, dec_inp), dec_out
      def bigram mapping(x):
          enc_inp = bigram_vec(x[:, 2])
          dec_inp = bigram_vec(x[:, 3])
          dec_out = bigram_vec(x[:, 4])
          return (enc_inp, dec_inp), dec_out
      def trigram mapping(x):
          enc_inp = trigram_vec(x[:, 2])
          dec_inp = trigram_vec(x[:, 3])
          dec_out = trigram_vec(x[:, 4])
          return (enc_inp, dec_inp), dec_out
      unigram_train_dataset = tf.data.Dataset.from_tensor_slices(unigram_train.
      -values).repeat().batch(batch_size).map(unigram_mapping).prefetch(1)
      unigram val dataset = tf.data.Dataset.from tensor slices(unigram val.values).
      →repeat().batch(batch_size).map(unigram_mapping).prefetch(1)
      bigram_train_dataset = tf.data.Dataset.from_tensor_slices(bigram_train.values).
      →repeat().batch(batch_size).map(bigram_mapping).prefetch(1)
      bigram val dataset = tf.data.Dataset.from tensor slices(bigram val.values).
      →repeat().batch(batch_size).map(bigram_mapping).prefetch(1)
      trigram_train_dataset = tf.data.Dataset.from_tensor_slices(trigram_train.
      →values).repeat().batch(batch_size).map(trigram_mapping).prefetch(1)
      trigram val dataset = tf.data.Dataset.from tensor slices(trigram val.values).
      →repeat().batch(batch_size).map(trigram_mapping).prefetch(1)
      a = unigram_train_dataset.as_numpy_iterator()
      next(a)
[17]: ((array([[54, 26, 23, ..., 0, 0, 0],
               [54, 42, 51, ..., 0, 0, 0],
               [54, 35, 7, ..., 0, 0, 0],
               [54, 10, 27, ..., 0, 0, 0],
               [54, 15, 7, ..., 0, 0, 0],
               [54, 7, 14, ..., 0, 0, 0]], dtype=int64),
        array([[54, 26, 23, ..., 0, 0, 0],
               [54, 42, 33, ..., 0, 0, 0],
               [54, 35, 7, ..., 0, 0, 0],
               ...,
```

def unigram_mapping(x):

```
[54, 10, 27, ..., 0, 0, 0],
[54, 15, 7, ..., 0, 0, 0],
[54, 7, 14, ..., 0, 0, 0]], dtype=int64)),
array([[26, 23, 22, ..., 0, 0, 0],
[42, 33, 51, ..., 0, 0, 0],
[35, 7, 25, ..., 0, 0, 0],
...,
[10, 27, 6, ..., 0, 0, 0],
[15, 7, 14, ..., 0, 0, 0],
[7, 14, 24, ..., 0, 0, 0]], dtype=int64))
```

1. Seq2Seq

```
[18]: class Encoder(tf.keras.Model):
          def __init__(self,inp_vocab_size,embedding_size,lstm_size,input_length):
              super(). init ()
              self.lstm size = lstm size
              #Initialize Embedding layer
              self.enc_embed = Embedding(input_dim = inp_vocab_size, output_dim =__
       →embedding_size, input_length= input_length)
              #Intialize Encoder LSTM layer
              self.enc lstm = LSTM(lstm_size, return_sequences = True, return_state = ___
       \rightarrowTrue, dropout = 0.4)
          def call(self,input_sequence,states):
              embedding = self.enc embed(input sequence)
              output_state, enc_h, enc_c = self.enc_lstm(embedding, initial_state = __
       ⇒states)
              return output_state, enc_h, enc_c
          def initialize_states(self,batch_size):
              return [tf.zeros((batch size, self.lstm size)), tf.zeros((batch size,
       →self.lstm_size))]
      class Decoder(tf.keras.Model):
          def __init__(self,out_vocab_size,embedding_size,lstm_size,input_length):
              super().__init__()
              #Initialize Embedding layer
              self.dec_embed = Embedding(input_dim = out_vocab_size, output_dim = u
       →embedding_size, input_length = input_length)
              #Intialize Decoder LSTM layer
              self.dec lstm = LSTM(lstm size, return sequences = True, return state = 11
       \rightarrowTrue, dropout = 0.4)
          def call(self,input_sequence, initial_states):
              embedding = self.dec_embed(input_sequence)
```

```
output_state, dec_h, dec_c = self.dec_lstm(embedding, initial_state =__
 →initial_states)
        return output_state, dec_h, dec_c
class Encoder_decoder(tf.keras.Model):
   def init (self,*params):
        super().__init__()
        #Create encoder object
        self.encoder = Encoder(inp_vocab_size = params[0], embedding_size = __
→params[2], lstm_size = params[3], input_length = params[4])
        #Create decoder object
        self.decoder = Decoder(out_vocab_size = params[1], embedding_size = __
 →params[2], lstm_size = params[3], input_length = params[5])
        #Intialize Dense layer(out_vocab_size) with activation='softmax'
        self.dense = Dense(params[1], activation='softmax')
   def call(self, params, training = True):
        enc_inp, dec_inp = params[0], params[1]
        # print(enc_inp, dec_inp)
        initial_state = self.encoder.initialize_states(batch_size)
        output_state, enc_h, enc_c = self.encoder(enc_inp, initial_state)
        output, _, _ = self.decoder(dec_inp ,[enc_h, enc_c])
        output = Dropout(0.5)(output)
       return self.dense(output)
class pred_Encoder_decoder(tf.keras.Model):
   def __init__(self,*params):
        super().__init__()
        #Create encoder object
        self.encoder = Encoder(inp_vocab_size = params[0], embedding_size = __
→params[2], lstm_size = params[3], input_length = params[4])
        #Create decoder object
        self.decoder = Decoder(out_vocab_size = params[1], embedding_size = __
 →params[2], lstm_size = params[3], input_length = params[5])
        #Intialize Dense layer(out_vocab_size) with activation='softmax'
        self.dense = Dense(params[1], activation='softmax')
        self.word_to_index = params[6]
   def call(self, params):
        enc_inp = params[0]
        initial_state = self.encoder.initialize_states(1)
        output_state, enc_h, enc_c = self.encoder(enc_inp, initial_state)
        pred = tf.expand_dims([self.word_to_index['<SOW>']], 0)
       dec_h = enc_h
       dec_c = enc_c
        all_pred = []
        for t in range(max_len):
```

```
pred, dec_h,dec_c = self.decoder(pred, [dec_h, dec_c])
pred = self.dense(pred)
pred = tf.argmax(pred, axis = -1)
all_pred.append(pred)
return all_pred
```

```
[19]: def predict(seq, vectorizer, index_to_word, gram ='uni'):
          if gram == 'uni':
              seq = ' '.join(list(seq))
              seq = '<SOW> '+seq+' <EOW>'
          else:
              seq = '*'.join(list(seq))
              seq = '<SOW>*'+seq+'*<EOW>'
          seq = vectorizer([seq])
          pred = pred_model.predict(tf.expand_dims(seq, 0))
          output = []
          for i in pred:
              word = index_to_word[i[0][0]]
              if word == '<EOW>':
                  break
              output.append(word)
          return ''.join(output)
```

1.1 UniGram

```
[67]: vocab_size = len(vec.get_vocabulary())
embedding_dim = 100
lstm_size = 256
max_len = 22
```

```
Epoch 00001: val_loss improved from inf to 1.08792, saving model to seq2seq.h5
val_loss: 1.0879
Epoch 2/50
258/258 [============ ] - ETA: Os - loss: 1.0246
Epoch 00002: val_loss improved from 1.08792 to 0.93814, saving model to
seq2seq.h5
val loss: 0.9381
Epoch 3/50
Epoch 00003: val_loss improved from 0.93814 to 0.84624, saving model to
seq2seq.h5
val_loss: 0.8462
Epoch 4/50
Epoch 00004: val_loss improved from 0.84624 to 0.78058, saving model to
seq2seq.h5
val loss: 0.7806
Epoch 5/50
Epoch 00005: val_loss improved from 0.78058 to 0.72511, saving model to
seq2seq.h5
val_loss: 0.7251
Epoch 6/50
Epoch 00006: val_loss improved from 0.72511 to 0.66346, saving model to
seq2seq.h5
val_loss: 0.6635
Epoch 7/50
258/258 [============ ] - ETA: Os - loss: 0.6937
Epoch 00007: val_loss improved from 0.66346 to 0.60634, saving model to
seq2seq.h5
val_loss: 0.6063
Epoch 8/50
Epoch 00008: val_loss improved from 0.60634 to 0.55700, saving model to
val_loss: 0.5570
Epoch 9/50
Epoch 00009: val_loss improved from 0.55700 to 0.49638, saving model to
```

```
seq2seq.h5
val_loss: 0.4964
Epoch 10/50
Epoch 00010: val_loss improved from 0.49638 to 0.45429, saving model to
seq2seq.h5
val loss: 0.4543
Epoch 11/50
Epoch 00011: val_loss improved from 0.45429 to 0.41674, saving model to
seq2seq.h5
val_loss: 0.4167
Epoch 12/50
Epoch 00012: val_loss improved from 0.41674 to 0.38192, saving model to
seq2seq.h5
val loss: 0.3819
Epoch 13/50
Epoch 00013: val_loss improved from 0.38192 to 0.34618, saving model to
seq2seq.h5
val_loss: 0.3462
Epoch 14/50
Epoch 00014: val_loss improved from 0.34618 to 0.29948, saving model to
seq2seq.h5
val_loss: 0.2995
Epoch 15/50
Epoch 00015: val_loss improved from 0.29948 to 0.27217, saving model to
seq2seq.h5
val_loss: 0.2722
Epoch 16/50
Epoch 00016: val_loss improved from 0.27217 to 0.24162, saving model to
val_loss: 0.2416
Epoch 17/50
Epoch 00017: val_loss improved from 0.24162 to 0.22571, saving model to
```

```
seq2seq.h5
val_loss: 0.2257
Epoch 18/50
Epoch 00018: val_loss improved from 0.22571 to 0.20805, saving model to
seq2seq.h5
val loss: 0.2080
Epoch 19/50
Epoch 00019: val_loss improved from 0.20805 to 0.19446, saving model to
seq2seq.h5
val_loss: 0.1945
Epoch 20/50
Epoch 00020: val_loss improved from 0.19446 to 0.18305, saving model to
seq2seq.h5
val loss: 0.1831
Epoch 21/50
loss:
Epoch 00021: val_loss improved from 0.18305 to 0.17706, saving model to
seq2seq.h5
val_loss: 0.1771
Epoch 22/50
Epoch 00022: val_loss improved from 0.17706 to 0.17050, saving model to
seq2seq.h5
val_loss: 0.1705
Epoch 23/50
258/258 [============ ] - ETA: Os - loss: 0.2013
Epoch 00023: val_loss improved from 0.17050 to 0.16339, saving model to
seq2seq.h5
val_loss: 0.1634
Epoch 24/50
Epoch 00024: val_loss improved from 0.16339 to 0.16087, saving model to
seq2seq.h5
val_loss: 0.1609
Epoch 25/50
```

```
Epoch 00025: val_loss improved from 0.16087 to 0.15730, saving model to
seq2seq.h5
val_loss: 0.1573
Epoch 26/50
Epoch 00026: val loss improved from 0.15730 to 0.15314, saving model to
seq2seq.h5
val_loss: 0.1531
Epoch 27/50
Epoch 00027: val_loss improved from 0.15314 to 0.15206, saving model to
seq2seq.h5
val_loss: 0.1521
Epoch 28/50
Epoch 00028: val_loss improved from 0.15206 to 0.14619, saving model to
seq2seq.h5
val loss: 0.1462
Epoch 29/50
Epoch 00029: val_loss did not improve from 0.14619
val_loss: 0.1487
Epoch 30/50
Epoch 00030: val_loss improved from 0.14619 to 0.14454, saving model to
seq2seq.h5
val_loss: 0.1445
Epoch 31/50
Epoch 00031: val_loss improved from 0.14454 to 0.14326, saving model to
seq2seq.h5
val_loss: 0.1433
Epoch 32/50
Epoch 00032: val_loss improved from 0.14326 to 0.14313, saving model to
val_loss: 0.1431
Epoch 33/50
Epoch 00033: val_loss improved from 0.14313 to 0.14277, saving model to
```

```
seq2seq.h5
val_loss: 0.1428
Epoch 34/50
Epoch 00034: val_loss improved from 0.14277 to 0.14092, saving model to
seq2seq.h5
val loss: 0.1409
Epoch 35/50
Epoch 00035: val_loss did not improve from 0.14092
val_loss: 0.1442
Epoch 36/50
Epoch 00036: val_loss did not improve from 0.14092
val_loss: 0.1426
Epoch 37/50
Epoch 00037: val_loss did not improve from 0.14092
Epoch 00037: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
val_loss: 0.1424
Epoch 38/50
Epoch 00038: val_loss improved from 0.14092 to 0.13504, saving model to
seq2seq.h5
val_loss: 0.1350
Epoch 39/50
Epoch 00039: val_loss improved from 0.13504 to 0.13468, saving model to
seq2seq.h5
val loss: 0.1347
Epoch 40/50
Epoch 00040: val_loss improved from 0.13468 to 0.13464, saving model to
seq2seq.h5
val_loss: 0.1346
Epoch 41/50
Epoch 00041: val_loss did not improve from 0.13464
```

```
val_loss: 0.1348
Epoch 42/50
Epoch 00042: val_loss did not improve from 0.13464
Epoch 00042: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
val_loss: 0.1352
Epoch 43/50
Epoch 00043: val_loss improved from 0.13464 to 0.13452, saving model to
val_loss: 0.1345
Epoch 44/50
Epoch 00044: val_loss improved from 0.13452 to 0.13444, saving model to
seq2seq.h5
val loss: 0.1344
Epoch 45/50
Epoch 00045: val_loss improved from 0.13444 to 0.13437, saving model to
seq2seq.h5
val_loss: 0.1344
Epoch 46/50
Epoch 00046: val_loss improved from 0.13437 to 0.13429, saving model to
seq2seq.h5
val_loss: 0.1343
Epoch 47/50
Epoch 00047: val loss did not improve from 0.13429
258/258 [============== ] - 3s 13ms/step - loss: 0.0956 -
val_loss: 0.1344
Epoch 48/50
Epoch 00048: val_loss did not improve from 0.13429
Epoch 00048: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.
val_loss: 0.1344
Epoch 49/50
Epoch 00049: val_loss did not improve from 0.13429
```

```
val_loss: 0.1344
     Epoch 50/50
     Epoch 00050: val_loss did not improve from 0.13429
     258/258 [============ ] - 3s 13ms/step - loss: 0.0956 -
     val_loss: 0.1344
[20]: <tensorflow.python.keras.callbacks.History at 0x298c84fd9c8>
[70]: pred model = pred_Encoder_decoder(vocab_size, vocab_size, embedding_dim,__
      →lstm_size, max_len, max_len)
     pred_model.compile(optimizer = 'Adam', loss = 'sparse_categorical_crossentropy')
     pred_model.build(input_shape=(None, 1, max_len))
     pred model.load weights('seq2seq.h5')
[71]: sentence = unigram_train['input'].values[5]
     print('input : ', sentence)
     result = predict(sentence, unigram_vec, unigram_index_to_word, gram = 'uni')
     print('predicted output : ',result)
     print('actual output :', unigram_train['output'].values[5])
     input : qitted
     predicted output : quitted
     actual output : quitted
[72]: sentence = unigram_train['input'].values[11]
     print('input : ', sentence)
     result = predict(sentence, unigram_vec, unigram_index_to_word, gram = 'uni')
     print('predicted output : ',result)
     print('actual output :', unigram_train['output'].values[11])
     input : fortissiemus
     predicted output : fortissimeus
     actual output : fortissimus
[73]: sentence = unigram_train['input'].values[14]
     print('input : ', sentence)
     result = predict(sentence, unigram_vec, unigram_index_to_word, gram = 'uni')
     print('predicted output : ',result)
     print('actual output :', unigram_train['output'].values[14])
     input : numbeGr
     predicted output : number
     actual output : number
[27]: val_bleu = 0
     for i in tqdm(range(val.shape[0])):
         inp = unigram_val['input'].values[i]
         out = unigram_val['output'].values[i]
```

```
pred = predict(inp, unigram_vec, unigram_index_to_word, gram = 'uni')
          val_bleu += sentence_bleu([out], pred)
      train_bleu = 0
      for i in tqdm(range(train.shape[0])):
          inp = unigram_train['input'].values[i];
          out = unigram_train['output'].values[i]
          pred = predict(inp, unigram_vec, unigram_index_to_word, gram = 'uni')
          train_bleu += sentence_bleu([out], pred)
      test bleu = 0
      for i in tqdm(range(test.shape[0])):
          inp = unigram_test['input'].values[i]
          out = unigram_test['output'].values[i]
          pred = predict(inp, unigram_vec, unigram_index_to_word, gram = 'uni')
          test_bleu += sentence_bleu([out], pred)
      print('BLEU Score on train: ',train_bleu/unigram_train.shape[0])
      print('BLEU Score on val: ',val_bleu/unigram_val.shape[0])
      print('BLEU Score on test: ',test_bleu/unigram_test.shape[0])
     100%|
       | 3678/3678 [03:16<00:00, 18.73it/s]
     100%|
     | 33101/33101 [29:07<00:00, 18.94it/s]
     100%|
       | 3150/3150 [02:46<00:00, 18.89it/s]
     BLEU Score on train: 0.8349934632437717
     BLEU Score on val: 0.7469809366693739
     BLEU Score on test: 0.6843990465288321
     1.2 BiGram
[20]: vocab_size = len(bigram_vec.get_vocabulary())
      embedding dim = 100
      lstm size = 256
      max len = 26
[28]: model = Encoder_decoder(vocab_size, vocab_size, embedding_dim, lstm_size,_u
      →max_len, max_len)
      model.compile(optimizer = 'Adam',loss = 'sparse_categorical_crossentropy')
      callbacks = [ModelCheckpoint('seq2seq bigram.h5', save_best_only= True, verbose_
      \hookrightarrow= 1),
                   EarlyStopping(patience = 5, verbose = 1),
                   ReduceLROnPlateau(patience = 3, verbose = 1)]
```

```
model.fit(x = bigram_train_dataset,
      steps_per_epoch = bigram_train.shape[0]//batch_size,
      validation_data = bigram_val_dataset,
      validation_steps = bigram_val.shape[0]//batch_size,
      epochs = 50,
      verbose = 1,
      callbacks = callbacks)
Epoch 1/50
Epoch 00001: val loss improved from inf to 0.11996, saving model to
seq2seq_bigram.h5
6910/6910 [============ ] - 96s 14ms/step - loss: 0.5047 -
val_loss: 0.1200
Epoch 2/50
Epoch 00002: val_loss improved from 0.11996 to 0.06599, saving model to
seq2seq bigram.h5
6910/6910 [============== ] - 100s 14ms/step - loss: 0.1246 -
val loss: 0.0660
Epoch 3/50
Epoch 00003: val_loss improved from 0.06599 to 0.05437, saving model to
seq2seq bigram.h5
6910/6910 [============== ] - 104s 15ms/step - loss: 0.0858 -
val loss: 0.0544
Epoch 4/50
Epoch 00004: val_loss improved from 0.05437 to 0.04924, saving model to
seq2seq_bigram.h5
val loss: 0.0492
Epoch 5/50
Epoch 00005: val_loss improved from 0.04924 to 0.04526, saving model to
seq2seq_bigram.h5
6910/6910 [============== ] - 105s 15ms/step - loss: 0.0649 -
val_loss: 0.0453
Epoch 6/50
Epoch 00006: val_loss improved from 0.04526 to 0.04325, saving model to
seq2seq_bigram.h5
val_loss: 0.0432
Epoch 7/50
```

Epoch 00007: val_loss improved from 0.04325 to 0.04161, saving model to

```
seq2seq_bigram.h5
val_loss: 0.0416
Epoch 8/50
Epoch 00008: val_loss improved from 0.04161 to 0.04037, saving model to
seq2seq bigram.h5
6910/6910 [============= ] - 106s 15ms/step - loss: 0.0539 -
val loss: 0.0404
Epoch 9/50
Epoch 00009: val_loss improved from 0.04037 to 0.03965, saving model to
seq2seq_bigram.h5
val_loss: 0.0396
Epoch 10/50
Epoch 00010: val_loss improved from 0.03965 to 0.03907, saving model to
seq2seq_bigram.h5
6910/6910 [============== ] - 104s 15ms/step - loss: 0.0499 -
val loss: 0.0391
Epoch 11/50
Epoch 00011: val_loss improved from 0.03907 to 0.03830, saving model to
seq2seq_bigram.h5
6910/6910 [============== ] - 103s 15ms/step - loss: 0.0484 -
val_loss: 0.0383
Epoch 12/50
Epoch 00012: val_loss improved from 0.03830 to 0.03783, saving model to
seq2seq bigram.h5
6910/6910 [============== ] - 105s 15ms/step - loss: 0.0471 -
val_loss: 0.0378
Epoch 13/50
Epoch 00013: val_loss improved from 0.03783 to 0.03727, saving model to
seq2seq bigram.h5
val_loss: 0.0373
Epoch 14/50
Epoch 00014: val_loss improved from 0.03727 to 0.03696, saving model to
seq2seq_bigram.h5
6910/6910 [============ ] - 105s 15ms/step - loss: 0.0450 -
val_loss: 0.0370
Epoch 15/50
Epoch 00015: val_loss improved from 0.03696 to 0.03681, saving model to
```

```
seq2seq_bigram.h5
6910/6910 [============= ] - 109s 16ms/step - loss: 0.0440 -
val_loss: 0.0368
Epoch 16/50
Epoch 00016: val_loss improved from 0.03681 to 0.03646, saving model to
seq2seq bigram.h5
6910/6910 [============= ] - 109s 16ms/step - loss: 0.0433 -
val loss: 0.0365
Epoch 17/50
Epoch 00017: val_loss improved from 0.03646 to 0.03598, saving model to
seq2seq_bigram.h5
6910/6910 [============= ] - 109s 16ms/step - loss: 0.0425 -
val_loss: 0.0360
Epoch 18/50
Epoch 00018: val_loss improved from 0.03598 to 0.03585, saving model to
seq2seq_bigram.h5
6910/6910 [============== ] - 109s 16ms/step - loss: 0.0418 -
val loss: 0.0359
Epoch 19/50
Epoch 00019: val_loss improved from 0.03585 to 0.03570, saving model to
seq2seq_bigram.h5
6910/6910 [============== ] - 113s 16ms/step - loss: 0.0412 -
val_loss: 0.0357
Epoch 20/50
Epoch 00020: val_loss improved from 0.03570 to 0.03565, saving model to
seq2seq bigram.h5
6910/6910 [============== ] - 112s 16ms/step - loss: 0.0406 -
val_loss: 0.0356
Epoch 21/50
Epoch 00021: val_loss improved from 0.03565 to 0.03554, saving model to
seq2seq bigram.h5
val_loss: 0.0355
Epoch 22/50
Epoch 00022: val_loss improved from 0.03554 to 0.03531, saving model to
seq2seq_bigram.h5
6910/6910 [============ ] - 109s 16ms/step - loss: 0.0396 -
val_loss: 0.0353
Epoch 23/50
Epoch 00023: val_loss improved from 0.03531 to 0.03517, saving model to
```

```
seq2seq_bigram.h5
6910/6910 [============== ] - 107s 15ms/step - loss: 0.0391 -
val_loss: 0.0352
Epoch 24/50
Epoch 00024: val_loss improved from 0.03517 to 0.03482, saving model to
seq2seq bigram.h5
6910/6910 [============= ] - 109s 16ms/step - loss: 0.0387 -
val loss: 0.0348
Epoch 25/50
Epoch 00025: val_loss improved from 0.03482 to 0.03456, saving model to
seq2seq_bigram.h5
val_loss: 0.0346
Epoch 26/50
Epoch 00026: val_loss did not improve from 0.03456
6910/6910 [============== ] - 109s 16ms/step - loss: 0.0379 -
val loss: 0.0348
Epoch 27/50
Epoch 00027: val_loss improved from 0.03456 to 0.03456, saving model to
seq2seq_bigram.h5
6910/6910 [============== ] - 109s 16ms/step - loss: 0.0375 -
val_loss: 0.0346
Epoch 28/50
6909/6910 [==============>.] - ETA: Os - loss: 0.0372
Epoch 00028: val_loss improved from 0.03456 to 0.03445, saving model to
seq2seq_bigram.h5
6910/6910 [============== ] - 109s 16ms/step - loss: 0.0372 -
val_loss: 0.0345
Epoch 29/50
Epoch 00029: val loss did not improve from 0.03445
6910/6910 [============== ] - 109s 16ms/step - loss: 0.0368 -
val loss: 0.0346
Epoch 30/50
Epoch 00030: val_loss did not improve from 0.03445
6910/6910 [============= ] - 110s 16ms/step - loss: 0.0366 -
val_loss: 0.0346
Epoch 31/50
Epoch 00031: val_loss did not improve from 0.03445
Epoch 00031: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
```

```
val_loss: 0.0346
Epoch 32/50
Epoch 00032: val_loss improved from 0.03445 to 0.03222, saving model to
seq2seq bigram.h5
6910/6910 [============== ] - 108s 16ms/step - loss: 0.0308 -
val loss: 0.0322
Epoch 33/50
Epoch 00033: val_loss improved from 0.03222 to 0.03200, saving model to
seq2seq_bigram.h5
val_loss: 0.0320
Epoch 34/50
Epoch 00034: val_loss improved from 0.03200 to 0.03186, saving model to
seq2seq_bigram.h5
6910/6910 [============== ] - 110s 16ms/step - loss: 0.0286 -
val loss: 0.0319
Epoch 35/50
Epoch 00035: val loss improved from 0.03186 to 0.03174, saving model to
seq2seq bigram.h5
6910/6910 [============== ] - 108s 16ms/step - loss: 0.0282 -
val loss: 0.0317
Epoch 36/50
Epoch 00036: val_loss improved from 0.03174 to 0.03169, saving model to
seq2seq bigram.h5
6910/6910 [============== ] - 108s 16ms/step - loss: 0.0279 -
val_loss: 0.0317
Epoch 37/50
Epoch 00037: val_loss did not improve from 0.03169
6910/6910 [============== ] - 108s 16ms/step - loss: 0.0276 -
val loss: 0.0317
Epoch 38/50
Epoch 00038: val_loss improved from 0.03169 to 0.03168, saving model to
seq2seq_bigram.h5
Epoch 00038: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
val loss: 0.0317
Epoch 39/50
Epoch 00039: val_loss improved from 0.03168 to 0.03158, saving model to
seq2seq_bigram.h5
```

```
6910/6910 [============== ] - 109s 16ms/step - loss: 0.0267 -
val_loss: 0.0316
Epoch 40/50
Epoch 00040: val_loss improved from 0.03158 to 0.03155, saving model to
seq2seq bigram.h5
6910/6910 [============== ] - 107s 15ms/step - loss: 0.0266 -
val loss: 0.0316
Epoch 41/50
Epoch 00041: val_loss improved from 0.03155 to 0.03152, saving model to
seq2seq_bigram.h5
6910/6910 [============== ] - 110s 16ms/step - loss: 0.0265 -
val loss: 0.0315
Epoch 42/50
Epoch 00042: val_loss did not improve from 0.03152
Epoch 00042: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.
6910/6910 [============= ] - 109s 16ms/step - loss: 0.0265 -
val loss: 0.0315
Epoch 43/50
Epoch 00043: val_loss improved from 0.03152 to 0.03151, saving model to
seq2seq_bigram.h5
6910/6910 [============== ] - 105s 15ms/step - loss: 0.0264 -
val_loss: 0.0315
Epoch 44/50
Epoch 00044: val_loss improved from 0.03151 to 0.03151, saving model to
seq2seq bigram.h5
6910/6910 [============== ] - 111s 16ms/step - loss: 0.0263 -
val_loss: 0.0315
Epoch 45/50
Epoch 00045: val_loss improved from 0.03151 to 0.03150, saving model to
seq2seq_bigram.h5
Epoch 00045: ReduceLROnPlateau reducing learning rate to 1.0000001111620805e-07.
val_loss: 0.0315
Epoch 46/50
Epoch 00046: val_loss improved from 0.03150 to 0.03149, saving model to
seq2seq_bigram.h5
6910/6910 [============== ] - 107s 15ms/step - loss: 0.0263 -
val_loss: 0.0315
Epoch 47/50
```

```
Epoch 00047: val_loss improved from 0.03149 to 0.03149, saving model to
    seq2seq_bigram.h5
    6910/6910 [============== ] - 106s 15ms/step - loss: 0.0263 -
    val loss: 0.0315
    Epoch 48/50
    Epoch 00048: val_loss improved from 0.03149 to 0.03149, saving model to
    seq2seq_bigram.h5
    Epoch 00048: ReduceLROnPlateau reducing learning rate to 1.000000082740371e-08.
    6910/6910 [============== ] - 105s 15ms/step - loss: 0.0264 -
    val_loss: 0.0315
    Epoch 49/50
    6910/6910 [============ ] - ETA: Os - loss: 0.0264
    Epoch 00049: val_loss improved from 0.03149 to 0.03149, saving model to
    seq2seq_bigram.h5
    6910/6910 [============== ] - 107s 15ms/step - loss: 0.0264 -
    val loss: 0.0315
    Epoch 50/50
    Epoch 00050: val loss improved from 0.03149 to 0.03149, saving model to
    seq2seq bigram.h5
    6910/6910 [============== ] - 108s 16ms/step - loss: 0.0263 -
    val loss: 0.0315
[28]: <tensorflow.python.keras.callbacks.History at 0x224068e7048>
[21]: pred_model = pred_Encoder_decoder(vocab_size, vocab_size, embedding_dim,__
     →lstm_size, max_len, max_len, bigram_word_to_index)
     pred model.compile(optimizer = 'Adam', loss = 'sparse categorical crossentropy')
     pred_model.build(input_shape=(None, 1, max_len))
     pred_model.load_weights('seq2seq_bigram.h5')
[42]: sentence = bigram_train['input'].values[4]
     print('input : ', sentence)
     result = predict(sentence, bigram_vec, bigram_index_to_word, gram = 'bi')
     print('predicted output : ',result)
     print('actual output :', bigram_train['output'].values[4])
    input : no Lne
    predicted output : no one
    actual output : no one
[45]: sentence = bigram_train['input'].values[6]
     print('input : ', sentence)
     result = predict(sentence, bigram_vec, bigram_index_to_word, gram = 'bi')
     print('predicted output : ',result)
```

```
print('actual output :', bigram_train['output'].values[6])
     input: for themseves
     predicted output : for themselves
     actual output : for themselves
[46]: sentence = bigram train['input'].values[7]
      print('input : ', sentence)
      result = predict(sentence, bigram_vec, bigram_index_to_word, gram = 'bi')
      print('predicted output : ',result)
      print('actual output :', bigram_train['output'].values[7])
     input: detil of
     predicted output : detail of
     actual output : detail of
 [3]: val_bleu = 0
      for i in tqdm(range(bigram_val.shape[0])):
          inp = bigram_val['input'].values[i]
          out = bigram_val['output'].values[i]
          pred = predict(inp, bigram vec, bigram index to word, gram = 'bi')
          val_bleu += sentence_bleu([out], pred)
      train bleu = 0
      for i in tqdm(range(bigram_train.shape[0])):
          inp = bigram_train['input'].values[i];
          out = bigram_train['output'].values[i]
          pred = predict(inp, bigram_vec, bigram_index_to_word, gram = 'bi')
          train_bleu += sentence_bleu([out], pred)
      test_bleu = 0
      for i in tqdm(range(bigram_test.shape[0])):
          inp = bigram_test['input'].values[i]
          out = bigram_test['output'].values[i]
          pred = predict(inp, bigram_vec, bigram_index_to_word, gram = 'bi')
          test_bleu += sentence_bleu([out], pred)
      print('BLEU Score on train: ',train bleu/bigram train.shape[0])
      print('BLEU Score on val: ',val_bleu/bigram_val.shape[0])
      print('BLEU Score on test: ',test_bleu/bigram_test.shape[0])
     BLEU Score on train: 0.9654521214897293
     BLEU Score on val: 0.9467498122935679
     BLEU Score on test: 0.931299275417208
     1.3 TriGram
[50]: vocab_size = len(bigram_vec.get_vocabulary())
      embedding_dim = 100
```

```
lstm_size = 256
max_len = 34
```

```
Epoch 1/50
Epoch 00001: val_loss improved from inf to 0.21410, saving model to
seq2seq_trigram.h5
val_loss: 0.2141
Epoch 2/50
Epoch 00002: val_loss improved from 0.21410 to 0.08815, saving model to
seq2seq_trigram.h5
6910/6910 [============== ] - 129s 19ms/step - loss: 0.1938 -
val_loss: 0.0882
Epoch 3/50
6909/6910 [============>.] - ETA: Os - loss: 0.1176
Epoch 00003: val_loss improved from 0.08815 to 0.06765, saving model to
seq2seq_trigram.h5
val loss: 0.0676
Epoch 4/50
Epoch 00004: val_loss improved from 0.06765 to 0.05852, saving model to
seq2seq trigram.h5
6910/6910 [============= ] - 130s 19ms/step - loss: 0.0948 -
val loss: 0.0585
Epoch 5/50
Epoch 00005: val_loss improved from 0.05852 to 0.05359, saving model to
seq2seq_trigram.h5
```

```
6910/6910 [============== ] - 131s 19ms/step - loss: 0.0832 -
val_loss: 0.0536
Epoch 6/50
Epoch 00006: val_loss improved from 0.05359 to 0.05043, saving model to
seq2seq trigram.h5
6910/6910 [============= ] - 135s 19ms/step - loss: 0.0759 -
val loss: 0.0504
Epoch 7/50
Epoch 00007: val_loss improved from 0.05043 to 0.04756, saving model to
seq2seq_trigram.h5
val loss: 0.0476
Epoch 8/50
Epoch 00008: val_loss improved from 0.04756 to 0.04655, saving model to
seq2seq_trigram.h5
6910/6910 [============== ] - 134s 19ms/step - loss: 0.0671 -
val loss: 0.0465
Epoch 9/50
Epoch 00009: val_loss improved from 0.04655 to 0.04472, saving model to
seq2seq_trigram.h5
6910/6910 [============== ] - 135s 20ms/step - loss: 0.0641 -
val_loss: 0.0447
Epoch 10/50
Epoch 00010: val_loss improved from 0.04472 to 0.04360, saving model to
seq2seq_trigram.h5
val_loss: 0.0436
Epoch 11/50
Epoch 00011: val loss improved from 0.04360 to 0.04321, saving model to
seq2seq trigram.h5
6910/6910 [============== ] - 136s 20ms/step - loss: 0.0595 -
val loss: 0.0432
Epoch 12/50
6910/6910 [============ ] - ETA: Os - loss: 0.0579
Epoch 00012: val_loss improved from 0.04321 to 0.04224, saving model to
seq2seq_trigram.h5
6910/6910 [============== ] - 137s 20ms/step - loss: 0.0579 -
val loss: 0.0422
Epoch 13/50
Epoch 00013: val_loss improved from 0.04224 to 0.04159, saving model to
seq2seq_trigram.h5
```

```
6910/6910 [============== ] - 136s 20ms/step - loss: 0.0564 -
val_loss: 0.0416
Epoch 14/50
Epoch 00014: val_loss improved from 0.04159 to 0.04106, saving model to
seq2seq trigram.h5
val loss: 0.0411
Epoch 15/50
Epoch 00015: val_loss improved from 0.04106 to 0.04039, saving model to
seq2seq_trigram.h5
6910/6910 [============== ] - 137s 20ms/step - loss: 0.0538 -
val loss: 0.0404
Epoch 16/50
Epoch 00016: val_loss improved from 0.04039 to 0.04007, saving model to
seq2seq_trigram.h5
6910/6910 [============== ] - 136s 20ms/step - loss: 0.0528 -
val loss: 0.0401
Epoch 17/50
Epoch 00017: val_loss improved from 0.04007 to 0.03975, saving model to
seq2seq_trigram.h5
6910/6910 [============== ] - 137s 20ms/step - loss: 0.0519 -
val_loss: 0.0398
Epoch 18/50
Epoch 00018: val_loss improved from 0.03975 to 0.03891, saving model to
seq2seq_trigram.h5
6910/6910 [============== ] - 137s 20ms/step - loss: 0.0510 -
val_loss: 0.0389
Epoch 19/50
Epoch 00019: val loss improved from 0.03891 to 0.03879, saving model to
seq2seq trigram.h5
val loss: 0.0388
Epoch 20/50
Epoch 00020: val_loss improved from 0.03879 to 0.03860, saving model to
seq2seq_trigram.h5
6910/6910 [============== ] - 137s 20ms/step - loss: 0.0494 -
val loss: 0.0386
Epoch 21/50
Epoch 00021: val_loss improved from 0.03860 to 0.03802, saving model to
seq2seq_trigram.h5
```

```
6910/6910 [============== ] - 137s 20ms/step - loss: 0.0488 -
val_loss: 0.0380
Epoch 22/50
Epoch 00022: val loss improved from 0.03802 to 0.03792, saving model to
seq2seq trigram.h5
val loss: 0.0379
Epoch 23/50
Epoch 00023: val_loss improved from 0.03792 to 0.03753, saving model to
seq2seq_trigram.h5
6910/6910 [============== ] - 137s 20ms/step - loss: 0.0475 -
val loss: 0.0375
Epoch 24/50
loss: 0.04
Epoch 00024: val_loss did not improve from 0.03753
6910/6910 [============== ] - 139s 20ms/step - loss: 0.0470 -
val loss: 0.0377
Epoch 25/50
Epoch 00025: val_loss improved from 0.03753 to 0.03730, saving model to
seq2seq_trigram.h5
6910/6910 [============== ] - 139s 20ms/step - loss: 0.0464 -
val_loss: 0.0373
Epoch 26/50
Epoch 00026: val_loss did not improve from 0.03730
val_loss: 0.0373
Epoch 27/50
6910/6910 [===========] - ETA: Os - loss: 0.0455
Epoch 00027: val_loss improved from 0.03730 to 0.03691, saving model to
seq2seq trigram.h5
6910/6910 [============== ] - 136s 20ms/step - loss: 0.0455 -
val loss: 0.0369
Epoch 28/50
Epoch 00028: val_loss did not improve from 0.03691
val_loss: 0.0370
Epoch 29/50
Epoch 00029: val_loss improved from 0.03691 to 0.03646, saving model to
seq2seq trigram.h5
6910/6910 [============== ] - 137s 20ms/step - loss: 0.0447 -
val_loss: 0.0365
```

```
Epoch 30/50
Epoch 00030: val_loss improved from 0.03646 to 0.03634, saving model to
seq2seq trigram.h5
6910/6910 [============== ] - 137s 20ms/step - loss: 0.0443 -
val loss: 0.0363
Epoch 31/50
6910/6910 [============ ] - ETA: Os - loss: 0.0439
Epoch 00031: val_loss improved from 0.03634 to 0.03623, saving model to
seq2seq_trigram.h5
6910/6910 [============= ] - 139s 20ms/step - loss: 0.0439 -
val_loss: 0.0362
Epoch 32/50
Epoch 00032: val_loss did not improve from 0.03623
val_loss: 0.0363
Epoch 33/50
Epoch 00033: val_loss improved from 0.03623 to 0.03611, saving model to
seq2seq trigram.h5
6910/6910 [============== ] - 137s 20ms/step - loss: 0.0432 -
val_loss: 0.0361
Epoch 34/50
Epoch 00034: val_loss improved from 0.03611 to 0.03586, saving model to
seq2seq_trigram.h5
6910/6910 [============ ] - 137s 20ms/step - loss: 0.0429 -
val_loss: 0.0359
Epoch 35/50
Epoch 00035: val_loss did not improve from 0.03586
6910/6910 [============== ] - 138s 20ms/step - loss: 0.0425 -
val_loss: 0.0362
Epoch 36/50
6910/6910 [============ ] - ETA: Os - loss: 0.0423
Epoch 00036: val loss did not improve from 0.03586
val_loss: 0.0359
Epoch 37/50
Epoch 00037: val_loss did not improve from 0.03586
Epoch 00037: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
val_loss: 0.0359
Epoch 38/50
```

```
Epoch 00038: val_loss improved from 0.03586 to 0.03275, saving model to
seq2seq_trigram.h5
6910/6910 [============ ] - 137s 20ms/step - loss: 0.0363 -
val loss: 0.0327
Epoch 39/50
Epoch 00039: val loss improved from 0.03275 to 0.03238, saving model to
seq2seq trigram.h5
6910/6910 [============== ] - 137s 20ms/step - loss: 0.0346 -
val loss: 0.0324
Epoch 40/50
Epoch 00040: val_loss improved from 0.03238 to 0.03222, saving model to
seq2seq trigram.h5
6910/6910 [============= ] - 138s 20ms/step - loss: 0.0339 -
val loss: 0.0322
Epoch 41/50
Epoch 00041: val_loss improved from 0.03222 to 0.03208, saving model to
seq2seq trigram.h5
6910/6910 [============= ] - 138s 20ms/step - loss: 0.0336 -
val loss: 0.0321
Epoch 42/50
Epoch 00042: val_loss improved from 0.03208 to 0.03205, saving model to
seq2seq_trigram.h5
6910/6910 [============= ] - 136s 20ms/step - loss: 0.0333 -
val_loss: 0.0321
Epoch 43/50
Epoch 00043: val_loss did not improve from 0.03205
val_loss: 0.0321
Epoch 44/50
6910/6910 [============ ] - ETA: Os - loss: 0.0329
Epoch 00044: val_loss improved from 0.03205 to 0.03197, saving model to
seq2seq trigram.h5
6910/6910 [============= ] - 139s 20ms/step - loss: 0.0329 -
val_loss: 0.0320
Epoch 45/50
6910/6910 [============= ] - ETA: Os - loss: 0.0327
Epoch 00045: val_loss improved from 0.03197 to 0.03190, saving model to
seq2seq_trigram.h5
6910/6910 [============ ] - 138s 20ms/step - loss: 0.0327 -
val_loss: 0.0319
Epoch 46/50
Epoch 00046: val_loss did not improve from 0.03190
```

```
val_loss: 0.0319
    Epoch 47/50
    6910/6910 [============= ] - ETA: Os - loss: 0.0324
    Epoch 00047: val loss did not improve from 0.03190
    Epoch 00047: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
    6910/6910 [============== ] - 135s 20ms/step - loss: 0.0324 -
    val loss: 0.0319
    Epoch 48/50
    Epoch 00048: val_loss improved from 0.03190 to 0.03173, saving model to
    seq2seq_trigram.h5
    6910/6910 [=============== ] - 136s 20ms/step - loss: 0.0318 -
    val_loss: 0.0317
    Epoch 49/50
    Epoch 00049: val_loss improved from 0.03173 to 0.03169, saving model to
    seq2seq_trigram.h5
    6910/6910 [============== ] - 134s 19ms/step - loss: 0.0316 -
    val loss: 0.0317
    Epoch 50/50
    Epoch 00050: val_loss improved from 0.03169 to 0.03166, saving model to
    seq2seq_trigram.h5
    6910/6910 [============== ] - 133s 19ms/step - loss: 0.0315 -
    val_loss: 0.0317
[52]: <tensorflow.python.keras.callbacks.History at 0x224099166c8>
[59]: from tensorflow.keras.optimizers import Adam
     model = Encoder_decoder(vocab_size, vocab_size, embedding_dim, lstm_size,_
     →max_len, max_len)
     model.compile(optimizer = Adam(1.0000000474974514e-05), loss = ___
     callbacks = [ModelCheckpoint('seq2seq_trigram.h5', save_best_only= True,_
     \rightarrowverbose = 1),
                EarlyStopping(patience = 5, verbose = 1),
                ReduceLROnPlateau(patience = 3, verbose = 1)]
     model.build(input_shape = (None, batch_size, max_len))
     model.load_weights('seq2seq_trigram.h5')
     model.fit(x = trigram_train_dataset,
             steps_per_epoch = trigram_train.shape[0]//batch_size,
             validation data = trigram val dataset,
```

```
epochs = 50.
       verbose = 1,
       callbacks = callbacks)
Epoch 1/50
6909/6910 [============>.] - ETA: Os - loss: 0.0315
Epoch 00001: val_loss improved from inf to 0.03166, saving model to
seq2seq trigram.h5
6910/6910 [============ ] - 123s 18ms/step - loss: 0.0315 -
val_loss: 0.0317
Epoch 2/50
Epoch 00002: val_loss improved from 0.03166 to 0.03165, saving model to
seq2seq_trigram.h5
6910/6910 [============== ] - 128s 19ms/step - loss: 0.0314 -
val loss: 0.0316
Epoch 3/50
Epoch 00003: val_loss did not improve from 0.03165
6910/6910 [============== ] - 130s 19ms/step - loss: 0.0314 -
val_loss: 0.0316
Epoch 4/50
Epoch 00004: val_loss improved from 0.03165 to 0.03163, saving model to
seq2seq_trigram.h5
Epoch 00004: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.
6910/6910 [============= ] - 131s 19ms/step - loss: 0.0315 -
val_loss: 0.0316
Epoch 5/50
Epoch 00005: val_loss improved from 0.03163 to 0.03161, saving model to
seq2seq trigram.h5
6910/6910 [============== ] - 132s 19ms/step - loss: 0.0314 -
val loss: 0.0316
Epoch 6/50
loss: 0.0
Epoch 00006: val_loss improved from 0.03161 to 0.03160, saving model to
seq2seq_trigram.h5
6910/6910 [============ ] - 130s 19ms/step - loss: 0.0313 -
val_loss: 0.0316
Epoch 7/50
Epoch 00007: val_loss improved from 0.03160 to 0.03159, saving model to
seq2seq_trigram.h5
```

validation_steps = trigram_val.shape[0]//batch_size,

```
Epoch 00007: ReduceLROnPlateau reducing learning rate to 1.0000001111620805e-07.
val_loss: 0.0316
Epoch 8/50
Epoch 00008: val_loss improved from 0.03159 to 0.03159, saving model to
seq2seq trigram.h5
val loss: 0.0316
Epoch 9/50
Epoch 00009: val_loss improved from 0.03159 to 0.03159, saving model to
seq2seq_trigram.h5
6910/6910 [============== ] - 131s 19ms/step - loss: 0.0313 -
val_loss: 0.0316
Epoch 10/50
Epoch 00010: val_loss improved from 0.03159 to 0.03159, saving model to
seq2seq_trigram.h5
Epoch 00010: ReduceLROnPlateau reducing learning rate to 1.000000082740371e-08.
val loss: 0.0316
Epoch 11/50
Epoch 00011: val_loss improved from 0.03159 to 0.03159, saving model to
seq2seq_trigram.h5
6910/6910 [============= ] - 133s 19ms/step - loss: 0.0314 -
val_loss: 0.0316
Epoch 12/50
Epoch 00012: val_loss improved from 0.03159 to 0.03159, saving model to
seq2seq_trigram.h5
6910/6910 [============= ] - 133s 19ms/step - loss: 0.0314 -
val loss: 0.0316
Epoch 13/50
Epoch 00013: val_loss improved from 0.03159 to 0.03159, saving model to
seq2seq_trigram.h5
Epoch 00013: ReduceLROnPlateau reducing learning rate to 1.000000082740371e-09.
val_loss: 0.0316
Epoch 14/50
Epoch 00014: val_loss did not improve from 0.03159
val_loss: 0.0316
```

```
Epoch 15/50
Epoch 00015: val_loss improved from 0.03159 to 0.03159, saving model to
seq2seq trigram.h5
6910/6910 [============= ] - 130s 19ms/step - loss: 0.0314 -
val loss: 0.0316
Epoch 16/50
Epoch 00016: val_loss improved from 0.03159 to 0.03159, saving model to
seq2seq_trigram.h5
Epoch 00016: ReduceLROnPlateau reducing learning rate to 1.000000082740371e-10.
val_loss: 0.0316
Epoch 17/50
Epoch 00017: val_loss improved from 0.03159 to 0.03159, saving model to
seq2seq_trigram.h5
6910/6910 [============= ] - 127s 18ms/step - loss: 0.0313 -
val loss: 0.0316
Epoch 18/50
Epoch 00018: val_loss did not improve from 0.03159
6910/6910 [============== ] - 127s 18ms/step - loss: 0.0313 -
val_loss: 0.0316
Epoch 19/50
Epoch 00019: val_loss did not improve from 0.03159
Epoch 00019: ReduceLROnPlateau reducing learning rate to 1.000000082740371e-11.
val_loss: 0.0316
Epoch 20/50
Epoch 00020: val loss did not improve from 0.03159
6910/6910 [============== ] - 128s 19ms/step - loss: 0.0314 -
val loss: 0.0316
Epoch 21/50
Epoch 00021: val_loss did not improve from 0.03159
val_loss: 0.0316
Epoch 22/50
Epoch 00022: val_loss did not improve from 0.03159
Epoch 00022: ReduceLROnPlateau reducing learning rate to 1.000000082740371e-12.
```

```
val_loss: 0.0316
     Epoch 00022: early stopping
[59]: <tensorflow.python.keras.callbacks.History at 0x224047a6788>
[67]: pred model = pred_Encoder_decoder(vocab_size, vocab_size, embedding_dim,__
      →lstm_size, max_len, max_len, trigram_word_to_index)
      pred_model.compile(optimizer = 'Adam', loss = 'sparse_categorical_crossentropy')
      pred model.build(input shape=(None, 1, max len))
      pred_model.load_weights('seq2seq_trigram.h5')
[68]: sentence = trigram_train['input'].values[4]
      print('input : ', sentence)
      result = predict(sentence, trigram_vec, trigram_index_to_word, gram = 'tri')
      print('predicted output : ',result)
      print('actual output :', trigram_train['output'].values[4])
     input: woman oAf him
     predicted output : woman of him
     actual output : woman of him
[72]: sentence = trigram_train['input'].values[7]
      print('input : ', sentence)
      result = predict(sentence, trigram_vec, trigram_index_to_word, gram = 'tri')
      print('predicted output : ',result)
      print('actual output :', trigram_train['output'].values[7])
     input : endurXe a collision
     predicted output : endure a collision
     actual output : endure a collision
[75]: sentence = trigram_train['input'].values[10]
      print('input : ', sentence)
      result = predict(sentence, trigram_vec, trigram_index_to_word, gram = 'tri')
      print('predicted output : ',result)
      print('actual output :', trigram_train['output'].values[10])
     input : marshals sitti g on
     predicted output : marshals sitting on
     actual output : marshals sitting on
 [4]: val bleu = 0
      for i in tqdm(range(trigram_val.shape[0])):
          inp = trigram_val['input'].values[i]
          out = trigram_val['output'].values[i]
          pred = predict(inp, trigram_vec, trigram_index_to_word, gram = 'tri')
          val_bleu += sentence_bleu([out], pred)
      train_bleu = 0
```

```
for i in tqdm(range(train.shape[0])):
    inp = trigram_train['input'].values[i];
    out = trigram_train['output'].values[i]
    pred = predict(inp, trigram_vec, trigram_index_to_word, gram = 'tri')
    train_bleu += sentence_bleu([out], pred)

test_bleu = 0
for i in tqdm(range(test.shape[0])):
    inp = trigram_test['input'].values[i]
    out = trigram_test['output'].values[i]
    pred = predict(inp, trigram_vec, trigram_index_to_word, gram = 'tri')
    test_bleu += sentence_bleu([out], pred)

print('BLEU Score on train: ',train_bleu/trigram_train.shape[0])
print('BLEU Score on test: ',val_bleu/trigram_val.shape[0])
print('BLEU Score on test: ',test_bleu/trigram_test.shape[0])
```

BLEU Score on train: 0.9684256422311769 BLEU Score on val: 0.9575594555349892 BLEU Score on test: 0.949065764861953

2. Seq2Seq with Attention Mechanism

```
[77]: class Encoder(tf.keras.layers.Layer):
          def __init__(self,inp_vocab_size,embedding_size,lstm_size,input_length):
              super(Encoder, self).__init__()
              self.lstm size = lstm size
              #Initialize Embedding layer
              self.enc_embed = Embedding(input_dim = inp_vocab_size, output_dim = __
       →embedding_size)
              #Intialize Encoder LSTM layer
              self.enc_lstm = LSTM(lstm_size, return_sequences = True, return_state =__
       \rightarrowTrue, dropout = 0.4)
          def call(self,input_sequence,states):
              embedding = self.enc_embed(input_sequence)
              output_state, enc_h, enc_c = self.enc_lstm(embedding, initial_state = __
       →states)
              return output_state, enc_h, enc_c
          def initialize states(self,batch size):
              return [tf.zeros((batch_size, self.lstm_size)), tf.zeros((batch_size, __
       ⇒self.lstm_size))]
      class Attention(tf.keras.layers.Layer):
          def __init__(self,scoring_function, att_units):
              super(Attention, self).__init__()
```

```
self.scoring_function = scoring_function
        if scoring_function == 'dot':
            self.dot = Dot(axes = (1, 2))
        elif scoring_function == 'general':
          # Intialize variables needed for General score function here
            self.W = Dense(att_units)
            self.dot = Dot(axes = (1, 2))
        elif scoring_function == 'concat':
          # Intialize variables needed for Concat score function here
            self.W1 = Dense(att units)
            self.W2 = Dense(att units)
            self.V = Dense(1)
    def call(self,decoder_hidden_state,encoder_output):
        decoder_hidden_state = tf.expand_dims(decoder_hidden_state, 1)
        if self.scoring_function == 'dot':
            # Implement Dot score function here
            score = tf.transpose(self.dot([tf.transpose(decoder_hidden_state,_u
\rightarrow (0, 2, 1)), encoder_output]), (0, 2,1))
        elif self.scoring function == 'general':
            # Implement General score function here
            mul = self.W(encoder_output)
            score = tf.transpose(self.dot([tf.transpose(decoder_hidden_state,_
\rightarrow (0, 2, 1)), mul]), (0, 2,1))
        elif self.scoring_function == 'concat':
            # Implement General score function here
            inter = self.W1(decoder_hidden_state) + self.W2(encoder_output)
            tan = tf.nn.tanh(inter)
            score = self.V(tan)
        attention_weights = tf.nn.softmax(score, axis =1)
        context vector = attention weights * encoder output
        context_vector = tf.reduce_sum(context_vector, axis=1)
        return context_vector, attention_weights
class OneStepDecoder(tf.keras.layers.Layer):
    def __init__(self,tar_vocab_size, embedding_dim, input_length, dec_units_
→,score_fun ,att_units):
        super(OneStepDecoder, self).__init__()
      # Initialize decoder embedding layer, LSTM and any other objects needed
        self.embed_dec = Embedding(input_dim = tar_vocab_size, output_dim =
 →embedding dim)
        self.lstm = LSTM(dec_units, return_sequences = True, return_state = __
 \rightarrowTrue, dropout = 0.4)
```

```
self.attention = Attention(scoring function = score fun, att_units = ___
 →att_units)
        self.fc = Dense(tar_vocab_size)
   def call(self,input_to_decoder, encoder_output, state_h,state_c):
        embed = self.embed dec(input to decoder)
        context_vect, attention_weights = self.attention(state_h,_
 →encoder_output)
       final_inp = tf.concat([tf.expand_dims(context_vect, 1), embed], axis =__
→-1)
       out, dec_h, dec_c = self.lstm(final_inp, [state_h, state_c])
        out = tf.reshape(out, (-1, out.shape[2]))
       output = self.fc(out)
       output = Dropout(0.5)(output)
        return output, dec_h, dec_c, attention_weights, context_vect
class encoder_decoder(tf.keras.Model):
   def __init__(self, inp_vocab_size, out_vocab_size, embedding_dim,__
→enc_units, dec_units, max_len_inp, max_len_out, score_fun, att_units, u
→batch_size):
        #Intialize objects from encoder decoder
        super(encoder_decoder, self).__init__()
        self.encoder = Encoder(inp_vocab_size, embedding_dim, enc_units,_
→max_len_inp)
        self.one_step_decoder = OneStepDecoder(out_vocab_size, embedding_dim,_u
 →max_len_out, dec_units ,score_fun ,att_units)
        self.batch_size = batch_size
   def call(self, data):
        enc_inp, dec_inp = data[0], data[1]
        initial_state = self.encoder.initialize_states(self.batch_size)
        enc_output, enc_h, enc_c = self.encoder(enc_inp, initial_state)
        all_outputs = tf.TensorArray(dtype = tf.float32, size= max_len)
       dec_h = enc_h
       dec_c = enc_c
        for timestep in range(max len):
            # Call onestepdecoder for each token in decoder_input
            output, dec_h, dec_c, _, _ = self.one_step_decoder(dec_inp[:,_
→timestep:timestep+1],
                                                                enc_output,
                                                                dec_h,
                                                                dec c)
            # Store the output in tensorarray
            all_outputs = all_outputs.write(timestep, output)
        # Return the tensor array
```

```
all_outputs = tf.transpose(all_outputs.stack(), (1, 0, 2))
              # return the decoder output
              return all_outputs
      class pred_Encoder_decoder(tf.keras.Model):
          def __init__(self, inp_vocab_size, out_vocab_size, embedding_dim,_
       →enc_units, dec_units, max_len_ita, max_len_eng, score_fun, att_units, u
       →word_to_index):
              #Intialize objects from encoder decoder
              super(pred_Encoder_decoder, self).__init__()
              self.encoder = Encoder(inp_vocab_size, embedding_dim, enc_units,_
       →max_len_ita)
              self.one_step_decoder = OneStepDecoder(out_vocab_size, embedding_dim,_u
       →max_len_eng, dec_units ,score_fun ,att_units)
              self.batch_size = batch_size
              self.word_to_index = word_to_index
          def call(self, params):
              enc_inp = params[0]
              initial_state = self.encoder.initialize_states(1)
              output_state, enc_h, enc_c = self.encoder(enc_inp, initial_state)
              pred = tf.expand_dims([self.word_to_index['<SOW>']], 0)
              dec h = enc h
              dec_c = enc_c
              all pred = []
              all_attention = []
              for t in range(max len):
                  output, dec_h,dec_c, attention, _ = self.one_step_decoder(pred,_
       →output_state, dec_h, dec_c)
                  pred = tf.argmax(output, axis = -1)
                  all_pred.append(pred)
                  pred = tf.expand_dims(pred, 0)
                  all attention.append(attention)
              return all_pred, all_attention
[78]: | loss_object = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True,_
       →reduction='none')
      def loss_function(real, pred):
          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_)
[79]: def predict(seq, vectorizer, index_to_word, gram = 'uni'):
          if gram =='uni':
              seq = ' < SOW > '+' '.join(list(seq))+' < EOW > '
```

```
else:
    seq = '<SOW>*'+'*'.join(list(seq))+'*<EOW>'
seq = vectorizer([seq])
pred, attention_weights = pred_model.predict(tf.expand_dims(seq, 0))
output = []
for i in pred:
    word = index_to_word[i[0]]
    if word == '<EOW>':
        break
    output.append(word)
return ''.join(output), np.squeeze(np.squeeze(np.array(attention_weights), u))
        -1), -1)
```

```
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker

def plot_attention(attention, sentence, predicted_sentence):
    fig = plt.figure(figsize=(10,10))
    ax = fig.add_subplot(1, 1, 1)
    ax.matshow(attention, cmap='viridis')

fontdict = {'fontsize': 14}

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

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

plt.show()
```

2.1 UniGram

```
[76]: lstm_size = 256
embedding_dim = 100
att_units = 256
maxlen = 22
```

```
model.fit(x = unigram_train_dataset,
       steps_per_epoch = unigram_train.shape[0]//batch_size,
       validation_data = unigram_val_dataset,
       validation_steps = unigram_val.shape[0]//batch_size,
       epochs = 50,
       verbose = 1,
       callbacks = callbacks)
Epoch 1/50
Epoch 00001: val_loss improved from inf to 0.96448, saving model to
Attention_concat_lstm.h5
val_loss: 0.9645
Epoch 2/50
Epoch 00002: val_loss improved from 0.96448 to 0.73190, saving model to
Attention concat lstm.h5
258/258 [=============== ] - 13s 50ms/step - loss: 1.1640 -
val_loss: 0.7319
Epoch 3/50
Epoch 00003: val_loss improved from 0.73190 to 0.44536, saving model to
Attention_concat_lstm.h5
val_loss: 0.4454
Epoch 4/50
Epoch 00004: val_loss improved from 0.44536 to 0.26591, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 13s 51ms/step - loss: 0.8934 -
val_loss: 0.2659
Epoch 5/50
Epoch 00005: val_loss improved from 0.26591 to 0.21211, saving model to
Attention concat lstm.h5
258/258 [============ ] - 13s 51ms/step - loss: 0.8349 -
val loss: 0.2121
Epoch 6/50
Epoch 00006: val_loss improved from 0.21211 to 0.18196, saving model to
Attention concat lstm.h5
258/258 [============= ] - 14s 54ms/step - loss: 0.8071 -
val_loss: 0.1820
Epoch 7/50
Epoch 00007: val_loss improved from 0.18196 to 0.16000, saving model to
Attention_concat_lstm.h5
```

```
258/258 [============= ] - 13s 52ms/step - loss: 0.7956 -
val_loss: 0.1600
Epoch 8/50
Epoch 00008: val_loss improved from 0.16000 to 0.15305, saving model to
Attention concat lstm.h5
258/258 [============== ] - 14s 52ms/step - loss: 0.7887 -
val_loss: 0.1530
Epoch 9/50
258/258 [============= ] - ETA: Os - loss: 0.7819
Epoch 00009: val_loss improved from 0.15305 to 0.14978, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 14s 54ms/step - loss: 0.7819 -
val_loss: 0.1498
Epoch 10/50
Epoch 00010: val_loss improved from 0.14978 to 0.14204, saving model to
Attention_concat_lstm.h5
val loss: 0.1420
Epoch 11/50
258/258 [============= ] - ETA: Os - loss: 0.7725
Epoch 00011: val_loss improved from 0.14204 to 0.13989, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 14s 53ms/step - loss: 0.7725 -
val_loss: 0.1399
Epoch 12/50
Epoch 00012: val_loss improved from 0.13989 to 0.13404, saving model to
Attention_concat_lstm.h5
258/258 [============= ] - 14s 53ms/step - loss: 0.7676 -
val_loss: 0.1340
Epoch 13/50
258/258 [============ ] - ETA: Os - loss: 0.7644
Epoch 00013: val loss improved from 0.13404 to 0.12980, saving model to
Attention concat lstm.h5
val_loss: 0.1298
Epoch 14/50
258/258 [============= ] - ETA: Os - loss: 0.7605
Epoch 00014: val_loss improved from 0.12980 to 0.12613, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 14s 54ms/step - loss: 0.7605 -
val_loss: 0.1261
Epoch 15/50
Epoch 00015: val_loss did not improve from 0.12613
258/258 [============ ] - 14s 53ms/step - loss: 0.7610 -
```

```
val_loss: 0.1295
Epoch 16/50
258/258 [============ ] - ETA: Os - loss: 0.7585
Epoch 00016: val_loss did not improve from 0.12613
258/258 [============ ] - 14s 53ms/step - loss: 0.7585 -
val_loss: 0.1265
Epoch 17/50
Epoch 00017: val_loss improved from 0.12613 to 0.12149, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 14s 53ms/step - loss: 0.7560 -
val_loss: 0.1215
Epoch 18/50
Epoch 00018: val_loss improved from 0.12149 to 0.12073, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 14s 55ms/step - loss: 0.7552 -
val_loss: 0.1207
Epoch 19/50
Epoch 00019: val_loss improved from 0.12073 to 0.11933, saving model to
Attention concat lstm.h5
val_loss: 0.1193
Epoch 20/50
Epoch 00020: val_loss improved from 0.11933 to 0.11756, saving model to
Attention_concat_lstm.h5
258/258 [============= ] - 14s 53ms/step - loss: 0.7519 -
val_loss: 0.1176
Epoch 21/50
Epoch 00021: val_loss improved from 0.11756 to 0.11589, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 14s 53ms/step - loss: 0.7454 -
val loss: 0.1159
Epoch 22/50
Epoch 00022: val_loss did not improve from 0.11589
258/258 [============ ] - 14s 52ms/step - loss: 0.7493 -
val_loss: 0.1170
Epoch 23/50
258/258 [============= ] - ETA: Os - loss: 0.7449
Epoch 00023: val_loss improved from 0.11589 to 0.11506, saving model to
Attention_concat_lstm.h5
val_loss: 0.1151
Epoch 24/50
```

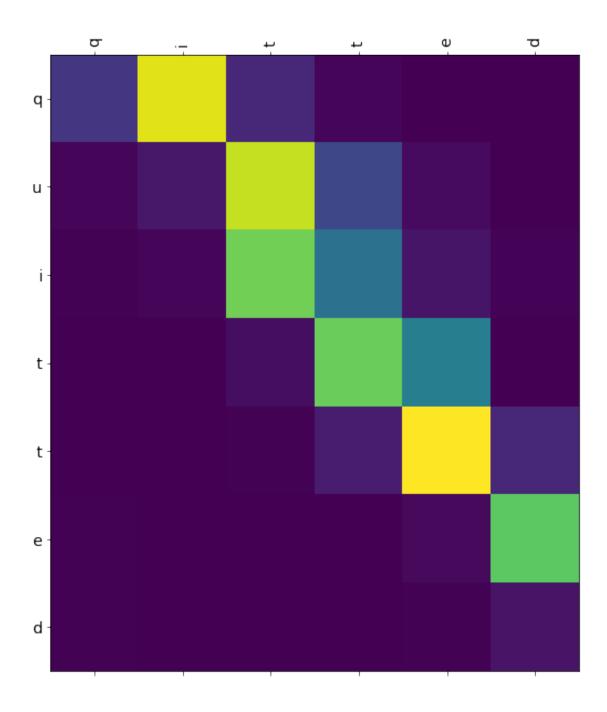
```
258/258 [============ ] - ETA: Os - loss: 0.7447
Epoch 00024: val_loss did not improve from 0.11506
258/258 [============= ] - 14s 53ms/step - loss: 0.7447 -
val_loss: 0.1168
Epoch 25/50
Epoch 00025: val loss did not improve from 0.11506
val loss: 0.1155
Epoch 26/50
258/258 [============= ] - ETA: Os - loss: 0.7442
Epoch 00026: val_loss improved from 0.11506 to 0.11340, saving model to
Attention_concat_lstm.h5
258/258 [============= ] - 14s 53ms/step - loss: 0.7442 -
val_loss: 0.1134
Epoch 27/50
Epoch 00027: val_loss improved from 0.11340 to 0.11310, saving model to
Attention concat lstm.h5
258/258 [============ ] - 14s 54ms/step - loss: 0.7413 -
val loss: 0.1131
Epoch 28/50
Epoch 00028: val_loss improved from 0.11310 to 0.11093, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 14s 53ms/step - loss: 0.7421 -
val_loss: 0.1109
Epoch 29/50
Epoch 00029: val_loss improved from 0.11093 to 0.10953, saving model to
Attention_concat_lstm.h5
258/258 [============= ] - 14s 53ms/step - loss: 0.7379 -
val_loss: 0.1095
Epoch 30/50
258/258 [============= ] - ETA: Os - loss: 0.7356
Epoch 00030: val_loss did not improve from 0.10953
258/258 [============ ] - 14s 53ms/step - loss: 0.7356 -
val_loss: 0.1112
Epoch 31/50
Epoch 00031: val_loss improved from 0.10953 to 0.10774, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 14s 53ms/step - loss: 0.7350 -
val_loss: 0.1077
Epoch 32/50
Epoch 00032: val_loss improved from 0.10774 to 0.10720, saving model to
Attention_concat_lstm.h5
```

```
258/258 [============= ] - 14s 53ms/step - loss: 0.7343 -
val_loss: 0.1072
Epoch 33/50
258/258 [============= ] - ETA: Os - loss: 0.7364
Epoch 00033: val loss did not improve from 0.10720
val loss: 0.1104
Epoch 34/50
Epoch 00034: val_loss improved from 0.10720 to 0.10713, saving model to
Attention_concat_lstm.h5
258/258 [============= ] - 14s 53ms/step - loss: 0.7355 -
val_loss: 0.1071
Epoch 35/50
Epoch 00035: val_loss did not improve from 0.10713
Epoch 00035: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
258/258 [============= ] - 14s 53ms/step - loss: 0.7311 -
val loss: 0.1073
Epoch 36/50
Epoch 00036: val_loss improved from 0.10713 to 0.10300, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 14s 54ms/step - loss: 0.7241 -
val_loss: 0.1030
Epoch 37/50
Epoch 00037: val_loss improved from 0.10300 to 0.10202, saving model to
Attention_concat_lstm.h5
258/258 [============= ] - 14s 53ms/step - loss: 0.7243 -
val_loss: 0.1020
Epoch 38/50
258/258 [============= ] - ETA: Os - loss: 0.7227
Epoch 00038: val loss improved from 0.10202 to 0.10193, saving model to
Attention concat lstm.h5
val_loss: 0.1019
Epoch 39/50
258/258 [============= ] - ETA: Os - loss: 0.7210
Epoch 00039: val_loss improved from 0.10193 to 0.10119, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 14s 53ms/step - loss: 0.7210 -
val_loss: 0.1012
Epoch 40/50
Epoch 00040: val_loss did not improve from 0.10119
258/258 [============ ] - 14s 54ms/step - loss: 0.7227 -
```

```
val_loss: 0.1014
Epoch 41/50
Epoch 00041: val_loss improved from 0.10119 to 0.10118, saving model to
Attention concat lstm.h5
258/258 [============ ] - 14s 53ms/step - loss: 0.7213 -
val loss: 0.1012
Epoch 42/50
258/258 [============ ] - ETA: Os - loss: 0.7175
Epoch 00042: val_loss did not improve from 0.10118
Epoch 00042: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
val loss: 0.1013
Epoch 43/50
258/258 [============ ] - ETA: Os - loss: 0.7193
Epoch 00043: val_loss improved from 0.10118 to 0.10111, saving model to
Attention_concat_lstm.h5
val loss: 0.1011
Epoch 44/50
258/258 [============= ] - ETA: Os - loss: 0.7186
Epoch 00044: val_loss improved from 0.10111 to 0.10101, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 14s 53ms/step - loss: 0.7186 -
val_loss: 0.1010
Epoch 45/50
Epoch 00045: val_loss improved from 0.10101 to 0.10088, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 14s 54ms/step - loss: 0.7193 -
val_loss: 0.1009
Epoch 46/50
258/258 [============ ] - ETA: Os - loss: 0.7194
Epoch 00046: val loss improved from 0.10088 to 0.10086, saving model to
Attention concat lstm.h5
258/258 [============ ] - 14s 53ms/step - loss: 0.7194 -
val loss: 0.1009
Epoch 47/50
258/258 [============= ] - ETA: Os - loss: 0.7210
Epoch 00047: val_loss improved from 0.10086 to 0.10083, saving model to
Attention_concat_lstm.h5
258/258 [============ ] - 14s 53ms/step - loss: 0.7210 -
val_loss: 0.1008
Epoch 48/50
Epoch 00048: val_loss did not improve from 0.10083
```

```
Epoch 00048: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.
    258/258 [============ ] - 14s 53ms/step - loss: 0.7186 -
    val_loss: 0.1009
    Epoch 49/50
    Epoch 00049: val_loss did not improve from 0.10083
    val loss: 0.1009
    Epoch 50/50
    258/258 [============= ] - ETA: Os - loss: 0.7206
    Epoch 00050: val_loss did not improve from 0.10083
    val_loss: 0.1008
[31]: <tensorflow.python.keras.callbacks.History at 0x298c951fd88>
[78]: pred_model = pred_Encoder_decoder(vocab_size, vocab_size, embedding_dim,__
     →lstm_size, lstm_size, maxlen, maxlen, 'concat', att_units)
     pred_model.compile(optimizer = 'Adam', loss = loss_function)
     pred_model.build(input_shape= (None, 1, maxlen))
     pred_model.load_weights('Attention_concat_lstm.h5')
[81]: sentence = unigram train['input'].values[5]
     result, attention_plot = predict(sentence, unigram_vec, unigram_index_to_word,_u

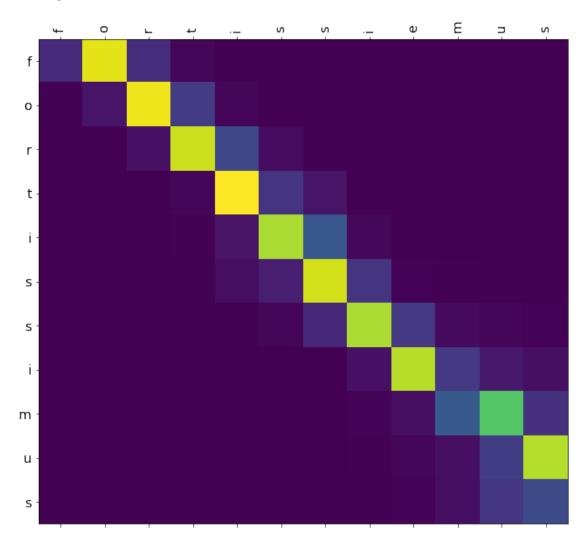
→gram = 'uni')
     print('input : ', sentence)
     print('predicted output : ',result)
     print('actual output :', unigram_train['output'].values[5])
     attention plot = attention plot[:len(list(result)), :len(list(sentence))]
     plot_attention(attention_plot, list(sentence), list(result))
    input : qitted
    predicted output : quitted
    actual output : quitted
```



```
attention_plot = attention_plot[:len(list(result)), :len(list(sentence))]
plot_attention(attention_plot, list(sentence), list(result))
```

input : fortissiemus

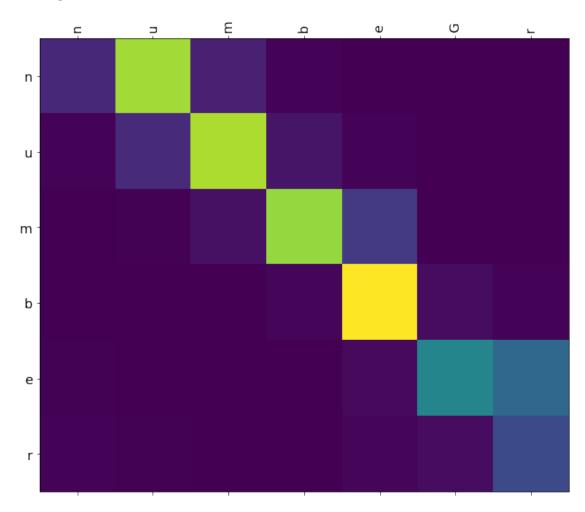
predicted output : fortissimus
actual output : fortissimus



```
attention_plot = attention_plot[:len(list(result)), :len(list(sentence))]
plot_attention(attention_plot, list(sentence), list(result))
```

input: numbeGr

predicted output: number
actual output: number



```
val_bleu = 0
for i in tqdm(range(unigram_val.shape[0])):
    inp = unigram_val['input'].values[i]
    out = unigram_val['output'].values[i]
    pred, _ = predict(inp, unigram_vec, unigram_index_to_word, gram = 'uni')
    val_bleu += sentence_bleu([out], pred)

train_bleu = 0
for i in tqdm(range(unigram_train.shape[0])):
    inp = unigram_train['input'].values[i];
```

```
out = unigram_train['output'].values[i]
          pred, _ = predict(inp, unigram_vec, unigram_index_to_word, gram = 'uni')
          train_bleu += sentence_bleu([out], pred)
      test_bleu = 0
      for i in tqdm(range(unigram_test.shape[0])):
          inp = unigram_test['input'].values[i]
          out = unigram_test['output'].values[i]
          pred, _ = predict(inp, unigram_vec, unigram_index_to_word, gram = 'uni')
          test_bleu += sentence_bleu([out], pred)
      print('BLEU Score on train: ',train_bleu/unigram_train.shape[0])
      print('BLEU Score on val: ',val_bleu/unigram_val.shape[0])
      print('BLEU Score on test: ',test_bleu/unigram_test.shape[0])
     100%|
       | 3678/3678 [03:40<00:00, 16.65it/s]
      | 33101/33101 [32:52<00:00, 16.78it/s]
     100%|
       | 3150/3150 [03:06<00:00, 16.88it/s]
     BLEU Score on train: 0.8698739128364643
     BLEU Score on val: 0.792070857805782
     BLEU Score on test: 0.7071433929743683
     2.2 BiGram
[83]: lstm_size = 256
      embedding_dim = 100
      att_units = 256
      maxlen = 26
[85]: model = encoder_decoder(vocab_size, vocab_size, embedding_dim, lstm_size,
      →lstm_size, maxlen, maxlen, 'concat', att_units, batch_size)
      model.compile(optimizer = 'Adam', loss = loss_function)
      callbacks = [ModelCheckpoint('Attention_concat_lstm_bigram.h5', save_best_only=_
      \hookrightarrowTrue, verbose = 1),
                   EarlyStopping(patience = 5, verbose = 1),
                   ReduceLROnPlateau(patience = 3, verbose = 1)]
      model.fit(x = bigram_train_dataset,
                steps_per_epoch = bigram_train.shape[0]//batch_size,
                validation data = bigram val dataset,
                validation_steps = bigram_val.shape[0]//batch_size,
                epochs = 100,
```

```
verbose = 1,
callbacks = callbacks)
```

```
Epoch 1/100
Epoch 00001: val_loss improved from inf to 0.06538, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0654
Epoch 2/100
Epoch 00002: val_loss improved from 0.06538 to 0.05269, saving model to
Attention_concat_lstm_bigram.h5
6910/6910 [============ ] - 486s 70ms/step - loss: 0.7482 -
val_loss: 0.0527
Epoch 3/100
Epoch 00003: val_loss improved from 0.05269 to 0.04566, saving model to
Attention_concat_lstm_bigram.h5
val loss: 0.0457
Epoch 4/100
Epoch 00004: val_loss improved from 0.04566 to 0.04211, saving model to
Attention concat 1stm bigram.h5
val_loss: 0.0421
Epoch 5/100
6910/6910 [============ ] - ETA: Os - loss: 0.7357
Epoch 00005: val_loss improved from 0.04211 to 0.03942, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0394
Epoch 6/100
6910/6910 [============ ] - ETA: Os - loss: 0.7333
Epoch 00006: val_loss improved from 0.03942 to 0.03707, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0371
Epoch 7/100
Epoch 00007: val_loss improved from 0.03707 to 0.03556, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0356
Epoch 8/100
6910/6910 [============ ] - ETA: Os - loss: 0.7315
Epoch 00008: val_loss improved from 0.03556 to 0.03482, saving model to
```

```
Attention_concat_lstm_bigram.h5
val_loss: 0.0348
Epoch 9/100
Epoch 00009: val_loss improved from 0.03482 to 0.03351, saving model to
Attention concat 1stm bigram.h5
val loss: 0.0335
Epoch 10/100
Epoch 00010: val_loss improved from 0.03351 to 0.03246, saving model to
Attention_concat_lstm_bigram.h5
6910/6910 [============== ] - 459s 66ms/step - loss: 0.7293 -
val_loss: 0.0325
Epoch 11/100
Epoch 00011: val_loss improved from 0.03246 to 0.03200, saving model to
Attention_concat_lstm_bigram.h5
val loss: 0.0320
Epoch 12/100
Epoch 00012: val_loss improved from 0.03200 to 0.03148, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0315
Epoch 13/100
Epoch 00013: val_loss improved from 0.03148 to 0.03059, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0306
Epoch 14/100
6910/6910 [============ ] - ETA: Os - loss: 0.7273
Epoch 00014: val_loss improved from 0.03059 to 0.02997, saving model to
Attention concat 1stm bigram.h5
val_loss: 0.0300
Epoch 15/100
Epoch 00015: val_loss improved from 0.02997 to 0.02988, saving model to
Attention_concat_lstm_bigram.h5
6910/6910 [============ ] - 468s 68ms/step - loss: 0.7262 -
val_loss: 0.0299
Epoch 16/100
Epoch 00016: val_loss improved from 0.02988 to 0.02935, saving model to
```

```
Attention_concat_lstm_bigram.h5
val_loss: 0.0294
Epoch 17/100
Epoch 00017: val_loss improved from 0.02935 to 0.02916, saving model to
Attention concat 1stm bigram.h5
val loss: 0.0292
Epoch 18/100
Epoch 00018: val_loss improved from 0.02916 to 0.02896, saving model to
Attention_concat_lstm_bigram.h5
6910/6910 [============ ] - 478s 69ms/step - loss: 0.7256 -
val_loss: 0.0290
Epoch 19/100
Epoch 00019: val_loss improved from 0.02896 to 0.02854, saving model to
Attention_concat_lstm_bigram.h5
val loss: 0.0285
Epoch 20/100
Epoch 00020: val_loss improved from 0.02854 to 0.02826, saving model to
Attention_concat_lstm_bigram.h5
6910/6910 [============== ] - 485s 70ms/step - loss: 0.7250 -
val_loss: 0.0283
Epoch 21/100
Epoch 00021: val_loss improved from 0.02826 to 0.02785, saving model to
Attention_concat_lstm_bigram.h5
6910/6910 [============== ] - 483s 70ms/step - loss: 0.7245 -
val_loss: 0.0278
Epoch 22/100
Epoch 00022: val_loss did not improve from 0.02785
val_loss: 0.0288
Epoch 23/100
Epoch 00023: val_loss did not improve from 0.02785
val_loss: 0.0279
Epoch 24/100
Epoch 00024: val_loss improved from 0.02785 to 0.02764, saving model to
Attention_concat_lstm_bigram.h5
```

```
val_loss: 0.0276
Epoch 25/100
Epoch 00025: val_loss improved from 0.02764 to 0.02751, saving model to
Attention concat 1stm bigram.h5
val loss: 0.0275
Epoch 26/100
Epoch 00026: val_loss did not improve from 0.02751
val_loss: 0.0277
Epoch 27/100
Epoch 00027: val_loss improved from 0.02751 to 0.02704, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0270
Epoch 28/100
Epoch 00028: val_loss did not improve from 0.02704
val_loss: 0.0271
Epoch 29/100
Epoch 00029: val_loss improved from 0.02704 to 0.02701, saving model to
Attention_concat_lstm_bigram.h5
6910/6910 [============= ] - 680s 98ms/step - loss: 0.7233 -
val_loss: 0.0270
Epoch 30/100
Epoch 00030: val_loss improved from 0.02701 to 0.02620, saving model to
Attention_concat_lstm_bigram.h5
val loss: 0.0262
Epoch 31/100
Epoch 00031: val_loss did not improve from 0.02620
val_loss: 0.0263
Epoch 32/100
Epoch 00032: val_loss improved from 0.02620 to 0.02616, saving model to
Attention_concat_lstm_bigram.h5
val loss: 0.0262
Epoch 33/100
```

```
Epoch 00033: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
val loss: 0.0263
Epoch 34/100
6910/6910 [============ ] - ETA: Os - loss: 0.7206
Epoch 00034: val_loss improved from 0.02616 to 0.02441, saving model to
Attention concat 1stm bigram.h5
val_loss: 0.0244
Epoch 35/100
Epoch 00035: val_loss improved from 0.02441 to 0.02397, saving model to
Attention_concat_lstm_bigram.h5
6910/6910 [============ ] - 472s 68ms/step - loss: 0.7193 -
val_loss: 0.0240
Epoch 36/100
Epoch 00036: val loss improved from 0.02397 to 0.02379, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0238
Epoch 37/100
Epoch 00037: val_loss improved from 0.02379 to 0.02357, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0236
Epoch 38/100
6910/6910 [============ ] - ETA: Os - loss: 0.7187
Epoch 00038: val_loss improved from 0.02357 to 0.02348, saving model to
Attention_concat_lstm_bigram.h5
val loss: 0.0235
Epoch 39/100
6910/6910 [============ ] - ETA: Os - loss: 0.7183
Epoch 00039: val_loss improved from 0.02348 to 0.02332, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0233
Epoch 40/100
Epoch 00040: val_loss did not improve from 0.02332
val loss: 0.0233
Epoch 41/100
```

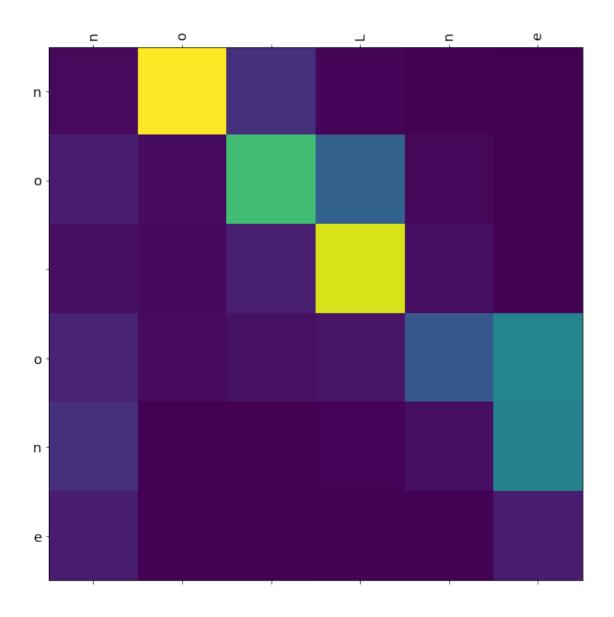
```
Epoch 00041: val_loss improved from 0.02332 to 0.02320, saving model to
Attention_concat_lstm_bigram.h5
6910/6910 [============ ] - 461s 67ms/step - loss: 0.7183 -
val loss: 0.0232
Epoch 42/100
Epoch 00042: val loss did not improve from 0.02320
val loss: 0.0232
Epoch 43/100
Epoch 00043: val_loss improved from 0.02320 to 0.02312, saving model to
Attention_concat_lstm_bigram.h5
6910/6910 [============ ] - 455s 66ms/step - loss: 0.7178 -
val_loss: 0.0231
Epoch 44/100
Epoch 00044: val_loss improved from 0.02312 to 0.02305, saving model to
Attention_concat_lstm_bigram.h5
val loss: 0.0230
Epoch 45/100
6910/6910 [============ ] - ETA: Os - loss: 0.7179
Epoch 00045: val_loss improved from 0.02305 to 0.02298, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0230
Epoch 46/100
Epoch 00046: val_loss improved from 0.02298 to 0.02295, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0229
Epoch 47/100
6910/6910 [============ ] - ETA: Os - loss: 0.7176
Epoch 00047: val_loss improved from 0.02295 to 0.02288, saving model to
Attention concat 1stm bigram.h5
val_loss: 0.0229
Epoch 48/100
Epoch 00048: val_loss improved from 0.02288 to 0.02276, saving model to
Attention_concat_lstm_bigram.h5
6910/6910 [============ ] - 456s 66ms/step - loss: 0.7171 -
val_loss: 0.0228
Epoch 49/100
Epoch 00049: val_loss did not improve from 0.02276
```

```
val_loss: 0.0228
Epoch 50/100
Epoch 00050: val_loss improved from 0.02276 to 0.02275, saving model to
Attention concat 1stm bigram.h5
val loss: 0.0227
Epoch 51/100
Epoch 00051: val_loss improved from 0.02275 to 0.02267, saving model to
Attention_concat_lstm_bigram.h5
Epoch 00051: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
val loss: 0.0227
Epoch 52/100
Epoch 00052: val_loss improved from 0.02267 to 0.02262, saving model to
Attention concat 1stm bigram.h5
val loss: 0.0226
Epoch 53/100
6910/6910 [============ ] - ETA: Os - loss: 0.7170
Epoch 00053: val_loss improved from 0.02262 to 0.02258, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0226
Epoch 54/100
Epoch 00054: val_loss improved from 0.02258 to 0.02256, saving model to
Attention_concat_lstm_bigram.h5
6910/6910 [============ ] - 458s 66ms/step - loss: 0.7168 -
val_loss: 0.0226
Epoch 55/100
6910/6910 [============ ] - ETA: Os - loss: 0.7165
Epoch 00055: val loss improved from 0.02256 to 0.02251, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0225
Epoch 56/100
Epoch 00056: val_loss improved from 0.02251 to 0.02251, saving model to
Attention_concat_lstm_bigram.h5
val loss: 0.0225
Epoch 57/100
```

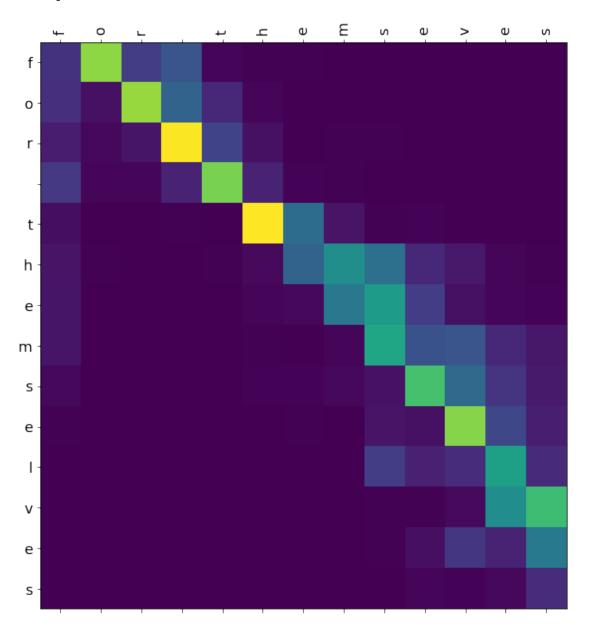
```
Epoch 00057: val_loss improved from 0.02251 to 0.02251, saving model to
Attention_concat_lstm_bigram.h5
6910/6910 [============ ] - 456s 66ms/step - loss: 0.7173 -
val loss: 0.0225
Epoch 58/100
Epoch 00058: val_loss improved from 0.02251 to 0.02250, saving model to
Attention_concat_lstm_bigram.h5
Epoch 00058: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.
val_loss: 0.0225
Epoch 59/100
Epoch 00059: val_loss did not improve from 0.02250
val_loss: 0.0225
Epoch 60/100
Epoch 00060: val_loss improved from 0.02250 to 0.02250, saving model to
Attention_concat_lstm_bigram.h5
val_loss: 0.0225
Epoch 61/100
Epoch 00061: val_loss did not improve from 0.02250
Epoch 00061: ReduceLROnPlateau reducing learning rate to 1.0000001111620805e-07.
val_loss: 0.0225
Epoch 62/100
Epoch 00062: val_loss did not improve from 0.02250
val loss: 0.0225
Epoch 63/100
Epoch 00063: val_loss did not improve from 0.02250
6910/6910 [============== ] - 459s 66ms/step - loss: 0.7165 -
val_loss: 0.0225
Epoch 64/100
Epoch 00064: val_loss did not improve from 0.02250
Epoch 00064: ReduceLROnPlateau reducing learning rate to 1.000000082740371e-08.
val_loss: 0.0225
Epoch 65/100
```

```
Epoch 00065: val_loss did not improve from 0.02250
    val_loss: 0.0225
    Epoch 00065: early stopping
[85]: <tensorflow.python.keras.callbacks.History at 0x224063cde88>
[87]: pred_model = pred_Encoder_decoder(vocab_size, vocab_size, embedding_dim,__
     →lstm_size, lstm_size, maxlen, maxlen, 'concat', att_units,
     →bigram_word_to_index)
     pred_model.compile(optimizer = 'Adam', loss = loss_function)
     pred_model.build(input_shape= (None, 1, maxlen))
     pred_model.load_weights('Attention_concat_lstm_bigram.h5')
[88]: sentence = bigram_train['input'].values[4]
     result, attention_plot = predict(sentence, bigram_vec, bigram_index_to_word,_u
     print('input : ', sentence)
     print('predicted output : ',result)
     print('actual output :', bigram_train['output'].values[4])
     attention plot = attention plot[:len(list(result)), :len(list(sentence))]
     plot_attention(attention_plot, list(sentence), list(result))
    input : no Lne
    predicted output : no one
```

actual output : no one



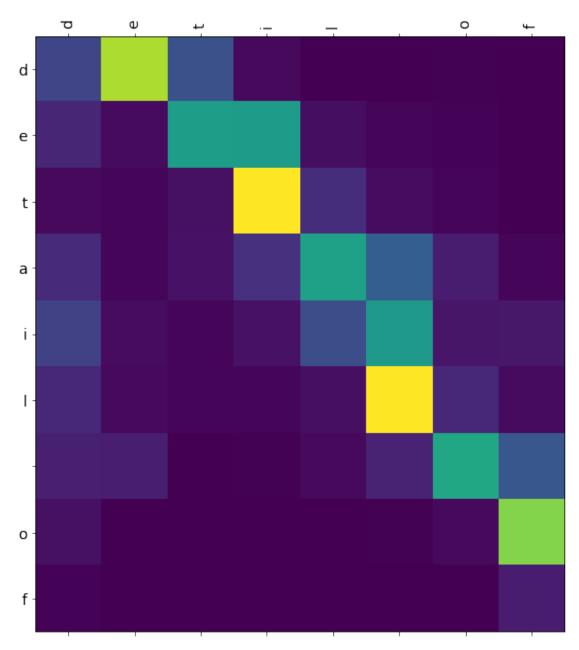
input : for themseves
predicted output : for themselves



```
attention_plot = attention_plot[:len(list(result)), :len(list(sentence))]
plot_attention(attention_plot, list(sentence), list(result))
```

input : detil of

predicted output : detail of
actual output : detail of



```
[5]: val_bleu = 0
for i in range(bigram_val.shape[0]):
```

```
inp = bigram_val['input'].values[i]
          out = bigram_val['output'].values[i]
          pred, _ = predict(inp, bigram_vec, bigram_index_to_word, gram = 'bi')
          val_bleu += sentence_bleu([out], pred)
      train_bleu = 0
      for i in range(bigram_train.shape[0]):
          inp = bigram_train['input'].values[i];
          out = bigram train['output'].values[i]
          pred, _ = predict(inp, bigram_vec, bigram_index_to_word, gram = 'bi')
          train bleu += sentence bleu([out], pred)
      test bleu = 0
      for i in range(bigram_test.shape[0]):
          inp = bigram_test['input'].values[i]
          out = bigram_test['output'].values[i]
          pred, _ = predict(inp, bigram_vec, bigram_index_to_word, gram = 'bi')
          test_bleu += sentence_bleu([out], pred)
      print('BLEU Score on train: ',train_bleu/bigram_train.shape[0])
      print('BLEU Score on val: ',val_bleu/bigram_val.shape[0])
      print('BLEU Score on test: ',test_bleu/bigram_test.shape[0])
     BLEU Score on train: 0.9719945427791346
     BLEU Score on val: 0.9588801560719675
     BLEU Score on test: 0.9460340413418259
     2.3 TriGram
[91]: lstm_size = 256
      embedding_dim = 100
      att_units = 256
      maxlen = 34
[92]: model = encoder_decoder(vocab_size, vocab_size, embedding_dim, lstm_size,
      →lstm_size, maxlen, maxlen, 'concat', att_units, batch_size)
      model.compile(optimizer = 'Adam', loss = loss_function)
      callbacks = [ModelCheckpoint('Attention_concat_lstm_trigram.h5',_
      ⇒save_best_only= True, verbose = 1),
                   EarlyStopping(patience = 5, verbose = 1),
                   ReduceLROnPlateau(patience = 3, verbose = 1)]
      model.fit(x = trigram_train_dataset,
                steps_per_epoch = trigram_train.shape[0]//batch_size,
                validation data = trigram val dataset,
                validation_steps = trigram_val.shape[0]//batch_size,
                epochs = 100,
```

```
verbose = 1,
callbacks = callbacks)
```

```
Epoch 1/100
Epoch 00001: val_loss improved from inf to 0.05902, saving model to
Attention_concat_lstm_trigram.h5
val_loss: 0.0590
Epoch 2/100
Epoch 00002: val_loss improved from 0.05902 to 0.04622, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============ ] - 622s 90ms/step - loss: 0.8491 -
val_loss: 0.0462
Epoch 3/100
Epoch 00003: val_loss improved from 0.04622 to 0.04152, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 625s 90ms/step - loss: 0.8422 -
val loss: 0.0415
Epoch 4/100
Epoch 00004: val_loss improved from 0.04152 to 0.03638, saving model to
Attention concat 1stm trigram.h5
6910/6910 [============== ] - 632s 91ms/step - loss: 0.8382 -
val loss: 0.0364
Epoch 5/100
Epoch 00005: val_loss improved from 0.03638 to 0.03372, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============= ] - 629s 91ms/step - loss: 0.8360 -
val_loss: 0.0337
Epoch 6/100
Epoch 00006: val_loss improved from 0.03372 to 0.03284, saving model to
Attention_concat_lstm_trigram.h5
val_loss: 0.0328
Epoch 7/100
Epoch 00007: val_loss improved from 0.03284 to 0.03111, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 626s 91ms/step - loss: 0.8329 -
val_loss: 0.0311
Epoch 8/100
6910/6910 [============ ] - ETA: Os - loss: 0.8318
Epoch 00008: val_loss improved from 0.03111 to 0.03011, saving model to
```

```
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 627s 91ms/step - loss: 0.8318 -
val_loss: 0.0301
Epoch 9/100
Epoch 00009: val_loss improved from 0.03011 to 0.02913, saving model to
Attention concat 1stm trigram.h5
6910/6910 [============= ] - 626s 91ms/step - loss: 0.8309 -
val loss: 0.0291
Epoch 10/100
Epoch 00010: val_loss improved from 0.02913 to 0.02846, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============ ] - 626s 91ms/step - loss: 0.8303 -
val_loss: 0.0285
Epoch 11/100
Epoch 00011: val_loss improved from 0.02846 to 0.02764, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 625s 90ms/step - loss: 0.8299 -
val loss: 0.0276
Epoch 12/100
Epoch 00012: val loss improved from 0.02764 to 0.02715, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 635s 92ms/step - loss: 0.8291 -
val_loss: 0.0272
Epoch 13/100
Epoch 00013: val_loss improved from 0.02715 to 0.02653, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 628s 91ms/step - loss: 0.8290 -
val_loss: 0.0265
Epoch 14/100
6910/6910 [============ ] - ETA: Os - loss: 0.8283
Epoch 00014: val_loss improved from 0.02653 to 0.02601, saving model to
Attention concat 1stm trigram.h5
6910/6910 [============= ] - 630s 91ms/step - loss: 0.8283 -
val_loss: 0.0260
Epoch 15/100
Epoch 00015: val_loss improved from 0.02601 to 0.02585, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [=========== ] - 631s 91ms/step - loss: 0.8282 -
val_loss: 0.0258
Epoch 16/100
Epoch 00016: val_loss improved from 0.02585 to 0.02510, saving model to
```

```
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 632s 91ms/step - loss: 0.8276 -
val_loss: 0.0251
Epoch 17/100
Epoch 00017: val_loss improved from 0.02510 to 0.02482, saving model to
Attention concat 1stm trigram.h5
6910/6910 [============== ] - 632s 91ms/step - loss: 0.8272 -
val loss: 0.0248
Epoch 18/100
Epoch 00018: val_loss improved from 0.02482 to 0.02455, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============ ] - 631s 91ms/step - loss: 0.8267 -
val_loss: 0.0245
Epoch 19/100
Epoch 00019: val_loss improved from 0.02455 to 0.02399, saving model to
Attention_concat_lstm_trigram.h5
val loss: 0.0240
Epoch 20/100
Epoch 00020: val_loss did not improve from 0.02399
val_loss: 0.0240
Epoch 21/100
Epoch 00021: val_loss did not improve from 0.02399
val_loss: 0.0243
Epoch 22/100
Epoch 00022: val_loss improved from 0.02399 to 0.02359, saving model to
Attention concat 1stm trigram.h5
6910/6910 [============ ] - 632s 92ms/step - loss: 0.8257 -
val loss: 0.0236
Epoch 23/100
Epoch 00023: val_loss improved from 0.02359 to 0.02338, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============= ] - 633s 92ms/step - loss: 0.8259 -
val_loss: 0.0234
Epoch 24/100
Epoch 00024: val_loss did not improve from 0.02338
6910/6910 [============= ] - 631s 91ms/step - loss: 0.8253 -
val_loss: 0.0234
```

```
Epoch 25/100
Epoch 00025: val_loss improved from 0.02338 to 0.02304, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============= ] - 647s 94ms/step - loss: 0.8251 -
val loss: 0.0230
Epoch 26/100
6910/6910 [============ ] - ETA: Os - loss: 0.8251
Epoch 00026: val_loss improved from 0.02304 to 0.02287, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 657s 95ms/step - loss: 0.8251 -
val_loss: 0.0229
Epoch 27/100
Epoch 00027: val_loss improved from 0.02287 to 0.02246, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============ ] - 701s 101ms/step - loss: 0.8246 -
val_loss: 0.0225
Epoch 28/100
Epoch 00028: val_loss improved from 0.02246 to 0.02219, saving model to
Attention concat 1stm trigram.h5
6910/6910 [============ ] - 700s 101ms/step - loss: 0.8247 -
val_loss: 0.0222
Epoch 29/100
Epoch 00029: val_loss did not improve from 0.02219
6910/6910 [============= ] - 657s 95ms/step - loss: 0.8247 -
val_loss: 0.0226
Epoch 30/100
Epoch 00030: val_loss did not improve from 0.02219
6910/6910 [============== ] - 648s 94ms/step - loss: 0.8284 -
val_loss: 0.0229
Epoch 31/100
Epoch 00031: val_loss did not improve from 0.02219
Epoch 00031: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
val_loss: 0.0227
Epoch 32/100
Epoch 00032: val_loss improved from 0.02219 to 0.02104, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============= ] - 660s 96ms/step - loss: 0.8227 -
val_loss: 0.0210
Epoch 33/100
```

```
Epoch 00033: val_loss improved from 0.02104 to 0.02061, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 679s 98ms/step - loss: 0.8221 -
val loss: 0.0206
Epoch 34/100
6910/6910 [============ ] - ETA: Os - loss: 0.8214
Epoch 00034: val_loss improved from 0.02061 to 0.02026, saving model to
Attention concat 1stm trigram.h5
val_loss: 0.0203
Epoch 35/100
Epoch 00035: val loss did not improve from 0.02026
val_loss: 0.0203
Epoch 36/100
Epoch 00036: val_loss improved from 0.02026 to 0.02003, saving model to
Attention concat 1stm trigram.h5
val loss: 0.0200
Epoch 37/100
Epoch 00037: val_loss improved from 0.02003 to 0.01989, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 656s 95ms/step - loss: 0.8209 -
val_loss: 0.0199
Epoch 38/100
Epoch 00038: val_loss improved from 0.01989 to 0.01973, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============ ] - 651s 94ms/step - loss: 0.8207 -
val_loss: 0.0197
Epoch 39/100
6910/6910 [============ ] - ETA: Os - loss: 0.8205
Epoch 00039: val loss did not improve from 0.01973
val_loss: 0.0197
Epoch 40/100
Epoch 00040: val_loss improved from 0.01973 to 0.01965, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============= ] - 694s 100ms/step - loss: 0.8203 -
val_loss: 0.0196
Epoch 41/100
Epoch 00041: val_loss improved from 0.01965 to 0.01948, saving model to
```

```
Attention_concat_lstm_trigram.h5
val_loss: 0.0195
Epoch 42/100
Epoch 00042: val_loss improved from 0.01948 to 0.01943, saving model to
Attention concat 1stm trigram.h5
6910/6910 [============== ] - 653s 94ms/step - loss: 0.8204 -
val loss: 0.0194
Epoch 43/100
Epoch 00043: val_loss improved from 0.01943 to 0.01934, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============ ] - 671s 97ms/step - loss: 0.8200 -
val_loss: 0.0193
Epoch 44/100
Epoch 00044: val_loss did not improve from 0.01934
6910/6910 [============ ] - 679s 98ms/step - loss: 0.8200 -
val loss: 0.0194
Epoch 45/100
Epoch 00045: val_loss improved from 0.01934 to 0.01928, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 658s 95ms/step - loss: 0.8203 -
val_loss: 0.0193
Epoch 46/100
Epoch 00046: val_loss improved from 0.01928 to 0.01921, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 653s 95ms/step - loss: 0.8198 -
val_loss: 0.0192
Epoch 47/100
Epoch 00047: val loss improved from 0.01921 to 0.01915, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============= ] - 650s 94ms/step - loss: 0.8194 -
val loss: 0.0191
Epoch 48/100
Epoch 00048: val_loss did not improve from 0.01915
val_loss: 0.0192
Epoch 49/100
Epoch 00049: val_loss improved from 0.01915 to 0.01910, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============= ] - 659s 95ms/step - loss: 0.8197 -
```

```
val_loss: 0.0191
Epoch 50/100
Epoch 00050: val_loss improved from 0.01910 to 0.01904, saving model to
Attention concat 1stm trigram.h5
val loss: 0.0190
Epoch 51/100
Epoch 00051: val_loss improved from 0.01904 to 0.01896, saving model to
Attention_concat_lstm_trigram.h5
val_loss: 0.0190
Epoch 52/100
Epoch 00052: val_loss improved from 0.01896 to 0.01895, saving model to
Attention_concat_lstm_trigram.h5
val loss: 0.0190
Epoch 53/100
Epoch 00053: val loss improved from 0.01895 to 0.01893, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============= ] - 670s 97ms/step - loss: 0.8198 -
val_loss: 0.0189
Epoch 54/100
Epoch 00054: val_loss improved from 0.01893 to 0.01883, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 657s 95ms/step - loss: 0.8194 -
val_loss: 0.0188
Epoch 55/100
Epoch 00055: val_loss improved from 0.01883 to 0.01872, saving model to
Attention concat 1stm trigram.h5
val loss: 0.0187
Epoch 56/100
Epoch 00056: val_loss did not improve from 0.01872
val_loss: 0.0188
Epoch 57/100
Epoch 00057: val_loss did not improve from 0.01872
6910/6910 [============= ] - 652s 94ms/step - loss: 0.8196 -
val_loss: 0.0188
Epoch 58/100
```

```
Epoch 00058: val_loss did not improve from 0.01872
Epoch 00058: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
6910/6910 [============ ] - 658s 95ms/step - loss: 0.8190 -
val loss: 0.0187
Epoch 59/100
Epoch 00059: val_loss improved from 0.01872 to 0.01862, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 660s 95ms/step - loss: 0.8188 -
val_loss: 0.0186
Epoch 60/100
Epoch 00060: val_loss improved from 0.01862 to 0.01860, saving model to
Attention_concat_lstm_trigram.h5
val_loss: 0.0186
Epoch 61/100
Epoch 00061: val_loss improved from 0.01860 to 0.01858, saving model to
Attention concat 1stm trigram.h5
6910/6910 [============== ] - 673s 97ms/step - loss: 0.8188 -
val_loss: 0.0186
Epoch 62/100
Epoch 00062: val_loss improved from 0.01858 to 0.01857, saving model to
Attention_concat_lstm_trigram.h5
Epoch 00062: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.
val_loss: 0.0186
Epoch 63/100
Epoch 00063: val loss improved from 0.01857 to 0.01856, saving model to
Attention_concat_lstm_trigram.h5
6910/6910 [============== ] - 650s 94ms/step - loss: 0.8191 -
val loss: 0.0186
Epoch 64/100
Epoch 00064: val_loss improved from 0.01856 to 0.01856, saving model to
Attention_concat_lstm_trigram.h5
val_loss: 0.0186
Epoch 65/100
Epoch 00065: val_loss improved from 0.01856 to 0.01854, saving model to
Attention_concat_lstm_trigram.h5
```

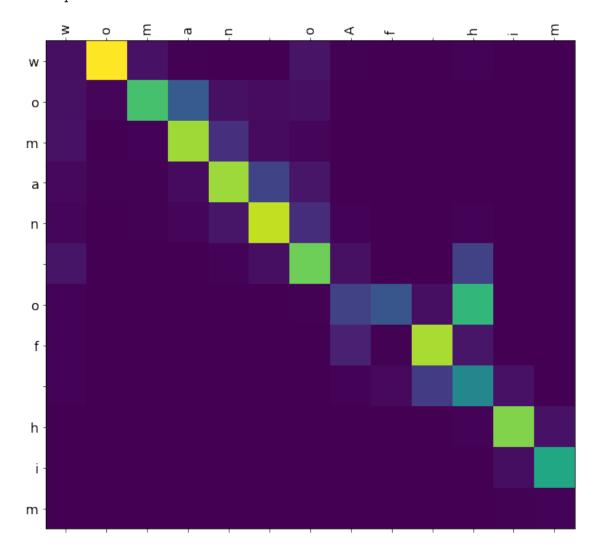
```
val loss: 0.0185
   Epoch 66/100
   Epoch 00066: val loss did not improve from 0.01854
   val loss: 0.0185
   Epoch 67/100
   Epoch 00067: val_loss did not improve from 0.01854
   val loss: 0.0185
   Epoch 68/100
   Epoch 00068: val_loss did not improve from 0.01854
   Epoch 00068: ReduceLROnPlateau reducing learning rate to 1.000000082740371e-08.
   val loss: 0.0185
   Epoch 69/100
   Epoch 00069: val_loss did not improve from 0.01854
   6910/6910 [============= ] - 689s 100ms/step - loss: 0.8188 -
   val_loss: 0.0185
   Epoch 70/100
   Epoch 00070: val_loss did not improve from 0.01854
   val_loss: 0.0185
   Epoch 00070: early stopping
[92]: <tensorflow.python.keras.callbacks.History at 0x2269658dcc8>
[93]: pred_model = pred_Encoder_decoder(vocab_size, vocab_size, embedding_dim,_u
    →lstm_size, lstm_size, maxlen, maxlen, 'concat', att_units,
    →trigram_word_to_index)
   pred_model.compile(optimizer = 'Adam', loss = loss_function)
   pred_model.build(input_shape= (None, 1, maxlen))
   pred_model.load_weights('Attention_concat_lstm_trigram.h5')
[97]: sentence = trigram_train['input'].values[4]
   result, attention_plot = predict(sentence, trigram_vec, trigram_index_to_word,_
    print('input : ', sentence)
```

Epoch 00065: ReduceLROnPlateau reducing learning rate to 1.0000001111620805e-07.

```
print('predicted output : ',result)
print('actual output :', trigram_train['output'].values[4])

attention_plot = attention_plot[:len(list(result)), :len(list(sentence))]
plot_attention(attention_plot, list(sentence), list(result))
```

input : woman oAf him
predicted output : woman of him
actual output : woman of him



```
[98]: sentence = trigram_train['input'].values[7]
result, attention_plot = predict(sentence, trigram_vec, trigram_index_to_word,

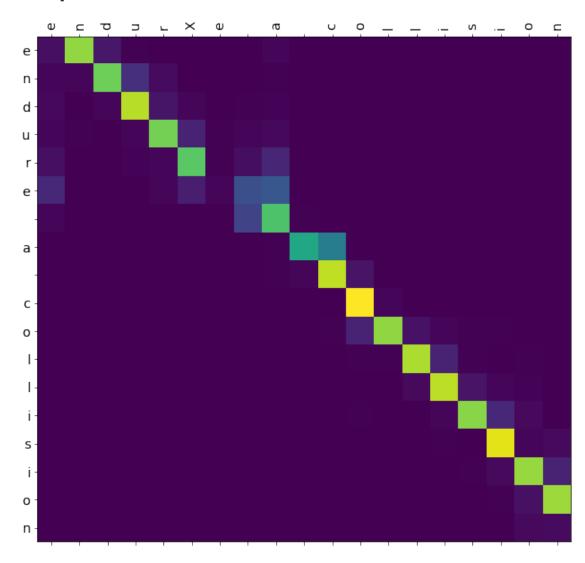
→gram = 'tri')

print('input : ', sentence)
```

```
print('predicted output : ',result)
print('actual output :', trigram_train['output'].values[7])

attention_plot = attention_plot[:len(list(result)), :len(list(sentence))]
plot_attention(attention_plot, list(sentence), list(result))
```

input : endurXe a collision
predicted output : endure a collision
actual output : endure a collision

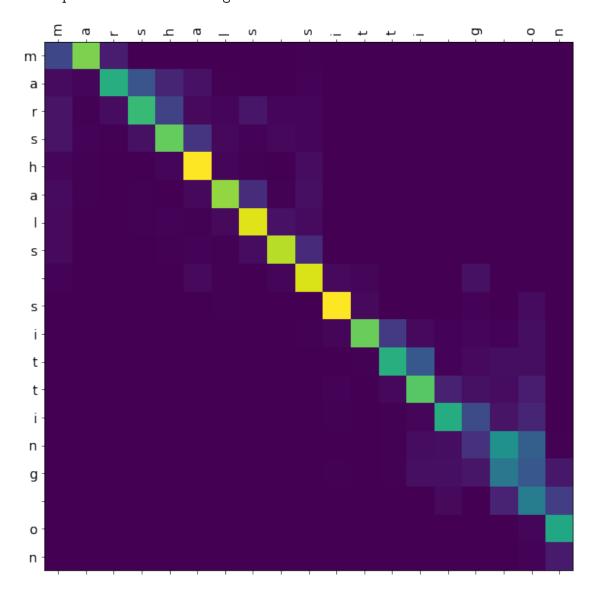


```
[99]: sentence = trigram_train['input'].values[10]
result, attention_plot = predict(sentence, trigram_vec, trigram_index_to_word,

→gram = 'tri')
```

```
print('input : ', sentence)
print('predicted output : ',result)
print('actual output :', trigram_train['output'].values[10])
attention_plot = attention_plot[:len(list(result)), :len(list(sentence))]
plot_attention(attention_plot, list(sentence), list(result))
```

input : marshals sitti g on
predicted output : marshals sitting on
actual output : marshals sitting on



```
[6]: val_bleu = 0
for i in range(trigram_val.shape[0]):
```

```
inp = trigram_val['input'].values[i]
    out = trigram_val['output'].values[i]
   pred, _ = predict(inp, trigram_vec, trigram_index_to_word, gram = 'tri')
   val bleu += sentence_bleu([out], pred)
train_bleu = 0
for i in range(trigram_train.shape[0]):
   inp = trigram_train['input'].values[i];
   out = trigram train['output'].values[i]
   pred, _ = predict(inp, trigram_vec, trigram_index_to_word, gram = 'tri')
   train bleu += sentence bleu([out], pred)
test bleu = 0
for i in range(trigram_test.shape[0]):
    inp = trigram_test['input'].values[i]
   out = trigram_test['output'].values[i]
   pred, _ = predict(inp, trigram_vec, trigram_index_to_word, gram = 'tri')
   test_bleu += sentence_bleu([out], pred)
print('BLEU Score on train: ',train_bleu/trigram_train.shape[0])
print('BLEU Score on val: ',val_bleu/trigram_val.shape[0])
print('BLEU Score on test: ',test_bleu/trigram_test.shape[0])
```

BLEU Score on train: 0.9811416412867453 BLEU Score on val: 0.9743928120876085 BLEU Score on test: 0.96227561809527

3. Seq2Seq Bi-LSTM with Attention Mechanism

```
[106]: class Encoder(tf.keras.layers.Layer):
           def __init__(self, vocab_size, embedding_size, lstm_size, input_length):
               super(Encoder, self).__init__()
               self.lstm_size = lstm_size
               self.enc_embed = Embedding(input_dim = vocab_size, output_dim = __
        →embedding_size)
               self.enc_lstm = Bidirectional(LSTM(lstm_size, return_sequences = True, __
        →return_state = True, dropout = 0.4))
           def call(self, input_sequence, states):
               embedding = self.enc_embed(input_sequence)
               output_state, enc_frwd_h, enc_frwd_c, enc_bkwd_h, enc_bkwd_c = self.
        →enc_lstm(embedding, initial_state = states)
               return output_state, enc_frwd_h, enc_frwd_c, enc_bkwd_h, enc_bkwd_c
           def initialize_states(self, batch_size):
               return [tf.zeros((batch_size, self.lstm_size)), tf.zeros((batch_size, ____
        ⇒self.lstm_size)),
```

```
tf.zeros((batch_size, self.lstm_size)), tf.zeros((batch_size,_
 →self.lstm_size))]
class Attention(tf.keras.layers.Layer):
    def __init__(self,scoring_function, att_units):
        super(Attention, self). init ()
        self.scoring function = scoring function
        if scoring_function == 'dot':
            self.dot = Dot(axes = (1, 2))
        elif scoring_function == 'general':
            self.W = Dense(att units)
            self.dot = Dot(axes = (1, 2))
        elif scoring_function == 'concat':
            self.W1 = Dense(att_units)
            self.W2 = Dense(att units)
            self.W3 = Dense(att_units)
            self.V = Dense(1)
    def call(self, dec frwd state, dec bkwd state, encoder output):
        dec_frwd_state = tf.expand_dims(dec_frwd_state, 1)
        dec bkwd state = tf.expand dims(dec bkwd state, 1)
        if self.scoring_function == 'dot':
            score = tf.transpose(self.dot([tf.transpose(decoder_hidden_state,_
\rightarrow (0, 2, 1)), encoder_output]), (0, 2,1))
        elif self.scoring_function == 'general':
            mul = self.W(encoder output)
            score = tf.transpose(self.dot([tf.transpose(decoder hidden state, ]])
\rightarrow (0, 2, 1)), mul]), (0, 2,1))
        elif self.scoring_function == 'concat':
            inter = self.W1(dec_frwd_state) + self.W2(dec_bkwd_state) + self.
 →W3(encoder_output)
            tan = tf.nn.tanh(inter)
            score = self.V(tan)
        attention weights = tf.nn.softmax(score, axis =1)
        context_vector = attention_weights * encoder_output
        context_vector = tf.reduce_sum(context_vector, axis=1)
        return context_vector, attention_weights
class OneStepDecoder(tf.keras.layers.Layer):
    def __init__(self, vocab_size, embedding_dim, input_length, dec_units⊔
→,score_fun ,att_units):
        super(OneStepDecoder, self).__init__()
      # Initialize decoder embedding layer, LSTM and any other objects needed
        self.embed_dec = Embedding(input_dim = vocab_size, output_dim =__
 →embedding_dim)
```

```
self.lstm = Bidirectional(LSTM(dec_units, return_sequences = True,__
 →return_state = True, dropout = 0.4))
        self.attention = Attention(scoring_function = score_fun, att_units = __ 
→att units)
        self.fc = Dense(vocab_size)
   def call(self,input_to_decoder, encoder_output, state_frwd_h, state_frwd_c,_
→state_bkwd_h, state_bkwd_c):
        embed = self.embed dec(input to decoder)
        context_vect, attention_weights = self.attention(state_frwd_h,__
⇒state_bkwd_h, encoder_output)
       final_inp = tf.concat([tf.expand_dims(context_vect, 1), embed], axis =__
→-1)
        out, dec_frwd_h, dec_frwd_c, dec_bkwd_h, dec_bkwd_c = self.
→lstm(final_inp, [state_frwd_h, state_frwd_c, state_bkwd_h, state_bkwd_c])
        out = tf.reshape(out, (-1, out.shape[2]))
        out = Dropout(0.5)(out)
        output = self.fc(out)
       return output, dec frwd h, dec frwd c, dec bkwd h, dec bkwd c, u
→attention_weights, context_vect
class encoder decoder(tf.keras.Model):
   def __init__(self, vocab_size, embedding_dim, enc_units, dec_units,_u
→max_len, score_fun, att_units, batch_size):
        #Intialize objects from encoder decoder
        super(encoder_decoder, self).__init__()
        self.encoder = Encoder(vocab_size, embedding_dim, enc_units, max_len)
        self.one_step_decoder = OneStepDecoder(vocab_size, embedding_dim,_
→max_len, dec_units ,score_fun ,att_units)
        self.batch_size = batch_size
   def call(self, data):
        enc_inp, dec_inp = data[0], data[1]
        initial_state = self.encoder.initialize_states(self.batch_size)
        enc_output, enc_frwd_h, enc_frwd_c, enc_bkwd_h, enc_bkwd_c = self.
→encoder(enc_inp, initial_state)
        all_outputs = tf.TensorArray(dtype = tf.float32, size= max_len)
       dec_frwd_h = enc_frwd_h
       dec_frwd_c = enc_frwd_c
        dec_bkwd_h = enc_bkwd_h
        dec_bkwd_c = enc_bkwd_c
       for timestep in range(max_len):
            # Call onestepdecoder for each token in decoder_input
```

```
output, dec_frwd h, dec_frwd_c, dec_bkwd_h, dec_bkwd_c, _, _ = self.
 →one_step_decoder(dec_inp[:, timestep:timestep+1], enc_output, dec_frwd_h,__
 →dec_frwd_c, dec_bkwd_h, dec_bkwd_c)
            # Store the output in tensorarray
            all_outputs = all_outputs.write(timestep, output)
        # Return the tensor array
        all_outputs = tf.transpose(all_outputs.stack(), (1, 0, 2))
        # return the decoder output
       return all_outputs
class pred_Encoder_decoder(tf.keras.Model):
   def __init__(self, inp_vocab_size, out_vocab_size, embedding_dim,_
→enc_units, dec_units, max_len_ita, max_len_eng, score_fun, att_units,
→word_to_index):
        #Intialize objects from encoder decoder
        super(pred_Encoder_decoder, self).__init__()
        self.encoder = Encoder(inp_vocab_size, embedding_dim, enc_units,_
→max_len_ita)
        self.one_step_decoder = OneStepDecoder(out_vocab_size, embedding_dim,_u
→max_len_eng, dec_units, score_fun, att_units)
        self.word to index = word to index
   def call(self, params):
        enc_inp = params[0]
        initial_state = self.encoder.initialize_states(1)
        enc_output, enc_frwd_h, enc_frwd_c, enc_bkwd_h, enc_bkwd_c = self.
→encoder(enc_inp, initial_state)
       pred = tf.expand_dims([self.word_to_index['<SOW>']], 0)
        all pred = []
       all_attention = []
       dec_frwd_h = enc_frwd_h
       dec frwd c = enc frwd c
       dec_bkwd_h = enc_bkwd_h
       dec_bkwd_c = enc_bkwd_c
        for timestep in range(max_len):
            # Call onestepdecoder for each token in decoder_input
            output, dec_frwd_h, dec_frwd_c, dec_bkwd_h, dec_bkwd_c, attention, u
 → = self.one_step_decoder(pred, enc_output, dec_frwd_h, dec_frwd_c,
 →dec_bkwd_h, dec_bkwd_c)
            pred = tf.argmax(output, axis = -1)
            all_pred.append(pred)
            pred = tf.expand dims(pred, 0)
            all_attention.append(attention)
        return all_pred, all_attention
```

3.1 UniGram

```
[]: lstm_size = 256
    embedding_dim = 100
    att_units = 256
    maxlen = 22
[41]: model = encoder_decoder(vocab_size, embedding_dim, lstm_size, lstm_size,
    →maxlen, 'concat', att_units, batch_size)
    model.compile(optimizer = 'Adam', loss = loss_function)
    callbacks = [ModelCheckpoint('concat_best.h5', save_best_only= True, verbose = __
     \hookrightarrow 1),
              EarlyStopping(patience = 5, verbose = 1),
              ReduceLROnPlateau(patience = 3, verbose = 1)]
    model.fit(x = unigram_train_dataset,
            steps_per_epoch = unigram_train.shape[0]//batch_size,
            validation_data = unigram_val_dataset,
            validation_steps = unigram_val.shape[0]//batch_size,
            epochs = 50,
            verbose = 1,
            callbacks = callbacks)
    Epoch 1/50
    Epoch 00001: val_loss improved from inf to 0.53295, saving model to
    concat_best.h5
    val_loss: 0.5329
    Epoch 2/50
    Epoch 00002: val_loss improved from 0.53295 to 0.16296, saving model to
    concat_best.h5
    258/258 [============ ] - 23s 89ms/step - loss: 0.3148 -
    val_loss: 0.1630
    Epoch 3/50
    Epoch 00003: val_loss improved from 0.16296 to 0.13154, saving model to
    concat best.h5
    258/258 [============= ] - 24s 91ms/step - loss: 0.1810 -
    val_loss: 0.1315
    Epoch 4/50
    Epoch 00004: val_loss improved from 0.13154 to 0.12262, saving model to
    concat best.h5
    258/258 [============= ] - 24s 93ms/step - loss: 0.1521 -
    val_loss: 0.1226
```

```
Epoch 5/50
258/258 [============= ] - ETA: Os - loss: 0.1372
Epoch 00005: val_loss improved from 0.12262 to 0.11498, saving model to
concat best.h5
258/258 [============= ] - 24s 93ms/step - loss: 0.1372 -
val loss: 0.1150
Epoch 6/50
Epoch 00006: val_loss improved from 0.11498 to 0.11055, saving model to
concat_best.h5
258/258 [============ ] - 24s 93ms/step - loss: 0.1274 -
val_loss: 0.1105
Epoch 7/50
Epoch 00007: val_loss improved from 0.11055 to 0.10576, saving model to
concat_best.h5
258/258 [============ ] - 24s 92ms/step - loss: 0.1208 -
val_loss: 0.1058
Epoch 8/50
Epoch 00008: val_loss did not improve from 0.10576
258/258 [============ ] - 24s 93ms/step - loss: 0.1139 -
val_loss: 0.1067
Epoch 9/50
258/258 [============ ] - ETA: Os - loss: 0.1096
Epoch 00009: val_loss improved from 0.10576 to 0.10549, saving model to
concat_best.h5
258/258 [============ ] - 24s 93ms/step - loss: 0.1096 -
val_loss: 0.1055
Epoch 10/50
Epoch 00010: val_loss improved from 0.10549 to 0.10507, saving model to
concat_best.h5
258/258 [============ ] - 24s 94ms/step - loss: 0.1053 -
val loss: 0.1051
Epoch 11/50
258/258 [============ ] - ETA: Os - loss: 0.1010
Epoch 00011: val_loss improved from 0.10507 to 0.10283, saving model to
concat_best.h5
258/258 [============ ] - 24s 94ms/step - loss: 0.1010 -
val_loss: 0.1028
Epoch 12/50
258/258 [============= ] - ETA: Os - loss: 0.0977
Epoch 00012: val_loss improved from 0.10283 to 0.10107, saving model to
concat_best.h5
258/258 [============= ] - 24s 95ms/step - loss: 0.0977 -
val_loss: 0.1011
Epoch 13/50
```

```
258/258 [============= ] - ETA: Os - loss: 0.0922
Epoch 00013: val_loss improved from 0.10107 to 0.10079, saving model to
concat_best.h5
258/258 [============= ] - 25s 95ms/step - loss: 0.0922 -
val loss: 0.1008
Epoch 14/50
258/258 [============ ] - ETA: Os - loss: 0.0890
Epoch 00014: val_loss did not improve from 0.10079
val_loss: 0.1013
Epoch 15/50
258/258 [============ ] - ETA: Os - loss: 0.0858
Epoch 00015: val_loss did not improve from 0.10079
258/258 [============== ] - 25s 95ms/step - loss: 0.0858 -
val_loss: 0.1018
Epoch 16/50
258/258 [============= ] - ETA: Os - loss: 0.0827- ETA
Epoch 00016: val_loss did not improve from 0.10079
Epoch 00016: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
258/258 [============ ] - 25s 96ms/step - loss: 0.0827 -
val loss: 0.1014
Epoch 17/50
258/258 [============= ] - ETA: Os - loss: 0.0728
Epoch 00017: val_loss improved from 0.10079 to 0.09775, saving model to
concat_best.h5
258/258 [============= ] - 25s 96ms/step - loss: 0.0728 -
val_loss: 0.0977
Epoch 18/50
258/258 [============= ] - ETA: Os - loss: 0.0703
Epoch 00018: val_loss improved from 0.09775 to 0.09762, saving model to
concat_best.h5
258/258 [============ ] - 25s 96ms/step - loss: 0.0703 -
val_loss: 0.0976
Epoch 19/50
258/258 [============= ] - ETA: Os - loss: 0.0689
Epoch 00019: val_loss improved from 0.09762 to 0.09739, saving model to
concat best.h5
val_loss: 0.0974
Epoch 20/50
258/258 [============ ] - ETA: Os - loss: 0.0680
Epoch 00020: val_loss did not improve from 0.09739
258/258 [============= ] - 25s 96ms/step - loss: 0.0680 -
val_loss: 0.0975
Epoch 21/50
258/258 [============= ] - ETA: Os - loss: 0.0665
Epoch 00021: val_loss improved from 0.09739 to 0.09734, saving model to
```

```
258/258 [============ ] - 25s 96ms/step - loss: 0.0665 -
    val_loss: 0.0973
    Epoch 22/50
    258/258 [============ ] - ETA: Os - loss: 0.0660
    Epoch 00022: val_loss did not improve from 0.09734
    Epoch 00022: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
    val loss: 0.0978
    Epoch 23/50
    258/258 [============ ] - ETA: Os - loss: 0.0643
    Epoch 00023: val_loss did not improve from 0.09734
    258/258 [============ ] - 25s 96ms/step - loss: 0.0643 -
    val_loss: 0.0977
    Epoch 24/50
    258/258 [============ ] - ETA: Os - loss: 0.0644
    Epoch 00024: val_loss did not improve from 0.09734
    258/258 [============ ] - 25s 96ms/step - loss: 0.0644 -
    val loss: 0.0976
    Epoch 25/50
    258/258 [============ ] - ETA: Os - loss: 0.0641
    Epoch 00025: val_loss did not improve from 0.09734
    Epoch 00025: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.
    val_loss: 0.0977
    Epoch 26/50
    Epoch 00026: val_loss did not improve from 0.09734
    val_loss: 0.0976
    Epoch 00026: early stopping
[41]: <tensorflow.python.keras.callbacks.History at 0x29a98dd50c8>
[43]: pred_model = pred_Encoder_decoder(vocab_size, vocab_size, embedding_dim,__
     ⇒lstm_size, lstm_size, max_len, max_len, 'concat', att_units)
    pred_model.compile(optimizer = 'Adam', loss = loss_function)
    pred_model.build(input_shape= (None, 1, maxlen))
    pred_model.load_weights('concat_best.h5')
[54]: sentence = unigram_train['input'].values[5]
    result, attention_plot = predict(sentence, unigram_vec, unigram_index_to_word,_

→gram = 'uni')
    print('input : ', sentence)
```

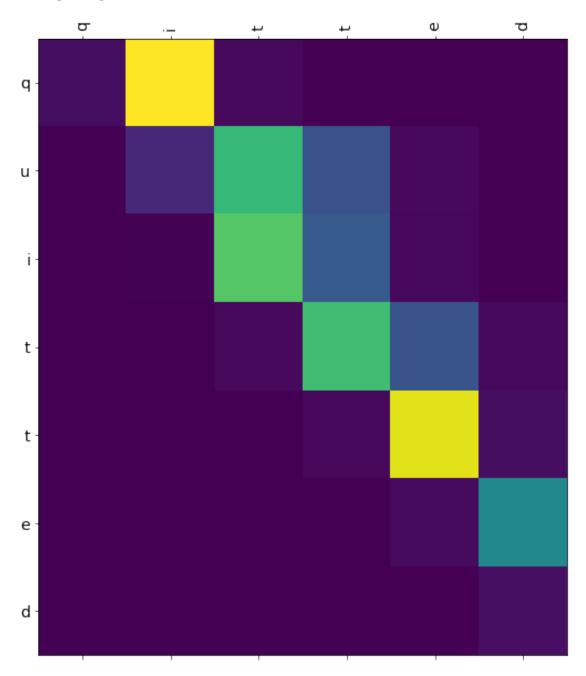
concat_best.h5

```
print('predicted output : ',result)
print('actual output :', unigram_train['output'].values[5])

attention_plot = attention_plot[:len(list(result)), :len(list(sentence))]
plot_attention(attention_plot, list(sentence), list(result))
```

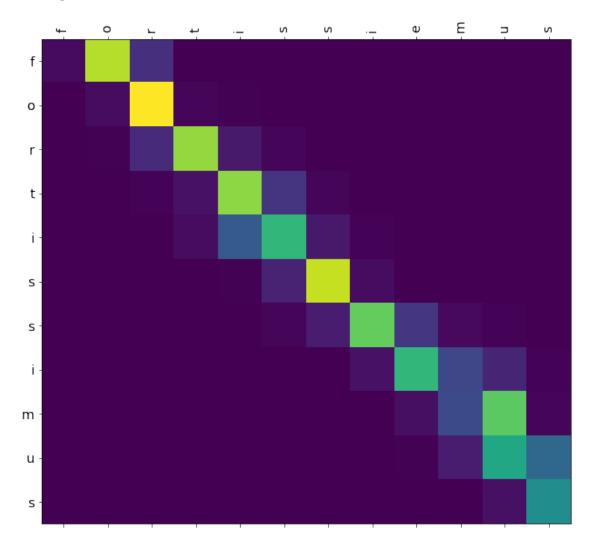
input: qitted

predicted output: quitted
actual output: quitted

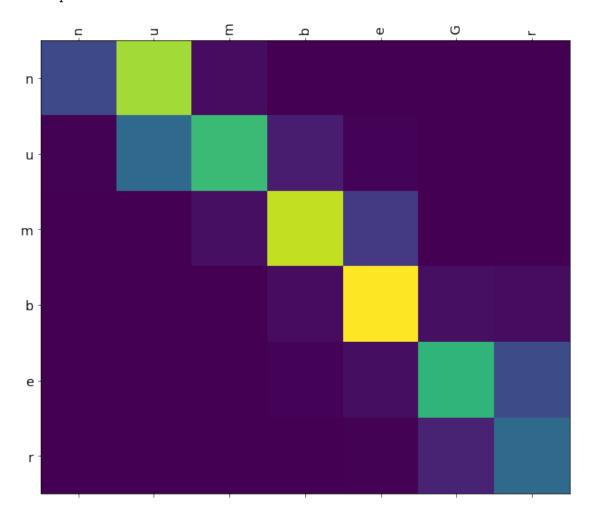


input: fortissiemus

predicted output: fortissimus
actual output: fortissimus



input: numbeGr
predicted output: number
actual output: number



```
[47]: val_bleu = 0
for i in tqdm(range(unigram_val.shape[0])):
```

```
inp = unigram_val['input'].values[i]
           out = unigram_val['output'].values[i]
           pred, _ = predict(inp, unigram_vec, unigram_index_to_word, gram = 'uni')
           val_bleu += sentence_bleu([out], pred)
       train_bleu = 0
       for i in tqdm(range(unigram_train.shape[0])):
           inp = unigram_train['input'].values[i];
           out = unigram train['output'].values[i]
           pred, _ = predict(inp, unigram_vec, unigram_index_to_word, gram = 'uni')
           train bleu += sentence bleu([out], pred)
       test bleu = 0
       for i in tqdm(range(unigram_test.shape[0])):
           inp = unigram_test['input'].values[i]
           out = unigram_test['output'].values[i]
           pred, = predict(inp, unigram_vec, unigram_index_to_word, gram = 'uni')
           test_bleu += sentence_bleu([out], pred)
       print('BLEU Score on train: ',train_bleu/unigram_train.shape[0])
       print('BLEU Score on val: ',val_bleu/unigram_val.shape[0])
       print('BLEU Score on test: ',test_bleu/unigram_test.shape[0])
      100%|
        | 3678/3678 [04:14<00:00, 14.46it/s]
      100%|
      | 33101/33101 [38:27<00:00, 14.35it/s]
      100%
        | 3150/3150 [03:38<00:00, 14.41it/s]
      BLEU Score on train: 0.8553528187207379
      BLEU Score on val: 0.8027546198959468
      BLEU Score on test: 0.712202060966304
      3.2 BiGram
[107]: | 1stm size = 256
       embedding_dim = 100
       att units = 256
      maxlen = 26
[104]: model = encoder_decoder(vocab_size, embedding_dim, lstm_size, lstm_size,
       →maxlen, 'concat', att_units, batch_size)
       model.compile(optimizer = 'Adam', loss = loss_function)
       callbacks = [ModelCheckpoint('concat_best_bigram.h5', save_best_only= True,__
        \rightarrowverbose = 1),
```

```
EarlyStopping(patience = 5, verbose = 1),
          ReduceLROnPlateau(patience = 3, verbose = 1)]
model.fit(x = bigram_train_dataset,
        steps_per_epoch = bigram_train.shape[0]//batch_size,
        validation_data = bigram_val_dataset,
        validation_steps = bigram_val.shape[0]//batch_size,
        epochs = 100,
        verbose = 1,
        callbacks = callbacks)
Epoch 1/100
Epoch 00001: val loss improved from inf to 0.04310, saving model to
concat_best_bigram.h5
6910/6910 [============ ] - 847s 123ms/step - loss: 0.1299 -
val loss: 0.0431
Epoch 2/100
6910/6910 [===========] - ETA: Os - loss: 0.0464
Epoch 00002: val_loss improved from 0.04310 to 0.03256, saving model to
concat best bigram.h5
6910/6910 [============= ] - 869s 126ms/step - loss: 0.0464 -
val loss: 0.0326
Epoch 3/100
Epoch 00003: val_loss improved from 0.03256 to 0.02836, saving model to
concat_best_bigram.h5
6910/6910 [============= ] - 878s 127ms/step - loss: 0.0377 -
val_loss: 0.0284
Epoch 4/100
Epoch 00004: val_loss improved from 0.02836 to 0.02540, saving model to
concat best bigram.h5
6910/6910 [============ ] - 890s 129ms/step - loss: 0.0334 -
val_loss: 0.0254
Epoch 5/100
Epoch 00005: val_loss improved from 0.02540 to 0.02419, saving model to
concat_best_bigram.h5
6910/6910 [============= ] - 877s 127ms/step - loss: 0.0305 -
val_loss: 0.0242
Epoch 6/100
Epoch 00006: val_loss improved from 0.02419 to 0.02344, saving model to
concat_best_bigram.h5
```

6910/6910 [============] - 864s 125ms/step - loss: 0.0285 -

val_loss: 0.0234 Epoch 7/100

```
Epoch 00007: val_loss improved from 0.02344 to 0.02228, saving model to
concat_best_bigram.h5
val loss: 0.0223
Epoch 8/100
Epoch 00008: val_loss improved from 0.02228 to 0.02181, saving model to
concat best bigram.h5
6910/6910 [============= ] - 934s 135ms/step - loss: 0.0260 -
val_loss: 0.0218
Epoch 9/100
Epoch 00009: val_loss improved from 0.02181 to 0.02144, saving model to
concat_best_bigram.h5
6910/6910 [============= ] - 922s 133ms/step - loss: 0.0250 -
val_loss: 0.0214
Epoch 10/100
Epoch 00010: val loss improved from 0.02144 to 0.02106, saving model to
concat best bigram.h5
val_loss: 0.0211
Epoch 11/100
Epoch 00011: val_loss improved from 0.02106 to 0.02065, saving model to
concat_best_bigram.h5
6910/6910 [============ ] - 871s 126ms/step - loss: 0.0235 -
val loss: 0.0207
Epoch 12/100
Epoch 00012: val_loss did not improve from 0.02065
6910/6910 [============ ] - 874s 126ms/step - loss: 0.0229 -
val_loss: 0.0207
Epoch 13/100
Epoch 00013: val loss improved from 0.02065 to 0.02025, saving model to
concat best bigram.h5
6910/6910 [============= ] - 978s 141ms/step - loss: 0.0223 -
val_loss: 0.0203
Epoch 14/100
Epoch 00014: val_loss improved from 0.02025 to 0.02014, saving model to
concat best bigram.h5
6910/6910 [============= ] - 836s 121ms/step - loss: 0.0218 -
val loss: 0.0201
Epoch 15/100
```

```
Epoch 00015: val_loss did not improve from 0.02014
6910/6910 [============ ] - 853s 123ms/step - loss: 0.0215 -
val_loss: 0.0202
Epoch 16/100
Epoch 00016: val_loss improved from 0.02014 to 0.01981, saving model to
concat best bigram.h5
6910/6910 [============= ] - 881s 128ms/step - loss: 0.0210 -
val loss: 0.0198
Epoch 17/100
Epoch 00017: val_loss improved from 0.01981 to 0.01966, saving model to
concat_best_bigram.h5
6910/6910 [============= ] - 849s 123ms/step - loss: 0.0206 -
val_loss: 0.0197
Epoch 18/100
Epoch 00018: val_loss improved from 0.01966 to 0.01951, saving model to
concat best bigram.h5
6910/6910 [============ ] - 830s 120ms/step - loss: 0.0203 -
val loss: 0.0195
Epoch 19/100
Epoch 00019: val_loss did not improve from 0.01951
6910/6910 [============= ] - 832s 120ms/step - loss: 0.0201 -
val_loss: 0.0195
Epoch 20/100
Epoch 00020: val_loss improved from 0.01951 to 0.01923, saving model to
concat_best_bigram.h5
val_loss: 0.0192
Epoch 21/100
Epoch 00021: val loss did not improve from 0.01923
6910/6910 [============ ] - 815s 118ms/step - loss: 0.0195 -
val loss: 0.0194
Epoch 22/100
Epoch 00022: val_loss did not improve from 0.01923
6910/6910 [============= ] - 846s 122ms/step - loss: 0.0191 -
val_loss: 0.0193
Epoch 23/100
Epoch 00023: val_loss improved from 0.01923 to 0.01905, saving model to
concat best bigram.h5
6910/6910 [============= ] - 844s 122ms/step - loss: 0.0190 -
val_loss: 0.0191
```

```
Epoch 24/100
Epoch 00024: val_loss did not improve from 0.01905
6910/6910 [============= ] - 843s 122ms/step - loss: 0.0187 -
val loss: 0.0196
Epoch 25/100
Epoch 00025: val_loss improved from 0.01905 to 0.01900, saving model to
concat best bigram.h5
6910/6910 [============ ] - 866s 125ms/step - loss: 0.0184 -
val_loss: 0.0190
Epoch 26/100
Epoch 00026: val_loss did not improve from 0.01900
Epoch 00026: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
val_loss: 0.0191
Epoch 27/100
Epoch 00027: val_loss improved from 0.01900 to 0.01819, saving model to
concat best bigram.h5
6910/6910 [============== ] - 881s 128ms/step - loss: 0.0159 -
val_loss: 0.0182
Epoch 28/100
Epoch 00028: val_loss improved from 0.01819 to 0.01799, saving model to
concat_best_bigram.h5
6910/6910 [============= ] - 836s 121ms/step - loss: 0.0148 -
val_loss: 0.0180
Epoch 29/100
Epoch 00029: val_loss improved from 0.01799 to 0.01787, saving model to
concat_best_bigram.h5
6910/6910 [============ ] - 834s 121ms/step - loss: 0.0143 -
val loss: 0.0179
Epoch 30/100
6910/6910 [============ ] - ETA: Os - loss: 0.0139
Epoch 00030: val_loss improved from 0.01787 to 0.01779, saving model to
concat_best_bigram.h5
6910/6910 [============= ] - 832s 120ms/step - loss: 0.0139 -
val_loss: 0.0178
Epoch 31/100
Epoch 00031: val_loss improved from 0.01779 to 0.01773, saving model to
concat best bigram.h5
6910/6910 [============= ] - 828s 120ms/step - loss: 0.0136 -
val_loss: 0.0177
```

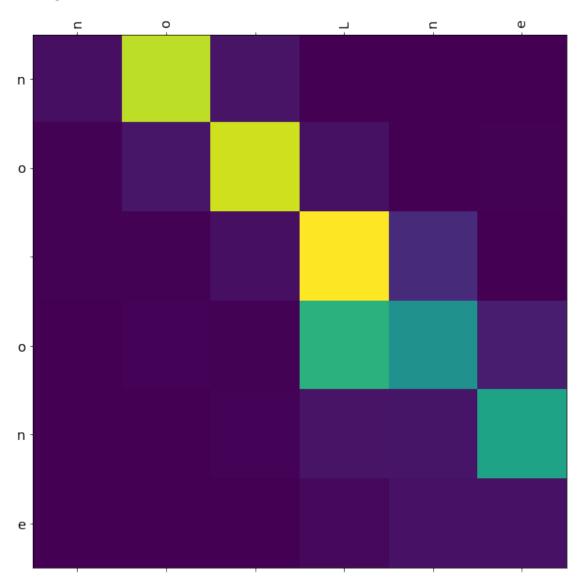
```
Epoch 32/100
     Epoch 00032: val_loss did not improve from 0.01773
     6910/6910 [============= ] - 829s 120ms/step - loss: 0.0134 -
     val loss: 0.0178
     Epoch 33/100
     6910/6910 [============ ] - ETA: Os - loss: 0.0132
     Epoch 00033: val_loss did not improve from 0.01773
     6910/6910 [============ ] - 820s 119ms/step - loss: 0.0132 -
     val_loss: 0.0178
     Epoch 34/100
     Epoch 00034: val_loss did not improve from 0.01773
     Epoch 00034: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
     6910/6910 [============= ] - 820s 119ms/step - loss: 0.0130 -
     val_loss: 0.0178
     Epoch 35/100
     Epoch 00035: val loss did not improve from 0.01773
     6910/6910 [============ ] - 819s 119ms/step - loss: 0.0127 -
     val loss: 0.0178
     Epoch 36/100
     Epoch 00036: val_loss did not improve from 0.01773
     6910/6910 [============= ] - 820s 119ms/step - loss: 0.0126 -
     val_loss: 0.0177
     Epoch 00036: early stopping
[104]: <tensorflow.python.keras.callbacks.History at 0x22706ba1ac8>
[108]: pred_model = pred_Encoder_decoder(vocab_size, vocab_size, embedding_dim,_
      →lstm_size, lstm_size, maxlen, maxlen, 'concat', att_units,
      →bigram_word_to_index)
     pred_model.compile(optimizer = 'Adam', loss = loss_function)
     pred_model.build(input_shape= (None, 1, maxlen))
     pred_model.load_weights('concat_best_bigram.h5')
[109]: sentence = bigram_train['input'].values[4]
     result, attention_plot = predict(sentence, bigram_vec, bigram_index_to_word,_u

→gram = 'bi')
     print('input : ', sentence)
     print('predicted output : ',result)
     print('actual output :', bigram_train['output'].values[4])
     attention_plot = attention_plot[:len(list(result)), :len(list(sentence))]
```

```
plot_attention(attention_plot, list(sentence), list(result))
```

input : no Lne

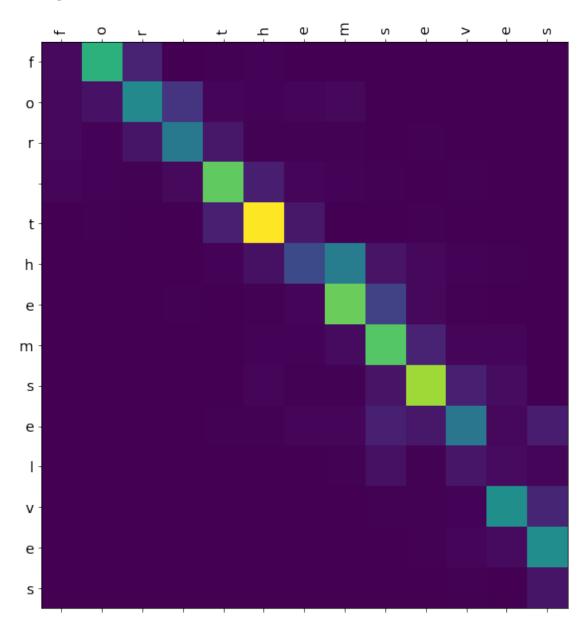
predicted output : no one
actual output : no one



```
attention_plot = attention_plot[:len(list(result)), :len(list(sentence))]
plot_attention(attention_plot, list(sentence), list(result))
```

input : for themseves

predicted output : for themselves
actual output : for themselves



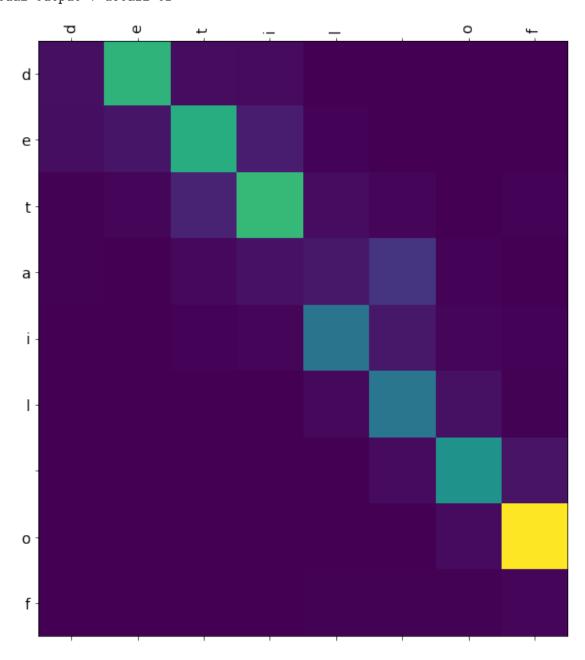
```
[111]: sentence = bigram_train['input'].values[7]
result, attention_plot = predict(sentence, bigram_vec, bigram_index_to_word, 

→gram = 'bi')
```

```
print('input : ', sentence)
print('predicted output : ',result)
print('actual output :', bigram_train['output'].values[7])

attention_plot = attention_plot[:len(list(result)), :len(list(sentence))]
plot_attention(attention_plot, list(sentence), list(result))
```

input : detil of
predicted output : detail of
actual output : detail of



```
[7]: val_bleu = 0
       for i in range(bigram_val.shape[0]):
           inp = bigram_val['input'].values[i]
           out = bigram_val['output'].values[i]
           pred, _ = predict(inp, bigram_vec, bigram_index_to_word, gram = 'bi')
           val_bleu += sentence_bleu([out], pred)
       train bleu = 0
       for i in range(bigram_train.shape[0]):
           inp = bigram train['input'].values[i];
           out = bigram_train['output'].values[i]
           pred, _ = predict(inp, bigram_vec, bigram_index_to_word, gram = 'bi')
           train_bleu += sentence_bleu([out], pred)
       test_bleu = 0
       for i in range(bigram_test.shape[0]):
           inp = bigram_test['input'].values[i]
           out = bigram_test['output'].values[i]
           pred, _ = predict(inp, bigram_vec, bigram_index_to_word, gram = 'bi')
           test_bleu += sentence_bleu([out], pred)
       print('BLEU Score on train: ',train_bleu/bigram_train.shape[0])
       print('BLEU Score on val: ',val bleu/bigram val.shape[0])
       print('BLEU Score on test: ',test_bleu/bigram_test.shape[0])
      BLEU Score on train: 0.9808526374708109
      BLEU Score on val: 0.9669617055111845
      BLEU Score on test: 0.9539630640021209
      3.3 TriGram
[112]: lstm_size = 256
       embedding_dim = 100
       att_units = 256
       maxlen = 34
[114]: model = encoder_decoder(vocab_size, embedding_dim, lstm_size, lstm_size,
       →maxlen, 'concat', att_units, batch_size)
       model.compile(optimizer = 'Adam', loss = loss_function)
       callbacks = [ModelCheckpoint('concat_best_trigram.h5', save_best_only= True,__
        \rightarrowverbose = 1),
                    EarlyStopping(patience = 5, verbose = 1),
                    ReduceLROnPlateau(patience = 3, verbose = 1)]
```

```
model.fit(x = trigram_train_dataset,
      steps_per_epoch = trigram_train.shape[0]//batch_size,
      validation_data = trigram_val_dataset,
      validation_steps = trigram_val.shape[0]//batch_size,
      epochs = 100,
      verbose = 1,
      callbacks = callbacks)
Epoch 1/100
Epoch 00001: val loss improved from inf to 0.04223, saving model to
concat_best_trigram.h5
val_loss: 0.0422
Epoch 2/100
Epoch 00002: val_loss improved from 0.04223 to 0.03123, saving model to
concat best trigram.h5
val loss: 0.0312
Epoch 3/100
Epoch 00003: val_loss improved from 0.03123 to 0.02453, saving model to
concat best trigram.h5
val loss: 0.0245
Epoch 4/100
Epoch 00004: val_loss improved from 0.02453 to 0.02350, saving model to
concat_best_trigram.h5
6910/6910 [============= ] - 1159s 168ms/step - loss: 0.0303 -
val_loss: 0.0235
Epoch 5/100
6910/6910 [============ ] - ETA: Os - loss: 0.0277
Epoch 00005: val_loss improved from 0.02350 to 0.02035, saving model to
concat_best_trigram.h5
val_loss: 0.0204
Epoch 6/100
Epoch 00006: val_loss improved from 0.02035 to 0.01934, saving model to
concat_best_trigram.h5
val_loss: 0.0193
Epoch 7/100
```

Epoch 00007: val_loss improved from 0.01934 to 0.01881, saving model to

```
concat_best_trigram.h5
val_loss: 0.0188
Epoch 8/100
Epoch 00008: val_loss improved from 0.01881 to 0.01879, saving model to
concat best trigram.h5
val loss: 0.0188
Epoch 9/100
Epoch 00009: val_loss improved from 0.01879 to 0.01782, saving model to
concat_best_trigram.h5
6910/6910 [============= ] - 1174s 170ms/step - loss: 0.0219 -
val_loss: 0.0178
Epoch 10/100
Epoch 00010: val_loss improved from 0.01782 to 0.01715, saving model to
concat best trigram.h5
val loss: 0.0171
Epoch 11/100
Epoch 00011: val_loss improved from 0.01715 to 0.01670, saving model to
concat_best_trigram.h5
val_loss: 0.0167
Epoch 12/100
Epoch 00012: val_loss improved from 0.01670 to 0.01650, saving model to
concat_best_trigram.h5
val_loss: 0.0165
Epoch 13/100
6910/6910 [============ ] - ETA: Os - loss: 0.0194
Epoch 00013: val_loss improved from 0.01650 to 0.01627, saving model to
concat best trigram.h5
val_loss: 0.0163
Epoch 14/100
Epoch 00014: val_loss improved from 0.01627 to 0.01613, saving model to
concat_best_trigram.h5
6910/6910 [============= ] - 1188s 172ms/step - loss: 0.0189 -
val_loss: 0.0161
Epoch 15/100
Epoch 00015: val_loss improved from 0.01613 to 0.01572, saving model to
```

```
concat_best_trigram.h5
val_loss: 0.0157
Epoch 16/100
Epoch 00016: val_loss improved from 0.01572 to 0.01561, saving model to
concat best trigram.h5
val loss: 0.0156
Epoch 17/100
Epoch 00017: val_loss did not improve from 0.01561
val loss: 0.0164
Epoch 18/100
Epoch 00018: val_loss improved from 0.01561 to 0.01544, saving model to
concat_best_trigram.h5
val loss: 0.0154
Epoch 19/100
Epoch 00019: val_loss improved from 0.01544 to 0.01532, saving model to
concat_best_trigram.h5
val_loss: 0.0153
Epoch 20/100
Epoch 00020: val_loss improved from 0.01532 to 0.01530, saving model to
concat_best_trigram.h5
val_loss: 0.0153
Epoch 21/100
Epoch 00021: val loss improved from 0.01530 to 0.01508, saving model to
concat best trigram.h5
val loss: 0.0151
Epoch 22/100
Epoch 00022: val_loss improved from 0.01508 to 0.01506, saving model to
concat_best_trigram.h5
val loss: 0.0151
Epoch 23/100
Epoch 00023: val_loss did not improve from 0.01506
```

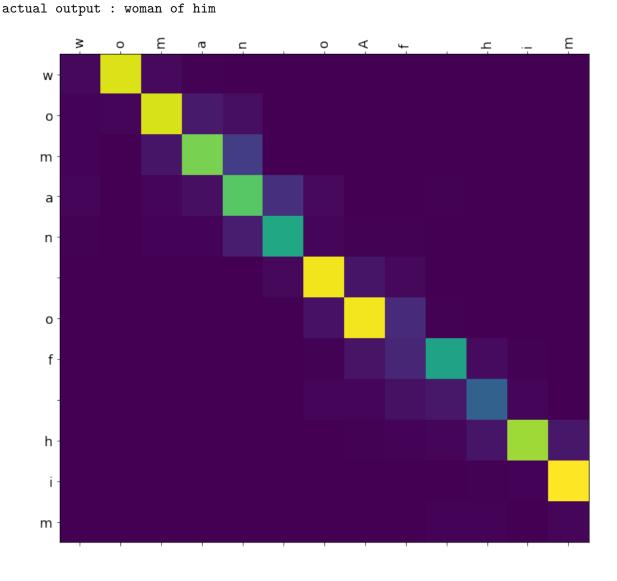
```
val_loss: 0.0151
Epoch 24/100
Epoch 00024: val_loss did not improve from 0.01506
Epoch 00024: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
val loss: 0.0158
Epoch 25/100
Epoch 00025: val_loss improved from 0.01506 to 0.01435, saving model to
concat_best_trigram.h5
val loss: 0.0144
Epoch 26/100
Epoch 00026: val_loss improved from 0.01435 to 0.01406, saving model to
concat_best_trigram.h5
val loss: 0.0141
Epoch 27/100
Epoch 00027: val_loss improved from 0.01406 to 0.01390, saving model to
concat_best_trigram.h5
val_loss: 0.0139
Epoch 28/100
Epoch 00028: val_loss improved from 0.01390 to 0.01382, saving model to
concat_best_trigram.h5
val_loss: 0.0138
Epoch 29/100
Epoch 00029: val loss improved from 0.01382 to 0.01374, saving model to
concat best trigram.h5
val loss: 0.0137
Epoch 30/100
Epoch 00030: val_loss improved from 0.01374 to 0.01366, saving model to
concat_best_trigram.h5
val loss: 0.0137
Epoch 31/100
Epoch 00031: val_loss improved from 0.01366 to 0.01364, saving model to
concat_best_trigram.h5
```

```
val_loss: 0.0136
Epoch 32/100
Epoch 00032: val loss did not improve from 0.01364
val loss: 0.0136
Epoch 33/100
6910/6910 [============ ] - ETA: Os - loss: 0.0114
Epoch 00033: val_loss improved from 0.01364 to 0.01358, saving model to
concat_best_trigram.h5
val_loss: 0.0136
Epoch 34/100
Epoch 00034: val_loss improved from 0.01358 to 0.01357, saving model to
concat_best_trigram.h5
Epoch 00034: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
6910/6910 [============= ] - 1287s 186ms/step - loss: 0.0113 -
val loss: 0.0136
Epoch 35/100
Epoch 00035: val_loss improved from 0.01357 to 0.01353, saving model to
concat_best_trigram.h5
val_loss: 0.0135
Epoch 36/100
Epoch 00036: val_loss improved from 0.01353 to 0.01350, saving model to
concat_best_trigram.h5
val_loss: 0.0135
Epoch 37/100
Epoch 00037: val_loss improved from 0.01350 to 0.01350, saving model to
concat best trigram.h5
val_loss: 0.0135
Epoch 38/100
Epoch 00038: val_loss improved from 0.01350 to 0.01349, saving model to
concat_best_trigram.h5
Epoch 00038: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.
val_loss: 0.0135
Epoch 39/100
```

```
Epoch 00039: val_loss did not improve from 0.01349
    val loss: 0.0135
    Epoch 40/100
    Epoch 00040: val loss did not improve from 0.01349
    val loss: 0.0135
    Epoch 41/100
    Epoch 00041: val_loss did not improve from 0.01349
    Epoch 00041: ReduceLROnPlateau reducing learning rate to 1.0000001111620805e-07.
    val loss: 0.0135
    Epoch 42/100
    6910/6910 [============ ] - ETA: Os - loss: 0.0109
    Epoch 00042: val_loss did not improve from 0.01349
    6910/6910 [============= ] - 1398s 202ms/step - loss: 0.0109 -
    val loss: 0.0135
    Epoch 43/100
    Epoch 00043: val_loss did not improve from 0.01349
    val_loss: 0.0135
    Epoch 00043: early stopping
[114]: <tensorflow.python.keras.callbacks.History at 0x226efe79bc8>
[115]: pred model = pred Encoder decoder(vocab size, vocab size, embedding dim,
     →lstm_size, lstm_size, maxlen, maxlen, 'concat', att_units,
     →trigram_word_to_index)
    pred_model.compile(optimizer = 'Adam', loss = loss_function)
    pred_model.build(input_shape= (None, 1, maxlen))
    pred_model.load_weights('concat_best_trigram.h5')
[116]: sentence = trigram_train['input'].values[4]
    result, attention_plot = predict(sentence, trigram_vec, trigram_index_to_word,_

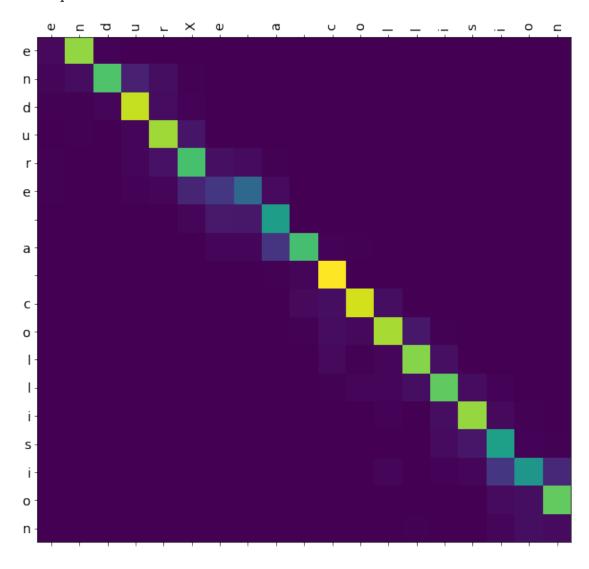
→gram = 'tri')
    print('input : ', sentence)
    print('predicted output : ',result)
    print('actual output :', trigram_train['output'].values[4])
    attention_plot = attention_plot[:len(list(result)), :len(list(sentence))]
    plot_attention(attention_plot, list(sentence), list(result))
```

 $\begin{array}{lll} \mbox{input} & : & \mbox{woman oAf him} \\ \mbox{predicted output} & : & \mbox{woman of him} \end{array}$



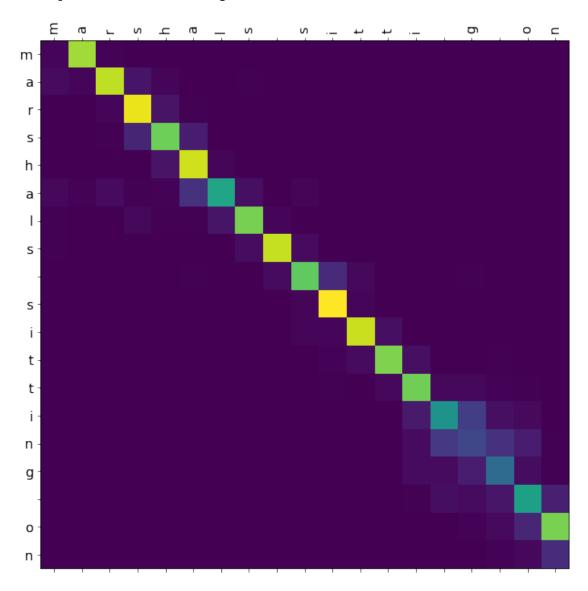
input : endurXe a collision

predicted output : endure a collision
actual output : endure a collision



input : marshals sitti g on

predicted output : marshals sitting on
actual output : marshals sitting on



```
[8]: val_bleu = 0
for i in range(trigram_val.shape[0]):
    inp = trigram_val['input'].values[i]
    out = trigram_val['output'].values[i]
    pred, _ = predict(inp, trigram_vec, trigram_index_to_word, gram = 'tri')
    val_bleu += sentence_bleu([out], pred)

train_bleu = 0
for i in range(trigram_train.shape[0]):
    inp = trigram_train['input'].values[i];
```

```
out = trigram_train['output'].values[i]
  pred, _ = predict(inp, trigram_vec, trigram_index_to_word, gram = 'tri')
  train_bleu += sentence_bleu([out], pred)

test_bleu = 0
for i in range(trigram_test.shape[0]):
  inp = trigram_test['input'].values[i]
  out = trigram_test['output'].values[i]
  pred, _ = predict(inp, trigram_vec, trigram_index_to_word, gram = 'tri')
  test_bleu += sentence_bleu([out], pred)

print('BLEU Score on train: ',train_bleu/trigram_train.shape[0])
print('BLEU Score on test: ',test_bleu/trigram_test.shape[0])
```

BLEU Score on train: 0.9889611211686458 BLEU Score on val: 0.9813112757412255 BLEU Score on test: 0.9693013446155896

3 Conclusion

```
[9]: from prettytable import PrettyTable
     myTable = PrettyTable(["n-gram", "Model Name", "Train BLEU Score", "Val BLEU⊔
     →Score", "Test BLEU Score"])
     myTable.add_row(["1-gram", "Seq2Seq", "0.834", "0.746", "0.684"])
     myTable.add_row(["2-gram", "Seq2Seq", "0.965", "0.947", "0.932"])
     myTable.add_row(["3-gram", "Seq2Seq", "0.968", "0.958", "0.949"])
     myTable.add_row(["1-gram", "Seq2Seq with Attention Mechanism", "0.869", "0.
      \hookrightarrow792", "0.707"])
     myTable.add_row(["2-gram", "Seq2Seq with Attention Mechanism", "0.972", "0.
      \rightarrow959", "0.946"])
     myTable.add_row(["3-gram", "Seq2Seq with Attention Mechanism", "0.981", "0.
      \rightarrow 974", "0.962"])
     myTable.add row(["1-gram", "Bi-directional Seq2Seq with Attention Mechanism", __
     \rightarrow"0.855", "0.802", "0.712"])
     myTable.add_row(["2-gram", "Bi-directional Seq2Seq with Attention Mechanism", __
      \rightarrow "0.980", "0.967", "0.954"])
     myTable.add row(["3-gram", "Bi-directional Seq2Seq with Attention Mechanism", __
      \rightarrow "0.989", "0.981", "0.969"])
     print(myTable)
```

Val BLEU Score Test BLEU Score	0.834 0.965	+
1-gram Seq2Seq 0.746 0.684		+
1-gram Seq2Seq 0.746 0.684		1
0.746 0.684		
2-gram Seq2Seq 0.947 0.932	0.965	
0.947 0.932	0.965	
· · · · · · · · · · · · · · · · · · ·		- 1
3-gram Seq2Seq		
	0.968	- 1
0.958 0.949		
1-gram Seq2Seq with Attention Mechanism	0.869	1
0.792 0.707		
2-gram Seq2Seq with Attention Mechanism	0.972	ı
0.959 0.946		•
3-gram Seq2Seq with Attention Mechanism	0.981	1
0.974 0.962	0.301	'
•	0.055	
1-gram Bi-directional Seq2Seq with Attention Mechanism	0.855	ı
0.802 0.712		_
2-gram Bi-directional Seq2Seq with Attention Mechanism	0.980	l
0.967 0.954		
3-gram Bi-directional Seq2Seq with Attention Mechanism	0.989	
0.981 0.969		