IMPORTING LIBRARY

```
import numpy as np
import pandas as pd
import re
import os
import json
import pickle
from tqdm import tqdm
import glob
import matplotlib.pyplot as plt
from bs4 import BeautifulSoup
from keras.preprocessing.text import Tokenizer
from keras.utils import pad_sequences
from keras_preprocessing.sequence import pad_sequences
from nltk.corpus import stopwords
from tensorflow.keras.layers import Input, LSTM, Embedding, Dense, Concatenate, TimeDistribut
from tensorflow.keras.models import Model
from tensorflow.keras.callbacks import EarlyStopping
import warnings
pd.set_option("display.max_colwidth", 200)
warnings.filterwarnings("ignore")
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

TAKING SEGMENTED DATASET

```
# load the meta data from the CSV file using 3 columns (abstract, title, authors),
df = pd.read_excel("/content/drive/MyDrive/Directed/metadataFinal.xlsx",usecols=["title", "ab
print(df.shape)
```

```
(10000, 2)
```

```
df.info
```

```
<bound method DataFrame.info of
title  \
0
Correction.
1
Correspondence.
2
```

```
Editorial.
3
Editorial.
4
Editorial.
...
...
9995                              Video-Observed Therapy With a Notification System
for Improving the Monitoring of Tuberculosis Treatment in Thailand: Usability Study
9996     Modelling the impact of the coronavirus pandemic on bowel cancer screening
outcomes in England: A decision analysis to prepare for future screening disruption
9997  Epidemiology, Clinical Features, and Outcomes of Multisystem Inflammatory
Syndrome in Children (MIS-C) and Adolescents—a Live Systematic Review and Meta-
analysis
9998
The Molecular Basis of Resilience: A Narrative Review
9999                                                                  “Exams by
You”: Having Students Write and Complete Their Own Exams During the COVID-19
Pandemic


abstract
0
[This corrects the article on p. 147 in vol. 33.].
1
NaN
2
NaN
3
NaN
4
NaN
...
...
9995  BACKGROUND: In Thailand, the health care system has struggled to cope with
COVID-19, resulting in directly observed therapy for tuberculosis being de-
emphasized. A video-observed therapy (VOT) sys...
9996  The English Bowel Cancer Screening Programme invites people between the ages
of 60 and 74 to take a Faecal Immunochemical Test every two years. This programme
was interrupted during the coronaviru...
9997  PURPOSE OF REVIEW: A multisystem inflammatory condition occurring in children
and adolescents with COVID-19 has become increasingly recognized and widely studied
globally. This review aims to inve...
9998  Resilience refers to the adaptability of a person – an ability to “bounce-
back” from stressors. We question if resilience can be strengthened, potentially to
decrease the risk of stress-related di...
9999  BACKGROUND: The COVID-19 pandemic made it difficult to proctor exams after the
forced transition to remote teaching and learning. OBJECTIVE: We evaluated students’
experiences creating and answeri...
```

```
df.head()
```

	title	abstract
0	Correction.	[This corrects the article on p. 147 in vol. 33.].
1	Correspondence.	NaN
2	Editorial.	NaN
3	Editorial.	NaN

DATA PREPROCESSING

```
df.isna().sum()
```

```
title          1
abstract    1184
dtype: int64
```

```
df.drop_duplicates(subset=['abstract'],inplace=True)#dropping duplicates
df.dropna(axis=0,inplace=True)#dropping na
```

```
data = df[['title','abstract']]
```

```
data.head()
```

	title	abstract
0	Correction.	[This corrects the article on p. 147 in vol. 33.].
11	A bioactive compliant vascular graft modulates macrophage polarization and maintains patency with robust vascular remodeling.	Conventional synthetic vascular grafts are associated with significant failure rates due to their mismatched mechanical properties with the native vessel and poor regenerative potential. Though di...
12	Strategies to increase rural maternal utilization of skilled health personnel for childbirth delivery in low- and middle-income countries: a narrative review.	BACKGROUND Skilled attendance at birth is considered key to accomplishing Sustainable Development Goal (SDG) 3.1 aimed at reducing maternal mortality. Many maternal deaths can be prevented if a wo...
13	A ‘Multiomic’ Approach of Saliva Metabolomics, Microbiota, and Serum Biomarkers to Assess the Need of Hospitalization in Coronavirus Disease 2019	Background and Aims The SARS-CoV-2 pandemic has overwhelmed the treatment capacity of the health care systems during the highest viral diffusion rate. Patients reaching the emergency department ha...

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8810 entries, 0 to 9999
Data columns (total 2 columns):
 #   Column    Non-Null Count  Dtype
```

```
 ---  ------    --------------  -----
  0   title     8810 non-null   object
  1   abstract  8810 non-null   object
dtypes: object(2)
memory usage: 206.5+ KB
```

```
from wordcloud import WordCloud, STOPWORDS

# Thanks : https://www.kaggle.com/aashita/word-clouds-of-various-shapes ##
def plot_wordcloud(text, mask=None, max_words=200, max_font_size=50, figure_size=(15.0,15.0),
                   title = None, title_size=20, image_color=False,color = None):
    stopwords = set(STOPWORDS)
    more_stopwords = {'one', 'br', 'Po', 'th', 'sayi', 'fo', 'Unknown'}
    stopwords = stopwords.union(more_stopwords)

    wordcloud = WordCloud(background_color=color,
                    stopwords = stopwords,
                    max_words = max_words,
                    max_font_size = max_font_size,
                    random_state = 42,
                    width=800,
                    height=400,
                    mask = mask)
    wordcloud.generate(str(text))

    plt.figure(figsize=figure_size)
    if image_color:
        image_colors = ImageColorGenerator(mask);
        plt.imshow(wordcloud.recolor(color_func=image_colors), interpolation="bilinear");
        plt.title(title, fontdict={'size': title_size,
                                   'verticalalignment': 'bottom'})
    else:
        plt.imshow(wordcloud);
        plt.title(title, fontdict={'size': title_size, 'color': 'black',
                                   'verticalalignment': 'bottom'})
    plt.axis('off');
    plt.tight_layout()

plot_wordcloud(data['title'].values, title="Word Cloud of Title",color = 'black')
plot_wordcloud(data['abstract'].values, title="Word Cloud of Abstarct",color = 'black')
```

Word Cloud of Title

Word Cloud of Abstarct

DATA CLEANING

```
# A list of contractions from http://stackoverflow.com/questions/19790188/expanding-english-l

contraction_mapping = {"ain't": "is not", "aren't": "are not","can't": "cannot", "'cause": "b
                           "didn't": "did not",  "doesn't": "does not", "don't": "do not", "h
                           "he'd": "he would","he'll": "he will", "he's": "he is", "how'd": "
                           "I'd": "I would", "I'd've": "I would have", "I'll": "I will", "I'l
                           "i'd've": "i would have", "i'll": "i will",  "i'll've": "i will ha
                           "it'd've": "it would have", "it'll": "it will", "it'll've": "it wi
                           "mayn't": "may not", "might've": "might have","mightn't": "might n
                           "mustn't": "must not", "mustn't've": "must not have", "needn't": "
                           "oughtn't": "ought not", "oughtn't've": "ought not have", "shan't"
                           "she'd": "she would", "she'd've": "she would have", "she'll": "she
                           "should've": "should have", "shouldn't": "should not", "shouldn't'
                           "this's": "this is","that'd": "that would", "that'd've": "that wou
                           "there'd've": "there would have", "there's": "there is", "here's":
                           "they'll": "they will", "they'll've": "they will have", "they're":
                           "wasn't": "was not", "we'd": "we would", "we'd've": "we would have
                           "we've": "we have", "weren't": "were not", "what'll": "what will",
                           "what's": "what is", "what've": "what have", "when's": "when is",
                           "where've": "where have", "who'll": "who will", "who'll've": "who
                           "why's": "why is", "why've": "why have", "will've": "will have", "
                           "would've": "would have", "wouldn't": "would not", "wouldn't've":
                           "y'all'd": "you all would","y'all'd've": "you all would have","y'a
                           "you'd": "you would", "you'd've": "you would have", "you'll": "you
                           "you're": "you are", "you've": "you have"}


import nltk
nltk.download('stopwords')

stop_words = set(stopwords.words('english'))

def text_cleaner(text,num):
    newString = text.lower()
    newString = BeautifulSoup(newString, "lxml").text
    newString = re.sub(r'\([^)]*\)', '', newString)
    newString = re.sub('"','', newString)
    newString = ' '.join([contraction_mapping[t] if t in contraction_mapping else t for t in
    newString = re.sub(r"'s\b","",newString)
    newString = re.sub("[^a-zA-Z]", " ", newString)
    newString = re.sub('[m]{2,}', 'mm', newString)
    if(num==0):
        tokens = [w for w in newString.split() if not w in stop_words]
    else:
        tokens=newString.split()
    long_words=[]
    for i in tokens:
```

```
        if len(i)>1:                                                 #removing short word
            long_words.append(i)
    return (" ".join(long_words)).strip()
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
#call the function
cleaned_text = []
for t in data['abstract']:
    cleaned_text.append(text_cleaner(t,0))
```

```
cleaned_text[:3]
```

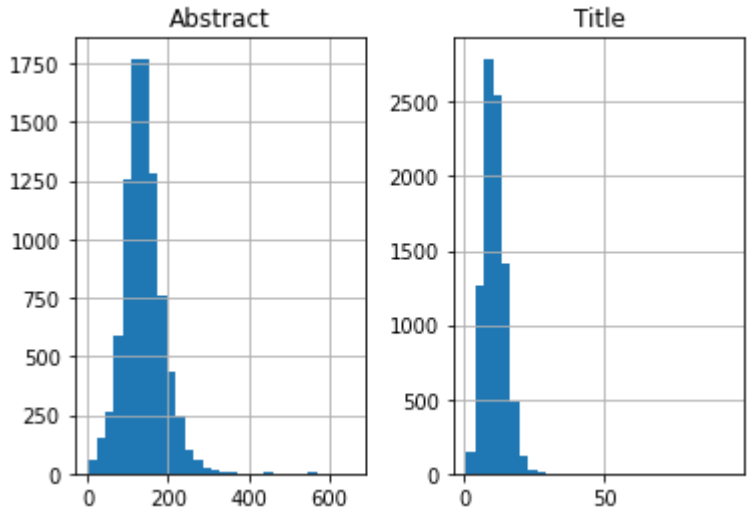
```
['corrects article vol',
 'conventional synthetic vascular grafts associated significant failure rates due mismatched mechanical properties native vessel poor regenerative potential though different tissue engineering approaches used improve biocompatibility synthetic vascular grafts still crucial develop new generation synthetic grafts match dynamics native vessel direct host response achieve robust vascular regeneration size pores within implanted biomaterials shown significant effects macrophage polarization confirmed necessary efficient vascular formation remodeling developed biodegradable autoclavable synthetic vascular grafts new polyurethane elastomer tailored grafts interconnected pore sizes promote macrophage populations pro regenerative phenotype improve vascular regeneration patency rate synthetic vascular grafts showed similar mechanical properties native blood vessels encouraged macrophage populations varying phenotypic expression maintained patency vascular regeneration one month rat carotid interposition model four month rat aortic interposition model innovative bioactive synthetic vascular graft holds promise treat clinical vascular diseases',
 'background skilled attendance birth considered key accomplishing sustainable development goal aimed reducing maternal mortality many maternal deaths prevented woman receives care skilled health personnel maternal utilization skilled health delivery services rural areas low middle income countries compared urban areas previous studies found community based interventions may increase rural maternal uptake skilled health delivery services evidence lacking strategies effective objective review effectiveness community based strategies increase rural maternal utilization skilled health personnel childbirth delivery low middle income countries methods conducted narrative review pubmed cinahl cochrane library psycinfo databases searched articles database inception november key search terms pre determined information extracted studies meeting inclusion criteria cluster randomized trials rural setting reproductive aged women community engagement low middle income countries studies considered effective statistically significant narrative synthesis conducted results ten cluster randomized trials candidate citations met inclusion criteria strategies included home based visits women groups combined approaches ten articles three studies found significantly increase maternal uptake skilled health personnel delivery used different strategy results inconclusive strategies effective limitations review include heterogeneity generalizability studies conclusions research suggests different strategies may effective improving maternal utilization skilled health personnel delivery certain rural settings ineffective others research warranted better understand context strategies may effective conditions']
```

```
#call the function
```

```
cleaned_summary = []
for t in data['title']:
    cleaned_summary.append(text_cleaner(t,0))

cleaned_summary[:5]
```

```
['correction',
 'bioactive compliant vascular graft modulates macrophage polarization maintains
patency robust vascular remodeling',
 'strategies increase rural maternal utilization skilled health personnel childbirth
delivery low middle income countries narrative review',
 'multiomic approach saliva metabolomics microbiota serum biomarkers assess need
hospitalization coronavirus disease',
 'chapter infectious disease emergencies']
```

```
data['cleaned_text']=cleaned_text
data['cleaned_summary']=cleaned_summary


text_word_count = []
summary_word_count = []

# populate the lists with sentence lengths
for i in data['cleaned_text']:
      text_word_count.append(len(i.split()))

for i in data['cleaned_summary']:
      summary_word_count.append(len(i.split()))

length_df = pd.DataFrame({'Abstract':text_word_count, 'Title':summary_word_count})

length_df.hist(bins = 30)
plt.show()
```




```
data['cleaned_summary'] = data['cleaned_summary'].apply(lambda x : 'sostok '+ x + ' eostok')
```

```
max_text_len = 100
max_summary_len = 35


from sklearn.model_selection import train_test_split
x_tr,x_val,y_tr,y_val=train_test_split(np.array(data['cleaned_text']),np.array(data['cleaned_


from keras.preprocessing.text import Tokenizer

#prepare a tokenizer for reviews on training data
x_tokenizer = Tokenizer()
x_tokenizer.fit_on_texts(list(x_tr))



thresh=5

cnt=0
tot_cnt=0
freq=0
tot_freq=0

for key,value in x_tokenizer.word_counts.items():
    tot_cnt=tot_cnt+1
    tot_freq=tot_freq+value
    if(value<thresh):
        cnt=cnt+1
        freq=freq+value

print("% of rare words in vocabulary:",(cnt/tot_cnt)*100)
print("Total Coverage of rare words:",(freq/tot_freq)*100)

     % of rare words in vocabulary: 62.23902087832973
     Total Coverage of rare words: 3.79966494955589


#prepare a tokenizer for reviews on training data
x_tokenizer = Tokenizer(num_words=tot_cnt-cnt)
x_tokenizer.fit_on_texts(list(x_tr))

#convert text sequences into integer sequences
x_tr_seq    =   x_tokenizer.texts_to_sequences(x_tr)
x_val_seq   =   x_tokenizer.texts_to_sequences(x_val)

#padding zero upto maximum lengath
x_tr    =   pad_sequences(x_tr_seq,maxlen=max_text_len, padding='post')
x_val   =   pad_sequences(x_val_seq,maxlen=max_text_len, padding='post')

#size of vocabulary ( +1 for padding token)
x_voc   =  x_tokenizer.num_words + 1
```

```
#prepare a tokenizer for reviews on training data
y_tokenizer = Tokenizer()
y_tokenizer.fit_on_texts(list(y_tr))


thresh=7

cnt=0
tot_cnt=0
freq=0
tot_freq=0

for key,value in y_tokenizer.word_counts.items():
    tot_cnt=tot_cnt+1
    tot_freq=tot_freq+value
    if(value<thresh):
        cnt=cnt+1
        freq=freq+value

print("% of rare words in vocabulary:",(cnt/tot_cnt)*100)
print("Total Coverage of rare words:",(freq/tot_freq)*100)
```

```
 % of rare words in vocabulary: 84.35897435897436
 Total Coverage of rare words: 19.54113081932631
```

```
#prepare a tokenizer for reviews on training data
y_tokenizer = Tokenizer(num_words=tot_cnt-cnt)
y_tokenizer.fit_on_texts(list(y_tr))

#convert text sequences into integer sequences
y_tr_seq    =   y_tokenizer.texts_to_sequences(y_tr)
y_val_seq   =   y_tokenizer.texts_to_sequences(y_val)

#padding zero upto maximum length
y_tr    =   pad_sequences(y_tr_seq, maxlen=max_summary_len, padding='post')
y_val   =   pad_sequences(y_val_seq, maxlen=max_summary_len, padding='post')

#size of vocabulary
y_voc  =   y_tokenizer.num_words +1


y_tokenizer.word_counts['sostok'],len(y_tr)
```

```
 (7929, 7929)
```

```
ind=[]
for i in range(len(y_tr)):
    cnt=0
    for j in y_tr[i]:
        if j!=0:
            cnt=cnt+1
```

```
    if(cnt==2):
        ind.append(i)

y_tr=np.delete(y_tr,ind, axis=0)
x_tr=np.delete(x_tr,ind, axis=0)

ind=[]
for i in range(len(y_val)):
    cnt=0
    for j in y_val[i]:
        if j!=0:
            cnt=cnt+1
    if(cnt==2):
        ind.append(i)

y_val=np.delete(y_val,ind, axis=0)
x_val=np.delete(x_val,ind, axis=0)
```

NLP MODEL

```
from tensorflow.keras import layers
import tensorflow as tf
from tensorflow.python.keras import backend as K

logger = tf.get_logger()


class AttentionLayer(tf.keras.layers.Layer):
    """
    This class implements Bahdanau attention (https://arxiv.org/pdf/1409.0473.pdf).
    There are three sets of weights introduced W_a, U_a, and V_a
     """

    def __init__(self, **kwargs):
        super(AttentionLayer, self).__init__(**kwargs)

    def build(self, input_shape):
        assert isinstance(input_shape, list)
        # Create a trainable weight variable for this layer.

        self.W_a = self.add_weight(name='W_a',
                                   shape=tf.TensorShape((input_shape[0][2], input_shape[0][2]
                                   initializer='uniform',
                                   trainable=True)
        self.U_a = self.add_weight(name='U_a',
                                   shape=tf.TensorShape((input_shape[1][2], input_shape[0][2]
                                   initializer='uniform',
                                   trainable=True)
```

```
            self.V_a = self.add_weight(name='V_a',
                                       shape=tf.TensorShape((input_shape[0][2], 1)),
                                       initializer='uniform',
                                       trainable=True)

            super(AttentionLayer, self).build(input_shape)  # Be sure to call this at the end

        def call(self, inputs):
            """
            inputs: [encoder_output_sequence, decoder_output_sequence]
            """
            assert type(inputs) == list
            encoder_out_seq, decoder_out_seq = inputs

            logger.debug(f"encoder_out_seq.shape = {encoder_out_seq.shape}")
            logger.debug(f"decoder_out_seq.shape = {decoder_out_seq.shape}")

            def energy_step(inputs, states):
                """ Step function for computing energy for a single decoder state
                inputs: (batchsize * 1 * de_in_dim)
                states: (batchsize * 1 * de_latent_dim)
                """

                logger.debug("Running energy computation step")

                if not isinstance(states, (list, tuple)):
                    raise TypeError(f"States must be an iterable. Got {states} of type {type(stat

                encoder_full_seq = states[-1]

                """ Computing S.Wa where S=[s0, s1, ..., si]"""
                # <= batch size * en_seq_len * latent_dim
                W_a_dot_s = K.dot(encoder_full_seq, self.W_a)

                """ Computing hj.Ua """
                U_a_dot_h = K.expand_dims(K.dot(inputs, self.U_a), 1)  # <= batch_size, 1, latent

                logger.debug(f"U_a_dot_h.shape = {U_a_dot_h.shape}")

                """ tanh(S.Wa + hj.Ua) """
                # <= batch_size*en_seq_len, latent_dim
                Ws_plus_Uh = K.tanh(W_a_dot_s + U_a_dot_h)

                logger.debug(f"Ws_plus_Uh.shape = {Ws_plus_Uh.shape}")

                """ softmax(va.tanh(S.Wa + hj.Ua)) """
                # <= batch_size, en_seq_len
                e_i = K.squeeze(K.dot(Ws_plus_Uh, self.V_a), axis=-1)
                # <= batch_size, en_seq_len
                e_i = K.softmax(e_i)
```

```
            logger.debug(f"ei.shape = {e_i.shape}")

            return e_i, [e_i]

        def context_step(inputs, states):
            """ Step function for computing ci using ei """

            logger.debug("Running attention vector computation step")

            if not isinstance(states, (list, tuple)):
                raise TypeError(f"States must be an iterable. Got {states} of type {type(stat

            encoder_full_seq = states[-1]

            # <= batch_size, hidden_size
            c_i = K.sum(encoder_full_seq * K.expand_dims(inputs, -1), axis=1)

            logger.debug(f"ci.shape = {c_i.shape}")

            return c_i, [c_i]

        # we don't maintain states between steps when computing attention
        # attention is stateless, so we're passing a fake state for RNN step function
        fake_state_c = K.sum(encoder_out_seq, axis=1)
        fake_state_e = K.sum(encoder_out_seq, axis=2)  # <= (batch_size, enc_seq_len, latent_

        """ Computing energy outputs """
        # e_outputs => (batch_size, de_seq_len, en_seq_len)
        last_out, e_outputs, _ = K.rnn(
            energy_step, decoder_out_seq, [fake_state_e], constants=[encoder_out_seq]
        )

        """ Computing context vectors """
        last_out, c_outputs, _ = K.rnn(
            context_step, e_outputs, [fake_state_c], constants=[encoder_out_seq]
        )

        return c_outputs, e_outputs

    def compute_output_shape(self, input_shape):
        """ Outputs produced by the layer """
        return [
            tf.TensorShape((input_shape[1][0], input_shape[1][1], input_shape[1][2])),
            tf.TensorShape((input_shape[1][0], input_shape[1][1], input_shape[0][1]))
        ]

from keras import backend as K
K.clear_session()

latent_dim = 150
embedding_dim=50
```

```
# Encoder
encoder_inputs = Input(shape=(max_text_len,))

#embedding layer
enc_emb =  Embedding(x_voc, embedding_dim,trainable=True)(encoder_inputs)

#encoder lstm 1
encoder_lstm1 = LSTM(latent_dim,return_sequences=True,return_state=True,dropout=0.4,recurrent
encoder_output1, state_h1, state_c1 = encoder_lstm1(enc_emb)

#encoder lstm 2
encoder_lstm2 = LSTM(latent_dim,return_sequences=True,return_state=True,dropout=0.4,recurrent
encoder_output2, state_h2, state_c2 = encoder_lstm2(encoder_output1)

#encoder lstm 3
encoder_lstm3=LSTM(latent_dim, return_state=True, return_sequences=True,dropout=0.4,recurrent
encoder_outputs, state_h, state_c= encoder_lstm3(encoder_output2)

# Set up the decoder, using `encoder_states` as initial state.
decoder_inputs = Input(shape=(None,))

#embedding layer
dec_emb_layer = Embedding(y_voc, embedding_dim,trainable=True)
dec_emb = dec_emb_layer(decoder_inputs)

decoder_lstm = LSTM(latent_dim, return_sequences=True, return_state=True,dropout=0.4,recurren
decoder_outputs,decoder_fwd_state, decoder_back_state = decoder_lstm(dec_emb,initial_state=[s

# Attention layer
attn_layer = AttentionLayer(name='attention_layer')
attn_out, attn_states = attn_layer([encoder_outputs, decoder_outputs])

# Concat attention input and decoder LSTM output
decoder_concat_input = Concatenate(axis=-1, name='concat_layer')([decoder_outputs, attn_out])

#dense layer
decoder_dense =  TimeDistributed(Dense(y_voc, activation='softmax'))
decoder_outputs = decoder_dense(decoder_concat_input)

# Define the model
model = Model([encoder_inputs, decoder_inputs], decoder_outputs)

model.summary()
```

```
Model: "model"
__________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==========================================================================================
 input_1 (InputLayer)           [(None, 100)]        0           []

 embedding (Embedding)          (None, 100, 50)      734350      ['input_1[0][0]']
```

```
lstm (LSTM)                    [(None, 100, 150),   120600      ['embedding[0][0]']
                                (None, 150),
                                (None, 150)]

input_2 (InputLayer)           [(None, None)]       0           []

lstm_1 (LSTM)                  [(None, 100, 150),   180600      ['lstm[0][0]']
                                (None, 150),
                                (None, 150)]

embedding_1 (Embedding)        (None, None, 50)     103750      ['input_2[0][0]']

lstm_2 (LSTM)                  [(None, 100, 150),   180600      ['lstm_1[0][0]']
                                (None, 150),
                                (None, 150)]

lstm_3 (LSTM)                  [(None, None, 150),  120600      ['embedding_1[0][0]',
                                (None, 150),                     'lstm_2[0][1]',
                                (None, 150)]                     'lstm_2[0][2]']

attention_layer (AttentionLaye  ((None, None, 150),  45150      ['lstm_2[0][0]',
r)                              (None, None, 100))               'lstm_3[0][0]']

concat_layer (Concatenate)     (None, None, 300)    0           ['lstm_3[0][0]',
                                                                 'attention_layer[0][0]

time_distributed (TimeDistribu  (None, None, 2075)  624575      ['concat_layer[0][0]']
ted)

==================================================================================================
Total params: 2,110,225
Trainable params: 2,110,225
Non-trainable params: 0
__________________________________________________________________________________________________
```

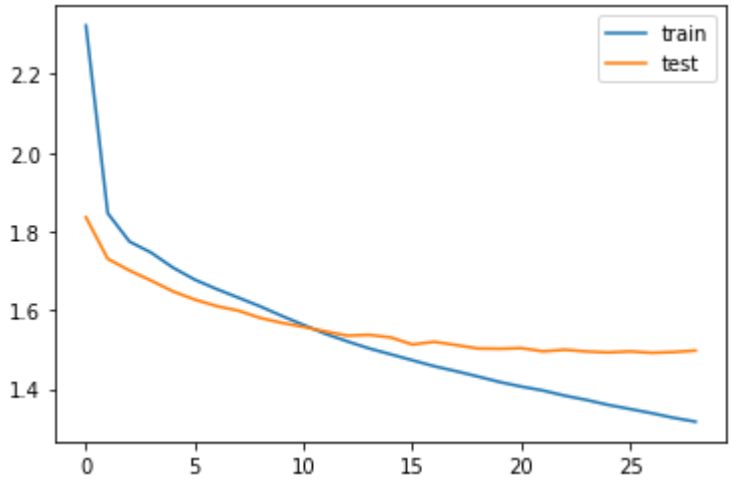
```
#converts the integer sequence to a one-hot vector using sparse_categorical_crossentropy
model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy')


es = EarlyStopping(monitor='val_loss', mode='min', verbose=1,patience=2)


#Model Training
history=model.fit([x_tr,y_tr[:,:-1]], y_tr.reshape(y_tr.shape[0],y_tr.shape[1], 1)[:,1:] ,epo
```

```
62/62 [==============================] - 436s 7s/step - loss: 2.3229 - val_loss: 1.83
Epoch 2/50
62/62 [==============================] - 366s 6s/step - loss: 1.8465 - val_loss: 1.73
Epoch 3/50
62/62 [==============================] - 361s 6s/step - loss: 1.7744 - val_loss: 1.70
Epoch 4/50
62/62 [==============================] - 363s 6s/step - loss: 1.7463 - val_loss: 1.67
Epoch 5/50
```

```
Epoch 5/50
62/62 [==============================] - 360s 6s/step - loss: 1.7083 - val_loss: 1.64
Epoch 6/50
62/62 [==============================] - 361s 6s/step - loss: 1.6778 - val_loss: 1.62
Epoch 7/50
62/62 [==============================] - 368s 6s/step - loss: 1.6540 - val_loss: 1.61
Epoch 8/50
62/62 [==============================] - 357s 6s/step - loss: 1.6321 - val_loss: 1.59
Epoch 9/50
62/62 [==============================] - 362s 6s/step - loss: 1.6101 - val_loss: 1.58
Epoch 10/50
62/62 [==============================] - 359s 6s/step - loss: 1.5858 - val_loss: 1.56
Epoch 11/50
62/62 [==============================] - 359s 6s/step - loss: 1.5628 - val_loss: 1.55
Epoch 12/50
62/62 [==============================] - 364s 6s/step - loss: 1.5403 - val_loss: 1.54
Epoch 13/50
62/62 [==============================] - 359s 6s/step - loss: 1.5213 - val_loss: 1.53
Epoch 14/50
62/62 [==============================] - 358s 6s/step - loss: 1.5034 - val_loss: 1.53
Epoch 15/50
62/62 [==============================] - 358s 6s/step - loss: 1.4883 - val_loss: 1.53
Epoch 16/50
62/62 [==============================] - 360s 6s/step - loss: 1.4731 - val_loss: 1.51
Epoch 17/50
62/62 [==============================] - 359s 6s/step - loss: 1.4581 - val_loss: 1.52
Epoch 18/50
62/62 [==============================] - 359s 6s/step - loss: 1.4454 - val_loss: 1.51
Epoch 19/50
62/62 [==============================] - 359s 6s/step - loss: 1.4320 - val_loss: 1.50
Epoch 20/50
62/62 [==============================] - 360s 6s/step - loss: 1.4180 - val_loss: 1.50
Epoch 21/50
62/62 [==============================] - 359s 6s/step - loss: 1.4064 - val_loss: 1.50
Epoch 22/50
62/62 [==============================] - 365s 6s/step - loss: 1.3964 - val_loss: 1.49
Epoch 23/50
62/62 [==============================] - 364s 6s/step - loss: 1.3832 - val_loss: 1.49
Epoch 24/50
62/62 [==============================] - 361s 6s/step - loss: 1.3724 - val_loss: 1.49
Epoch 25/50
62/62 [==============================] - 359s 6s/step - loss: 1.3598 - val_loss: 1.49
Epoch 26/50
62/62 [==============================] - 358s 6s/step - loss: 1.3494 - val_loss: 1.49
Epoch 27/50
62/62 [==============================] - 360s 6s/step - loss: 1.3387 - val_loss: 1.49
Epoch 28/50
62/62 [==============================] - 359s 6s/step - loss: 1.3271 - val_loss: 1.49
Epoch 29/50
62/62 [==============================] - 359s 6s/step - loss: 1.3173 - val_loss: 1.49
```

PLOT OF TRAINING & TESTING

```
from matplotlib import pyplot
pyplot.plot(history.history['loss'], label='train')
pyplot.plot(history.history['val_loss'], label='test')
pyplot.legend()
pyplot.show()
```




```
reverse_target_word_index=y_tokenizer.index_word
reverse_source_word_index=x_tokenizer.index_word
target_word_index=y_tokenizer.word_index


# Encode the input sequence to get the feature vector
encoder_model = Model(inputs=encoder_inputs,outputs=[encoder_outputs, state_h, state_c])

# Decoder setup
# Below tensors will hold the states of the previous time step
decoder_state_input_h = Input(shape=(latent_dim,))
decoder_state_input_c = Input(shape=(latent_dim,))
decoder_hidden_state_input = Input(shape=(max_text_len,latent_dim))

# Get the embeddings of the decoder sequence
dec_emb2= dec_emb_layer(decoder_inputs)
# To predict the next word in the sequence, set the initial states to the states from the pre
decoder_outputs2, state_h2, state_c2 = decoder_lstm(dec_emb2, initial_state=[decoder_state_in

#attention inference
attn_out_inf, attn_states_inf = attn_layer([decoder_hidden_state_input, decoder_outputs2])
decoder_inf_concat = Concatenate(axis=-1, name='concat')([decoder_outputs2, attn_out_inf])

# A dense softmax layer to generate prob dist. over the target vocabulary
decoder_outputs2 = decoder_dense(decoder_inf_concat)

# Final decoder model
decoder_model = Model(
    [decoder_inputs] + [decoder_hidden_state_input,decoder_state_input_h, decoder_state_input
    [decoder_outputs2] + [state_h2, state_c2])
```

```
def decode_sequence(input_seq):
    # Encode the input as state vectors.
    e_out, e_h, e_c = encoder_model.predict(input_seq)

    # Generate empty target sequence of length 1.
    target_seq = np.zeros((1,1))

    # Populate the first word of target sequence with the start word.
    target_seq[0, 0] = target_word_index['sostok']

    stop_condition = False
    decoded_sentence = ''
    while not stop_condition:

        output_tokens, h, c = decoder_model.predict([target_seq] + [e_out, e_h, e_c])

        # Sample a token
        sampled_token_index = np.argmax(output_tokens[0, -1, :])
        sampled_token = reverse_target_word_index[sampled_token_index]

        if(sampled_token!='eostok'):
            decoded_sentence += ' '+sampled_token

        # Exit condition: either hit max length or find stop word.
        if (sampled_token == 'eostok'  or len(decoded_sentence.split()) >= (max_summary_len-1
            stop_condition = True

        # Update the target sequence (of length 1).
        target_seq = np.zeros((1,1))
        target_seq[0, 0] = sampled_token_index

        # Update internal states
        e_h, e_c = h, c

    return decoded_sentence


def seq2summary(input_seq):
    newString=''
    for i in input_seq:
        if((i!=0 and i!=target_word_index['sostok']) and i!=target_word_index['eostok']):
            newString=newString+reverse_target_word_index[i]+' '
    return newString

def seq2text(input_seq):
    newString=''
    for i in input_seq:
        if(i!=0):
            newString=newString+reverse_source_word_index[i]+' '
    return newString
```

PREDICTION

```
predicted = []
title =[]

for i in range(0,100):
    print("Abstract:",seq2text(x_tr[i]))
    print("Original Title:",seq2summary(y_tr[i]))
    print("Predicted Title:",decode_sequence(x_tr[i].reshape(1, max_text_len)))
    print("\n")
    predicted.append(decode_sequence(x_tr[i].reshape(1, max_text_len)))
    title.append(seq2summary(y_tr[i]))
```

```
Abstract: models revealed housing insecurity experiences predicted poorer self rated
Original Title: longitudinal analysis relationship housing insecurity physical health
1/1 [==============================] - 0s 152ms/step
1/1 [==============================] - 0s 45ms/step
1/1 [==============================] - 0s 39ms/step
1/1 [==============================] - 0s 56ms/step
1/1 [==============================] - 0s 64ms/step
1/1 [==============================] - 0s 39ms/step
1/1 [==============================] - 0s 38ms/step
1/1 [==============================] - 0s 25ms/step
Predicted Title:  mental health covid pandemic among adults


1/1 [==============================] - 0s 88ms/step
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 26ms/step
Abstract: dataset finally standardized tests reference intervals obtained compared pu
Original Title: determination using outpatient data
1/1 [==============================] - 0s 89ms/step
1/1 [==============================] - 0s 27ms/step
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 32ms/step
Predicted Title:  impact covid pandemic


1/1 [==============================] - 0s 75ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 26ms/step
Abstract: jet injectors administer assessing impact jet injection pharmaceutical phys
Original Title: free exploring potential unexpected
1/1 [==============================] - 0s 80ms/step
```

```
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 26ms/step
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 25ms/step
Predicted Title:  effects based based drug drug drug drug resistant


1/1 [==============================] - 0s 85ms/step
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 25ms/step
```

ROUGE SCORE

```
! pip install rouge
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/pub
Collecting rouge
  Downloading rouge-1.0.1-py3-none-any.whl (13 kB)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from rouge
Installing collected packages: rouge
Successfully installed rouge-1.0.1
```

```
from rouge import Rouge


rouge = Rouge()
rouge.get_scores(title, predicted,avg=True, ignore_empty=True)
```

```
{'rouge-1': {'r': 0.23024999999999995,
  'p': 0.10339693639693637,
  'f': 0.1381351230556726},
 'rouge-2': {'r': 0.09092857142857143,
  'p': 0.036539682539682546,
  'f': 0.04997186876638159},
 'rouge-l': {'r': 0.21791666666666662,
  'p': 0.097043401043401,
  'f': 0.12980358531237018}}
```

```
res = pd.DataFrame(predicted)
res.columns = ['predicted']
```

```
res.to_csv("/content/drive/MyDrive/Directed/prediction_result1.csv")
```

Colab paid products - Cancel contracts here

✓ 0s completed at 6:48 PM