PRABAL GHOSH

Deep Learning Lab = Sequence to Sequence (seq2seq) and Attention and Transformer

English to Spanish Translation

You must submit a notebook with execution traces and perfectly written corresponding to the course on Seq2Seq, Seq2Seq with Attention and Transformer architectures. This notebook will identify at least 5 sections:

- Introduction: presentation of the problem and how to proceed
- Data pre-processing
- Seq2Seq architecture
- Seq2Seq architecture with Attention (specify which attention model you used)
- Transformer-based architecture
- Use of a model from huggingface.co (transfer learning) to address the same problem (optional)
- Conclusion: comparison of approaches and personal remarks

Submit also a pdf version of your notebook

Some important links for Sequence to Sequence (seq2seq) variable length and Attention and Transformer

Data is dowlnloaded from the following link

https://www.manythings.org/anki/ (https://www.manythings.org/anki/)(Tab-delimited Bilingual Sentence Pairs)

The following tutorial is followed to understand the Sequence to Sequence and attention and Transformer, Bert

- "https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html" (https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html") (basics+attention part)
- "https://towardsdatascience.com/classic-seq2seq-model-vs-seq2seq-model-with-attention-31527c77b28a" (https://towardsdatascience.com/classic-seq2seq-model-vs-seq2seq-model-with-attention-31527c77b28a")
- "https://wikidocs.net/178419" (https://wikidocs.net/178419")
- "https://www.jeremyjordan.me/attention/" (https://www.jeremyjordan.me/attention/")
- "https://machinelearningmastery.com/a-gentle-introduction-to-positional-encoding-in-transformer-models-part-1/" (https://machinelearningmastery.com/a-gentle-introduction-to-positional-encoding-in-transformer-models-part-1/")
- "https://www.tensorflow.org/text/tutorials/transformer" (https://www.tensorflow.org/text/tutorials/transformer")

- "https://blog.keras.io/a-ten-minute-introduction-to-sequence-to-sequence-learning-in-keras.html" (https://blog.keras.io/a-ten-minute-introduction-to-sequence-to-sequence-learning-in-keras.html") (A ten-minute introduction to sequence-to-sequence learning in Keras)

The following youtube videos are good to understand the concepts on Sequence to Sequence and attention and Transformer, Bert

- "https://www.youtube.com/watch?v=XfpMkf4rD6E" (https://www.youtube.com/watch?v=XfpMkf4rD6E")
- "https://www.youtube.com/watch?v=RRP0czWtOeM&list=PLQflnv_s49v-4aH-xFcTykTpcyWSY4Tww&index=5" (https://www.youtube.com/watch?v=RRP0czWtOeM&list=PLQflnv_s49v-4aH-xFcTykTpcyWSY4Tww&index=5")
- "https://www.youtube.com/watch?v=7gHqxK1o7MU" (https://www.youtube.com/watch?v=7gHqxK1o7MU")
- "https://www.youtube.com/watch?v=rj5V6q6-XUM&list=PLKnIA16_RmvYuZauWaPlRTC54KxSNLtNn&index=69" (https://www.youtube.com/watch?v=rj5V6q6-XUM&list=PLKnIA16_RmvYuZauWaPlRTC54KxSNLtNn&index=69")
- "https://www.youtube.com/playlist?list=PLH0lCpFdVeJuqQLyYNBlEfRydl2L-CBb" (https://www.youtube.com/playlist?list=PLH0lCpFdVeJuqQLyYNBlEfRydl2L-CBb")
- "https://www.youtube.com/playlist?list=PL_iWQOsE6TfVmKkQHucjPAoRtIJYt8a5A" (https://www.youtube.com/playlist?list=PL_iWQOsE6TfVmKkQHucjPAoRtIJYt8a5A")

Transformer implementation coding references to understand

- "https://www.youtube.com/watch?v=Xg5JG30bYik&list=PLTl9hO2Oobd97qfWC40gOSU8C0iu0m2l4&index=14" (https://www.youtube.com/watch?v=Xg5JG30bYik&list=PLTl9hO2Oobd97qfWC40gOSU8C0iu0m2l4&index=14")
- "https://www.youtube.com/watch?v=5ToW5Hpi8Qc&list=PLbMO9c_jUD46TAokjFxdyGoWvLWaZ3uCE&index=8" (https://www.youtube.com/watch?v=5ToW5Hpi8Qc&list=PLbMO9c_jUD46TAokjFxdyGoWvLWaZ3uCE&index=8")
- "https://pylessons.com/transformers-training" (https://pylessons.com/transformers-training")
- "https://www.youtube.com/watch?v=81LeULNc2_c&list=PLyFpZIg7OtNQHbWjyy_QApMOHhqvzS-9o&index=4" (https://www.youtube.com/watch?v=81LeULNc2_c&list=PLyFpZIg7OtNQHbWjyy_QApMOHhqvzS-9o&index=4")
- "https://pylessons.com/transformers-introduction" (https://pylessons.com/transformers-introduction")
- "https://pylessons.com/build-transformer" (https://pylessons.com/build-transformer")
- "https://keras.io/examples/nlp/neural_machine_translation_with_transformer/" (https://keras.io/examples/nlp/neural_machine_translation_with_transformer/")
- "https://machinelearningmastery.com/building-transformer-models-with-attention-crash-course-build-a-neural-machine-translator-in-12-days/" (https://machinelearningmastery.com/building-transformer-models-with-attention-crash-course-build-a-neural-machine-translator-in-12-days/")
- "https://www.scaler.com/topics/keras/neural-machine-translation-model-in-keras/" (https://www.scaler.com/topics/keras/neural-machine-translation-model-in-keras/")
- "https://www.kaggle.com/code/sani84/transformers-language-translator-eng-to-french" (https://www.kaggle.com/code/sani84/transformers-language-translator-eng-to-french")

- "https://colab.research.google.com/github/tensorflow/text/blob/master/docs/tutorials/trans hl=fr" (https://colab.research.google.com/github/tensorflow/text/blob/master/docs/tutorials/trans hl=fr")
- "https://www.tensorflow.org/text/tutorials/transformer?hl=fr" (https://www.tensorflow.org/text/tutorials/transformer?hl=fr")
- "https://nlp.seas.harvard.edu/2018/04/03/attention.html" (https://nlp.seas.harvard.edu/2018/04/03/attention.html")
- "https://huggingface.co/docs/transformers/tasks/translation" (https://huggingface.co/docs/transformers/tasks/translation")
- "https://www.youtube.com/watch?v=XAR8jnZZuUs" (https://www.youtube.com/watch?v=XAR8jnZZuUs")
- "https://www.youtube.com/watch?v=1JvfrvZgi6c" (https://www.youtube.com/watch?v=1JvfrvZgi6c")
- "https://github.com/christianversloot/machine-learning-articles/blob/main/introduction-to-transformers-in-machine-learning.md" (https://github.com/christianversloot/machine-learning-articles/blob/main/introduction-to-transformers-in-machine-learning.md")

-"https://github.com/christianversloot/machine-learning-articles/blob/main/easy-machine-translation-with-machine-learning-and-huggingface-transformers.md" (https://github.com/christianversloot/machine-learning-articles/blob/main/easy-machine-translation-with-machine-learning-and-huggingface-transformers.md")

- "https://huggingface.co/Helsinki-NLP/opus-mt-tc-big-en-es" (https://huggingface.co/Helsinki-NLP/opus-mt-tc-big-en-es")

import libraries

In [2]:

```
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
import numpy as np
import pandas as pd
```

In [3]:

```
import tensorflow as tf
import keras
import unicodedata
import re
import os
import io
import time
```

In [4]:
```
import tensorflow as tf

from tensorflow.keras.models import Model
from tensorflow.keras import optimizers
from tensorflow.keras import layers
from tensorflow.keras.layers import Input, Dense,Concatenate

from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.utils import plot_model
```

In [4]:
```
```

In [5]:
```
import unicodedata
import re
import numpy as np
import pandas as pd
import os
import io
import time

import tensorflow as tf

from tensorflow.keras.models import Model
from tensorflow.keras import optimizers
from tensorflow.keras import layers
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.utils import plot_model

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

Data Preprocessing

The data is available here: [http://www.manythings.org/anki/ (http://www.manythings.org/anki/)](http://www.manythings.org/anki/). They consist of a set of pairs in the following format:

```
hi .  hola .
```

There are a variety of languages available, English-Spanish data will be used.

The processing of the data will consist of the following steps:

1. Removal of special characters
2. adding a start or end token to each sentence.
3. Creating the vectorizer for each of the two languages

Limit the number of examples is 10000 for faster processing

In [48]:
```
from google.colab import files
uploades = files.upload()
```

Choose Files No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving spa.txt to spa (1).txt
```

In [49]:
```
import pandas as pd  # Import pandas library for data manipulation
import re  # Import re library for regular expressions
import unicodedata  # Import unicodedata library for handling Unicode chara

# Load dataset from file
# dataset = 'C:/Users/praba\Documents/GitHub/deep_learning_uca_2/spa-eng/sp
dataset = 'spa.txt'

df = data = pd.read_table(dataset)  # Read data from file into a DataFrame
```

In [50]:
```
import pandas as pd  # Import pandas library for data manipulation
import re  # Import re library for regular expressions
import unicodedata  # Import unicodedata library for handling Unicode chara

# Load dataset from file
# dataset = 'C:/Users/praba\Documents/GitHub/deep_learning_uca_2/spa-eng/sp
# data = pd.read_table(dataset)  # Read data from file into a DataFrame

# Extract source (X) and target (y) sentences from the DataFrame
X = data.iloc[:, 0]  # Extract the first column as source sentences
y = data.iloc[:, 1]  # Extract the second column as target sentences

# Limit the number of examples for faster processing
X = X[:10000]  # Limit the number of source sentences to 10000
y = y[:10000]  # Limit the number of target sentences to 10000

# Define a function to preprocess a sentence
def step1(sent):
    # Function to preprocess a sentence
    def unicode_to_ascii(s):
        # Normalize Unicode characters and remove accents
        return ''.join(c for c in unicodedata.normalize('NFD', s) if unicod

    # Convert the sentence to lowercase and remove leading/trailing whitesp
    sent = unicode_to_ascii(sent.lower().strip())

    # Add spaces between words and punctuation
    sent = re.sub(r"([?.!,¿])", r" \1 ", sent)
    sent = re.sub(r'[" "]+', " ", sent)

    # Replace everything except letters, punctuation, and some special char
    sent = re.sub(r"[^a-zA-Z?.!,¿]+", " ", sent)

    # Add <start> and <end> tokens to the sentence
    return '<start> ' + sent.strip() + ' <end>'

# Apply the preprocessing function to each source and target sentence
X_processed = X.apply(step1)  # Preprocess source sentences
y_processed = y.apply(step1)  # Preprocess target sentences

# Print the first few preprocessed sentences to check
print(X_processed.head())
print(y_processed.head())
```

```
0     <start> go . <end>
1     <start> go . <end>
2     <start> go . <end>
3     <start> hi . <end>
4    <start> run ! <end>
Name: Go., dtype: object
0      <start> vete . <end>
1      <start> vaya . <end>
2    <start> vayase . <end>
3      <start> hola . <end>
4     <start> corre ! <end>
Name: Ve., dtype: object
```

In [51]:
```
# Convert processed English sentences to numpy array
english_sentences = X_processed_array = np.array(X_processed)
# Convert processed Spanish sentences to numpy array
spanish_sentences = y_processed_array = np.array(y_processed)
X_processed_array.shape, y_processed.shape
```

Out[51]: ((10000,), (10000,))

In [52]:
```
# from sklearn.model_selection import train_test_split
# X_train, X_test, y_train, y_test = train_test_split(
#     X_processed_array, y_processed_array, test_size=0.20, random_state=42
```

In [53]:
```
# Search vocabulary and max_length for each language
def voc(lang):
    # a list of sentences in the same language
    lengths = [len(txt.split()) for txt in lang]
    vocab = set([w for txt in lang for w in txt.split()])

    return max(lengths), list(vocab), len(vocab)+2 # for padding and OOV

max_length_spanish, vocab_spanish, vocab_size_spanish = voc(y_processed_arr
max_length_english, vocab_english, vocab_size_english = voc(X_processed_arr
```

In [54]:
```
# vocab_english
```

In [55]:
```
max_length_spanish,max_length_english
```

Out[55]: (13, 8)

In [56]:
```
vocab_size_spanish,vocab_size_english
```

Out[56]: (4576, 2206)

In [56]:

In [57]:
```
# Build vectorizer layer
english_vectorizer = layers.TextVectorization(standardize=None, output_mode
                                              vocabulary=vocab_english,
                                              name="English_vect")
# On peut connaitre le vocabulaire par english_vectorizer.get_vocabulary()

# Do the same for spanish
spanish_vectorizer = layers.TextVectorization(standardize=None, output_mode
                                              vocabulary=vocab_spanish,
                                              name="Spanish_vect")
```

In [57]:

In [58]:
```
BATCH_SIZE = 32  # Batch size for training or inference
embedding_dim = 100  # Dimensionality of the embedding space
latent_dim = 64  # Dimensionality of the latent space
dropout = 0.2  # Dropout rate,
```

In [58]:
```
```

In [59]:
```
# spanish_embedded_data = spanish_vectorizer(y_processed_array)
english_embedded_data = english_vectorizer(X_processed_array)
english_embedded_data[1]
```

Out[59]:
```
<tf.Tensor: shape=(8,), dtype=int64, numpy=array([1280, 1090,  412, 1866,
0,    0,    0,    0])>
```

In [60]:
```
# y_processed_array
```

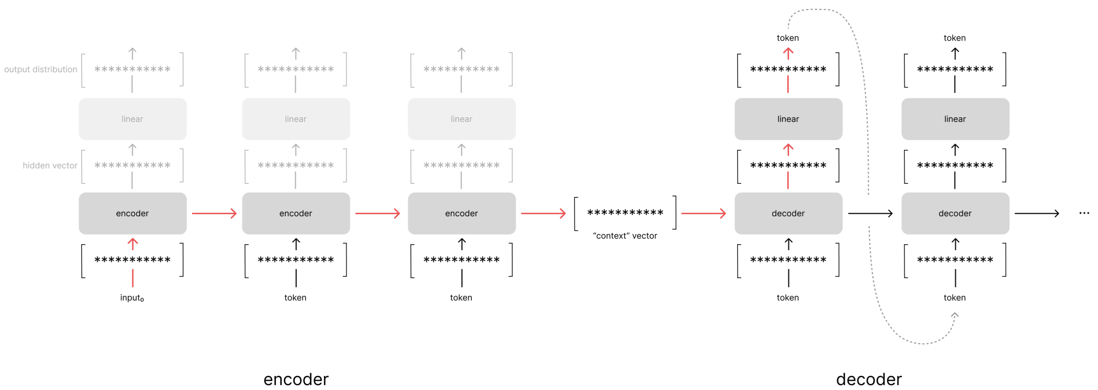
In [61]:
```
spanish_teacher_enc  = spanish_vectorizer(y_processed_array) #.numpy() # Te
spanish_target_enc = np.zeros_like(spanish_teacher_enc)
spanish_target_enc[:,:-1] = spanish_teacher_enc[:,1:] # To predict
spanish_target_enc.shape
```

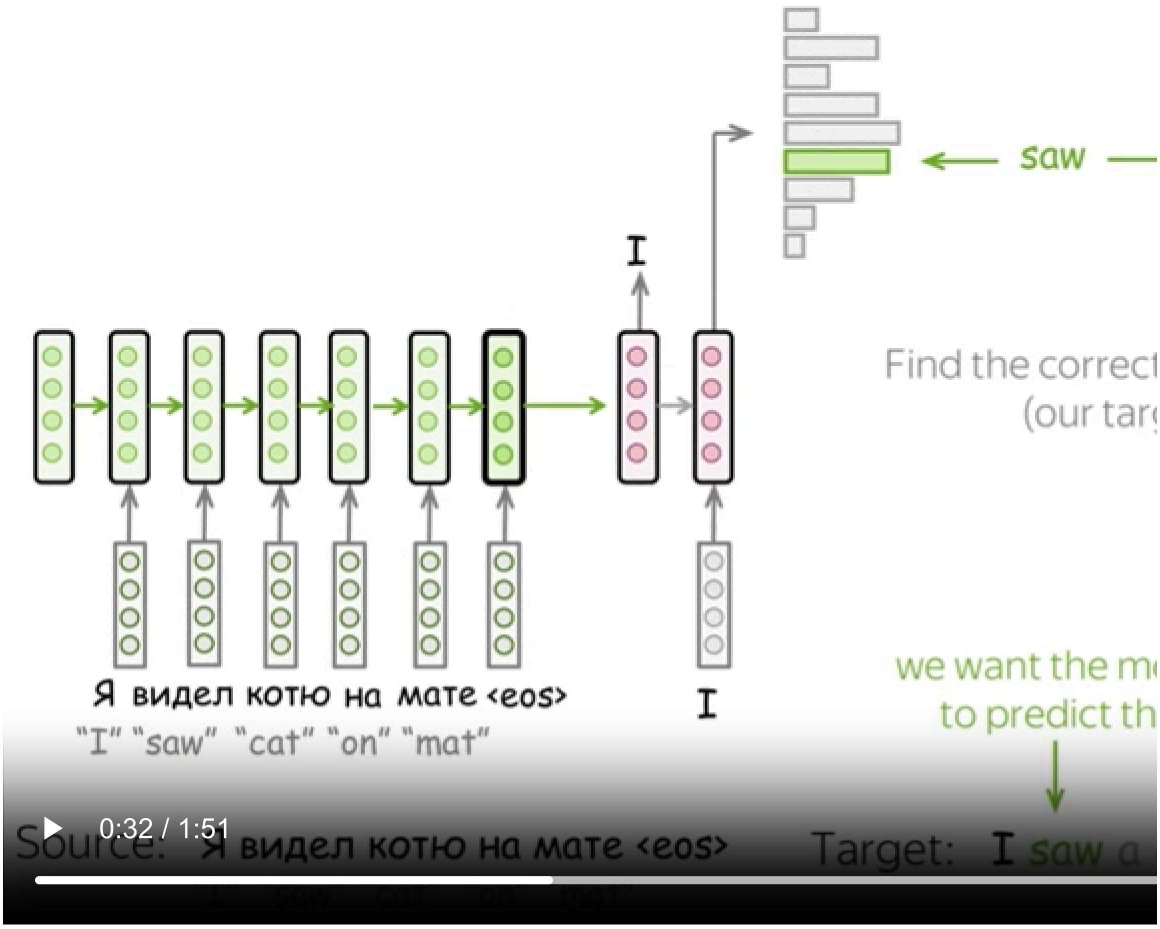
Out[61]:
```
(10000, 13)
```

In [61]:
```
```

In [61]:
```
```

Normal Sequence to Sequence (seq2seq)





[https://machinelearningmastery.com/define-encoder-decoder-sequence-sequence-model-neural-machine-translation-keras/ (https://machinelearningmastery.com/define-encoder-decoder-sequence-sequence-model-neural-machine-translation-keras/)](https://machinelearningmastery.com/define-encoder-decoder-sequence-sequence-model-neural-machine-translation-keras/)

In [ ]:

```

```

basic model

ENCODER

In [41]:
```
from keras.models import Model
from keras.layers import Input, LSTM, Dense

# Define an input sequence and process it.
encoder_inputs = Input(shape=(None,))
layer_embedding = layers.Embedding(vocab_size_english, embedding_dim)
embedding_layer_final = layer_embedding(encoder_inputs)

encoder = LSTM(latent_dim, return_state=True)
encoder_outputs, state_h, state_c = encoder(embedding_layer_final)
# We discard `encoder_outputs` and only keep the states.
encoder_states = [state_h, state_c]
```

DECODER

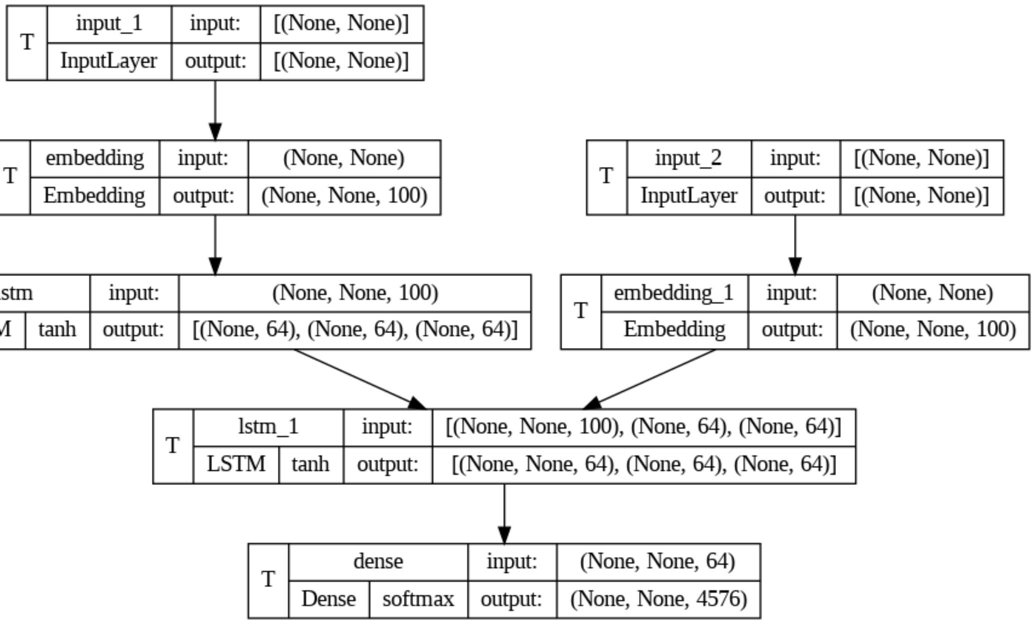
In [42]:
```
# Set up the decoder, using `encoder_states` as initial state.
decoder_inputs = Input(shape=(None,))
# We set up our decoder to return full output sequences,
# and to return internal states as well. We don't use the
# return states in the training model, but we will use them in inference.

layer_embedding_decoder = layers.Embedding(vocab_size_spanish, embedding_di
x =layer_embedding_decoder(decoder_inputs)

decoder_lstm = LSTM(latent_dim, return_sequences=True, return_state=True)
decoder_outputs, _, _ = decoder_lstm(x,
                                     initial_state=encoder_states)
decoder_dense = Dense(vocab_size_spanish, activation='softmax')
decoder_outputs = decoder_dense(decoder_outputs)

# Define the model that will turn
# `encoder_input_data` & `decoder_input_data` into `decoder_target_data`
model_encoder_training = Model([encoder_inputs, decoder_inputs], decoder_ou
```

In [43]:
```
model_encoder_training.summary()
```

```
Model: "model_encoder_training"
__________________________________________________________________________________________________
 Layer (type)                Output Shape                 Param #   Connec
ted to
==================================================================================================
 input_1 (InputLayer)        [(None, None)]               0         []

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

 embedding (Embedding)       (None, None, 100)            220600    ['inpu
t_1[0][0]']

 embedding_1 (Embedding)     (None, None, 100)            457600    ['inpu
t_2[0][0]']

 lstm (LSTM)                 [(None, 64),                 42240     ['embe
dding[0][0]']
                              (None, 64),
                              (None, 64)]

 lstm_1 (LSTM)               [(None, None, 64),           42240     ['embe
dding_1[0][0]',
                              (None, 64),                            'lstm
[0][1]',
                              (None, 64)]                            'lstm
[0][2]']

 dense (Dense)               (None, None, 4576)           297440    ['lstm
_1[0][0]']

==================================================================================================
Total params: 1060120 (4.04 MB)
Trainable params: 1060120 (4.04 MB)
Non-trainable params: 0 (0.00 Byte)
__________________________________________________________________________________________________
```

In [44]:
```
# from tensorflow.keras.utils import plot_model
from keras.utils import plot_model

plot_model(model_encoder_training, to_file='model_plot2.png',
    show_shapes=True,
    show_layer_names=True,
    layer_range=None,
    show_layer_activations=True,
    show_trainable=True)
```

Out[44]:



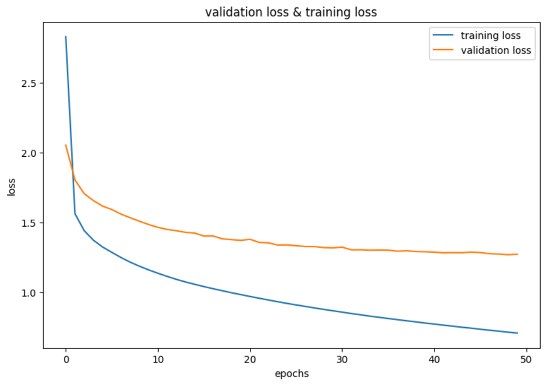
In [45]:
```
# Run training
model_encoder_training.compile(loss='sparse_categorical_crossentropy', opti
```

In [46]:
```
# spanish_embedded_data_test = spanish_vectorizer(y_test)
# english_teacher_enc_test = english_vectorizer(X_test)
```

In [47]:
```
# model  training
history = model_encoder_training.fit([english_embedded_data, spanish_teache
                    validation_split=0.1,
                    epochs=50, batch_size=BATCH_SIZE,
                    verbose=1)
```

```
Epoch 1/50
282/282 [==============================] - 14s 33ms/step - loss: 2.8307
- accuracy: 0.6652 - val_loss: 2.0544 - val_accuracy: 0.6944
Epoch 2/50
282/282 [==============================] - 4s 13ms/step - loss: 1.5635
- accuracy: 0.7771 - val_loss: 1.8055 - val_accuracy: 0.7378
Epoch 3/50
282/282 [==============================] - 3s 12ms/step - loss: 1.4424
- accuracy: 0.7848 - val_loss: 1.7069 - val_accuracy: 0.7446
Epoch 4/50
282/282 [==============================] - 3s 10ms/step - loss: 1.3741
- accuracy: 0.7975 - val_loss: 1.6575 - val_accuracy: 0.7597
Epoch 5/50
282/282 [==============================] - 3s 11ms/step - loss: 1.3252
- accuracy: 0.8032 - val_loss: 1.6179 - val_accuracy: 0.7645
Epoch 6/50
282/282 [==============================] - 3s 10ms/step - loss: 1.2871
- accuracy: 0.8071 - val_loss: 1.5935 - val_accuracy: 0.7701
Epoch 7/50
```

In [48]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(20, 6))
# Plot the first subplot  loss)
plt.subplot(1, 2, 1)  # 1 row, 2 columns, first subplot
plt.plot(history.history["loss"])
plt.plot(history.history["val_loss"])
plt.title("validation loss & training loss")
plt.xlabel("epochs")
plt.ylabel("loss")
leg = plt.legend(["training loss", "validation loss"],loc ="upper right");

# Plot the second subplot ( accuracy)
plt.subplot(1, 2, 2)  # 1 row, 2 columns, second subplot
plt.plot(history.history["accuracy"])
plt.plot(history.history["val_accuracy"])
plt.title("validation accuracy & training loaccuracyss")
plt.xlabel("epochs")
plt.ylabel("accuracy")
leg = plt.legend(["training accuracy", "validation accuracy"],loc ="upper l

plt.show()
```



In [48]:

Inference

In [49]:
```
# tmp, outh, outc = model_encoder_training.get_layer("lstm_2").output
# encoder_model = Model(encoder_inputs, [outh, outc])

# encoder_model = Model(encoder_inputs, [outh, outc])
encoder_model = Model(inputs=encoder_inputs, outputs=encoder_states)

decoder_state_input_h = Input(shape=(latent_dim,))
decoder_state_input_c = Input(shape=(latent_dim,))
decoder_states_inputs = [decoder_state_input_h, decoder_state_input_c]

layer_embedding_decoder_inf = layer_embedding_decoder(decoder_inputs)
decoder_outputs, state_h, state_c = decoder_lstm(
    layer_embedding_decoder_inf , initial_state=decoder_states_inputs)


decoder_states = [state_h, state_c]
decoder_outputs = decoder_dense(decoder_outputs)
decoder_model = Model(
    [decoder_inputs] + decoder_states_inputs,
    [decoder_outputs] + decoder_states)
```

In [50]:
```
import numpy as np

def decode_sequence(input_sentence):

    input_seq = step1(input_sentence)
    input_seq_transformed = english_vectorizer([input_seq])

    states_value = encoder_model.predict(input_seq_transformed)


    target_seq = np.zeros((1, 1))

    target_seq[0, 0] = vocab_spanish.index('<start>')

    stop_condition = False
    decoded_sentence = ''
    while not stop_condition:

        output_tokens, h, c = decoder_model.predict([target_seq] + states_v


        sampled_token_index = np.argmax(output_tokens[0, -1, :])
        sampled_word = list(vocab_spanish)[sampled_token_index]
        decoded_sentence += ' ' + sampled_word


        if (sampled_word == '<end>' or len(decoded_sentence) > max_length_e
            stop_condition = True


        target_seq = np.zeros((1, 1))
        target_seq[0, 0] = sampled_token_index

        states_value = [h, c]

    return decoded_sentence
```

In [51]:
```
for english_sent, spanish_sent in zip(english_sentences[-10:], spanish_sent
    print("="*50)
    english_sent = english_sent.replace('<start>', '').replace('<end>', '')
    spanish_sent = spanish_sent.replace('<start>', '').replace('<end>', '')
    print("English:", english_sent, "--> Expected Spanish:", spanish_sent)
    decoded_sentence = decode_sequence(english_sent)
    print("Model's translation:", decoded_sentence)
```

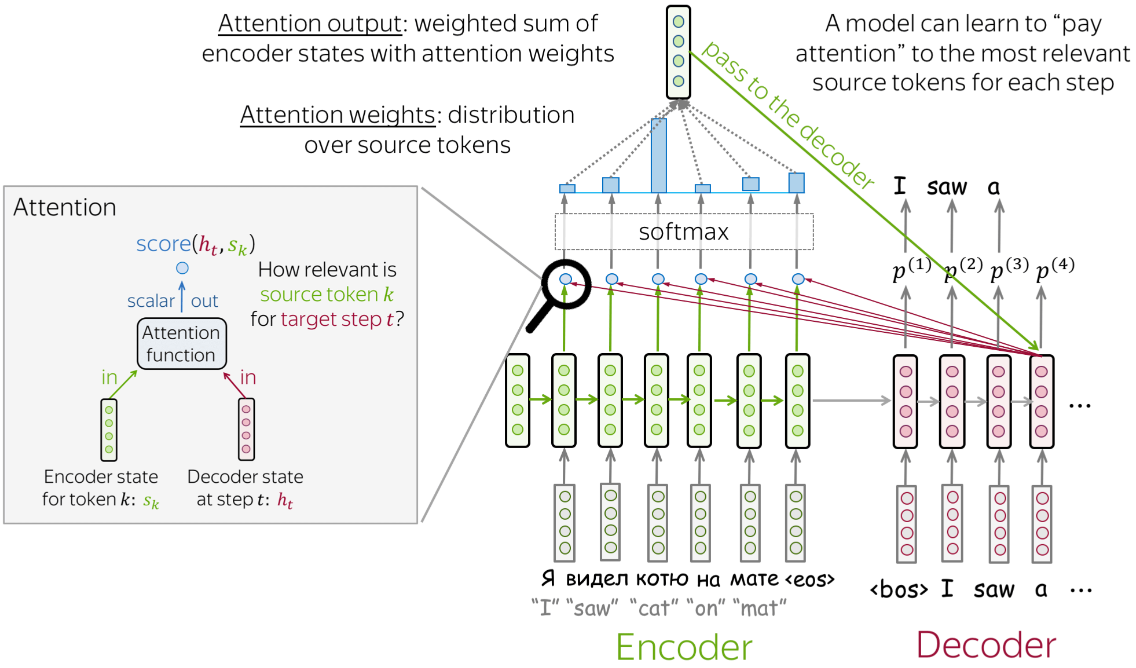
```
==================================================
English:  i can t whistle .  --> Expected Spanish:  no se silbar .
1/1 [==============================] - 0s 374ms/step
1/1 [==============================] - 0s 382ms/step
1/1 [==============================] - 0s 18ms/step
Model's translation:  vemos caravana
==================================================
English:  i caught a cold .  --> Expected Spanish:  me resfrie .
1/1 [==============================] - 0s 16ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 18ms/step
Model's translation:  vacios rellena
==================================================
English:  i caught a cold .  --> Expected Spanish:  pille un resfriado .
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 20ms/step
Model's translation:  vacios rellena
==================================================
English:  i caught a fish !  --> Expected Spanish:  atrape un pez !
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 20ms/step
Model's translation:  llevanos
==================================================
English:  i caught an eel .  --> Expected Spanish:  capture una anguila .
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 20ms/step
Model's translation:  vacios vacios
==================================================
English:  i caught an eel .  --> Expected Spanish:  cogi una anguila .
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 27ms/step
1/1 [==============================] - 0s 19ms/step
Model's translation:  vacios vacios
==================================================
English:  i chickened out .  --> Expected Spanish:  me acobarde .
1/1 [==============================] - 0s 335ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 18ms/step
Model's translation:  tropece averiguemoslo
==================================================
English:  i cooked dinner .  --> Expected Spanish:  cocine la cena .
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 19ms/step
Model's translation:  sentarme
==================================================
English:  i couldn t move .  --> Expected Spanish:  no me podia mover .
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 19ms/step
Model's translation:  vemos sentarme
==================================================
English:  i couldn t stop .  --> Expected Spanish:  no podria parar .
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 18ms/step
Model's translation:  vemos sentarme
```

In [51]:

In [51]:

Sequence to Sequence Attention

In [51]:



[https://machinelearningmastery.com/encoder-decoder-attention-sequence-to-sequence-prediction-keras/ (https://machinelearningmastery.com/encoder-decoder-attention-sequence-to-sequence-prediction-keras/)](https://machinelearningmastery.com/encoder-decoder-attention-sequence-to-sequence-prediction-keras/)

Method -1. (Attention layer is directly imported from keras)

tf.keras.layers.Attention()

Type *Markdown* and LaTeX: α^2

ENCODER

In [20]:

```
from keras.models import Model
from keras.layers import Input, LSTM, Dense
import tensorflow as tf

# Define an input sequence and process it.
# encoder_inputs = Input(shape=(1,), dtype=tf.string, name="spanish_input")
encoder_inputs = Input(shape=(None,), name="english_input")

# encoder_vectorizer = spanish_vectorizer(encoder_inputs)

# enc = layers.Embedding(vocab_size_spanish, embedding_dim, name="sp_embedd

layer_embedding = layers.Embedding(vocab_size_english, embedding_dim)
embedding_layer_final = layer_embedding(encoder_inputs)

encoder = LSTM(latent_dim,  return_sequences=True, return_state=True,
                                   dropout=dropout, recurrent_dropout=dropo
enc_state_ouput, enc_state_h, enc_state_c = encoder(embedding_layer_final)
# We discard `encoder_outputs` and only keep the states.
encoder_states = [enc_state_h, enc_state_c]
```

DECODER

In [21]:

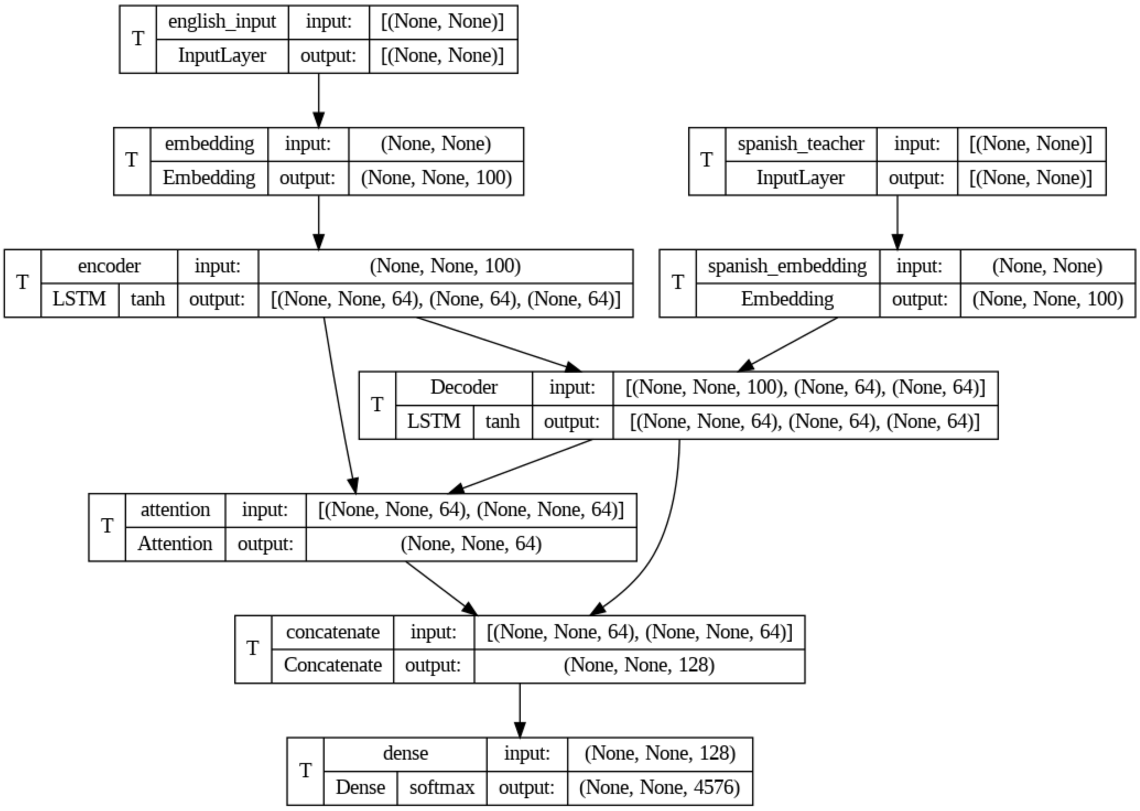
```
decoder_inputs = Input(shape=(None,), name="spanish_teacher")
# decoder_inputs = Input(shape=(None,), dtype=tf.int32, name="english_teach
layer_embedding_decoder = layers.Embedding(vocab_size_spanish, embedding_di
x =layer_embedding_decoder(decoder_inputs)

# Adding the Attention mechanism

decoder_lstm = layers.LSTM(latent_dim, return_sequences=True, return_state=
                           dropout=dropout, recurrent_dropout=dropout, name
decoder_outputs,decoder_state_h, decoder_state_c = decoder_lstm(x, initial_

attention_layer = tf.keras.layers.Attention()
attention=attention_layer([decoder_outputs, enc_state_ouput])  # Using the
# decoder_combined_context = layers.concatenate([decoder_outputs,attention]
decoder_combined_context = Concatenate(axis=-1)([decoder_outputs,attention]

decoder_dense = layers.Dense(vocab_size_spanish, activation='softmax')
# decoder_outputs_final = decoder_dense(attention)
decoder_outputs_final = decoder_dense(decoder_combined_context)


# Define the model
model2 = Model([encoder_inputs, decoder_inputs], decoder_outputs_final)
```

In [22]:
```
model2.summary()
```

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

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

 embedding (Embedding)          (None, None, 100)    220600      ['english_input[0][0]']

 spanish_embedding (Embedding)  (None, None, 100)    457600      ['spanish_teacher[0][0]']

 encoder (LSTM)                 [(None, None, 64),   42240       ['embedding[0][0]']
                                 (None, 64),
                                 (None, 64)]

 Decoder (LSTM)                 [(None, None, 64),   42240       ['spanish_embedding[0][0]',
                                 (None, 64),                      'encoder[0][1]',
                                 (None, 64)]                      'encoder[0][2]']

 attention (Attention)          (None, None, 64)     0           ['Decoder[0][0]',
                                                                  'encoder[0][0]']

 concatenate (Concatenate)      (None, None, 128)    0           ['Decoder[0][0]',
                                                                  'attention[0][0]']

 dense (Dense)                  (None, None, 4576)   590304      ['concatenate[0][0]']

==================================================================================================
Total params: 1352984 (5.16 MB)
Trainable params: 1352984 (5.16 MB)
Non-trainable params: 0 (0.00 Byte)
__________________________________________________________________________________________________
```

In [23]:
```
# from tensorflow.keras.utils import plot_model

# plot_model(model2, to_file='model_plot3.png', show_shapes=True, show_laye


# from tensorflow.keras.utils import plot_model
from keras.utils import plot_model


plot_model(model2, to_file='model_plot3.png',
    show_shapes=True,
    show_layer_names=True,
    layer_range=None,
    show_layer_activations=True,
    show_trainable=True)
```

Out[23]:



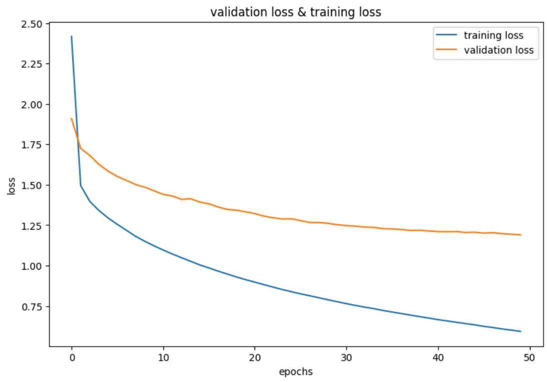
In [24]:
```
model2.compile(loss='sparse_categorical_crossentropy', optimizer='rmsprop',
```

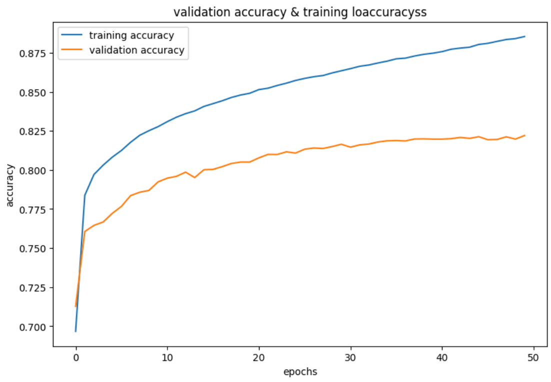
In [25]:

```
history = model2.fit([english_embedded_data, spanish_teacher_enc], spanish_
                    validation_split=0.1,
                    epochs=50, batch_size=BATCH_SIZE,
                    verbose=1)
```

```
Epoch 1/50
282/282 [==============================] - 38s 107ms/step - loss: 2.417
2 - accuracy: 0.6967 - val_loss: 1.9091 - val_accuracy: 0.7127
Epoch 2/50
282/282 [==============================] - 34s 119ms/step - loss: 1.494
8 - accuracy: 0.7838 - val_loss: 1.7249 - val_accuracy: 0.7606
Epoch 3/50
282/282 [==============================] - 31s 108ms/step - loss: 1.396
4 - accuracy: 0.7971 - val_loss: 1.6809 - val_accuracy: 0.7645
Epoch 4/50
282/282 [==============================] - 33s 116ms/step - loss: 1.340
2 - accuracy: 0.8031 - val_loss: 1.6254 - val_accuracy: 0.7667
Epoch 5/50
282/282 [==============================] - 32s 115ms/step - loss: 1.293
9 - accuracy: 0.8082 - val_loss: 1.5841 - val_accuracy: 0.7722
Epoch 6/50
282/282 [==============================] - 31s 111ms/step - loss: 1.254
9 - accuracy: 0.8125 - val_loss: 1.5511 - val_accuracy: 0.7767
Epoch 7/50
```

In [27]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(20, 6))
# Plot the first subplot  loss)
plt.subplot(1, 2, 1)  # 1 row, 2 columns, first subplot
plt.plot(history.history["loss"])
plt.plot(history.history["val_loss"])
plt.title("validation loss & training loss")
plt.xlabel("epochs")
plt.ylabel("loss")
leg = plt.legend(["training loss", "validation loss"],loc ="upper right");

# Plot the second subplot ( accuracy)
plt.subplot(1, 2, 2)  # 1 row, 2 columns, second subplot
plt.plot(history.history["accuracy"])
plt.plot(history.history["val_accuracy"])
plt.title("validation accuracy & training loaccuracyss")
plt.xlabel("epochs")
plt.ylabel("accuracy")
leg = plt.legend(["training accuracy", "validation accuracy"],loc ="upper l

plt.show()
```





In [61]:

INFERENCE

In [74]:
```
# enc_state_ouput, enc_state_h, enc_state_c
```

In [29]:
```
# tmp, outh, outc = model_encoder_training.get_layer("lstm_2").output
# encoder_model = Model(encoder_inputs, [outh, outc])

# encoder_model = Model(encoder_inputs, [outh, outc])
encoder_model = Model(inputs=encoder_inputs, outputs=encoder_states)

# encoder_model = Model(inputs=encoder_inputs, outputs=[enc_state_ouput, en


decoder_state_input_h = Input(shape=(latent_dim,))
decoder_state_input_c = Input(shape=(latent_dim,))
decoder_states_inputs = [decoder_state_input_h, decoder_state_input_c]

layer_embedding_decoder_inf = layer_embedding_decoder(decoder_inputs)
decoder_outputs, state_h, state_c = decoder_lstm(
    layer_embedding_decoder_inf , initial_state=decoder_states_inputs)

# attention = attention_layer([decoder_outputs, encoder_outputs])
attention = attention_layer([decoder_outputs, enc_state_ouput])


# decoder_combined_context = layers.concatenate([attention, decoder_outputs

# decoder_combined_context = layers.concatenate(axis=-1)([ decoder_outputs,

decoder_combined_context = Concatenate(axis=-1)([decoder_outputs,attention]

decoder_outputs_final = decoder_dense(decoder_combined_context)


decoder_states = [state_h, state_c]
# decoder_model = Model(
#     [decoder_inputs] + decoder_states_inputs,
#     [decoder_outputs_final] + decoder_states)
```

In [30]:
```
import numpy as np

def decode_sequence(input_sentence):

    input_seq = step1(input_sentence)
    input_seq_transformed = english_vectorizer([input_seq])

    states_value = encoder_model.predict(input_seq_transformed)


    target_seq = np.zeros((1, 1))

    target_seq[0, 0] = vocab_spanish.index('<start>')

    stop_condition = False
    decoded_sentence = ''
    while not stop_condition:

        output_tokens, h, c = decoder_model.predict([target_seq] + states_v


        sampled_token_index = np.argmax(output_tokens[0, -1, :])
        sampled_word = list(vocab_spanish)[sampled_token_index]
        decoded_sentence += ' ' + sampled_word


        if (sampled_word == '<end>' or len(decoded_sentence) > max_length_e
            stop_condition = True


        target_seq = np.zeros((1, 1))
        target_seq[0, 0] = sampled_token_index

        states_value = [h, c]

    return decoded_sentence
```

In [ ]:
```
# for english_sent, spanish_sent in zip(english_sentences[-10:], spanish_se
#     print("="*50)
#     english_sent = english_sent.replace('<start>', '').replace('<end>', '
#     spanish_sent = spanish_sent.replace('<start>', '').replace('<end>', '
#     print("English:", english_sent, "--> Expected Spanish:", spanish_sent
#     decoded_sentence = decode_sequence(english_sent)
#     print("Model's translation:", decoded_sentence)
```

Method -2. (Attention layer is implemented by using dot products == Luong_Attention)

Encoder

In [76]:
```
from keras.models import Model
from keras.layers import Input, LSTM, Dense

# Define an input sequence and process it.
# encoder_inputs = Input(shape=(None, num_encoder_tokens))
# A_encoder_inputs = Input(shape=(1,),dtype=tf.string, name="english_input"
A_encoder_inputs = Input(shape=(None,), name="english_input")

# A_encoder_vectorizer = spanish_vectorizer(A_encoder_inputs)

# A_enc = layers.Embedding(vocab_size_spanish, embedding_dim, name="en_embe
A_enc = layers.Embedding(vocab_size_english, embedding_dim, name="en_embedd

encoder_outputs, A_enc_state_h, A_enc_state_c = LSTM(latent_dim,  return_se
                                   dropout=dropout, recurrent_dropout=dropo
# We discard `encoder_outputs` and only keep the states.
A_encoder_states = [A_enc_state_h, A_enc_state_c]
```

```
WARNING:tensorflow:Layer encoder will not use cuDNN kernels since it does
n't meet the criteria. It will use a generic GPU kernel as fallback when r
unning on GPU.
```

DECODER

In [77]:
```
# decoder_inputs = Input(shape=(None,), dtype=tf.int32, name="spanish_teach
decoder_inputs = Input(shape=(None,), name="spanish_teacher")

x = layers.Embedding(vocab_size_spanish, embedding_dim
                     ,name="spanish_embedding")(decoder_inputs)
decoder_lstm = layers.LSTM(latent_dim, return_sequences=True, return_state=
                           dropout=dropout, recurrent_dropout=dropout, name
decoder_outputs, _, _ = decoder_lstm(x, initial_state=A_encoder_states)
```

```
WARNING:tensorflow:Layer Decoder will not use cuDNN kernels since it does
n't meet the criteria. It will use a generic GPU kernel as fallback when r
unning on GPU.
```

Attentional part

In [78]:
```
attention = layers.dot([decoder_outputs, encoder_outputs], axes=[2,2], name
```

Context vector

In [79]:
```
context = layers.dot([attention, encoder_outputs], axes=[2,1], name="Attent
print(context.shape)
```

```
(None, None, 64)
```

Combine attention with decoder ouput

In [80]:

```
decoder_combined_context = layers.concatenate([context, decoder_outputs], n
print(decoder_combined_context.shape)
```

```
(None, None, 128)
```

Ouput of the model

In [81]:

```
ouputs = layers.Dense(vocab_size_spanish, activation='softmax', name="Outpu
print(decoder_outputs.shape)
```

```
(None, None, 64)
```

In [82]:

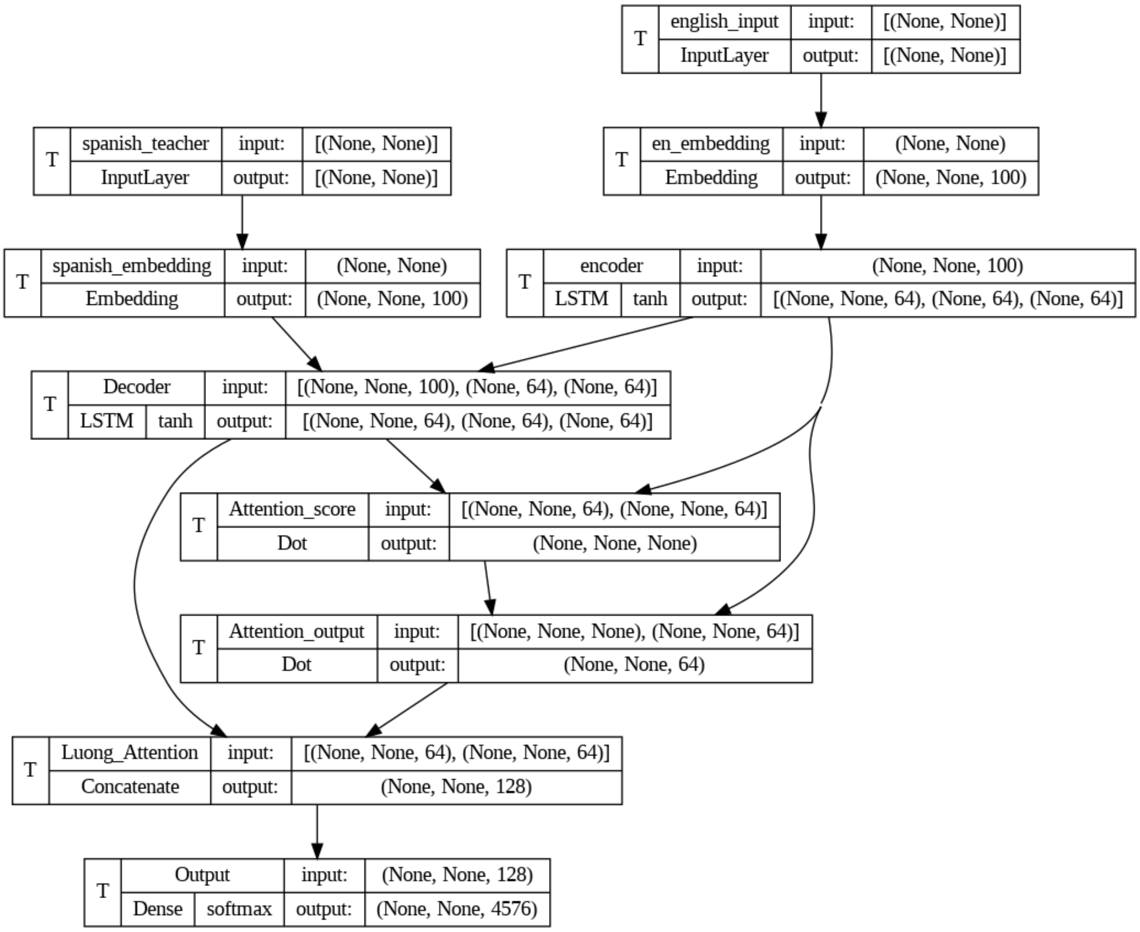
```
model3 = Model([A_encoder_inputs, decoder_inputs], ouputs)
```

In [83]:
```
model3.summary()
```

```
Model: "model_12"
__________________________________________________________________________
________________________
 Layer (type)                Output Shape                 Param #   Connec
ted to
==========================================================================
========================
 english_input (InputLayer)  [(None, None)]               0         []

 spanish_teacher (InputLaye  [(None, None)]               0         []
 r)

 en_embedding (Embedding)    (None, None, 100)            220600    ['engl
ish_input[0][0]']

 spanish_embedding (Embeddi  (None, None, 100)            457600    ['span
ish_teacher[0][0]']
 ng)

 encoder (LSTM)              [(None, None, 64),           42240     ['en_e
mbedding[0][0]']
                              (None, 64),
                              (None, 64)]

 Decoder (LSTM)              [(None, None, 64),           42240     ['span
ish_embedding[0][0]',
                              (None, 64),                             'enco
der[0][1]',
                              (None, 64)]                             'enco
der[0][2]']

 Attention_score (Dot)       (None, None, None)           0         ['Deco
der[0][0]',
                                                                      'enco
der[0][0]']

 Attention_output (Dot)      (None, None, 64)             0         ['Atte
ntion_score[0][0]',
                                                                      'enco
der[0][0]']

 Luong_Attention (Concatena  (None, None, 128)            0         ['Atte
ntion_output[0][0]',
 te)                                                                  'Deco
der[0][0]']

 Output (Dense)              (None, None, 4576)           590304    ['Luon
g_Attention[0][0]']

==========================================================================
========================
Total params: 1352984 (5.16 MB)
Trainable params: 1352984 (5.16 MB)
Non-trainable params: 0 (0.00 Byte)
__________________________________________________________________________
________________________
```

In [84]:
```
# from tensorflow.keras.utils import plot_model

# plot_model(model3, to_file='model_plot4.png', show_shapes=True, show_laye

# from tensorflow.keras.utils import plot_model
from keras.utils import plot_model

# plot_model(model3, to_file='model_plot4.png', show_shapes=True, show_laye

plot_model(model3, to_file='model_plot4.png',
    show_shapes=True,
    show_layer_names=True,
    layer_range=None,
    show_layer_activations=True,
    show_trainable=True)
```

Out[84]:



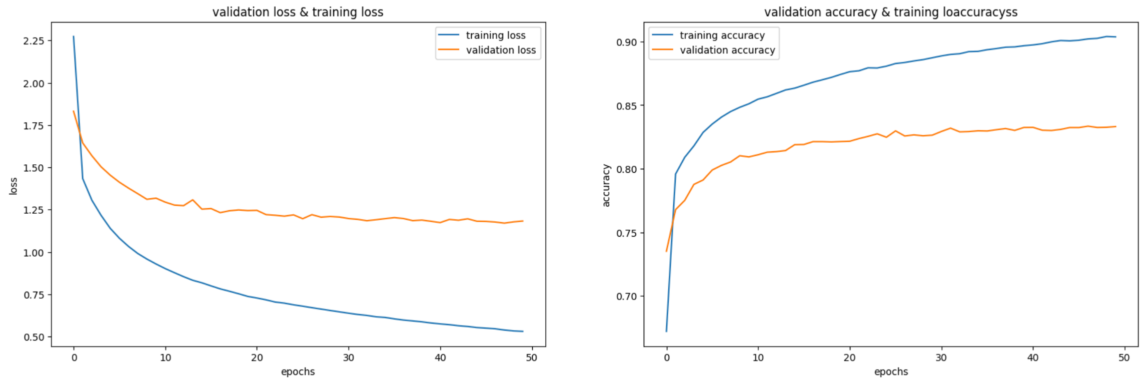
In [85]:
```
model3.compile(loss='sparse_categorical_crossentropy', optimizer='rmsprop',
```

In [85]:

In [86]:
```
history = model3.fit([english_embedded_data, spanish_teacher_enc], spanish_
                     validation_split=0.1,
                     epochs=50, batch_size=BATCH_SIZE,
                     verbose=1)
```

```
Epoch 1/50
282/282 [==============================] - 31s 89ms/step - loss: 2.2734
- accuracy: 0.6721 - val_loss: 1.8314 - val_accuracy: 0.7352
Epoch 2/50
282/282 [==============================] - 22s 78ms/step - loss: 1.4331
- accuracy: 0.7958 - val_loss: 1.6440 - val_accuracy: 0.7678
Epoch 3/50
282/282 [==============================] - 22s 79ms/step - loss: 1.3053
- accuracy: 0.8090 - val_loss: 1.5683 - val_accuracy: 0.7752
Epoch 4/50
282/282 [==============================] - 22s 78ms/step - loss: 1.2162
- accuracy: 0.8180 - val_loss: 1.5031 - val_accuracy: 0.7877
Epoch 5/50
282/282 [==============================] - 21s 76ms/step - loss: 1.1394
- accuracy: 0.8286 - val_loss: 1.4536 - val_accuracy: 0.7912
Epoch 6/50
282/282 [==============================] - 21s 75ms/step - loss: 1.0808
- accuracy: 0.8351 - val_loss: 1.4119 - val_accuracy: 0.7990
Epoch 7/50
```

In [88]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(20, 6))
# Plot the first subplot  loss)
plt.subplot(1, 2, 1)  # 1 row, 2 columns, first subplot
plt.plot(history.history["loss"])
plt.plot(history.history["val_loss"])
plt.title("validation loss & training loss")
plt.xlabel("epochs")
plt.ylabel("loss")
leg = plt.legend(["training loss", "validation loss"],loc ="upper right");

# Plot the second subplot ( accuracy)
plt.subplot(1, 2, 2)  # 1 row, 2 columns, second subplot
plt.plot(history.history["accuracy"])
plt.plot(history.history["val_accuracy"])
plt.title("validation accuracy & training loaccuracyss")
plt.xlabel("epochs")
plt.ylabel("accuracy")
leg = plt.legend(["training accuracy", "validation accuracy"],loc ="upper l

plt.show()
```



In [ ]:

In [ ]:

Method-1- Transformer(build transformer from scratch using keras)

Someimportant links for transformer

[https://www.youtube.com/watch?v=81LeULNc2_c&list=PLyFpZIg7OtNQHbWjyy_QApMOHhqvzS-9o&index=7 (https://www.youtube.com/watch?v=81LeULNc2_c&list=PLyFpZIg7OtNQHbWjyy_QApMOHhqvzS-9o&index=7)](https://www.youtube.com/watch?v=81LeULNc2_c&list=PLyFpZIg7OtNQHbWjyy_QApMOHhqvzS-9o&index=7)

https://machinelearningmastery.com/building-transformer-models-with-attention-crash-course-build-a-neural-machine-translator-in-12-days/ (https://machinelearningmastery.com/building-transformer-models-with-attention-crash-course-build-a-neural-machine-translator-in-12-days/)

In [92]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os

import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.layers import Embedding, Dense, Input, Dropout, Layer
```

In [94]:
```
# devices = tf.config.experimental.list_physical_devices("GPU")
# for device in devices:
#     tf.config.experimental.set_memory_growth(device=device, enable=True)
```

In [ ]:
```
# # df = pd.read_csv("C:\\Users\\praba\\Documents\\GitHub\\UCA SEMESTER 2 M
# df = pd.read_csv("C:\\Users\\praba\\Documents\\GitHub\\UCA SEMESTER 2 M1\

# df.columns = ["en", "fr"]
# df.head(10)
```

In [95]:
```
import pandas as pd  # Import pandas library for data manipulation
import re  # Import re library for regular expressions
import unicodedata  # Import unicodedata library for handling Unicode chara

# Load dataset from file
# dataset = 'C:/Users/praba\Documents/GitHub/deep_learning_uca_2/spa-eng/sp
dataset = 'spa.txt'

df = pd.read_table(dataset)  # Read data from file into a DataFrame
```

In [95]:

In [96]:
```
df.columns = ["en", "fr","not_needed"]
df.head(10)
```

Out[96]:

	en	fr	not_needed
0	Go.	Vete.	CC-BY 2.0 (France) Attribution: tatoeba.org #2...
1	Go.	Vaya.	CC-BY 2.0 (France) Attribution: tatoeba.org #2...
2	Go.	Váyase.	CC-BY 2.0 (France) Attribution: tatoeba.org #2...
3	Hi.	Hola.	CC-BY 2.0 (France) Attribution: tatoeba.org #5...
4	Run!	¡Corre!	CC-BY 2.0 (France) Attribution: tatoeba.org #9...
5	Run!	¡Corran!	CC-BY 2.0 (France) Attribution: tatoeba.org #9...
6	Run!	¡Huye!	CC-BY 2.0 (France) Attribution: tatoeba.org #9...
7	Run!	¡Corra!	CC-BY 2.0 (France) Attribution: tatoeba.org #9...
8	Run!	¡Corred!	CC-BY 2.0 (France) Attribution: tatoeba.org #9...
9	Run.	Corra.	CC-BY 2.0 (France) Attribution: tatoeba.org #4...

In [97]:
```
df = df.iloc[:, [0, 1]]
```

In [98]:
```
df["en"] = df["en"].str.lower()
df["fr"] = df["fr"].str.lower()
```

In [99]:
```
en_data = df["en"].values
fr_data =df["fr"].values
```

In [100]:
```
# en_data[:10]
```

In [101]:
```
for i in range(fr_data.shape[0]):
    en_data[i] = "sos " + str(en_data[i]) + " eos"
    fr_data[i] = "sos " + str(fr_data[i]) + " eos"
```

In [102]:
```
num_words = 10000
tokenizer_en = Tokenizer(num_words=num_words, filters='!"#$%&\'()*+,-./:;<=
tokenizer_en.fit_on_texts(en_data)
englist_sentances = tokenizer_en.texts_to_sequences(en_data)
```

In [103]:
```
word_index = tokenizer_en.word_index
print(f"Num words in English: {len(word_index)}")
```

```
Num words in English: 13996
```

In [104]:
```
tokenizer_fr = Tokenizer(num_words=num_words, filters='!"#$%&\'()*+,-./:;<=
tokenizer_fr.fit_on_texts(fr_data)
spanish_sentences = tokenizer_fr.texts_to_sequences(fr_data)

word_index_fr = tokenizer_fr.word_index
print(f"Num words in Spanish: {len(word_index_fr)}")
```

```
Num words in Spanish: 29208
```

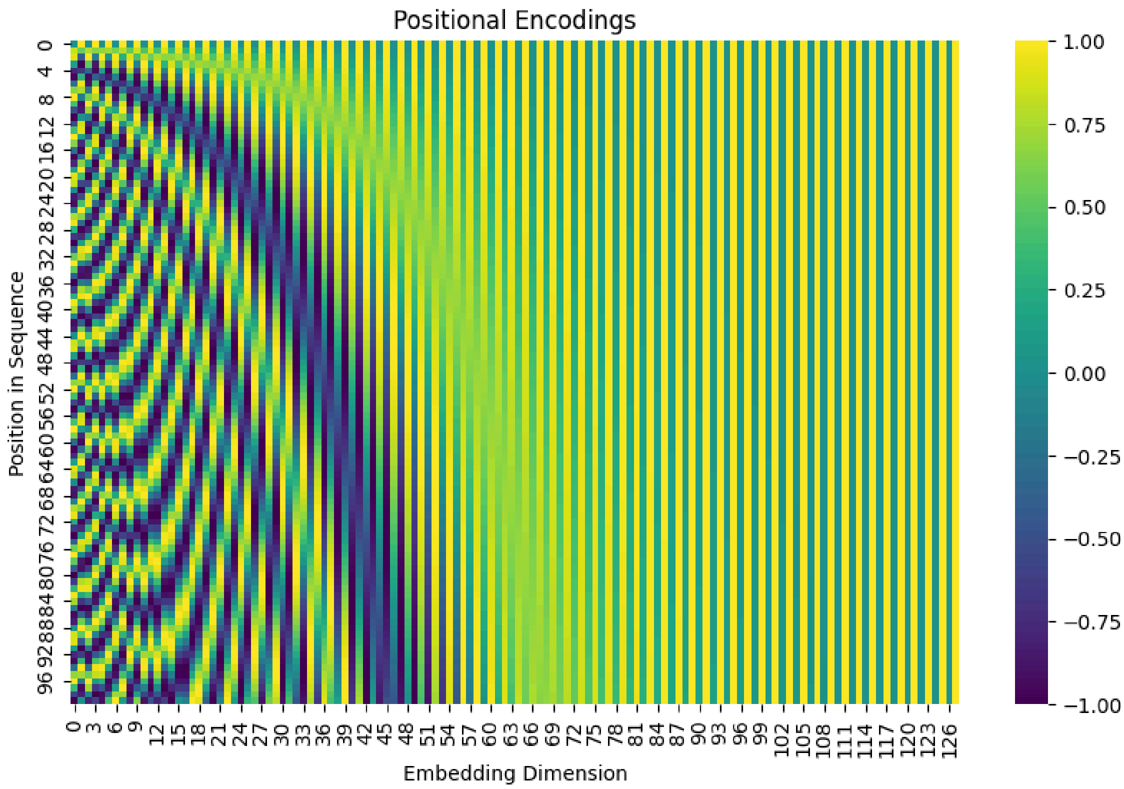
In [105]:
```
# word_index_fr
```

In [106]:
```
english_sentences = pad_sequences(englist_sentances, maxlen = 7, padding='p
spanish_sentences = pad_sequences(spanish_sentences, maxlen=7, padding='pos
```

In [107]:
```
def get_angles(pos, i, embedding_dim):
    """
    Function to compute the angles for positional encoding.

    Returns the angle computed
    """
    angle_rates = 1 / np.power(10000, (2 * (i//2)) / np.float32(embedding_d
    return pos * angle_rates
```

In [108]:
```
def positional_encoding(position, embedding_dim):
    """
    Adds  positional encoding to the Embeddings to be fed to the Transforme

    Computes a sin and cos of the angles determined by the get_angles() fun
    and adds the value computed to an axis of the embeddings.
    """
    angle_rads = get_angles(np.arange(position)[:, np.newaxis],
                            np.arange(embedding_dim)[np.newaxis, :], embeddi

    # apply sin to even indices in the array. ie 2i
    angle_rads[:, 0::2] = np.sin(angle_rads[:, 0::2])

    # apply cos to odd indices in the array. ie 2i+1
    angle_rads[:, 1::2] = np.cos(angle_rads[:, 1::2])

    pos_encoding = angle_rads[np.newaxis, ...]
    return tf.cast(pos_encoding, dtype=tf.float32)
```

In [109]:
```python
# Generate positional encodings
pos_encodings = positional_encoding(100, 128)

# Visualize the encodings as a heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(pos_encodings[0], cmap='viridis')
plt.xlabel('Embedding Dimension')
plt.ylabel('Position in Sequence')
plt.title('Positional Encodings')
plt.show()
```



In [110]:
```python
def create_padding_mask(seq):
    seq = tf.cast(tf.math.equal(seq, 0), tf.float32)
    return seq[:, tf.newaxis, tf.newaxis, :]
```

In [111]:
```python
def create_look_ahead_mask(size):
    mask = 1 - tf.linalg.band_part(tf.ones((size, size)), -1, 0)
    return mask
```

In [112]:
```python
def create_masks(inputs, targets):
    enc_padding_mask = create_padding_mask(inputs)
    dec_padding_mask = create_padding_mask(inputs)
    look_ahead_mask = create_look_ahead_mask(tf.shape(targets)[1])
    dec_target_padding_mask = create_padding_mask(targets)
    combine_mask = tf.maximum(dec_target_padding_mask, look_ahead_mask)
    return enc_padding_mask, combine_mask, dec_padding_mask
```

In [113]:
```
def scaled_dot_product_attention(q, k, v, mask):
    matmul_qk = tf.matmul(q, k, transpose_b=True)
    dk = tf.cast(tf.shape(k)[-1], dtype=tf.float32)
    scaled_dk = tf.math.sqrt(dk)
    scaled_attention_logits = matmul_qk/scaled_dk
    if mask is not None:
        scaled_attention_logits += (mask * -1e9)
    attention_weights = tf.nn.softmax(scaled_attention_logits, axis = -1)
    output = tf.matmul(attention_weights, v)
    return output, attention_weights
```

MultiHeadAttention

In [114]:
```
class MultiHeadAttention(tf.keras.layers.Layer):

    def __init__(self, key_dim, num_heads, dropout_rate=0.0):

        super(MultiHeadAttention, self).__init__()
        self.num_heads = num_heads
        self.key_dim = key_dim
        #  ensure  that the dimension of the embedding can be evenly split
        assert key_dim % num_heads == 0
        self.depth = self.key_dim // self.num_heads

        # dense layers to project the input into queries, keys and values
        self.wq = Dense(key_dim)
        self.wk = Dense(key_dim)
        self.wv = Dense(key_dim)

        # dropout layer
        self.dropout = Dropout(dropout_rate)

        # dense layer to project the output of the attention heads
        self.dense = Dense(key_dim)

    def split_heads(self, x, batch_size):
        x = tf.reshape(x, (batch_size, -1, self.num_heads, self.depth))
        return tf.transpose(x, perm=[0, 2, 1, 3])

    def call(self, v, k, q, mask=None):

        batch_size = tf.shape(q)[0]

        # Dense on the q, k, v vectors
        q = self.wq(q)
        k = self.wk(k)
        v = self.wv(v)

        # split the heads
        q = self.split_heads(q, batch_size)
        k = self.split_heads(k, batch_size)
        v = self.split_heads(v, batch_size)

        # split the queries, keys and values into multiple heads
        scaled_attention, attention_weights = scaled_dot_product_attention(
        scaled_attention = tf.transpose(scaled_attention, perm=[0, 2, 1, 3]

        # reshape and add Dense layer
        concat_attention = tf.reshape(scaled_attention, (batch_size, -1, se
        output = self.dense(concat_attention)
        output = self.dropout(output)

        return output, attention_weights
```

FeedForward

In [115]:
```
def FeedForward(embedding_dim, fully_connected_dim):
    model = tf.keras.Sequential([
        tf.keras.layers.Dense(fully_connected_dim, activation='relu'),
        tf.keras.layers.Dense(embedding_dim)
    ])
    return model
```

In [116]:
```
class EncoderLayer(tf.keras.layers.Layer):
    def __init__(self, embedding_dim, num_heads, fully_connected_dim, dropo
        """
        A single layer of the encoder in a Transformer model.

        Args:
            embedding_dim (int): The dimension of the input embeddings.
            num_heads (int): The number of attention heads in the multi-hea
            fully_connected_dim (int): The dimension of the fully connected
            dropout_rate (float, optional): The dropout rate to be applied.
        """
        super(EncoderLayer, self).__init__()

        self.mha = MultiHeadAttention(embedding_dim, num_heads, dropout_rat

        self.layernorm1 = LayerNormalization(epsilon=1e-6)
        self.layernorm2 = LayerNormalization(epsilon=1e-6)

        # Dropout
        self.dropout = Dropout(dropout_rate)

        # Feedforward network
        self.ffn = FeedForward(embedding_dim, fully_connected_dim)

    def call(self, x, training, mask):
        """
        Forward pass through the encoder layer.

        Args:
            x (tf.Tensor): The input tensor.
            training (bool): Whether the model is in training mode.
            mask: The mask to be applied in multi-head attention.

        Returns:
            tf.Tensor: The output tensor after passing through the encoder
        """

        # Apply multi-head self-attention mechanism to input tensor
        attn_output, _ = self.mha(x, x, x, mask)

        # Apply first layer normalization and add residual connection
        out1 = self.layernorm1(attn_output + x)

        # Apply feedforward network to output of first layer normalization
        ffn_output = self.ffn(out1)
        ffn_output = self.dropout(ffn_output, training=training)

        # Apply second layer normalization and add residual connection
        out2 = self.layernorm2(ffn_output + out1)

        return out2
```

In [ ]:

Encoder

In [117]:
```
class Encoder(tf.keras.layers.Layer):
    def __init__(self, num_layers, embedding_dim, num_heads, fully_connecte

        """
        Args:
            num_layers (int): The number of encoder layers.
            embedding_dim (int): The dimension of the input embeddings.
            num_heads (int): The number of attention heads in the multi-hea
            fully_connected_dim (int): The dimension of the fully connected
            input_vocab_size (int): The size of the input vocabulary.
            maximum_position_encoding (int): The maximum position for posit
            dropout_rate (float, optional): The dropout rate to be applied.
        """

        super(Encoder, self).__init__()

        self.num_layers = num_layers
        self.embedding_dim = embedding_dim

        # Embedding layer
        self.embedding = Embedding(input_vocab_size, embedding_dim)

        # Positional encoding
        self.pos_encoding = positional_encoding(maximum_position_encoding,

        # Encoder layers
        self.enc_layers = [EncoderLayer(embedding_dim, num_heads, fully_con

        # Dropout layer
        self.dropout = Dropout(dropout_rate)

    def call(self, inputs, training, mask):

        """
        Forward pass through the encoder.

        Args:
            inputs (tf.Tensor): The input sequence tensor.
            training (bool): Whether the model is in training mode.
            mask: The mask to be applied in multi-head attention.

        Returns:
            tf.Tensor: The encoded sequence tensor.
        """

        # Get the sequence length
        seq_len = tf.shape(inputs)[1]

        # Embed the input sequence
        inputs = self.embedding(inputs)

        # Scale the embeddings by sqrt(embedding_dim)
        inputs *= tf.math.sqrt(tf.cast(self.embedding_dim, tf.float32))

        # Add positional encodings to the input sequence
        inputs += self.pos_encoding[:, :seq_len, :]

        # Apply dropout to the input sequence
        inputs = self.dropout(inputs, training=training)

        # Pass the input sequence through the encoder layers
```

```
        for i in range(self.num_layers):
            inputs = self.enc_layers[i](inputs, training, mask)

        # Return the encoded sequence
        return inputs
```

In [118]:
```
class DecoderLayer(tf.keras.layers.Layer):
    def __init__(self, embedding_dim, num_heads, fully_connected_dim, dropo
        """
        Initializes a single decoder layer of the transformer model.

        Args:
            embedding_dim: The dimension of the embedding space.
            num_heads: The number of attention heads to use.
            fully_connected_dim: The dimension of the feedforward network.
            rate: The dropout rate for regularization.
        """
        super(DecoderLayer, self).__init__()

        # Instantiate two instances of MultiHeadAttention.
        self.mha1 = MultiHeadAttention(embedding_dim, num_heads, dropout_ra
        self.mha2 = MultiHeadAttention(embedding_dim, num_heads, dropout_ra

        # Instantiate a fully connected feedforward network.
        self.ffn = FeedForward(embedding_dim, fully_connected_dim)

        # Instantiate three layer normalization layers with epsilon=1e-6.
        self.layernorm1 = LayerNormalization(epsilon=1e-6)
        self.layernorm2 = LayerNormalization(epsilon=1e-6)
        self.layernorm3 = LayerNormalization(epsilon=1e-6)

        # Instantiate a dropout layer for regularization.
        self.dropout3 = Dropout(dropout_rate)

    def call(self, x, enc_output, training, look_ahead_mask, padding_mask):

        """
        Forward pass through the decoder layer.

        Args:
            x (tf.Tensor): The input tensor.
            enc_output (tf.Tensor): The output from the encoder layer.
            training (bool): Whether the model is in training mode.
            look_ahead_mask: The mask for look-ahead in multi-head attentio
            padding_mask: The mask for padding in multi-head attention.

        Returns:
            tf.Tensor: The output tensor after passing through the decoder
            tf.Tensor: The attention weights for the first multi-head atten
            tf.Tensor: The attention weights for the second multi-head atte
        """

        # Apply the first multi-head attention layer to the query vector x.
        # We pass x as all three inputs to the layer because this is a self
        attn1, attn_weights_block1 = self.mha1(x, x, x, look_ahead_mask)

        # Add the original input to the output of the attention layer and a
        out1 = self.layernorm1(attn1 + x)

        # Apply the second multi-head attention layer to the output from th
        attn2, attn_weights_block2 = self.mha2(enc_output, enc_output, out1

        # Add the output from the first layer to the output of the second l
        out2 = self.layernorm2(attn2 + out1)

        # Apply the feedforward network to the output of the second layer a
        ffn_output = self.ffn(out2)
```

```
        ffn_output = self.dropout3(ffn_output, training=training)

        # Add the output from the second layer to the output of the feedfor
        out3 = self.layernorm3(ffn_output + out2)

        return out3, attn_weights_block1, attn_weights_block2
```

In [ ]:

```

```

Decoder

In [119]:
```
class Decoder(tf.keras.layers.Layer):
    def __init__(self, num_layers, embedding_dim, num_heads, fully_connecte

        """
        The decoder component of a Transformer model.

        Args:
            num_layers (int): The number of decoder layers.
            embedding_dim (int): The dimension of the input embeddings.
            num_heads (int): The number of attention heads to use.
            fully_connected_dim (int): The dimension of the feedforward net
            target_vocab_size (int): The size of the target vocabulary.
            maximum_position_encoding (int): The maximum position for posit
            dropout_rate (float, optional): The dropout rate for regulariza
        """

        super(Decoder, self).__init__()

        self.num_layers = num_layers
        self.embedding_dim = embedding_dim

        # create layers
        self.embedding = Embedding(target_vocab_size, embedding_dim)
        self.pos_encoding = positional_encoding(maximum_position_encoding,
        self.dec_layers = [DecoderLayer(embedding_dim, num_heads, fully_con
        self.dropout = Dropout(dropout_rate)

    def call(self, x, enc_output, training, look_ahead_mask, padding_mask):

        """
        Forward pass through the decoder.

        Args:
            x (tf.Tensor): The input sequence tensor.
            enc_output (tf.Tensor): The output from the encoder layer.
            training (bool): Whether the model is in training mode.
            look_ahead_mask: The mask for look-ahead in multi-head attentio
            padding_mask: The mask for padding in multi-head attention.

        Returns:
            tf.Tensor: The decoded sequence tensor.
            dict: Dictionary containing attention weights for each decoder
        """

        seq_len = tf.shape(x)[1]
        attention_weights = {}

        # add embedding and positional encoding
        x = self.embedding(x)
        x *= tf.math.sqrt(tf.cast(self.embedding_dim, tf.float32))
        x += self.pos_encoding[:, :seq_len, :]
        x = self.dropout(x, training=training)

        # apply each layer of the decoder
        for i in range(self.num_layers):
            # pass through decoder layer i
            x, block1, block2 = self.dec_layers[i](x, enc_output, training,

            # record attention weights for block1 and block2
            attention_weights[f"decoder_layer{i + 1}_block1"] = block1
            attention_weights[f"decoder_layer{i + 1}_block2"] = block2
```

```
        return x, attention_weights
```

In [120]:
```
class Transformer(tf.keras.Model):

    def __init__(self, num_layers, embedding_dim, num_heads, fully_connecte

        """
        The Transformer model.

        Args:
            num_layers (int): The number of layers in the encoder and decod
            embedding_dim (int): The dimension of the input embeddings.
            num_heads (int): The number of attention heads to use.
            fully_connected_dim (int): The dimension of the feedforward net
            input_vocab_size (int): The size of the input vocabulary.
            target_vocab_size (int): The size of the target vocabulary.
            max_positional_encoding_input (int): The maximum positional enc
            max_positional_encoding_target (int): The maximum positional en
            dropout_rate (float, optional): The dropout rate for regulariza
        """

        super(Transformer, self).__init__()

        # Initialize the Encoder and Decoder layers
        self.encoder = Encoder(num_layers, embedding_dim, num_heads, fully_
        self.decoder = Decoder(num_layers, embedding_dim, num_heads, fully_

        # Add a final dense layer to make the final prediction
        self.final_layer = tf.keras.layers.Dense(target_vocab_size, activat

    def call(self, inp, tar, training, enc_padding_mask, look_ahead_mask, d

        """
        Forward pass through the Transformer.

        Args:
            inp (tf.Tensor): The input sequence tensor.
            tar (tf.Tensor): The target sequence tensor.
            training (bool): Whether the model is in training mode.
            enc_padding_mask: The mask for padding in the encoder.
            look_ahead_mask: The mask for look-ahead in the decoder.
            dec_padding_mask: The mask for padding in the decoder.

        Returns:
            tf.Tensor: The final prediction tensor.
            dict: Dictionary containing attention weights from the decoder.
        """

        # Pass the input sequence through the Encoder
        enc_output = self.encoder(inp, training, enc_padding_mask)

        # Pass the target sequence and the output of the Encoder through th
        dec_output, attention_weights = self.decoder(tar, enc_output, train

        # Pass the output of the Decoder through the final dense layer to g
        final_output = self.final_layer(dec_output)

        return final_output, attention_weights
```

In [121]:
```
# Set hyperparameters for the Transformer model
embedding_dim = 256  # dimensionality of the embeddings used for tokens in
fully_connected_dim = 512  # dimensionality of the hidden layer of the feed
num_layers = 4  # number of Transformer blocks in the encoder and decoder s
num_heads = 8  # number of heads in the multi-head attention mechanism
dropout_rate = 0.1  # dropout rate for regularization

# Set vocabulary sizes for input and target sequences
input_vocab_size = len(tokenizer_fr.word_index) + 2  # add 2 for the start
target_vocab_size = len(tokenizer_en.word_index) + 2  # add 2 for the start

# Set maximum positional encoding values for input and target sequences
max_positional_encoding_input = input_vocab_size  # maximum positional enco
max_positional_encoding_target = target_vocab_size  # maximum positional en

# Set the number of epochs and batch size for training
EPOCHS = 50
batch_size = 512
```

In [122]:
```
class CustomSchedule(tf.keras.optimizers.schedules.LearningRateSchedule):
    def __init__(self, embedding_dim, warmup_steps=4000):
        super(CustomSchedule, self).__init__()
        self.embedding_dim = tf.cast(embedding_dim, dtype=tf.float32)
        self.warmup_steps = tf.cast(warmup_steps, dtype=tf.float32)

    def __call__(self, step):

        step = tf.cast(step, dtype=tf.float32)
        arg1 = tf.math.rsqrt(step)
        arg2 = step * (self.warmup_steps ** -1.5)
        return tf.math.rsqrt(self.embedding_dim) * tf.math.minimum(arg1, ar

# Create an instance of the custom learning rate schedule
learning_rate = CustomSchedule(embedding_dim)
```

In [123]:
```
transformer = Transformer(num_layers, embedding_dim, num_heads,
                           fully_connected_dim, input_vocab_size, target_vo
                           max_positional_encoding_input, max_positional_en

# Define the optimizer
optimizer = tf.keras.optimizers.Adam(learning_rate, beta_1=0.9, beta_2 = 0.

# Define the loss object
loss_object = tf.keras.losses.SparseCategoricalCrossentropy()
```

In [124]:

```
def loss_function(true_values, predictions):
    """
    Calculate the loss value for a given target sequence.

    Args:
        true_values (tf.Tensor): The true target sequence.
        predictions (tf.Tensor): The predicted target sequence.

    Returns:
        float: The loss value for the given target sequence.
    """
    # Create a mask to exclude the padding tokens
    mask = tf.math.logical_not(tf.math.equal(true_values, 0))

    # Compute the loss value using the loss object
    loss_ = loss_object(true_values, predictions)

    # Apply the mask to exclude the padding tokens
    mask = tf.cast(mask, dtype=loss_.dtype)
    loss_ *= mask

    # Calculate the mean loss value
    return tf.reduce_sum(loss_) / tf.reduce_sum(mask)

def accuracy_function(true_values, predictions):
    """
    Calculate the accuracy for a given target sequence.

    Args:
        true_values (tf.Tensor): The true target sequence.
        predictions (tf.Tensor): The predicted target sequence.

    Returns:
        float: The accuracy value for the given target sequence.
    """
    # Compute the accuracies using the true and predicted target sequences
    accuracies = tf.equal(true_values, tf.argmax(predictions, axis=2))

    # Create a mask to exclude the padding tokens
    mask = tf.math.logical_not(tf.math.equal(true_values, 0))

    # Apply the mask to exclude the padding tokens from the accuracies
    accuracies = tf.math.logical_and(mask, accuracies)
    accuracies = tf.cast(accuracies, dtype=tf.float32)
    mask = tf.cast(mask, dtype=tf.float32)

    # Calculate the mean accuracy value
    return tf.reduce_sum(accuracies) / tf.reduce_sum(mask)

# Define the training metrics
train_loss = tf.keras.metrics.Mean(name='train_loss')
train_accuracy = tf.keras.metrics.SparseCategoricalAccuracy(name='train_acc
```

In [125]:
```
train_step_signature = [
    tf.TensorSpec(shape=(batch_size, 30), dtype=tf.int64),
    tf.TensorSpec(shape=(batch_size,30), dtype=tf.int64),
]
```

In [126]:
```
@tf.function()
def train_step(encoder_input, target):
    """
    Function to perform a single training step.

    Args:
    encoder_input (tf.Tensor): The input tensor for the encoder.
    target (tf.Tensor): The target tensor for the decoder.

    Returns:
    None.
    """

    # Slice the target tensor to get the input for the decoder
    decoder_input = target[:, :-1]

    # Slice the target tensor to get the expected output of the decoder
    expected_output = target[:, 1:]

    # Create masks for the encoder input, decoder input and the padding
    enc_padding_mask, combined_mask, dec_padding_mask = create_masks(encode

    # Perform a forward pass through the model
    with tf.GradientTape() as tape:
        predictions, _ = transformer(encoder_input, decoder_input, True, en

        # Calculate the loss between the predicted output and the expected
        loss = loss_function(expected_output, predictions)

    # Calculate gradients and update the model parameters
    gradients = tape.gradient(loss, transformer.trainable_variables)
    optimizer.apply_gradients(zip(gradients, transformer.trainable_variable

    # Update the training loss and accuracy metrics
    train_loss(loss)
    train_accuracy(expected_output, predictions)
```

In [127]:
```
EPOCHS = 20
```

In [128]:
```
# for epoch in range(0, EPOCHS+1):
for epoch in range(0, EPOCHS+1):

    # Reset the metrics at the start of the next epoch
    train_loss.reset_states()
    train_accuracy.reset_states()
    current_batch_index = 0

    # iterate through the dataset in batches of batch_size
    for i in range(int(len(english_sentences)/batch_size)):
        # get the input and target batch
        input_batch = tf.convert_to_tensor(np.array(english_sentences[curre
        target_batch = tf.convert_to_tensor(np.array(spanish_sentences[curr

        current_batch_index = current_batch_index + batch_size
        # call the train_step function to train the model using the current
        train_step(input_batch, target_batch)

    # print the epoch loss and accuracy after iterating through the dataset
    print (f'Epoch {epoch} Loss {train_loss.result():.4f} Accuracy {train_a
```

```
Epoch 0 Loss 8.5504 Accuracy 0.0750
Epoch 1 Loss 6.1008 Accuracy 0.2019
Epoch 2 Loss 4.8176 Accuracy 0.3061
Epoch 3 Loss 4.0328 Accuracy 0.3657
Epoch 4 Loss 3.4182 Accuracy 0.4326
Epoch 5 Loss 2.8023 Accuracy 0.5133
Epoch 6 Loss 2.3108 Accuracy 0.5828
Epoch 7 Loss 1.9625 Accuracy 0.6289
Epoch 8 Loss 1.7163 Accuracy 0.6597
Epoch 9 Loss 1.5517 Accuracy 0.6797
Epoch 10 Loss 1.4203 Accuracy 0.6968
Epoch 11 Loss 1.3113 Accuracy 0.7125
Epoch 12 Loss 1.2355 Accuracy 0.7229
Epoch 13 Loss 1.1699 Accuracy 0.7315
Epoch 14 Loss 1.1298 Accuracy 0.7370
Epoch 15 Loss 1.0670 Accuracy 0.7472
Epoch 16 Loss 1.0007 Accuracy 0.7582
Epoch 17 Loss 0.9419 Accuracy 0.7684
Epoch 18 Loss 0.8918 Accuracy 0.7771
Epoch 19 Loss 0.8425 Accuracy 0.7866
Epoch 20 Loss 0.7987 Accuracy 0.7944
```

In [129]:
```
transformer.summary()
```

```
Model: "transformer"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 encoder (Encoder)           multiple                  9586176

 decoder (Decoder)           multiple                  10640896

 dense_67 (Dense)            multiple                  3597486

=================================================================
Total params: 23824558 (90.88 MB)
Trainable params: 23824558 (90.88 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [130]:
```
# save model
# save tokenizer
transformer.save("transformer")
```

```
WARNING:absl:<__main__.MultiHeadAttention object at 0x7e82eb41ccd0> has th
e same name 'MultiHeadAttention' as a built-in Keras object. Consider rena
ming <class '__main__.MultiHeadAttention'> to avoid naming conflicts when
loading with `tf.keras.models.load_model`. If renaming is not possible, pa
ss the object in the `custom_objects` parameter of the load function.
WARNING:absl:<__main__.MultiHeadAttention object at 0x7e829981c3a0> has th
e same name 'MultiHeadAttention' as a built-in Keras object. Consider rena
ming <class '__main__.MultiHeadAttention'> to avoid naming conflicts when
loading with `tf.keras.models.load_model`. If renaming is not possible, pa
ss the object in the `custom_objects` parameter of the load function.
WARNING:absl:<__main__.MultiHeadAttention object at 0x7e82998603a0> has th
e same name 'MultiHeadAttention' as a built-in Keras object. Consider rena
ming <class '__main__.MultiHeadAttention'> to avoid naming conflicts when
loading with `tf.keras.models.load_model`. If renaming is not possible, pa
ss the object in the `custom_objects` parameter of the load function.
WARNING:absl:<__main__.MultiHeadAttention object at 0x7e8299862f20> has th
e same name 'MultiHeadAttention' as a built-in Keras object. Consider rena
ming <class '__main__.MultiHeadAttention'> to avoid naming conflicts when
loading with `tf.keras.models.load_model`. If renaming is not possible, pa
ss the object in the `custom_objects` parameter of the load function.
WARNING:absl:<__main__.MultiHeadAttention object at 0x7e829984a890> has th
e same name 'MultiHeadAttention' as a built-in Keras object. Consider rena
ming <class '__main__.MultiHeadAttention'> to avoid naming conflicts when
loading with `tf.keras.models.load_model`. If renaming is not possible, pa
ss the object in the `custom_objects` parameter of the load function.
WARNING:absl:<__main__.MultiHeadAttention object at 0x7e829984be80> has th
e same name 'MultiHeadAttention' as a built-in Keras object. Consider rena
ming <class '__main__.MultiHeadAttention'> to avoid naming conflicts when
loading with `tf.keras.models.load_model`. If renaming is not possible, pa
ss the object in the `custom_objects` parameter of the load function.
WARNING:absl:<__main__.MultiHeadAttention object at 0x7e829984ef20> has th
e same name 'MultiHeadAttention' as a built-in Keras object. Consider rena
ming <class '__main__.MultiHeadAttention'> to avoid naming conflicts when
loading with `tf.keras.models.load_model`. If renaming is not possible, pa
ss the object in the `custom_objects` parameter of the load function.
WARNING:absl:<__main__.MultiHeadAttention object at 0x7e8299870550> has th
e same name 'MultiHeadAttention' as a built-in Keras object. Consider rena
ming <class '__main__.MultiHeadAttention'> to avoid naming conflicts when
loading with `tf.keras.models.load_model`. If renaming is not possible, pa
ss the object in the `custom_objects` parameter of the load function.
WARNING:absl:<__main__.MultiHeadAttention object at 0x7e82998735b0> has th
e same name 'MultiHeadAttention' as a built-in Keras object. Consider rena
ming <class '__main__.MultiHeadAttention'> to avoid naming conflicts when
loading with `tf.keras.models.load_model`. If renaming is not possible, pa
ss the object in the `custom_objects` parameter of the load function.
WARNING:absl:<__main__.MultiHeadAttention object at 0x7e8299864be0> has th
e same name 'MultiHeadAttention' as a built-in Keras object. Consider rena
ming <class '__main__.MultiHeadAttention'> to avoid naming conflicts when
loading with `tf.keras.models.load_model`. If renaming is not possible, pa
ss the object in the `custom_objects` parameter of the load function.
WARNING:absl:<__main__.MultiHeadAttention object at 0x7e8299867c40> has th
e same name 'MultiHeadAttention' as a built-in Keras object. Consider rena
ming <class '__main__.MultiHeadAttention'> to avoid naming conflicts when
loading with `tf.keras.models.load_model`. If renaming is not possible, pa
ss the object in the `custom_objects` parameter of the load function.
WARNING:absl:<__main__.MultiHeadAttention object at 0x7e8299769270> has th
e same name 'MultiHeadAttention' as a built-in Keras object. Consider rena
ming <class '__main__.MultiHeadAttention'> to avoid naming conflicts when
loading with `tf.keras.models.load_model`. If renaming is not possible, pa
ss the object in the `custom_objects` parameter of the load function.
```

In [131]:
```
# transformer.load_weights("C:\\Users\\praba\\Downloads\\transformer\\varia
```

In [132]:
```
transformer.load_weights("transformer/variables/variables")
```

Out[132]:
```
<tensorflow.python.checkpoint.checkpoint.CheckpointLoadStatus at 0x7e835c2
121a0>
```

In [133]:
```
# .data-00000-of-00001
```

In [134]:
```
# Converting the input sequence to a tensor
text = "hi how are you"
text = "sos " + text.lower() + " eos"
inp_seq = pad_sequences(tokenizer_en.texts_to_sequences([text]), maxlen=10,
out_seq = tf.convert_to_tensor([[tokenizer_fr.word_index["sos"]]])
# Creating a mask for the input sequence
enc_padding_mask, combined_mask, dec_padding_mask = create_masks(inp_seq, o
# # Creating a mask for the output sequence
output_tokens = []
# # Looping until the maximum length of the output sequence is reached or t
for i in range(100):
    # Calling the Transformer model on the input and output sequences and m
    output, attn_weights = transformer(inp_seq, out_seq, False, enc_padding
    # Getting the last token from the output sequence
    last_token = output[:, -1:, :]
    # Getting the token with the highest probability from the last token
    predicted_token = tf.cast(tf.argmax(last_token, axis=-1), tf.int32)
    # Checking if the predicted token is the <end> token
    if predicted_token == tokenizer_fr.word_index["eos"]:
        break
    # Appending the predicted token to the output tokens list
    output_tokens.append(predicted_token[0][0].numpy())
    # Concatenating the predicted token to the output sequence
    out_seq = tf.concat([out_seq, predicted_token], axis=-1)
    # Updating the mask for the output sequence
    decoder_padding_mask, look_ahead_mask = create_padding_mask(out_seq), c
    combined_mask = tf.maximum(decoder_padding_mask, look_ahead_mask)
# Converting the output tokens list to a tensor
output_tokens = tf.convert_to_tensor([output_tokens])
# Detokenizing and decoding the output tokens to get the translation
# translation = tokenizer_fr.sequences_to_texts(output_tokens)[0]
```

In [135]:
```
tokenizer_fr.sequences_to_texts(output_tokens.numpy())
```

Out[135]:
```
['hola ¿cómo estás']
```

In [136]:
```
tokenizer_en.sequences_to_texts(inp_seq)
```

Out[136]:
```
['sos hi how are you eos']
```

In [136]:

In [136]:

Method-2- Transformer(import transformer from keras-nlp)

https://keras.io/guides/keras_nlp/transformer_pretraining/
(https://keras.io/guides/keras_nlp/transformer_pretraining/)

https://www.youtube.com/watch?
v=9t1Lr4luGqk&list=PLyFpZIg7OtNQHbWjyy_QApMOHhqvzS-9o&index=4&t=449s
(https://www.youtube.com/watch?
v=9t1Lr4luGqk&list=PLyFpZIg7OtNQHbWjyy_QApMOHhqvzS-9o&index=4&t=449s)

preprocessing

In [31]:
```
dataset = 'spa.txt'

data = pd.read_table(dataset)  # Read data from file into a DataFrame
```

In [32]:
```
data.columns = ["en", "sp","not_needed"]
# data.head(5)
```

In [33]:
```
df = data.iloc[:10000, [0, 1]]
# df =data
# df
```

In [154]:
```
```

In [34]:
```
import re
from unicodedata import normalize

# Function to clean text by removing non-alphabetic characters and normaliz
def clean_text(text):
    text = normalize('NFD', text.lower())
    text = re.sub('[^A-Za-z ]+', '', text)
    return text

# Function to clean and prepare text for sequence processing, adding start
def clean_and_prepare_text(text):
    text = '[start] ' + clean_text(text) + ' [end]'
    return text

# Apply cleaning and preparation functions to English and Spanish columns i
df['en'] = df['en'].apply(lambda row: clean_text(row))
df['sp'] = df['sp'].apply(lambda row: clean_and_prepare_text(row))

# Display the updated DataFrame
df.head()
```

Out[34]:

	en	sp
0	go	[start] vete [end]
1	go	[start] vaya [end]
2	go	[start] vayase [end]
3	hi	[start] hola [end]
4	run	[start] corre [end]

In [34]:

In [34]:

In [35]:
```
# Extract English and Spanish sentences from DataFrame columns
en = df['en']
sp = df['sp']

# Calculate maximum lengths of English and Spanish phrases
en_max_len = max(len(line.split()) for line in en)
sp_max_len = max(len(line.split()) for line in sp)

# Determine sequence length as the maximum of English and Spanish phrase le
sequence_len = max(en_max_len, sp_max_len)

# Print out the maximum phrase lengths and the determined sequence length
print(f'Max phrase length (English): {en_max_len}')
print(f'Max phrase length (Spanish): {sp_max_len}')
print(f'Sequence length: {sequence_len}')
```

```
Max phrase length (English): 5
Max phrase length (Spanish): 11
Sequence length: 11
```

In [36]:
```
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Tokenize English sentences
en_tokenizer = Tokenizer()
en_tokenizer.fit_on_texts(en)
en_sequences = en_tokenizer.texts_to_sequences(en)
en_x = pad_sequences(en_sequences, maxlen=sequence_len, padding='post')

# Tokenize Spanish sentences
# Set custom filters to include special characters like apostrophe (') in w
sp_tokenizer = Tokenizer(filters='!"#$%&()*+,-./:;<=>?@\\^_`{|}~\t\n')
sp_tokenizer.fit_on_texts(sp)
sp_sequences = sp_tokenizer.texts_to_sequences(sp)
# Pad Spanish sequences with an extra token to handle the decoder input
sp_y = pad_sequences(sp_sequences, maxlen=sequence_len + 1, padding='post')
```

In [36]:

In [37]:
```
# Calculate vocabulary sizes for English and Spanish using tokenizers
en_vocab_size = len(en_tokenizer.word_index) + 1
sp_vocab_size = len(sp_tokenizer.word_index) + 1

# Print out the vocabulary sizes for English and Spanish
print(f'Vocabulary size (English): {en_vocab_size}')
print(f'Vocabulary size (Spanish): {sp_vocab_size}')
```

```
Vocabulary size (English): 2241
Vocabulary size (Spanish): 4570
```

In [37]:

Finally, create the features and the labels the model will be trained with. The features are the padded English sequences and the padded spanish sequences minus the [end] tokens. The labels are the padded spanish sequences minus the [start] tokens. Package the features in a dictionary so they can be input to a model that accepts multiple inputs.

In [38]:
```
# Define inputs for the model, consisting of encoder input (English sequenc
inputs = { 'encoder_input': en_x, 'decoder_input': sp_y[:, :-1] }

# Define outputs for the model, consisting of decoder output (Spanish seque
outputs = sp_y[:, 1:]
```

In [38]:

Build and train a model

Now use Keras's functional API to define a model that includes a transformer encoder and a transformer decoder. The model accepts two inputs: padded English sequences for the encoder, and padded Spanish sequences for the decoder. The output from the decoder is fed to a softmax output layer for classification.

In [39]:
```
!pip install keras_nlp
```

```
Collecting keras_nlp
  Downloading keras_nlp-0.8.2-py3-none-any.whl (465 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 465.3/465.3 kB 5.4 MB/s eta
0:00:00
Collecting keras-core (from keras_nlp)
  Downloading keras_core-0.1.7-py3-none-any.whl (950 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 950.8/950.8 kB 10.3 MB/s eta
0:00:00
Requirement already satisfied: absl-py in /usr/local/lib/python3.10/dist-p
ackages (from keras_nlp) (1.4.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-pac
kages (from keras_nlp) (1.25.2)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist
-packages (from keras_nlp) (23.2)
Requirement already satisfied: regex in /usr/local/lib/python3.10/dist-pac
kages (from keras_nlp) (2023.12.25)
Requirement already satisfied: rich in /usr/local/lib/python3.10/dist-pack
ages (from keras_nlp) (13.7.1)
Requirement already satisfied: dm-tree in /usr/local/lib/python3.10/dist-p
ackages (from keras_nlp) (0.1.8)
Requirement already satisfied: kagglehub in /usr/local/lib/python3.10/dist
-packages (from keras_nlp) (0.2.0)
Collecting tensorflow-text (from keras_nlp)
  Downloading tensorflow_text-2.15.0-cp310-cp310-manylinux_2_17_x86_64.man
ylinux2014_x86_64.whl (5.2 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5.2/5.2 MB 20.5 MB/s eta 0:0
0:00
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-
packages (from kagglehub->keras_nlp) (2.31.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-pack
ages (from kagglehub->keras_nlp) (4.66.2)
Collecting namex (from keras-core->keras_nlp)
  Downloading namex-0.0.7-py3-none-any.whl (5.8 kB)
Requirement already satisfied: h5py in /usr/local/lib/python3.10/dist-pack
ages (from keras-core->keras_nlp) (3.9.0)
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/pyt
hon3.10/dist-packages (from rich->keras_nlp) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/p
ython3.10/dist-packages (from rich->keras_nlp) (2.16.1)
Requirement already satisfied: tensorflow-hub>=0.13.0 in /usr/local/lib/py
thon3.10/dist-packages (from tensorflow-text->keras_nlp) (0.16.1)
Requirement already satisfied: tensorflow<2.16,>=2.15.0 in /usr/local/lib/
python3.10/dist-packages (from tensorflow-text->keras_nlp) (2.15.0)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.10/dis
t-packages (from markdown-it-py>=2.2.0->rich->keras_nlp) (0.1.2)
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python
3.10/dist-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->keras_
nlp) (1.6.3)
Requirement already satisfied: flatbuffers>=23.5.26 in /usr/local/lib/pyth
on3.10/dist-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->kera
s_nlp) (23.5.26)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in /us
r/local/lib/python3.10/dist-packages (from tensorflow<2.16,>=2.15.0->tenso
rflow-text->keras_nlp) (0.5.4)
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/pytho
n3.10/dist-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->keras
_nlp) (0.2.0)
Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.
10/dist-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->keras_nl
p) (16.0.6)
Requirement already satisfied: ml-dtypes~=0.2.0 in /usr/local/lib/python3.
```

```
10/dist-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->keras_nl
p) (0.2.0)
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python
3.10/dist-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->keras_
nlp) (3.3.0)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.
3,!=4.21.4,!=4.21.5,<5.0.0dev,>=3.20.3 in /usr/local/lib/python3.10/dist-p
ackages (from tensorflow<2.16,>=2.15.0->tensorflow-text->keras_nlp) (3.20.
3)
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dis
t-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->keras_nlp) (6
7.7.2)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.10/di
st-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->keras_nlp)
(1.16.0)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.
10/dist-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->keras_nl
p) (2.4.0)
Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/
python3.10/dist-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->
keras_nlp) (4.10.0)
Requirement already satisfied: wrapt<1.15,>=1.11.0 in /usr/local/lib/pytho
n3.10/dist-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->keras
_nlp) (1.14.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /us
r/local/lib/python3.10/dist-packages (from tensorflow<2.16,>=2.15.0->tenso
rflow-text->keras_nlp) (0.36.0)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/pytho
n3.10/dist-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->keras
_nlp) (1.62.0)
Requirement already satisfied: tensorboard<2.16,>=2.15 in /usr/local/lib/p
ython3.10/dist-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->k
eras_nlp) (2.15.2)
Requirement already satisfied: tensorflow-estimator<2.16,>=2.15.0 in /usr/
local/lib/python3.10/dist-packages (from tensorflow<2.16,>=2.15.0->tensorf
low-text->keras_nlp) (2.15.0)
Requirement already satisfied: keras<2.16,>=2.15.0 in /usr/local/lib/pytho
n3.10/dist-packages (from tensorflow<2.16,>=2.15.0->tensorflow-text->keras
_nlp) (2.15.0)
Requirement already satisfied: tf-keras>=2.14.1 in /usr/local/lib/python3.
10/dist-packages (from tensorflow-hub>=0.13.0->tensorflow-text->keras_nlp)
(2.15.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/
python3.10/dist-packages (from requests->kagglehub->keras_nlp) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/d
ist-packages (from requests->kagglehub->keras_nlp) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python
3.10/dist-packages (from requests->kagglehub->keras_nlp) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python
3.10/dist-packages (from requests->kagglehub->keras_nlp) (2024.2.2)
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python
3.10/dist-packages (from astunparse>=1.6.0->tensorflow<2.16,>=2.15.0->tens
orflow-text->keras_nlp) (0.42.0)
Requirement already satisfied: google-auth<3,>=1.6.3 in /usr/local/lib/pyt
hon3.10/dist-packages (from tensorboard<2.16,>=2.15->tensorflow<2.16,>=2.1
5.0->tensorflow-text->keras_nlp) (2.27.0)
Requirement already satisfied: google-auth-oauthlib<2,>=0.5 in /usr/local/
lib/python3.10/dist-packages (from tensorboard<2.16,>=2.15->tensorflow<2.1
6,>=2.15.0->tensorflow-text->keras_nlp) (1.2.0)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.1
0/dist-packages (from tensorboard<2.16,>=2.15->tensorflow<2.16,>=2.15.0->t
```

```
ensorflow-text->keras_nlp) (3.5.2)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /u
sr/local/lib/python3.10/dist-packages (from tensorboard<2.16,>=2.15->tenso
rflow<2.16,>=2.15.0->tensorflow-text->keras_nlp) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.1
0/dist-packages (from tensorboard<2.16,>=2.15->tensorflow<2.16,>=2.15.0->t
ensorflow-text->keras_nlp) (3.0.1)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /usr/local/lib/py
thon3.10/dist-packages (from google-auth<3,>=1.6.3->tensorboard<2.16,>=2.1
5->tensorflow<2.16,>=2.15.0->tensorflow-text->keras_nlp) (5.3.3)
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/pyt
hon3.10/dist-packages (from google-auth<3,>=1.6.3->tensorboard<2.16,>=2.15
->tensorflow<2.16,>=2.15.0->tensorflow-text->keras_nlp) (0.3.0)
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.10/
dist-packages (from google-auth<3,>=1.6.3->tensorboard<2.16,>=2.15->tensor
flow<2.16,>=2.15.0->tensorflow-text->keras_nlp) (4.9)
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/
python3.10/dist-packages (from google-auth-oauthlib<2,>=0.5->tensorboard<
2.16,>=2.15->tensorflow<2.16,>=2.15.0->tensorflow-text->keras_nlp) (1.3.1)
Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python
3.10/dist-packages (from werkzeug>=1.0.1->tensorboard<2.16,>=2.15->tensorf
low<2.16,>=2.15.0->tensorflow-text->keras_nlp) (2.1.5)
Requirement already satisfied: pyasn1<0.6.0,>=0.4.6 in /usr/local/lib/pyth
on3.10/dist-packages (from pyasn1-modules>=0.2.1->google-auth<3,>=1.6.3->t
ensorboard<2.16,>=2.15->tensorflow<2.16,>=2.15.0->tensorflow-text->keras_n
lp) (0.5.1)
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.1
0/dist-packages (from requests-oauthlib>=0.7.0->google-auth-oauthlib<2,>=
0.5->tensorboard<2.16,>=2.15->tensorflow<2.16,>=2.15.0->tensorflow-text->k
eras_nlp) (3.2.2)
Installing collected packages: namex, keras-core, tensorflow-text, keras_n
lp
Successfully installed keras-core-0.1.7 keras_nlp-0.8.2 namex-0.0.7 tensor
flow-text-2.15.0
```

In [40]:

```
import keras_nlp
import numpy as np
import tensorflow as tf
from tensorflow.keras import Model
from tensorflow.keras.layers import Input, Dense, Dropout
from keras_nlp.layers import TokenAndPositionEmbedding, TransformerEncoder
from keras_nlp.layers import TransformerDecoder
import numpy as np
import tensorflow as tf
from tensorflow.keras.layers import Input, Dense, Dropout
# from transformer_layers import TokenAndPositionEmbedding, TransformerEnco
```

```
Using TensorFlow backend
```

In [41]:
```
import numpy as np
import tensorflow as tf
from tensorflow.keras import Model
from tensorflow.keras.layers import Input, Dense, Dropout
from keras_nlp.layers import TokenAndPositionEmbedding, TransformerEncoder
from keras_nlp.layers import TransformerDecoder

np.random.seed(42)
tf.random.set_seed(42)

num_heads = 8
embed_dim = 256

encoder_input = Input(shape=(None,), dtype='int64', name='encoder_input')
x = TokenAndPositionEmbedding(en_vocab_size, sequence_len, embed_dim)(encod
encoder_output = TransformerEncoder(embed_dim, num_heads)(x)
encoded_seq_input = Input(shape=(None, embed_dim))

decoder_input = Input(shape=(None,), dtype='int64', name='decoder_input')
x = TokenAndPositionEmbedding(sp_vocab_size, sequence_len, embed_dim, mask_
x = TransformerDecoder(embed_dim, num_heads)(x, encoded_seq_input)
x = Dropout(0.4)(x)

decoder_output = Dense(sp_vocab_size, activation='softmax')(x)
decoder = Model([decoder_input, encoded_seq_input], decoder_output)
decoder_output = decoder([decoder_input, encoder_output])

model = Model([encoder_input, decoder_input], decoder_output)
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', met
model.summary(line_length=120)
```

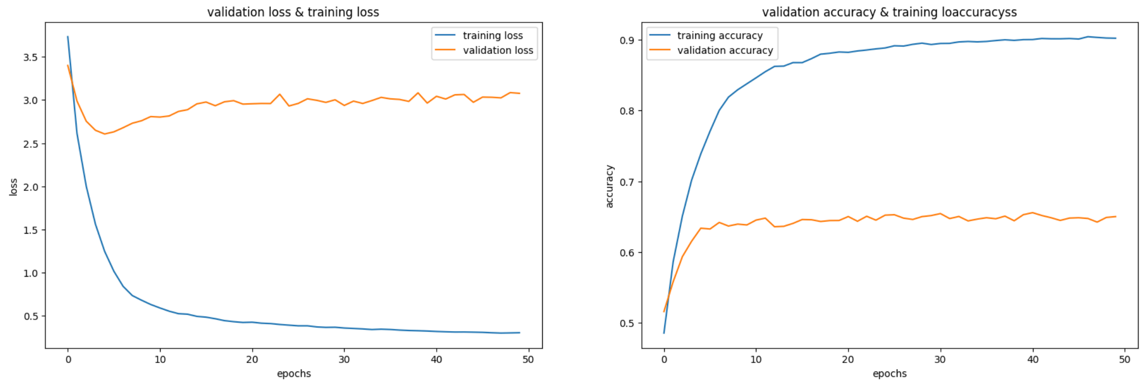
```
Model: "model_3"
____________________________________________________________________________
__________________________________________________
 Layer (type)                   Output Shape                      Pa
ram #     Connected to
============================================================================
==============================================
 encoder_input (InputLayer)     [(None, None)]                   0
[]

 token_and_position_embedding (Tok  (None, None, 256)             57
6512      ['encoder_input[0][0]']
 enAndPositionEmbedding)

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

 transformer_encoder (TransformerE  (None, None, 256)             39
5776      ['token_and_position_embedding[0][0]
 ncoder)
']

 model_2 (Functional)           (None, None, 4570)                30
06682     ['decoder_input[0][0]',

'transformer_encoder[0][0]']

============================================================================
==============================================
Total params: 3978970 (15.18 MB)
Trainable params: 3978970 (15.18 MB)
Non-trainable params: 0 (0.00 Byte)
____________________________________________________________________________
__________________________________________________
```

In [42]:

```python
hist = model.fit(inputs, outputs, epochs=50, validation_split=0.2)
```

```
Epoch 1/50
250/250 [==============================] - 77s 245ms/step - loss: 3.732
6 - accuracy: 0.4856 - val_loss: 3.3995 - val_accuracy: 0.5160
Epoch 2/50
250/250 [==============================] - 49s 198ms/step - loss: 2.611
6 - accuracy: 0.5862 - val_loss: 2.9868 - val_accuracy: 0.5580
Epoch 3/50
250/250 [==============================] - 48s 192ms/step - loss: 2.002
1 - accuracy: 0.6507 - val_loss: 2.7544 - val_accuracy: 0.5935
Epoch 4/50
250/250 [==============================] - 72s 287ms/step - loss: 1.561
4 - accuracy: 0.7014 - val_loss: 2.6488 - val_accuracy: 0.6152
Epoch 5/50
250/250 [==============================] - 55s 220ms/step - loss: 1.246
1 - accuracy: 0.7386 - val_loss: 2.6058 - val_accuracy: 0.6337
Epoch 6/50
250/250 [==============================] - 60s 239ms/step - loss: 1.016
3 - accuracy: 0.7705 - val_loss: 2.6307 - val_accuracy: 0.6325
Epoch 7/50
```

In [43]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(20, 6))
# Plot the first subplot  loss)
plt.subplot(1, 2, 1)  # 1 row, 2 columns, first subplot
plt.plot(hist.history["loss"])
plt.plot(hist.history["val_loss"])
plt.title("validation loss & training loss")
plt.xlabel("epochs")
plt.ylabel("loss")
leg = plt.legend(["training loss", "validation loss"],loc ="upper right");

# Plot the second subplot ( accuracy)
plt.subplot(1, 2, 2)  # 1 row, 2 columns, second subplot
plt.plot(hist.history["accuracy"])
plt.plot(hist.history["val_accuracy"])
plt.title("validation accuracy & training loaccuracyss")
plt.xlabel("epochs")
plt.ylabel("accuracy")
leg = plt.legend(["training accuracy", "validation accuracy"],loc ="upper l

plt.show()
```



Use the model to translate text

In [44]:
```
def translate_text(text, model, en_tokenizer, sp_tokenizer, sp_index_lookup
    # Tokenize input text
    input_sequence = en_tokenizer.texts_to_sequences([text])
    # Pad input sequence
    padded_input_sequence = pad_sequences(input_sequence, maxlen=sequence_l
    # Initialize decoded text with start token
    decoded_text = '[start]'

    # Iterate over sequence length
    for i in range(sequence_len):
        # Tokenize decoded text
        target_sequence = sp_tokenizer.texts_to_sequences([decoded_text])
        # Pad decoded text sequence
        padded_target_sequence = pad_sequences(target_sequence, maxlen=sequ

        # Generate prediction using the model
        prediction = model([padded_input_sequence, padded_target_sequence])

        # Get index of highest probability token
        idx = np.argmax(prediction[0, i, :]) - 1
        # Lookup token in index
        token = sp_index_lookup[idx]
        # Append token to decoded text
        decoded_text += ' ' + token

        # Break loop if end token is predicted
        if token == '[end]':
            break

    # Remove start and end tokens from decoded text
    return decoded_text[8:-6]  # Remove [start] and [end] tokens

# Create a dictionary to look up tokens from their index
sp_vocab = sp_tokenizer.word_index
sp_index_lookup = dict(zip(range(len(sp_vocab)), sp_vocab))
# Select a subset of English texts for translation
texts = en[40000:40010].values

# Iterate over selected English texts and translate them
for text in texts:
    translated = translate_text(text, model, en_tokenizer, sp_tokenizer, sp
    print(f'{text} => {translated}')
```

In [45]:
```
# Translate the input text using the translate_text function
translated_text = translate_text('hi how are you', model, en_tokenizer, sp_
print(translated_text)
```

```
hola que estas
```

Perfectly translating

In [45]:

Method-3- HuggingFace Transformer

[https://huggingface.co/Helsinki-NLP/opus-mt-tc-big-en-es (https://huggingface.co/Helsinki-NLP/opus-mt-tc-big-en-es)](https://huggingface.co/Helsinki-NLP/opus-mt-tc-big-en-es)

In [46]:

```
from transformers import pipeline

# Init translator
translator = pipeline("translation", model="Helsinki-NLP/opus-mt-tc-big-en-

# Translate text
text = "Hello! How are you doing today?"
translation = translator(text)

# Print translation
print(translation)
```

```
/usr/local/lib/python3.10/dist-packages/huggingface_hub/utils/_token.py:8
8: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings
tab (https://huggingface.co/settings/tokens), set it as secret in your Goo
gle Colab and restart your session.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to acces
s public models or datasets.
  warnings.warn(

config.json:   0%|          | 0.00/1.08k [00:00<?, ?B/s]

model.safetensors:   0%|          | 0.00/466M [00:00<?, ?B/s]

generation_config.json:   0%|          | 0.00/301 [00:00<?, ?B/s]

tokenizer_config.json:   0%|          | 0.00/337 [00:00<?, ?B/s]

source.spm:   0%|          | 0.00/804k [00:00<?, ?B/s]

target.spm:   0%|          | 0.00/824k [00:00<?, ?B/s]

vocab.json:   0%|          | 0.00/1.38M [00:00<?, ?B/s]

special_tokens_map.json:   0%|          | 0.00/65.0 [00:00<?, ?B/s]

/usr/local/lib/python3.10/dist-packages/transformers/models/marian/tokeniz
ation_marian.py:197: UserWarning: Recommended: pip install sacremoses.
  warnings.warn("Recommended: pip install sacremoses.")

[{'translation_text': 'Hola, ¿cómo estás hoy?'}]
```

In [47]:
```
# Translate text
text = "Hi, I am a student"
translation = translator(text)

# Print translation
print(translation)
```

```
[{'translation_text': 'Hola, soy estudiante'}]
```

In [ ]:

Normal seq2seq is performing suboptimally with just 10,000 data points. Seq2Seq with attention yields slightly better prediction accuracy. However, the Transformer model, built from scratch and trained on the entire dataset, excels in translating English to Spanish with remarkable proficiency. Also the Haggingface transformer and the transformer using keras-nlp is working fine.

In [ ]: