AhmedHesham_EnglishArabicTranslation

August 30, 2023

```
[1]: !pip install datasets
     !pip install dataset
     !pip install transformers
     !pip install sacrebleu
     !pip install SentencePiece
     !pip install transformers[torch]
    Collecting datasets
      Downloading datasets-2.14.4-py3-none-any.whl (519 kB)
                               519.3/519.3
    kB 6.3 MB/s eta 0:00:00
    Requirement already satisfied: numpy>=1.17 in
    /usr/local/lib/python3.10/dist-packages (from datasets) (1.23.5)
    Requirement already satisfied: pyarrow>=8.0.0 in /usr/local/lib/python3.10/dist-
    packages (from datasets) (9.0.0)
    Collecting dill<0.3.8,>=0.3.0 (from datasets)
      Downloading dill-0.3.7-py3-none-any.whl (115 kB)
                              115.3/115.3 kB
    13.4 MB/s eta 0:00:00
    Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-
    packages (from datasets) (1.5.3)
    Requirement already satisfied: requests>=2.19.0 in
    /usr/local/lib/python3.10/dist-packages (from datasets) (2.31.0)
    Requirement already satisfied: tqdm>=4.62.1 in /usr/local/lib/python3.10/dist-
    packages (from datasets) (4.66.1)
    Collecting xxhash (from datasets)
      Downloading
    xxhash-3.3.0-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (194 kB)
                              194.1/194.1 kB
    21.8 MB/s eta 0:00:00
    Collecting multiprocess (from datasets)
      Downloading multiprocess-0.70.15-py310-none-any.whl (134 kB)
                              134.8/134.8 kB
    12.6 MB/s eta 0:00:00
    Requirement already satisfied: fsspec[http]>=2021.11.1 in
    /usr/local/lib/python3.10/dist-packages (from datasets) (2023.6.0)
    Requirement already satisfied: aiohttp in /usr/local/lib/python3.10/dist-
```

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packages (from datasets) (3.8.5)
Collecting huggingface-hub<1.0.0,>=0.14.0 (from datasets)
  Downloading huggingface_hub-0.16.4-py3-none-any.whl (268 kB)
                          268.8/268.8 kB
18.5 MB/s eta 0:00:00
Requirement already satisfied: packaging in
/usr/local/lib/python3.10/dist-packages (from datasets) (23.1)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.10/dist-
packages (from datasets) (6.0.1)
Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.10/dist-
packages (from aiohttp->datasets) (23.1.0)
Requirement already satisfied: charset-normalizer<4.0,>=2.0 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (3.2.0)
Requirement already satisfied: multidict<7.0,>=4.5 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (6.0.4)
Requirement already satisfied: async-timeout<5.0,>=4.0.0a3 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (4.0.3)
Requirement already satisfied: yarl<2.0,>=1.0 in /usr/local/lib/python3.10/dist-
packages (from aiohttp->datasets) (1.9.2)
Requirement already satisfied: frozenlist>=1.1.1 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (1.4.0)
Requirement already satisfied: aiosignal>=1.1.2 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (1.3.1)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-
packages (from huggingface-hub<1.0.0,>=0.14.0->datasets) (3.12.2)
Requirement already satisfied: typing-extensions>=3.7.4.3 in
/usr/local/lib/python3.10/dist-packages (from huggingface-
hub<1.0.0,>=0.14.0->datasets) (4.7.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
packages (from requests>=2.19.0->datasets) (3.4)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->datasets)
(2.0.4)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->datasets)
(2023.7.22)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/dist-packages (from pandas->datasets) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas->datasets) (2023.3)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
packages (from python-dateutil>=2.8.1->pandas->datasets) (1.16.0)
Installing collected packages: xxhash, dill, multiprocess, huggingface-hub,
datasets
Successfully installed datasets-2.14.4 dill-0.3.7 huggingface-hub-0.16.4
multiprocess-0.70.15 xxhash-3.3.0
Collecting dataset
  Downloading dataset-1.6.2-py2.py3-none-any.whl (18 kB)
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Collecting sqlalchemy<2.0.0,>=1.3.2 (from dataset)
 Downloading SQLAlchemy-1.4.49-cp310-cp310-
manylinux 2 5 x86 64.manylinux1 x86 64.manylinux 2 17 x86 64.manylinux2014 x86 6
4.whl (1.6 MB)
                           1.6/1.6 MB
7.1 MB/s eta 0:00:00
Collecting alembic>=0.6.2 (from dataset)
 Downloading alembic-1.11.3-py3-none-any.whl (225 kB)
                           225.4/225.4
kB 7.7 MB/s eta 0:00:00
Collecting banal>=1.0.1 (from dataset)
  Downloading banal-1.0.6-py2.py3-none-any.whl (6.1 kB)
Collecting Mako (from alembic>=0.6.2->dataset)
 Downloading Mako-1.2.4-py3-none-any.whl (78 kB)
                           78.7/78.7 kB
10.6 MB/s eta 0:00:00
Requirement already satisfied: typing-extensions>=4 in
/usr/local/lib/python3.10/dist-packages (from alembic>=0.6.2->dataset) (4.7.1)
Requirement already satisfied: greenlet!=0.4.17 in
/usr/local/lib/python3.10/dist-packages (from sqlalchemy<2.0.0,>=1.3.2->dataset)
(2.0.2)
Requirement already satisfied: MarkupSafe>=0.9.2 in
/usr/local/lib/python3.10/dist-packages (from Mako->alembic>=0.6.2->dataset)
(2.1.3)
Installing collected packages: banal, sqlalchemy, Mako, alembic, dataset
  Attempting uninstall: sqlalchemy
   Found existing installation: SQLAlchemy 2.0.20
   Uninstalling SQLAlchemy-2.0.20:
      Successfully uninstalled SQLAlchemy-2.0.20
ERROR: pip's dependency resolver does not currently take into account all
the packages that are installed. This behaviour is the source of the following
dependency conflicts.
ipython-sql 0.5.0 requires sqlalchemy>=2.0, but you have sqlalchemy 1.4.49 which
is incompatible.
Successfully installed Mako-1.2.4 alembic-1.11.3 banal-1.0.6 dataset-1.6.2
sqlalchemy-1.4.49
Collecting transformers
 Downloading transformers-4.32.1-py3-none-any.whl (7.5 MB)
                           7.5/7.5 \text{ MB}
50.0 MB/s eta 0:00:00
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-
packages (from transformers) (3.12.2)
Requirement already satisfied: huggingface-hub<1.0,>=0.15.1 in
/usr/local/lib/python3.10/dist-packages (from transformers) (0.16.4)
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Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-
packages (from transformers) (1.23.5)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from transformers) (23.1)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.10/dist-
packages (from transformers) (6.0.1)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.10/dist-packages (from transformers) (2023.6.3)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-
packages (from transformers) (2.31.0)
Collecting tokenizers!=0.11.3,<0.14,>=0.11.1 (from transformers)
  Downloading
tokenizers-0.13.3-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl
(7.8 MB)
                           7.8/7.8 MB
107.8 MB/s eta 0:00:00
Collecting safetensors>=0.3.1 (from transformers)
 Downloading
safetensors-0.3.3-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl
(1.3 MB)
                           1.3/1.3 MB
68.3 MB/s eta 0:00:00
Requirement already satisfied: tqdm>=4.27 in
/usr/local/lib/python3.10/dist-packages (from transformers) (4.66.1)
Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages
(from huggingface-hub<1.0,>=0.15.1->transformers) (2023.6.0)
Requirement already satisfied: typing-extensions>=3.7.4.3 in
/usr/local/lib/python3.10/dist-packages (from huggingface-
hub<1.0,>=0.15.1->transformers) (4.7.1)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers) (3.2.0)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
packages (from requests->transformers) (3.4)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers) (2.0.4)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->transformers)
(2023.7.22)
Installing collected packages: tokenizers, safetensors, transformers
Successfully installed safetensors-0.3.3 tokenizers-0.13.3 transformers-4.32.1
Collecting sacrebleu
  Downloading sacrebleu-2.3.1-py3-none-any.whl (118 kB)
                           118.9/118.9
kB 2.5 MB/s eta 0:00:00
Collecting portalocker (from sacrebleu)
  Downloading portalocker-2.7.0-py2.py3-none-any.whl (15 kB)
Requirement already satisfied: regex in /usr/local/lib/python3.10/dist-packages
```

```
(from sacrebleu) (2023.6.3)
Requirement already satisfied: tabulate>=0.8.9 in
/usr/local/lib/python3.10/dist-packages (from sacrebleu) (0.9.0)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-
packages (from sacrebleu) (1.23.5)
Collecting colorama (from sacrebleu)
  Downloading colorama-0.4.6-py2.py3-none-any.whl (25 kB)
Requirement already satisfied: lxml in /usr/local/lib/python3.10/dist-packages
(from sacrebleu) (4.9.3)
Installing collected packages: portalocker, colorama, sacrebleu
Successfully installed colorama-0.4.6 portalocker-2.7.0 sacrebleu-2.3.1
Collecting SentencePiece
  Downloading
sentencepiece-0.1.99-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl
(1.3 MB)
                           1.3/1.3 MB
9.0 MB/s eta 0:00:00
Installing collected packages: SentencePiece
Successfully installed SentencePiece-0.1.99
Requirement already satisfied: transformers[torch] in
/usr/local/lib/python3.10/dist-packages (4.32.1)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-
packages (from transformers[torch]) (3.12.2)
Requirement already satisfied: huggingface-hub<1.0,>=0.15.1 in
/usr/local/lib/python3.10/dist-packages (from transformers[torch]) (0.16.4)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-
packages (from transformers[torch]) (1.23.5)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from transformers[torch]) (23.1)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.10/dist-
packages (from transformers[torch]) (6.0.1)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.10/dist-packages (from transformers[torch]) (2023.6.3)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-
packages (from transformers[torch]) (2.31.0)
Requirement already satisfied: tokenizers!=0.11.3,<0.14,>=0.11.1 in
/usr/local/lib/python3.10/dist-packages (from transformers[torch]) (0.13.3)
Requirement already satisfied: safetensors>=0.3.1 in
/usr/local/lib/python3.10/dist-packages (from transformers[torch]) (0.3.3)
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.10/dist-
packages (from transformers[torch]) (4.66.1)
Requirement already satisfied: torch!=1.12.0,>=1.9 in
/usr/local/lib/python3.10/dist-packages (from transformers[torch]) (2.0.1+cu118)
Collecting accelerate>=0.20.3 (from transformers[torch])
 Downloading accelerate-0.22.0-py3-none-any.whl (251 kB)
                          251.2/251.2
```

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Requirement already satisfied: psutil in /usr/local/lib/python3.10/dist-
    packages (from accelerate>=0.20.3->transformers[torch]) (5.9.5)
    Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages
    (from huggingface-hub<1.0,>=0.15.1->transformers[torch]) (2023.6.0)
    Requirement already satisfied: typing-extensions>=3.7.4.3 in
    /usr/local/lib/python3.10/dist-packages (from huggingface-
    hub<1.0,>=0.15.1->transformers[torch]) (4.7.1)
    Requirement already satisfied: sympy in /usr/local/lib/python3.10/dist-packages
    (from torch!=1.12.0,>=1.9->transformers[torch]) (1.12)
    Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-
    packages (from torch!=1.12.0,>=1.9->transformers[torch]) (3.1)
    Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages
    (from torch!=1.12.0,>=1.9->transformers[torch]) (3.1.2)
    Requirement already satisfied: triton==2.0.0 in /usr/local/lib/python3.10/dist-
    packages (from torch!=1.12.0,>=1.9->transformers[torch]) (2.0.0)
    Requirement already satisfied: cmake in /usr/local/lib/python3.10/dist-packages
    (from triton==2.0.0->torch!=1.12.0,>=1.9->transformers[torch]) (3.27.2)
    Requirement already satisfied: lit in /usr/local/lib/python3.10/dist-packages
    (from triton==2.0.0->torch!=1.12.0,>=1.9->transformers[torch]) (16.0.6)
    Requirement already satisfied: charset-normalizer<4,>=2 in
    /usr/local/lib/python3.10/dist-packages (from requests->transformers[torch])
    (3.2.0)
    Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
    packages (from requests->transformers[torch]) (3.4)
    Requirement already satisfied: urllib3<3,>=1.21.1 in
    /usr/local/lib/python3.10/dist-packages (from requests->transformers[torch])
    (2.0.4)
    Requirement already satisfied: certifi>=2017.4.17 in
    /usr/local/lib/python3.10/dist-packages (from requests->transformers[torch])
    (2023.7.22)
    Requirement already satisfied: MarkupSafe>=2.0 in
    /usr/local/lib/python3.10/dist-packages (from
    jinja2->torch!=1.12.0,>=1.9->transformers[torch]) (2.1.3)
    Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.10/dist-
    packages (from sympy->torch!=1.12.0,>=1.9->transformers[torch]) (1.3.0)
    Installing collected packages: accelerate
    Successfully installed accelerate-0.22.0
[2]: import pandas as pd
     import numpy as np
     import re
     import string
     import warnings
     from collections import Counter
     from unicodedata import normalize
     from scipy.stats import pearsonr
```

```
import tensorflow as tf
     import torch
     import torch.nn.functional as F
     from sklearn.model_selection import train_test_split
     from keras.models import Sequential, Model, load_model
     from keras.layers import LSTM, Dense, Embedding, RepeatVector, TimeDistributed,
      →Bidirectional, Dropout, Input
     from keras.preprocessing.text import Tokenizer
     from keras.preprocessing.sequence import pad_sequences
     from keras.utils import pad_sequences, to_categorical
     from keras.callbacks import EarlyStopping
     from keras.optimizers import Adam
     from tensorflow.keras.layers import Attention, Concatenate
     from transformers import MT5ForConditionalGeneration, T5Tokenizer,
      ⊸TrainingArguments, Trainer, MBartForConditionalGeneration, MBartTokenizer, ⊔
      →MarianTokenizer, MarianMTModel
     from torch.utils.data import Dataset
     import nltk
     from nltk.util import ngrams
     from nltk.probability import FreqDist
     from nltk.corpus import stopwords
     from bidi.algorithm import get_display
     import arabic_reshaper
     import sacrebleu
     from nltk.translate.bleu score import corpus bleu, sentence bleu
     import matplotlib.pyplot as plt
     from wordcloud import WordCloud
     from IPython.display import Markdown, display
[3]: nltk.download('punkt')
     nltk.download('stopwords')
    [nltk_data] Downloading package punkt to /root/nltk_data...
    [nltk_data]
                  Unzipping tokenizers/punkt.zip.
    [nltk_data] Downloading package stopwords to /root/nltk_data...
    [nltk_data]
                  Unzipping corpora/stopwords.zip.
[3]: True
[4]: def clean_english_text(text):
        text = text.lower()
         text = re.sub(r'\n', '', text)
         text = re.sub(r'\d+', '', text)
         text = re.sub(f'[{string.punctuation}]', '', text)
```

```
text = re.sub(r'\s+', '', text)
   return text
def clean_arabic_text(text):
   text = re.sub("[]", "", text)
   text = re.sub(" ", "", text)
   text = re.sub("[ ]", "", text)
   text = re.sub(" ", " ", text)
   text = re.sub("[]", "", text)
   text = re.sub(" ", " ", text)
   text = re.sub(f'[{string.punctuation}]', '', text)
   text = re.sub(r'\d+', '', text)
   text = re.sub(r'[^\s -]', '', text)
   return text
df = pd.read_csv("ara_eng.txt", delimiter="\t", names=["english", "arabic"])
df.dropna(inplace=True)
english_sentences = df['english'].tolist()
arabic_sentences = df['arabic'].tolist()
df['arabic_length'] = df['arabic'].apply(lambda x: len(x.split()))
df['english_length'] = df['english'].apply(lambda x: len(x.split()))
english_sentences_clean = [clean_english_text(sentence) for sentence in_
 ⇔english sentences]
arabic_sentences_clean = [clean_arabic_text(sentence) for sentence in_u
 ⇔arabic_sentences]
zero_length_english_indices = [i for i, sentence in_
 -enumerate(english_sentences_clean) if len(sentence.split()) == 0]
zero_length_arabic_indices = [i for i, sentence in_
 →enumerate(arabic_sentences_clean) if len(sentence.split()) == 0]
indices_to_remove = set(zero_length_english_indices +_
 ⇒zero_length_arabic_indices)
english_sentences_clean = ["<bos> " + sentence + " <eos>"for i, sentence in_u
 -enumerate(english_sentences_clean) if i not in indices_to_remove]
arabic_sentences_clean = ["<bos> " + sentence + " <eos>"for i, sentence in_
 Genumerate(arabic_sentences_clean) if i not in indices_to_remove]
```

```
[10]: portion_length = int(0.4 * len(arabic_sentences_clean))
arabic_sentences_clean = arabic_sentences_clean[:portion_length]
english_sentences_clean = english_sentences_clean[:portion_length]
```

```
test_proportion = 0.1
train_test_threshold = int((1 - test_proportion) * len(arabic_sentences_clean))
train_ar, test_ar = arabic_sentences_clean[:train_test_threshold],__
 →arabic_sentences_clean[train_test_threshold:]
train en, test en = english sentences clean[:train test threshold],
 ⇔english sentences clean[train test threshold:]
def create_tokenizer(lines):
   tokenizer = Tokenizer()
   tokenizer.fit_on_texts(lines)
   return tokenizer
def max_len(lines):
   return max(len(line.split()) for line in lines)
def encode_sequences(tokenizer, length, lines):
   X = tokenizer.texts_to_sequences(lines)
   X = pad_sequences(X, maxlen=length, padding='post')
   return X
def encode_output(sequences, vocab_size):
   ylist = [to_categorical(sequence, num_classes=vocab_size) for sequence in_
 ⇒sequences]
   y = np.array(ylist)
   y = y.reshape(sequences.shape[0], sequences.shape[1], vocab_size)
   return y
tar_tokenizer = create_tokenizer(english_sentences_clean)
tar_vocab_size = len(tar_tokenizer.word_index) + 1
tar_length = max_len(english_sentences_clean)
src_tokenizer = create_tokenizer(arabic_sentences_clean)
src_vocab_size = len(src_tokenizer.word_index) + 1
src_length = max_len(arabic_sentences_clean)
trainX = encode_sequences(src_tokenizer, src_length, train_ar)
trainY = encode_sequences(tar_tokenizer, tar_length, train_en)
trainY = encode_output(trainY, tar_vocab_size)
testX = encode_sequences(src_tokenizer, src_length, test_ar)
testY = encode_sequences(tar_tokenizer, tar_length, test_en)
testY = encode_output(testY, tar_vocab_size)
```

1 Descriptive Analytics

1.1 Data Exploration:

```
[]: english_sentence_lengths = [len(sentence.split()) for sentence in_
      ⇔english_sentences_clean]
     arabic_sentence_lengths = [len(sentence.split()) for sentence in_{\sqcup}
      ⇔arabic_sentences_clean]
     english_vocab_size = len(tokenizer_eng.word_index) + 1
     arabic vocab size = len(tokenizer ar.word index) + 1
     avg_word_length_eng = np.mean([len(word) for sentence in_
      →english_sentences_clean for word in sentence.split()])
     avg word length ar = np.mean([len(word) for sentence in arabic sentences clean,

¬for word in sentence.split()])
     avg_words_per_sentence_eng = np.mean([len(sentence.split()) for sentence in_
      ⇔english_sentences_clean])
     avg_words_per_sentence_ar = np.mean([len(sentence.split()) for sentence in_
      →arabic_sentences_clean])
     print(f"English: \n Average word length: {avg_word_length_eng} \n Average_\( \)
      onumber of words per sentence: {avg_words_per_sentence_eng} \n Max sentence \_
      →length: {max(english_sentence_lengths)} \n Min sentence length:
      →{min(english_sentence_lengths)} \n Average sentence length:
      →{sum(english_sentence_lengths)/len(english_sentence_lengths)} \n Vocabulary

Size: {english_vocab_size}")
     print("\n")
     print(f"Arabic: \n Average word length: {avg_word_length_ar} \n Average number_
      of words per sentence: {avg_words_per_sentence_ar} \n Max sentence length:⊔
      →{max(arabic_sentence_lengths)} \n Min sentence length:
      ⇔{min(arabic_sentence_lengths)} \n Average sentence length:
      →{sum(arabic_sentence_lengths)/len(arabic_sentence_lengths)} \n Vocabulary
      ⇔Size: {arabic vocab size}")
    English:
     Average word length: 4.7768838806086995
     Average number of words per sentence: 17.62807971749807
     Max sentence length: 225
     Min sentence length: 1
     Average sentence length: 17.62807971749807
     Vocabulary Size: 25998
```

Arabic:

Average word length: 4.793183536782975

```
Average number of words per sentence: 15.029427284166092

Max sentence length: 225

Min sentence length: 1

Average sentence length: 15.029427284166092

Vocabulary Size: 52737

[]: correlation, _ = pearsonr(english_sentence_lengths, arabic_sentence_lengths)

print('Pearson correlation (correlation between english and arabic sentence_lengths): %.3f' % correlation)
```

Pearson correlation: 0.978

Findings based on the above statistics:

- The vocabulary size of Arabic is about twice as much as English. This isn't surprising considering Arabic is a morphologically rich language and tends to have more unique words due to variations in word forms.
- English sentences tend to be longer, which indicates that English translations might use more words to express the same concepts as in Arabic, or the English dataset could contain more detailed or elaborate sentences.
- The average word length for both English and Arabic sentences is quite close. This similarity might indicate that, in general, the complexity in terms of individual word length is comparable between the two languages in your dataset.

1.2 Word Frequency Analysis:

```
[]: stop_words_eng = set(stopwords.words('english'))
     stop_words_ar = set(nltk.corpus.stopwords.words("arabic"))
     english_word_lengths = [len(word) for word in nltk.word_tokenize(' '.
      →join(english_sentences_clean)) if word.lower() not in stop_words_eng]
     arabic_word_lengths = [len(word) for word in nltk.word_tokenize(' '.
      →join(arabic_sentences_clean)) if word not in stop_words_ar]
     english_word_length_freq = FreqDist(english_word_lengths)
     arabic_word_length_freq = FreqDist(arabic_word_lengths)
     english_most_common_word_lengths = english_word_length_freq.most_common(10)
     arabic_most_common_word_lengths = arabic_word_length_freq.most_common(10)
     num_unique_words_eng = len(set(word for sentence in english_sentences_clean for_
      ⇔word in sentence.split()))
     num_unique_words_ar = len(set(word for sentence in arabic_sentences_clean for_
      ⇔word in sentence.split()))
     english_word_freq = FreqDist(nltk.word_tokenize(' '.
      →join(english_sentences_clean)))
```

```
arabic_word_freq = FreqDist(nltk.word_tokenize(' '.
 ⇔join(arabic_sentences_clean)))
english rare words = [word for word, count in english word freq.items() if |
 \hookrightarrowcount == 1]
arabic_rare_words = [word for word, count in arabic_word_freq.items() if count__
 <sub>∽</sub>== 1]
english_sample_rare_words = english_rare_words[:10]
arabic_sample_rare_words = arabic_rare_words[:10]
freq dist eng no stopwords = FreqDist(word for sentence in ...
 ⇔stop_words_eng)
freq_dist_ar_no_stopwords = FreqDist(word for sentence in_
 →arabic_sentences_clean for word in sentence.split() if word not in_
⇔stop_words_ar)
english_most_common_no_stopwords = freq_dist_eng_no_stopwords.most_common(10)
arabic_most_common_no_stopwords = freq_dist_ar_no_stopwords.most_common(10)
freq_dist_eng = FreqDist(word for sentence in english_sentences_clean for word_
 →in sentence.split())
freq_dist_ar = FreqDist(word for sentence in arabic_sentences_clean for word in_
⇔sentence.split())
num_stop_words_eng = len([word for sentence in english_sentences_clean for word_
 →in sentence.split() if word in stop_words_eng])
english stop word counts = {word: freq dist eng[word] for word in_
stop_words_eng if word in freq_dist_eng}
most_common stop_words_eng = sorted(english_stop_word_counts.items(),_
 →key=lambda x: x[1], reverse=True)[:10]
num_stop_words_ar = len([word for sentence in arabic_sentences_clean for word_
→in sentence.split() if word in stop_words_ar])
arabic_stop_word_counts = {word: freq_dist_ar[word] for word in stop_words_ar_u

→if word in freq_dist_ar}
most_common_stop_words_ar = sorted(arabic_stop_word_counts.items(), key=lambda_
 \Rightarrowx: x[1], reverse=True)[:10]
def extract_ngrams(sentences, n):
   ngram_list = []
   for sentence in sentences:
       tokens = sentence.split()
       ngram_list.extend(list(nltk.ngrams(tokens, n)))
   return ngram_list
```

```
english bigrams = extract ngrams(english sentences clean, 2)
english_trigrams = extract_ngrams(english_sentences_clean, 3)
arabic_bigrams = extract_ngrams(arabic_sentences_clean, 2)
arabic_trigrams = extract_ngrams(arabic_sentences_clean, 3)
english_bigram_freq = nltk.FreqDist(english_bigrams)
english_trigram_freq = nltk.FreqDist(english_trigrams)
arabic bigram freq = nltk.FreqDist(arabic bigrams)
arabic_trigram_freq = nltk.FreqDist(arabic_trigrams)
print(f"English: \n Word length distribution:
 →{english_most_common_word_lengths} \n Number of unique words:
 → {num_unique_words_eng} \n Number of rare words: {len(english_rare_words)} \n_∪
  →Number of stop words: {num_stop_words_eng} \n Most common stop words: ⊔
 الله (most_common_stop_words_eng) \n Most common unique words(unigrams):
 →{english_most_common_no_stopwords} \n Sample of rare words:
 → {english_sample_rare_words} \n Most common bigrams: {english_bigram_freq.
 →most_common(10)} \n Most common trigrams: {english_trigram_freq.
 →most common(10)}")
print("\n")
print(f"Arabic: \n Word length distribution: {arabic_most_common_word_lengths}_u
 →\n Number of unique words: {num_unique_words_ar} \n Number of rare words: ⊔
 →{len(arabic_rare_words)} \n Number of stop words: {num_stop_words_ar} \n_⊔
 →Most common stop words: {most_common_stop_words_ar} \n Most common unique_
  words(unigrams): {arabic_most_common_no_stopwords} \n Sample of rare words
English:
 Word length distribution: [(6, 43059), (5, 41125), (4, 39546), (7, 35365), (8,
26764), (9, 17854), (3, 16163), (10, 11574), (11, 6310), (2, 5599)]
Number of unique words: 25997
Number of rare words: 11842
Number of stop words: 184508
Most common stop words: [('the', 23882), ('of', 11606), ('to', 11292), ('in',
9824), ('and', 9761), ('a', 9324), ('is', 5216), ('on', 4171), ('i', 4046),
('for', 3963)]
Most common unique words(unigrams): [('global', 2708), ('voices', 2691),
('people', 1035), ('one', 1012), ('tom', 971), ('like', 776), ('also', 761),
('new', 726), ('media', 721), ('world', 719)]
Sample of rare words: ['waved', 'unsure', 'yawned', 'discreet', 'merciful',
'windy', 'tvs', 'gawking', 'observant', 'lasagna']
Most common bigrams: [(('of', 'the'), 2775), (('global', 'voices'), 2532),
```

(('in', 'the'), 2033), (('to', 'the'), 1109), (('on', 'the'), 1030), (('for', 'the'), 632), (('is', 'a'), 578), (('and', 'the'), 559), (('from', 'the'), 544),

(('in', 'a'), 521)]

```
Most common trigrams: [(('one', 'of', 'the'), 205), (('used', 'with',
'permission'), 154), (('as', 'well', 'as'), 137), (('around', 'the', 'world'),
130), (('is', 'part', 'of'), 117), (('a', 'lot', 'of'), 101), (('this', 'post',
'is'), 100), (('part', 'of', 'our'), 99), (('post', 'is', 'part'), 96), (('our',
'special', 'coverage'), 91)]
Arabic:
Word length distribution: [(5, 63371), (4, 59634), (6, 52043), (7, 41089), (3,
34536), (8, 22076), (2, 9888), (9, 8078), (10, 3331), (11, 1233)]
 Number of unique words: 52736
Number of rare words: 28077
 Number of stop words: 74587
 Most common stop words: [(' ', 12661), (' ', 10929), (' ', 6542), (' ',
2895), (' ', 2030), (' ', 1997), (' ', 1784), (' ', 1720), (' ', 1467),
('', 1335)]
Most common unique words(unigrams): [(' ', 4361), (' ', 2826), ('
2817), (' ', 2733), (' ', 1031), (' ', 1029), (' ', 959),
(' ', 793), (' ', 768), (' ', 709)]
Sample of rare words: [' ', ' ', ' ', ' ', ' ', ' ', ' ',
' ', ' ', ' ', ' '[
Most common bigrams: [((' ', ' '(, 2637), ((' ', ' '(, 443), ((' ', ' '(, 347), ((' ', ' '(, 345), ((' ', ' '(, 317),
((' ', ' '(, 295), ((' ', ' '(, 241), ((' ', ' '(, 224), ((' ',
' '(, 224), ((' ', ' '(, 208)]
Most common trigrams: [((' ', ' ', ' ', 186), ((' ', ' ',
' '(, 180), ((' ', ' ', ' '(, 86), ((' ', ' ', ' '(,
85), ((' ', ' ', ' ', 84), ((' ', ' ', ' ', 76), ((' ',
' ', ' '(, 74), ((' ', ' ', ' ', ' ', 74), ((' ', ' ', ' ', ' ', 64)]
```

Findings based on the above statistics:

- There is a minor shift in the peak word lengths in Arabic when compared to English.
- The dataset appears to have recurring themes or expressions like 'global voices', 'used with permission', and 'special coverage'. These can provide insights into the type of content (perhaps news articles or blog posts) and their sourcing and categorization.
- There seems to be an overlap in the core themes and topics between the English and Arabic datasets. Terms related to global voices, media, and the internet consistently appear in both, implying that the dataset might be from a source discussing global events, trends, or news.
- The vast difference in vocabulary size between the two languages could pose challenges in translation. Given that Arabic has a more extensive vocabulary in this dataset, ensuring a comprehensive translation without loss of nuanced meanings can be tricky.
- The average word length for both English and Arabic sentences is quite close. This similarity might indicate that, in general, the complexity in terms of individual word length is comparable between the two languages in your dataset.

1.3 Visualizations:

```
[]: def generate_bar_chart_eng(freq_list, title):
         words = [i[0] for i in freq list]
         counts = [i[1] for i in freq_list]
         plt.figure(figsize=(10,5))
         plt.bar(words, counts, color='blue')
         plt.title(title)
         plt.xticks(rotation=45)
         plt.show()
     def generate_bar_chart_ar(freq_list, title):
         words = [i[0] for i in freq_list]
         counts = [i[1] for i in freq_list]
         reshaped_words = [get_display(arabic_reshaper.reshape(word)) for word in_u
      ∽words]
         plt.figure(figsize=(10,5))
         plt.bar(reshaped_words, counts, color='blue')
         plt.title(title)
         plt.xticks(rotation=45)
         plt.show()
     def generate_word_cloud(freq_dict, title):
         wordcloud = WordCloud(width=800, height=400, max_words=100,__
      →background_color='white').generate_from_frequencies(freq_dict)
         plt.figure(figsize=(10,5))
         plt.imshow(wordcloud, interpolation="bilinear")
         plt.axis('off')
         plt.title(title)
         plt.show()
     generate_word_cloud(freq_dist_eng_no_stopwords, 'English Unique Words Wordu

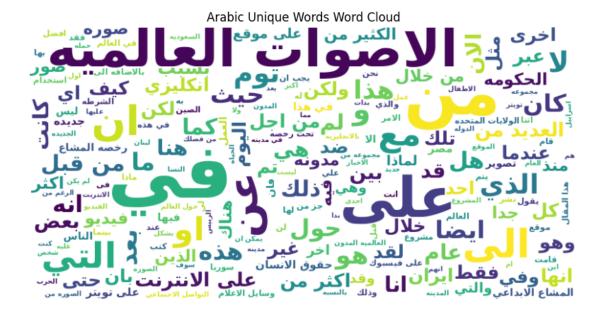
Gloud')
     wordcloud = WordCloud(font_path='/usr/local/lib/python3.10/dist-packages/cv2/qt/
      ⇔fonts/DejaVuSans-Bold.ttf',
                           width=800,
                           height=400,
                           random_state=21,
                           max_font_size=110,
                           background_color='white',
                           relative_scaling=0.5,
                           colormap='viridis').generate(' '.
      →join(arabic_sentences_clean))
     plt.figure(figsize=(10, 7))
     plt.imshow(wordcloud, interpolation="bilinear")
     plt.axis('off')
```

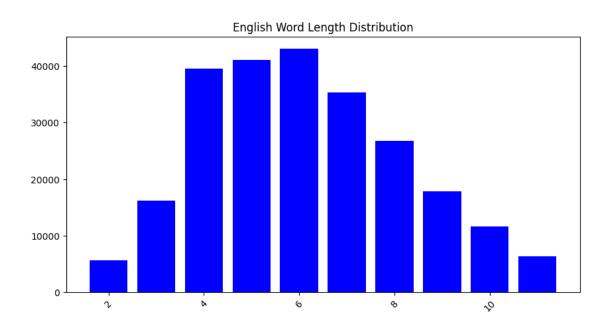
```
plt.title('Arabic Unique Words Word Cloud')
plt.show()
generate bar chart eng(english most common word lengths, 'English Word Length,
 ⇔Distribution')
generate bar chart eng(arabic most common word lengths, 'Arabic Word Length,
 ⇔Distribution')
generate bar chart eng(english most common no stopwords, 'Most Common English

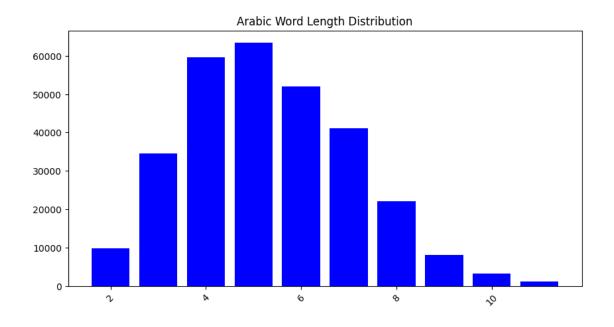
¬Unique Words (Unigrams)')
generate_bar_chart_ar(arabic_most_common_no_stopwords, 'Most Common Arabic_

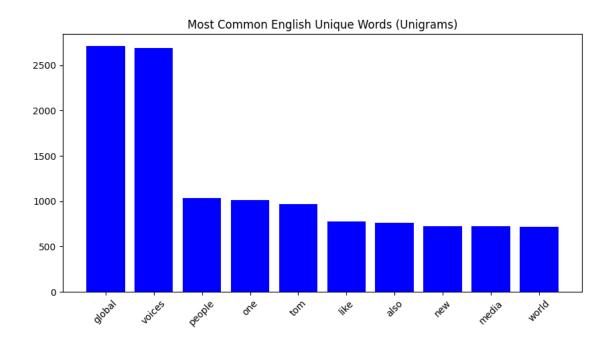
→Unique Words (Unigrams)')
english_bigrams_counts = [(str(bigram), count) for bigram, count in_
 →english_bigram_freq.most_common(10)]
arabic_bigrams_counts = [(str(bigram), count) for bigram, count in_
 →arabic_bigram_freq.most_common(10)]
generate_bar_chart_eng(english_bigrams_counts, 'Most Common English Bigrams')
generate_bar_chart_ar(arabic_bigrams_counts, 'Most Common Arabic Bigrams')
```

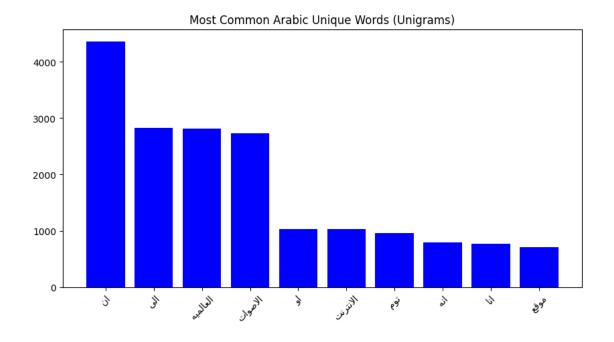


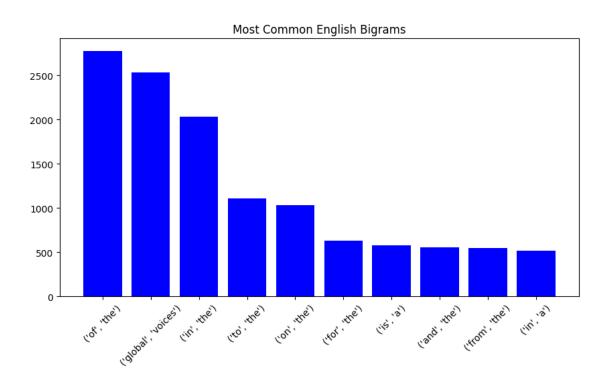


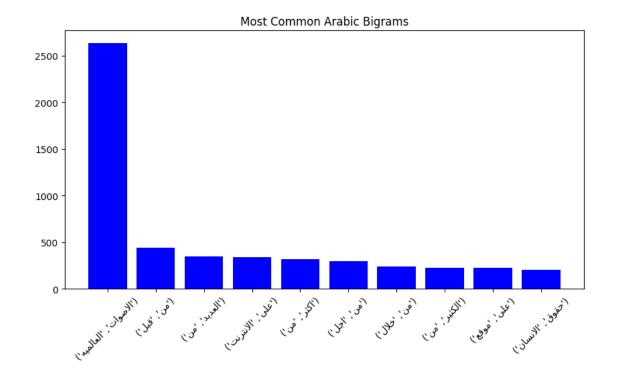










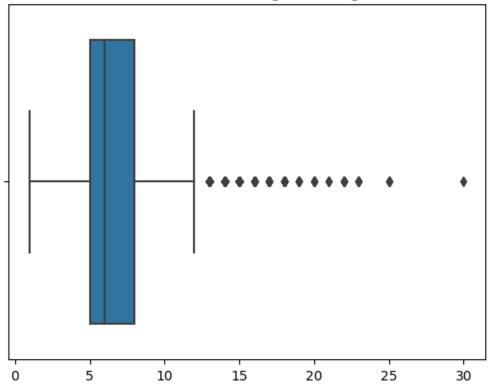


```
[]: import seaborn as sns
     # Create box plots for word lengths
    sns.boxplot(x=english_word_lengths).set_title('Box Plot of Word Lengths in_
     ⇔English')
    plt.show()
    sns.boxplot(x=arabic_word_lengths).set_title('Box Plot of Word Lengths in_
      →Arabic')
    plt.show()
    # Create box plots for sentence lengths
    sns.boxplot(x=english_sentence_lengths).set_title('Box Plot of Sentence Lengths_
     plt.show()
    sns.boxplot(x=arabic_sentence_lengths).set_title('Box Plot of Sentence Lengths_

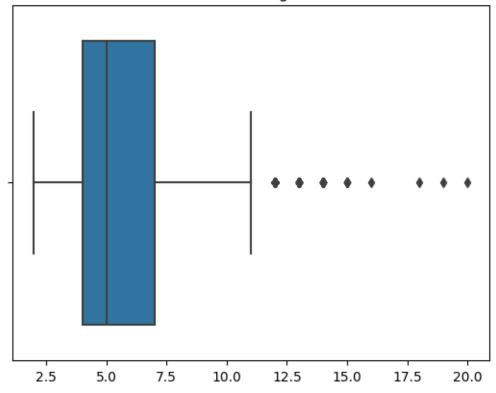
¬in Arabic')
    plt.show()
    # Sort sentence lengths for line plot
    english sentence lengths_sorted = sorted(english_sentence_lengths)
    arabic_sentence_lengths_sorted = sorted(arabic_sentence_lengths)
    # Plotting sentence lengths over the sentences
    plt.figure(figsize=(8,6))
```

```
plt.plot(english_sentence_lengths_sorted, label='English')
plt.plot(arabic_sentence_lengths_sorted, label='Arabic')
plt.title('Line Plot of Sentence Lengths: English vs Arabic')
plt.xlabel('Sentence number')
plt.ylabel('Sentence length')
plt.legend()
plt.show()
```

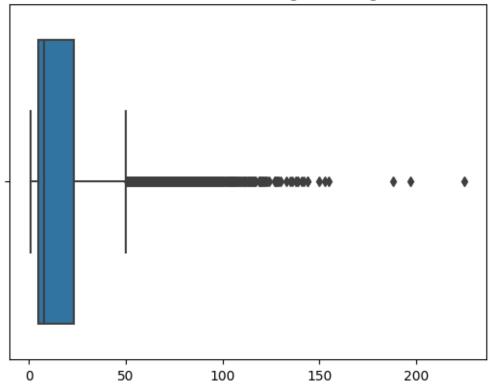
Box Plot of Word Lengths in English

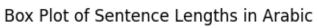


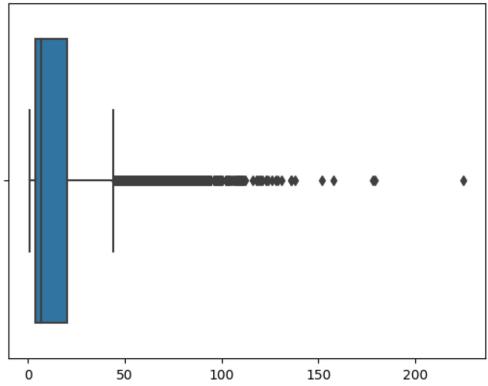
Box Plot of Word Lengths in Arabic



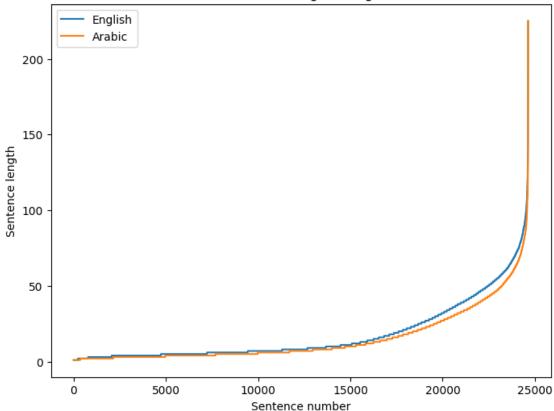












2 Translation Models

2.1 Simple LSTM Model

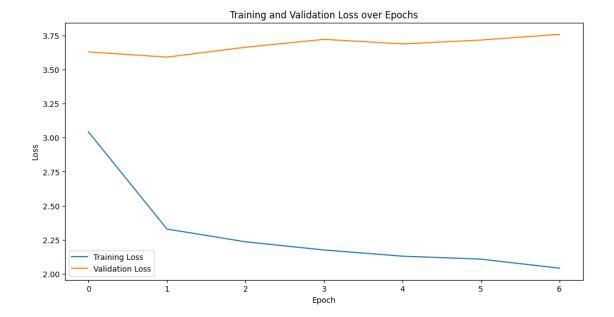
```
[11]: src_vocab = src_vocab_size
   tar_vocab = tar_vocab_size
   src_timesteps = src_length
   tar_timesteps = tar_length
   n_units = 512

model = Sequential()
model.add(Embedding(src_vocab, n_units, input_length=src_timesteps,u_mask_zero=True))
model.add(LSTM(n_units))
model.add(RepeatVector(tar_timesteps))
model.add(LSTM(n_units, return_sequences=True))
model.add(TimeDistributed(Dense(tar_vocab, activation='softmax')))
model.compile(optimizer='adam', loss='categorical_crossentropy')
```

```
history = model.fit(trainX, trainY, epochs=200, batch_size=64,__
    ⇒validation_split=0.1, verbose=1,
    ⇔callbacks=[EarlyStopping(monitor='val_loss', patience=5, __
    →restore_best_weights=True)])
   Epoch 1/200
   val_loss: 3.6289
   Epoch 2/200
   val_loss: 3.5909
   Epoch 3/200
   val_loss: 3.6633
   Epoch 4/200
   val loss: 3.7213
   Epoch 5/200
   val_loss: 3.6879
   Epoch 6/200
   val_loss: 3.7161
   Epoch 7/200
   125/125 [============ ] - 4s 32ms/step - loss: 2.0419 -
   val_loss: 3.7580
[12]: plt.figure(figsize=(12, 6))
   plt.plot(history.history['loss'], label='Training Loss')
   plt.plot(history.history['val_loss'], label='Validation Loss')
   plt.title('Training and Validation Loss over Epochs')
```

plt.xlabel('Epoch')
plt.ylabel('Loss')

plt.legend()



```
[15]: def word_for_id(integer, tokenizer):
          for word, index in tokenizer.word_index.items():
              if index == integer:
                  return word
          return None
      def predict_seq(model, tokenizer, source):
          prediction = model.predict(source, verbose=0)[0]
          integers = [np.argmax(vector) for vector in prediction]
          target = [word_for_id(i, tokenizer) for i in integers if word_for_id(i,__
       →tokenizer) is not None]
          return ' '.join(target)
      def compare_prediction(model, tokenizer, sources, raw_dataset_ar,_
       →raw_dataset_en, limit=20):
          print(f"{'(SOURCE) Arabic':30} {'(TARGET) English':25} {'AUTOMATIC_
       →TRANSLATION IN English'}")
          for i, source in enumerate(sources):
              source = source.reshape((1, source.shape[0]))
              translation = predict_seq(model, tokenizer, source)
              raw_target, raw_src = raw_dataset_en[i], raw_dataset_ar[i]
              print(f"{raw_src:30} {raw_target:25} {translation}")
              if i >= limit:
                  break
      compare_prediction(model, tar_tokenizer, trainX, train_ar, train_en)
      compare_prediction(model, tar_tokenizer, testX, test_ar, test_en)
```

Result on the Training Set ### (SOURCE) Arabic (TARGET) English AUTOMATIC TRANSLATION IN English <bos> <eos> <bos> hi <eos> bos i eos eos <bos> run <eos> <bos> <eos> bos i you eos <bos> <eos> <bos> help <eos> bos i eos <bos> <eos> <bos> jump <eos> bos i you eos <bos> <eos> <bos> stop <eos> bos i you eos <bos> <eos> <bos> go on <eos> bos i you eos <bos> <eos> <bos> go on <eos> bos i eos eos <bos> <eos> <bos> hello <eos> bos i eos eos <bos> <eos> <bos> hurry <eos> bos i eos eos <bos> <eos> <bos> hurry <eos> bos i eos eos <bos> <eos> <bos> i see <eos> bos i you eos <bos> <eos> <bos> i won <eos> bos i eos eos <bos> <eos> <bos> relax <eos> bos i you eos eos <bos> smile <eos> bos i eos <bos> <eos> <bos> cheers <eos> bos i is eos eos <bos> <eos> <eos> <bos> got it <eos> bos i is you eos eos <bos> <bos> <eos> <bos> he ran <eos> bos i eos eos <bos> <eos> <bos> i know <eos> bos i you eos eos <bos> i know <eos> <bos> <eos> bos i is you eos eos bos i is eos eos <bos> <eos> <bos> i know <eos> <bos> <eos> <bos> im <eos> bos i you eos eos ### Result on the Test Set ### (SOURCE) Arabic (TARGET) English AUTOMATIC TRANSLATION IN English <bos> <eos> <bos> when i grow up i want to be a king <eos> bos i is is to to eos eos <eos> <bos> when did you begin studying english <eos> bos i is you to eos eos eos <bos> <eos> <bos> when do you plan to leave for japan <eos> bos i is you to to eos eos <bos> where is the entrance to the museum <eos> <eos> bos i is you to eos eos <eos> <bos> why dont we just agree to disagree <eos> bos i is you to to eos eos <eos> <bos> will you allow me to play the piano <eos> bos i is you eos eos eos <eos> <bos> would you prefer to speak in french <eos> bos i is you to eos eos <eos> <bos> you are responsible for what you do <eos> bos i is you to eos eos

<eos> <bos> you dont seem to care what happens

<bos>

```
<eos> <bos> you must gather further
     information <eos> bos i is you to eos eos
                               <eos> <bos> you ought to have come here
     earlier <eos> bos i is you to eos eos eos
                       <eos> <bos> you should acknowledge your failure <eos>
     bos i is you to eos eos
     <bos>
                        <eos> <bos> you should have accepted his advice <eos>
     bos i is you to eos eos
     <bos>
                         <eos> <bos> youre either with us or against us <eos>
     bos i is you to eos eos
                      <eos> <bos> a drowning man will catch at a straw <eos>
     bos i is you eos eos eos
                             <eos> <bos> a lot of tourists invaded the
     island <eos> bos i is you to eos eos
                               <eos> <bos> a lot of tourists invaded the
     island <eos> bos i is you to eos eos eos
     <bos>
                              <eos> <bos> a loud noise in the night
     scared him <eos> bos i is you to eos eos
                        <eos> <bos> all of a sudden a dog began barking <eos>
     bos i is you to eos eos eos
                                <eos> <bos> any student can answer that
     question <eos> bos i is you to to eos eos
[16]: def calculate_bleu_score(model, tokenizer, sources, raw_targets):
          actual, predicted = [], []
          for i, source in enumerate(sources):
              source = source.reshape((1, source.shape[0]))
              translation = predict_seq(model, tokenizer, source)
              raw_target = raw_targets[i].split()
             predicted.append(translation.split())
              actual.append([raw_target])
          return corpus_bleu(actual, predicted)
      test_bleu = calculate_bleu_score(model, tar_tokenizer, testX, test_en)
      print(f"Testing BLEU Score: {test_bleu:.4f}")
     Testing BLEU Score: 0.0000
     Inference Function
 []: def translate(model, src_tokenizer, tar_tokenizer, src_length, source):
          source_seq = encode_sequences(src_tokenizer, src_length, [source])
          prediction = model.predict(source_seq, verbose=0)[0]
          int_seq = [np.argmax(vector) for vector in prediction]
```

<eos> <bos> you may have read this book already

<eos> bos i is you to eos eos

<eos> bos i is you to eos eos

<bos>

Arabic:

Predicted English: though though painful painful painful painful painful painful painful painful

2.2 enc-dec model

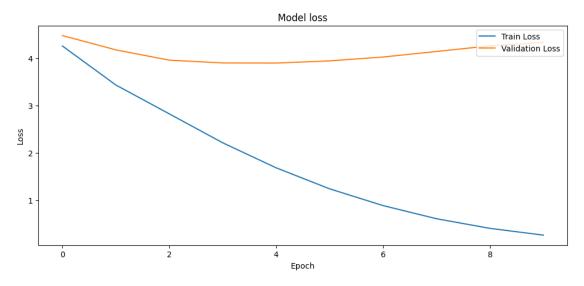
2.2.1 without Attention

```
[17]: src_vocab = src_vocab_size
      tar_vocab = tar_vocab_size
      src_timesteps = src_length
      tar_timesteps = tar_length
      n_units = 512
      encoder_inputs = Input(shape=(src_timesteps,))
      enc_emb = Embedding(src_vocab, n_units, mask_zero=True)(encoder_inputs)
      encoder lstm = LSTM(n units, return sequences=True, return state=True)
      encoder_outputs, state_h, state_c = encoder_lstm(enc_emb)
      encoder_states = [state_h, state_c]
      decoder_inputs = Input(shape=(tar_timesteps,))
      dec_emb_layer = Embedding(tar_vocab, n_units, mask_zero=True)
      dec_emb = dec_emb_layer(decoder_inputs)
      decoder lstm = LSTM(n units, return sequences=True, return state=True)
      decoder_outputs, _, _ = decoder_lstm(dec_emb, initial_state=encoder states)
      decoder_dense = TimeDistributed(Dense(tar_vocab, activation='softmax'))
      decoder_outputs = decoder_dense(decoder_outputs)
      model = Model([encoder_inputs, decoder_inputs], decoder_outputs)
      opt = Adam(learning_rate=0.001, clipnorm=1.0)
      model.compile(optimizer=opt, loss='categorical_crossentropy')
      decoder_input_data = np.zeros_like(trainY)
      decoder_input_data[:, 1:] = trainY[:, :-1]
      decoder_input_data = np.argmax(decoder_input_data, axis=-1)
      history = model.fit(
          [trainX, decoder_input_data],
```

```
trainY,
  epochs=200,
  batch_size=18,
  validation_split=0.1,
  verbose=1,
  callbacks=[
     EarlyStopping(
       monitor='val_loss',
       patience=5,
       restore_best_weights=True
  ]
)
Epoch 1/200
val_loss: 4.4788
Epoch 2/200
```

```
val_loss: 4.1769
   Epoch 3/200
   val_loss: 3.9597
   Epoch 4/200
   444/444 [============] - 31s 69ms/step - loss: 2.2157 -
   val_loss: 3.9010
   Epoch 5/200
   444/444 [============== ] - 31s 69ms/step - loss: 1.6877 -
   val_loss: 3.8983
   Epoch 6/200
   val_loss: 3.9448
   Epoch 7/200
   444/444 [============== ] - 30s 68ms/step - loss: 0.8907 -
   val_loss: 4.0263
   Epoch 8/200
   val_loss: 4.1429
   Epoch 9/200
   444/444 [============] - 30s 68ms/step - loss: 0.4099 -
   val_loss: 4.2615
   Epoch 10/200
   444/444 [============== ] - 32s 72ms/step - loss: 0.2670 -
   val_loss: 4.3315
[18]: plt.figure(figsize=(12, 5))
    plt.plot(history.history['loss'], label='Train Loss')
```

```
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(loc='upper right')
plt.show()
```



```
[24]: def predict_seq(encoder_model, decoder_model, tokenizer, source,
       →max_output_length):
          state_h, state_c = encoder_model.predict(source, verbose=0)
          encoder_states = [state_h, state_c]
          target_seq = np.zeros((1, 1))
          target_seq[0, 0] = tokenizer.word_index['<bos>']
          decoded_sentence = []
          for _ in range(max_output_length):
              output_tokens, h, c = decoder_model.predict([target_seq] +__
       ⇔encoder_states, verbose=0)
              sampled_token_index = np.argmax(output_tokens[0, -1, :])
              sampled_word = word_for_id(sampled_token_index, tokenizer)
              if sampled_word is None or sampled_word == '<eos>':
                  break
              decoded_sentence.append(sampled_word)
              encoder_states = [h, c]
              target seq = np.zeros((1, 1))
              target_seq[0, 0] = sampled_token_index
```

```
return ' '.join(decoded_sentence)
def word_for_id(integer, tokenizer):
   for word, index in tokenizer.word_index.items():
        if index == integer:
            return word
   return None
def compare prediction(encoder model, decoder model, tokenizer, sources,
 →raw_dataset_ar, raw_dataset_en, max_output_length, limit=20):
   actual, predicted = [], []
   src = '(SOURCE) Arabic'
   tgt = '(TARGET) English'
   pred = 'AUTOMATIC TRANSLATION IN English'
   print(f'{src:30} {tgt:25} {pred}\n')
   for i. source in enumerate(sources):
        source = source.reshape((1, source.shape[0]))
        translation = predict_seq(encoder_model, decoder_model, tokenizer,_
 ⇒source, max_output_length)
       raw_target, raw_src = raw_dataset_en[i], raw_dataset_ar[i]
       print(f'{raw_src:30} {raw_target:25} {translation}')
        if i >= limit:
            break
encoder_model = Model(encoder_inputs, encoder_states)
decoder_state_input_h = Input(shape=(n_units,))
decoder_state_input_c = Input(shape=(n_units,))
decoder_states_inputs = [decoder_state_input_h, decoder_state_input_c]
dec_emb2 = dec_emb_layer(decoder_inputs)
decoder_outputs2, state_h2, state_c2 = decoder_lstm(dec_emb2,_
 →initial_state=decoder_states_inputs)
decoder_states2 = [state_h2, state_c2]
decoder_outputs2 = decoder_dense(decoder_outputs2)
decoder model = Model(
    [decoder_inputs] + decoder_states_inputs,
    [decoder_outputs2] + decoder_states2
print('### Result on the Training Set ###')
compare_prediction(encoder_model, decoder_model, tar_tokenizer, trainX,_
 →train_ar, train_en, tar_length)
```

```
print('\n\n### Result on the Test Set ###')
compare_prediction(encoder_model, decoder_model, tar_tokenizer, testX, test_ar,_
  →test_en, tar_length)
### Result on the Training Set ###
                                                         AUTOMATIC TRANSLATION
(SOURCE) Arabic
                               (TARGET) English
IN English
<bos>
         <eos>
                            <bos> hi <eos>
                                                       eos
<bos>
         <eos>
                             <bos> run <eos>
                                                       eos
<bos>
                            <bos> help <eos>
         <eos>
                                                      eos
<bos>
        <eos>
                            <bos> jump <eos>
                                                       eos
<bos> <eos>
                             <bos> stop <eos>
<bos>
       <eos>
                             <bos> go on <eos>
                                                       the car eos
<bos>
        <eos>
                            <bos> go on <eos>
                                                      the room eos
<bos>
                            <bos> hello <eos>
        <eos>
                                                      eos
<bos>
        <eos>
                            <bos> hurry <eos>
                                                       eos
<bos>
        <eos>
                            <bos> hurry <eos>
                                                      eos
<bos>
          <eos>
                            <bos> i see <eos>
                                                      i am eos
<bos>
                            <bos> i won <eos>
           <eos>
                                                      i am eos
                            <bos> relax <eos>
<bos>
         <eos>
                                                      well eos
<bos>
         <eos>
                            <bos> smile <eos>
                                                      eos
                            <bos> cheers <eos>
<bos>
           <eos>
                                                      she is past past eos
<bos>
           <eos>
                            <bos> got it <eos>
                                                      did you miss me eos
                             <bos> he ran <eos>
<bos>
                                                      he is eos
       <eos>
<bos>
                            <bos> i know <eos>
                                                      i know eos
        <e0s>
<bos>
           <eos>
                           <bos> i know <eos>
                                                     i know eos
                           <bos> i know <eos>
<bos>
                                                     i know eos
          <eos>
                            <bos> im <eos>
<bos>
           <eos>
                                                     im in eos
### Result on the Test Set ###
(SOURCE) Arabic
                               (TARGET) English
                                                        AUTOMATIC TRANSLATION
IN English
<bos>
                       <eos> <bos> when i grow up i want to be a king
<eos> my mother made me a lot of patients eos
                         <eos> <bos> when did you begin studying
english <eos> when did you go home eos
<bos>
                      <eos> <bos> when do you plan to leave for japan
<eos> how long do you go to japan eos
<bos>
                <eos>
                         <bos> where is the entrance to the museum <eos>
where is the pain eos
<bos>
                        <eos> <bos> why dont we just agree to
disagree <eos> why dont we have any evidence eos
                       <eos> <bos> will you allow me to play the
```

piano <eos> may i use your book to your room eos

```
<eos> is there to do something eos
                       <eos> <bos> you are responsible for what you do <eos>
     <bos>
     you are always complaining eos
     <bos>
                            <eos> <bos> you dont seem to care what happens
     <eos> you look very tired eos
                           <eos> <bos> you may have read this book already
     <eos> he is busy doing that eos
                                <eos> <bos> you must gather further
     information <eos> you should have more than me eos
     <bos>
                               <eos> <bos> you ought to have come here
     earlier <eos> you should have a lot to do eos
                        <eos> <bos> you should acknowledge your failure <eos>
     you must study hard eos
                        <eos> <bos> you should have accepted his advice <eos>
     you should have a car eos
     <bos>
                         <eos> <bos> youre either with us or against us <eos>
     you are always complaining eos
     <bos>
                      <eos> <bos> a drowning man will catch at a straw <eos>
     she kept on the letter eos
                             <eos> <bos> a lot of tourists invaded the
     island <eos> she was busy in the housework eos
                               <eos> <bos> a lot of tourists invaded the
     island <eos> she asked me of being a liar eos
     <bos>
                              <eos> <bos> a loud noise in the night
     scared him <eos> she asked me a lot of water eos
                        <eos> <bos> all of a sudden a dog began barking <eos>
     i wrote a book to my mother eos
                                <eos> <bos> any student can answer that
     question <eos> that old woman lives by herself eos
[13]: import numpy as np
      from nltk.translate.bleu_score import sentence_bleu
      def generate_translation(encoder_model, decoder_model, tokenizer, source, u
       →max_output_length):
          translation = predict_seq(encoder_model, decoder_model, tokenizer, source, ___
       →max_output_length)
          return translation.split()
      def compute_bleu(encoder_model, decoder_model, tokenizer, sources, references, u
       →max output length):
          predicted_translations = [generate_translation(encoder_model,_
       ⇒decoder_model, tokenizer, src.reshape((1, src.shape[0])), max_output_length)
       ofor src in sources]
          bleu_scores = [sentence_bleu([ref.split()], pred) for ref, pred in_
       →zip(references, predicted_translations)]
```

<eos> <bos> would you prefer to speak in french

<bos>

```
return np.mean(bleu_scores)

bleu_score_test = compute_bleu(encoder_model, decoder_model, tar_tokenizer,u

otestX, test_en, tar_length)

print(f'BLEU score on the test set: {bleu_score_test:.4f}')
```

BLEU score on the test set: 0.0048

Inference Function

```
[29]: arabic_sentence = " "

translation = translate_sentence(arabic_sentence, encoder_model, decoder_model, userc_tokenizer, tar_tokenizer, src_length)

print(f"Original: {arabic_sentence}\nTranslation: {translation}")
```

Original:

Translation: i was busy for a doctor eos

2.2.2 With Attention

```
[30]: src_vocab = src_vocab_size
    tar_vocab = tar_vocab_size
    src_timesteps = src_length
    tar_timesteps = tar_length
    n_units = 512

encoder_inputs = Input(shape=(src_timesteps,))
    enc_emb = Embedding(src_vocab, n_units, mask_zero=True)(encoder_inputs)
    encoder_lstm = LSTM(n_units, return_sequences=True, return_state=True)
    encoder_outputs, state_h, state_c = encoder_lstm(enc_emb)
    encoder_states = [state_h, state_c]

decoder_inputs = Input(shape=(tar_timesteps,))
    dec_emb_layer = Embedding(tar_vocab, n_units, mask_zero=True)
    dec_emb = dec_emb_layer(decoder_inputs)
    decoder_lstm = LSTM(n_units, return_sequences=True, return_state=True)
    decoder_outputs, _, _ = decoder_lstm(dec_emb, initial_state=encoder_states)
```

```
attention = Attention(use_scale=True, name='attention')
attn_out = attention([decoder_outputs, encoder_outputs])
decoder_concat_input = tf.keras.layers.Concatenate(axis=-1,__
 →name='concat_layer')([decoder_outputs, attn_out])
decoder_dense = TimeDistributed(Dense(tar_vocab, activation='softmax'))
decoder_outputs = decoder_dense(decoder_concat_input)
model = Model([encoder_inputs, decoder_inputs], decoder_outputs)
opt = Adam(learning_rate=0.001, clipnorm=1.0)
model.compile(optimizer=opt, loss='categorical_crossentropy')
decoder_input_data = np.zeros_like(trainY)
decoder_input_data[:, 1:] = trainY[:, :-1]
decoder_input_data = np.argmax(decoder_input_data, axis=-1)
history = model.fit(
    [trainX, decoder_input_data],
    trainY,
    epochs=200,
    batch_size=18,
    validation_split=0.1,
    verbose=1,
    callbacks=[
        EarlyStopping(
            monitor='val_loss',
            patience=5,
            restore_best_weights=True
        )
    ]
)
```

```
val_loss: 3.8983
    Epoch 5/200
    444/444 [============= ] - 32s 71ms/step - loss: 1.0444 -
    val_loss: 4.0650
    Epoch 6/200
    val loss: 4.2095
    Epoch 7/200
    444/444 [=============] - 31s 71ms/step - loss: 0.3579 -
    val_loss: 4.3600
    Epoch 8/200
    444/444 [============= ] - 32s 71ms/step - loss: 0.2198 -
    val_loss: 4.5281
[31]: import matplotlib.pyplot as plt
     # Plotting the training and validation loss
     plt.plot(history.history['loss'], label='Training Loss')
     plt.plot(history.history['val_loss'], label='Validation Loss')
     plt.legend()
    plt.title('Training and Validation Loss')
     plt.xlabel('Epochs')
     plt.ylabel('Loss')
     plt.show()
```



```
[36]: def predict_seq(encoder_model, decoder_model, tokenizer, source,
       →max_output_length):
          encoder_out_and_states = encoder_model.predict(source, verbose=0)
          encoder_outputs = encoder_out_and_states[0]
          state_h, state_c = encoder_out_and_states[1], encoder_out_and_states[2]
          encoder_states = [state_h, state_c]
          target_seq = np.zeros((1, 1))
          target_seq[0, 0] = tokenizer.word_index['<bos>']
          decoded_sentence = []
          for _ in range(max_output_length):
              output_tokens, h, c = decoder_model.predict([target_seq,__
       →encoder_outputs] + encoder_states, verbose=0)
              sampled_token_index = np.argmax(output_tokens[0, -1, :])
              sampled_word = word_for_id(sampled_token_index, tokenizer)
              if sampled_word is None or sampled_word == '<eos>':
                  break
```

```
decoded_sentence.append(sampled_word)
        encoder_states = [h, c]
        target_seq = np.zeros((1, 1))
        target_seq[0, 0] = sampled_token_index
   return ' '.join(decoded_sentence)
def word_for_id(integer, tokenizer):
   for word, index in tokenizer.word_index.items():
        if index == integer:
           return word
   return None
def compare prediction(encoder model, decoder model, tokenizer, sources, u
 →raw_dataset_ar, raw_dataset_en, max_output_length, limit=20):
   actual, predicted = [], []
   src = '(SOURCE) Arabic'
   tgt = '(TARGET) English'
   pred = 'AUTOMATIC TRANSLATION IN English'
   print(f'{src:30} {tgt:25} {pred}\n')
   for i, source in enumerate(sources):
        source = source.reshape((1, source.shape[0]))
        translation = predict_seq(encoder_model, decoder_model, tokenizer,_
 ⇔source, max_output_length)
       raw_target, raw_src = raw_dataset_en[i], raw_dataset_ar[i]
       print(f'{raw_src:30} {raw_target:25} {translation}')
       if i >= limit:
            break
encoder_model = Model(encoder_inputs, [encoder_outputs] + encoder_states)
decoder_state_input_h = Input(shape=(n_units,))
decoder_state_input_c = Input(shape=(n_units,))
decoder_states_inputs = [decoder_state_input_h, decoder_state_input_c]
dec_emb2 = dec_emb_layer(decoder_inputs)
decoder_outputs2, state_h2, state_c2 = decoder_lstm(dec_emb2,_
 →initial_state=decoder_states_inputs)
decoder_states2 = [state_h2, state_c2]
encoder_outputs_input = Input(shape=(src_timesteps, n_units))
attn_out2 = attention([decoder_outputs2, encoder_outputs_input])
```

```
decoder_concat_input2 = Concatenate(axis=-1,__
 →name='concat_layer_2')([decoder_outputs2, attn_out2])
decoder_outputs2 = decoder_dense(decoder_concat_input2)
decoder_model = Model(
    [decoder inputs, encoder outputs input] + decoder states inputs,
    [decoder_outputs2] + decoder_states2
)
print('### Result on the Training Set ###')
compare_prediction(encoder_model, decoder_model, tar_tokenizer, trainX,_

→train_ar, train_en, tar_length)
print('\n\n### Result on the Test Set ###')
compare_prediction(encoder_model, decoder_model, tar_tokenizer, testX, test_ar,_
  →test_en, tar_length)
### Result on the Training Set ###
(SOURCE) Arabic
                              (TARGET) English AUTOMATIC TRANSLATION
IN English
WARNING:tensorflow:5 out of the last 318 calls to <function
Model.make_predict_function.<locals>.predict_function at 0x7a01bfe6b1c0>
triggered tf.function retracing. Tracing is expensive and the excessive number
of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2)
passing tensors with different shapes, (3) passing Python objects instead of
tensors. For (1), please define your @tf.function outside of the loop. For (2),
@tf.function has reduce_retracing=True option that can avoid unnecessary
retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for more details.
<bos>
                            <bos> hi <eos>
         <eos>
                                                     succeeded eos
<bos>
                            <bos> run <eos>
                                                      succeeded succeeded
         <eos>
bunch bunch divorce divorce divorce does it like me eos
<bos>
        <eos>
                           <bos> help <eos>
                                                     eos
<bos> <eos>
                            <bos> jump <eos>
                                                     eos
<bos> <eos>
                            <bos> stop <eos>
                                                     eos
<bos>
      <eos>
                           <bos> go on <eos>
                                                     eos
<bos>
        <eos>
                           <bos> go on <eos>
                                                     eos
                                                     succeeded eos
<bos>
                            <bos> hello <eos>
        <eos>
<bos>
        <eos>
                            <bos> hurry <eos>
                                                     succeeded succeeded
bunch divorce divorce divorce divorce course cab i have to
                                                     succeeded succeeded
<bos>
          <eos>
                           <bos> hurry <eos>
succeeded divorce divorce course those are you doing eos
<bos>
          <eos>
                           <bos> i see <eos>
                                                     eos
```

<pre><bos></bos></pre>
honest honest meant unusual divorce divorce divorce divorce divorce
<pre><bos> <eos></eos></bos></pre>
succeeded divorce course are you talking
<pre><bos> <eos> <bos> smile <eos> eos <bos> cheers <eos> eye eos</eos></bos></eos></bos></eos></bos></pre>
, and the second se
<pre><bos> <eos></eos></bos></pre>
<pre><bos></bos></pre>
<pre><bos></bos></pre>
<pre><bos></bos></pre>
<pre> <</pre>
Result on the Test Set
(SOURCE) Arabic (TARGET) English AUTOMATIC TRANSLATION
IN English
<pre><bos></bos></pre>
<pre><eos> would you have to do that eos <bos> when did you begin studying</bos></eos></pre>
english <eos> when time will we do this eos</eos>
<pre> <</pre>
<pre><eos> when shall we do what we do eos</eos></pre>
<pre> <</pre>
where where does it live eos
<pre><bos></bos></pre>
disagree <eos> why i cant do it again eos</eos>
<pre><bos></bos></pre>
piano <eos> may i have a lot of questions eos</eos>
<pre><bos></bos></pre>
<pre><eos> is your own business eos</eos></pre>
<pre><bos></bos></pre>
are you doing your mother eos
<pre><bos></bos></pre>
<pre><eos> dont look at you eos</eos></pre>
<pre><bos></bos></pre>
<pre><eos> its not a book to do that eos</eos></pre>
<pre><bos></bos></pre>
information <eos> you must be a doctor eos</eos>
<pre><bos></bos></pre>
earlier <eos> you should go to the hospital eos</eos>
<pre><bos></bos></pre>
you must help your room eos
<pre><bos></bos></pre>
was you look eos
<pre> <</pre>
are you doing the truth eos

```
<eos> <bos> a drowning man will catch at a straw <eos>
     <bos>
     they took the same mistake eos
                             <eos> <bos> a lot of tourists invaded the
     <bos>
     island <eos> cats was a lot of the garden eos
                               <eos> <bos> a lot of tourists invaded the
     <bos>
     island <eos> dr leaves leaves smith cholesterol levels levels entered the
     best key eos
     <bos>
                              <eos> <bos> a loud noise in the night
     scared him <eos> leaves in the same floor in the floor eos
                        <eos> <bos> all of a sudden a dog began barking <eos>
     i was a good man eos
                                <eos> <bos> any student can answer that
     <bos>
     question <eos> which car can do that eos
[15]: import numpy as np
      from nltk.translate.bleu_score import sentence_bleu
      def generate_translation(encoder_model, decoder_model, tokenizer, source, u
       →max_output_length):
          translation = predict_seq(encoder_model, decoder_model, tokenizer, source, __
       →max_output_length)
          return translation.split()
      def compute_bleu(encoder_model, decoder_model, tokenizer, sources, references, u
       →max output length):
          predicted_translations = [generate_translation(encoder_model,__
       →decoder_model, tokenizer, src.reshape((1, src.shape[0])), max_output_length)

→for src in sources]
          bleu_scores = [sentence_bleu([ref.split()], pred) for ref, pred in_
       \sip(references, predicted_translations)]
          return np.mean(bleu_scores)
      bleu_score_test = compute_bleu(encoder_model, decoder_model, tar_tokenizer,__
       →testX, test_en, tar_length)
      print(f'BLEU score on the test set: {bleu_score_test:.4f}')
```

BLEU score on the test set: 0.0063

Inference Function

return translated_sentence

```
[38]: arabic_sentence = " "

translation = translate_sentence(arabic_sentence, encoder_model, decoder_model, userc_tokenizer, tar_tokenizer, src_length)

print(f"Original: {arabic_sentence}\nTranslation: {translation}")
```

Original:

Translation: would you want to do it eos

2.3 Analysis:

- Overfitting: All three models exhibit signs of overfitting. As training progresses, validation loss rises after a few epochs, while training loss steadily decreases. This suggests that while the models are fitting well to the training data dues to the amount of the data and the complexity of the models.
- Translation Quality: The Encoder-Decoder with Attention model delivered the highest BLEU score, indicating best translation performance. Yet, all models displayed challenges in generating entirely accurate translations, with repeated tokens commonly observed.
- Model Complexity: As the models progressed from the simple LSTM network to LSTM encoder-decoder and then to the attention mechanism, their complexity increased. This added complexity led to some improvements in translation quality.

2.4 Why the Encoder-Decoder with Attention Model is the Best:

- Handles Long Sequences Better: Traditional encoder-decoder models might forget some parts of a long input when converting it to a fixed-size vector. The attention mechanism lets the model focus on different input parts when producing each output, reducing information loss.
- Selective Focus: The model doesn't treat all input words equally. It gives more importance to the words that are more relevant to the current word being translated, which results in better translation accuracy.
- Complex Sentences: Especially when translating between languages with different sentence structures, having attention helps the model pick out and rearrange the right information.

2.5 Pretrained Models

```
zero_length_arabic_indices = [i for i, sentence in_u enumerate(arabic_sentences_clean) if len(sentence.split()) == 0]

indices_to_remove = set(zero_length_english_indices +_u ezero_length_arabic_indices)

english_sentences_clean = [sentence for i, sentence in_u enumerate(english_sentences_clean) if i not in indices_to_remove]

arabic_sentences_clean = [sentence for i, sentence in_u enumerate(arabic_sentences_clean) if i not in indices_to_remove]
```

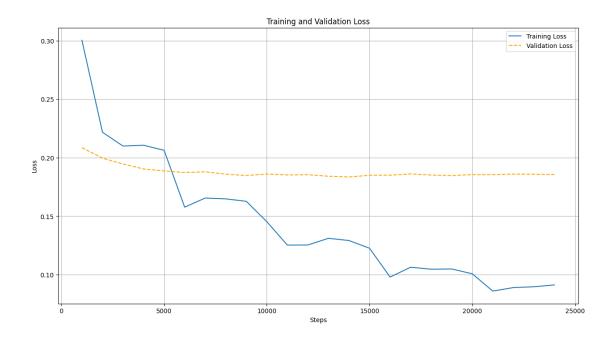
2.5.1 Marian NMT

```
[23]: model_name = "Helsinki-NLP/opus-mt-ar-en"
      tokenizer = MarianTokenizer.from_pretrained(model_name)
      MAX_LENGTH = 256
      def tokenize_data(arabic, english):
          tokenized_data = tokenizer.prepare_seq2seq_batch(src_texts=arabic,
                                                            tgt_texts=english,
                                                            max_length=MAX_LENGTH,
                                                            padding="max_length",
                                                            return_tensors="pt",
                                                            truncation=True)
          return tokenized_data
      tokenized_datasets = tokenize_data(arabic_sentences_clean,__
       ⇔english_sentences_clean)
      class CustomDataset(Dataset):
          def __init__(self, tokenized_data):
              self.input_ids = tokenized_data["input_ids"]
              self.attention_mask = tokenized_data["attention_mask"]
              self.target_ids = tokenized_data["labels"]
          def __len__(self):
              return len(self.input_ids)
          def __getitem__(self, idx):
              return {
                  "input_ids": self.input_ids[idx],
                  "attention_mask": self.attention_mask[idx],
                  "labels": self.target_ids[idx]
              }
      full_dataset = CustomDataset(tokenized_datasets)
      train_size = int(0.8 * len(full_dataset))
```

```
val_size = len(full_dataset) - train_size
train_dataset, val_dataset = torch.utils.data.random_split(full_dataset,__
 →[train_size, val_size])
model = MarianMTModel.from pretrained(model name)
training args = TrainingArguments(
    output dir="./results marian",
    per_device_train_batch_size=4,
    per_device_eval_batch_size=4,
    num_train_epochs=5,
    evaluation_strategy="steps",
    save_strategy="steps",
    logging_dir="./logs_marian",
    logging_steps=1000,
    eval_steps=1000,
    do_train=True,
    do eval=True,
    no_cuda=False,
    push_to_hub=False,
    logging_first_step=True,
    report_to=["tensorboard"]
)
trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=val_dataset,
    tokenizer=tokenizer,
trainer.train()
/usr/local/lib/python3.10/dist-
packages/transformers/models/marian/tokenization_marian.py:194: UserWarning:
Recommended: pip install sacremoses.
  warnings.warn("Recommended: pip install sacremoses.")
/usr/local/lib/python3.10/dist-
packages/transformers/tokenization_utils_base.py:3786: FutureWarning:
`prepare_seq2seq_batch` is deprecated and will be removed in version 5 of
HuggingFace Transformers. Use the regular
`__call__` method to prepare your inputs and targets.
Here is a short example:
model_inputs = tokenizer(src_texts, text_target=tgt_texts, ...)
```

```
texts, you should do two calls like
     this:
     model inputs = tokenizer(src texts, ...)
     labels = tokenizer(text target=tgt texts, ...)
     model inputs["labels"] = labels["input ids"]
     See the documentation of your specific tokenizer for more details on the
     specific arguments to the tokenizer of choice.
     For a more complete example, see the implementation of `prepare seq2seq batch`.
       warnings.warn(formatted_warning, FutureWarning)
     /usr/local/lib/python3.10/dist-
     packages/transformers/tokenization_utils_base.py:3660: UserWarning:
     `as_target_tokenizer` is deprecated and will be removed in v5 of Transformers.
     You can tokenize your labels by using the argument `text_target` of the regular
     `__call__` method (either in the same call as your input texts if you use the
     same keyword arguments, or in a separate call.
       warnings.warn(
     <IPython.core.display.HTML object>
[23]: TrainOutput(global step=24640, training loss=0.14302249024440716,
     metrics={'train_runtime': 6968.6279, 'train_samples_per_second': 14.141,
      'train_steps_per_second': 3.536, 'total_flos': 6681028743659520.0, 'train_loss':
      0.14302249024440716, 'epoch': 5.0})
[24]: logs = trainer.state.log_history
      train_steps = [x['step'] for x in logs if 'loss' in x][1:]
      train_loss = [x['loss'] for x in logs if 'loss' in x][1:]
      eval_steps = [x['step'] for x in logs if 'eval_loss' in x]
      eval_loss = [x['eval_loss'] for x in logs if 'eval_loss' in x]
      plt.figure(figsize=(15, 8))
      plt.plot(train_steps, train_loss, label='Training Loss')
      plt.plot(eval_steps, eval_loss, label='Validation Loss', linestyle='--',u
       ⇔color='orange')
      plt.xlabel('Steps')
      plt.ylabel('Loss')
      plt.legend()
      plt.title('Training and Validation Loss')
      plt.grid(True)
      plt.show()
```

If you either need to use different keyword arguments for the source and target



```
[25]: device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
      def compute_bleu(model, dataset, tokenizer):
          reference_texts = []
          translated_texts = []
          for data in dataset:
              data = {key: val.to(device) for key, val in data.items()}
              reference_text = tokenizer.decode(data["labels"],__
       ⇔skip_special_tokens=True)
              reference_texts.append(reference_text)
              model.eval()
              with torch.no_grad():
                  output = model.generate(data["input_ids"].unsqueeze(0),__
       attention_mask=data["attention_mask"].unsqueeze(0))
              translated_texts.append(tokenizer.decode(output[0],__
       ⇔skip_special_tokens=True))
          bleu_score = sacrebleu.corpus_bleu(translated_texts, [reference_texts])
          return bleu_score.score
      bleu = compute_bleu(model, val_dataset, tokenizer)
```

```
[26]: print(f"Bleu Score: {bleu:.2f}")
```

Bleu Score: 28.65

Inference

Original:

Translation: i want to eat

2.5.2 MBART

```
[]: tokenizer = MBartTokenizer.from_pretrained("facebook/mbart-large-cc25")
     MAX_LENGTH = 230
     def tokenize_data(english, arabic):
         tokenized_data = tokenizer.prepare_seq2seq_batch(src_texts=arabic,
                                                           tgt_texts=english,
                                                           src_lang="ar_AR",
                                                           tgt_lang="en_XX",
                                                           max_length=MAX_LENGTH,
                                                           padding="max_length",
                                                           return tensors="pt",
                                                           truncation=True)
         return tokenized data
     tokenized_datasets = tokenize_data(english_sentences_clean,_
      ⇒arabic_sentences_clean)
     class CustomDataset(Dataset):
         def __init__(self, tokenized_data):
             self.input_ids = tokenized_data["input_ids"]
             self.attention_mask = tokenized_data["attention_mask"]
             self.target_ids = tokenized_data["labels"]
         def __len__(self):
             return len(self.input_ids)
         def __getitem__(self, idx):
             return {
```

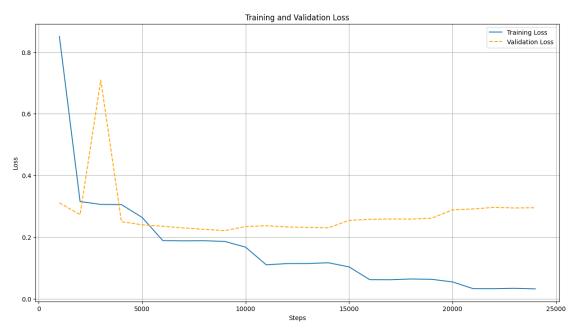
```
"input_ids": self.input_ids[idx],
            "attention_mask": self.attention_mask[idx],
            "labels": self.target_ids[idx]
       }
full_dataset = CustomDataset(tokenized_datasets)
train size = int(0.8 * len(full dataset))
val_size = len(full_dataset) - train_size
train_dataset, val_dataset = torch.utils.data.random_split(full_dataset,_
model = MBartForConditionalGeneration.from_pretrained("facebook/
 ⇔mbart-large-cc25")
training args = TrainingArguments(
   output_dir="./results",
   per_device_train_batch_size=4,
   per_device_eval_batch_size=4,
   num_train_epochs=5,
   evaluation_strategy="steps",
   save_strategy="steps",
   logging_dir="./logs",
   logging_steps=1000,
   eval_steps=1000,
   do_train=True,
   do_eval=True,
   no_cuda=False,
   push_to_hub=False,
   logging first step=True,
   report_to=["tensorboard"]
)
trainer = Trainer(
   model=model,
   args=training_args,
   train_dataset=train_dataset,
   eval_dataset=val_dataset,
   tokenizer=tokenizer,
trainer.train()
```

/l/users/ahmed.aboeitta/espnet/tools/anaconda/envs/espnet/lib/python3.8/site-packages/transformers/tokenization_utils_base.py:3766: FutureWarning: `prepare_seq2seq_batch` is deprecated and will be removed in version 5 of HuggingFace Transformers. Use the regular `__call__` method to prepare your inputs and targets.

Here is a short example:

```
model_inputs = tokenizer(src_texts, text_target=tgt_texts, ...)
    If you either need to use different keyword arguments for the source and target
    texts, you should do two calls like
    this:
    model_inputs = tokenizer(src_texts, ...)
    labels = tokenizer(text_target=tgt_texts, ...)
    model_inputs["labels"] = labels["input_ids"]
    See the documentation of your specific tokenizer for more details on the
    specific arguments to the tokenizer of choice.
    For a more complete example, see the implementation of `prepare seq2seq batch`.
      warnings.warn(formatted_warning, FutureWarning)
    /l/users/ahmed.aboeitta/espnet/tools/anaconda/envs/espnet/lib/python3.8/site-
    packages/transformers/tokenization_utils_base.py:3640: UserWarning:
    `as_target_tokenizer` is deprecated and will be removed in v5 of Transformers.
    You can tokenize your labels by using the argument `text_target` of the regular
    `__call__` method (either in the same call as your input texts if you use the
    same keyword arguments, or in a separate call.
      warnings.warn(
    /l/users/ahmed.aboeitta/espnet/tools/anaconda/envs/espnet/lib/python3.8/site-
    packages/transformers/optimization.py:411: FutureWarning: This implementation of
    AdamW is deprecated and will be removed in a future version. Use the PyTorch
    implementation torch.optim.AdamW instead, or set `no_deprecation_warning=True`
    to disable this warning
      warnings.warn(
    <IPython.core.display.HTML object>
[]: TrainOutput(global_step=24640, training_loss=0.1625452343519632,
    metrics={'train_runtime': 10758.7544, 'train_samples_per_second': 9.16,
     'train_steps_per_second': 2.29, 'total_flos': 4.79675338727424e+16,
     'train_loss': 0.1625452343519632, 'epoch': 5.0})
[]: logs = trainer.state.log_history
     train_steps = [x['step'] for x in logs if 'loss' in x][1:]
     train_loss = [x['loss'] for x in logs if 'loss' in x][1:]
     eval_steps = [x['step'] for x in logs if 'eval_loss' in x]
     eval_loss = [x['eval_loss'] for x in logs if 'eval_loss' in x]
     plt.figure(figsize=(15, 8))
     plt.plot(train_steps, train_loss, label='Training Loss')
     plt.plot(eval_steps, eval_loss, label='Validation Loss', linestyle='--', u
      ⇔color='orange')
     plt.xlabel('Steps')
```

```
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss')
plt.grid(True)
plt.show()
```



```
[]: device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
     def compute_bleu(model, dataset, tokenizer):
         reference_texts = []
         translated_texts = []
         for data in dataset:
             data = {key: val.to(device) for key, val in data.items()}
             reference_text = tokenizer.decode(data["labels"],__
      ⇔skip_special_tokens=True)
             reference_texts.append(reference_text)
             model.eval()
             with torch.no_grad():
                 output = model.generate(data["input_ids"].unsqueeze(0),__
      →attention_mask=data["attention_mask"].unsqueeze(0))
             translated_texts.append(tokenizer.decode(output[0],_
      ⇔skip_special_tokens=True))
         bleu_score = sacrebleu.corpus_bleu(translated_texts, [reference_texts])
```

```
return bleu_score.score
bleu = compute_bleu(model, val_dataset, tokenizer)
```

/l/users/ahmed.aboeitta/espnet/tools/anaconda/envs/espnet/lib/python3.8/site-packages/transformers/generation/utils.py:1369: UserWarning: Using `max_length`'s default (1024) to control the generation length. This behaviour is deprecated and will be removed from the config in v5 of Transformers -- we recommend using `max_new_tokens` to control the maximum length of the generation.

warnings.warn(

```
[]: print(f"Bleu Score: {bleu:.2f}")
```

Bleu Score: 20.47

Inference

```
[]: def translate_arabic_to_english_mbart(model, tokenizer, arabic_sentence,_
      →device):
         model.to(device).eval()
         inputs = tokenizer.prepare_seq2seq_batch(src_texts=[arabic_sentence],
                                                  src_lang="ar_AR",
                                                  tgt_lang="en_XX",
                                                  return tensors="pt",
                                                  max_length=MAX_LENGTH,
                                                  truncation=True)
         inputs = {k: v.to(device) for k, v in inputs.items()}
         with torch.no_grad():
             outputs = model.generate(**inputs, max length=MAX LENGTH, num beams=4,,,
      →early_stopping=True)
         translated text = tokenizer.decode(outputs[0], skip_special_tokens=True)
         return translated_text
     arabic test sentence = "
     translated_sentence = translate_arabic_to_english_mbart(model, tokenizer,_
      →arabic_test_sentence, device)
     print(translated_sentence)
```

welcome to the library

/l/users/ahmed.aboeitta/espnet/tools/anaconda/envs/espnet/lib/python3.8/site-packages/transformers/tokenization_utils_base.py:3766: FutureWarning: `prepare_seq2seq_batch` is deprecated and will be removed in version 5 of HuggingFace Transformers. Use the regular `__call__` method to prepare your inputs and targets.

Here is a short example:

```
model_inputs = tokenizer(src_texts, text_target=tgt_texts, ...)

If you either need to use different keyword arguments for the source and target texts, you should do two calls like this:

model_inputs = tokenizer(src_texts, ...)
labels = tokenizer(text_target=tgt_texts, ...)
model_inputs["labels"] = labels["input_ids"]

See the documentation of your specific tokenizer for more details on the specific arguments to the tokenizer of choice.
For a more complete example, see the implementation of `prepare_seq2seq_batch`.

warnings.warn(formatted_warning, FutureWarning)
```

2.5.3 MT5

```
[]: tokenizer = T5Tokenizer.from_pretrained("google/mt5-small")
     MAX_LENGTH = 230
     def tokenize_data(english, arabic):
         source_texts = ['translate Arabic to English: ' + txt for txt in arabic]
         tokenized_data = tokenizer.prepare_seq2seq_batch(src_texts=source_texts,
                                                          tgt_texts=english,
                                                          max_length=MAX_LENGTH,
                                                          padding="max_length",
                                                          return_tensors="pt",
                                                          truncation=True)
         return tokenized data
     tokenized_datasets = tokenize_data(english_sentences_clean,_
      →arabic_sentences_clean)
     class CustomDataset(Dataset):
         def __init__(self, tokenized_data):
             self.input_ids = tokenized_data["input_ids"]
             self.attention_mask = tokenized_data["attention_mask"]
             self.target_ids = tokenized_data["labels"]
         def len (self):
             return len(self.input_ids)
         def __getitem__(self, idx):
             return {
                 "input_ids": self.input_ids[idx],
```

```
"attention_mask": self.attention_mask[idx],
            "labels": self.target_ids[idx]
       }
full_dataset = CustomDataset(tokenized_datasets)
train_size = int(0.8 * len(full_dataset))
val_size = len(full_dataset) - train_size
train_dataset, val_dataset = torch.utils.data.random_split(full_dataset,__
 model = MT5ForConditionalGeneration.from_pretrained("google/mt5-base")
training_args = TrainingArguments(
   output_dir="./results_mt5",
   per_device_train_batch_size=4,
   per_device_eval_batch_size=4,
   num_train_epochs=10,
   evaluation_strategy="steps",
   save_strategy="steps",
   logging_dir="./logs_mt5",
   logging_steps=1000,
   eval steps=1000,
   do_train=True,
   do_eval=True,
   no_cuda=False,
   push_to_hub=False,
   logging_first_step=True,
   report_to=["tensorboard"]
)
trainer = Trainer(
   model=model,
   args=training_args,
   train_dataset=train_dataset,
   eval dataset=val dataset,
   tokenizer=tokenizer
)
trainer.train()
```

```
You are using the legacy behaviour of the <class 'transformers.models.t5.tokenization_t5.T5Tokenizer'>. This means that tokens that come after special tokens will not be properly handled. We recommend you to read the related pull request available at https://github.com/huggingface/transformers/pull/24565 /l/users/ahmed.aboeitta/espnet/tools/anaconda/envs/espnet/lib/python3.8/site-packages/transformers/tokenization_utils_base.py:3766: FutureWarning: `prepare_seq2seq_batch` is deprecated and will be removed in version 5 of
```

```
HuggingFace Transformers. Use the regular
`__call__` method to prepare your inputs and targets.
Here is a short example:
model_inputs = tokenizer(src_texts, text_target=tgt_texts, ...)
If you either need to use different keyword arguments for the source and target
texts, you should do two calls like
this:
model_inputs = tokenizer(src_texts, ...)
labels = tokenizer(text_target=tgt_texts, ...)
model_inputs["labels"] = labels["input_ids"]
See the documentation of your specific tokenizer for more details on the
specific arguments to the tokenizer of choice.
For a more complete example, see the implementation of `prepare seq2seq batch`.
  warnings.warn(formatted warning, FutureWarning)
/l/users/ahmed.aboeitta/espnet/tools/anaconda/envs/espnet/lib/python3.8/site-
packages/transformers/tokenization utils base.py:3640: UserWarning:
`as_target_tokenizer` is deprecated and will be removed in v5 of Transformers.
You can tokenize your labels by using the argument `text_target` of the regular
`__call__` method (either in the same call as your input texts if you use the
same keyword arguments, or in a separate call.
  warnings.warn(
/l/users/ahmed.aboeitta/espnet/tools/anaconda/envs/espnet/lib/python3.8/site-
packages/transformers/optimization.py:411: FutureWarning: This implementation of
AdamW is deprecated and will be removed in a future version. Use the PyTorch
implementation torch.optim.AdamW instead, or set `no_deprecation_warning=True`
to disable this warning
  warnings.warn(
/home/ahmed.aboeitta/.local/lib/python3.8/site-
packages/torch/nn/parallel/ functions.py:68: UserWarning: Was asked to gather
along dimension 0, but all input tensors were scalars; will instead unsqueeze
and return a vector.
  warnings.warn('Was asked to gather along dimension 0, but all '
<IPython.core.display.HTML object>
/home/ahmed.aboeitta/.local/lib/python3.8/site-
packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather
along dimension 0, but all input tensors were scalars; will instead unsqueeze
and return a vector.
  warnings.warn('Was asked to gather along dimension 0, but all '
/home/ahmed.aboeitta/.local/lib/python3.8/site-
packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather
```

along dimension 0, but all input tensors were scalars; will instead unsqueeze

and return a vector.

warnings.warn('Was asked to gather along dimension 0, but all '

/home/ahmed.aboeitta/.local/lib/python3.8/site-

packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

warnings.warn('Was asked to gather along dimension 0, but all '

/home/ahmed.aboeitta/.local/lib/python3.8/site-

packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

warnings.warn('Was asked to gather along dimension 0, but all '

/home/ahmed.aboeitta/.local/lib/python3.8/site-

packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

warnings.warn('Was asked to gather along dimension 0, but all '

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warnings.warn('Was asked to gather along dimension 0, but all '

/home/ahmed.aboeitta/.local/lib/python3.8/site-

packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

warnings.warn('Was asked to gather along dimension 0, but all '

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packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

warnings.warn('Was asked to gather along dimension 0, but all '

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packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

warnings.warn('Was asked to gather along dimension 0, but all '
/home/ahmed.aboeitta/.local/lib/python3.8/site-

packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

warnings.warn('Was asked to gather along dimension 0, but all '/home/ahmed.aboeitta/.local/lib/python3.8/site-

packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

warnings.warn('Was asked to gather along dimension 0, but all '
/home/ahmed.aboeitta/.local/lib/python3.8/site-

packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

warnings.warn('Was asked to gather along dimension 0, but all '/home/ahmed.aboeitta/.local/lib/python3.8/site-

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warnings.warn('Was asked to gather along dimension 0, but all '/home/ahmed.aboeitta/.local/lib/python3.8/site-

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warnings.warn('Was asked to gather along dimension 0, but all '
/home/ahmed.aboeitta/.local/lib/python3.8/site-

packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

warnings.warn('Was asked to gather along dimension 0, but all '

/home/ahmed.aboeitta/.local/lib/python3.8/site-

packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

warnings.warn('Was asked to gather along dimension 0, but all '/home/ahmed.aboeitta/.local/lib/python3.8/site-

packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

warnings.warn('Was asked to gather along dimension 0, but all '
/home/ahmed.aboeitta/.local/lib/python3.8/site-

packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

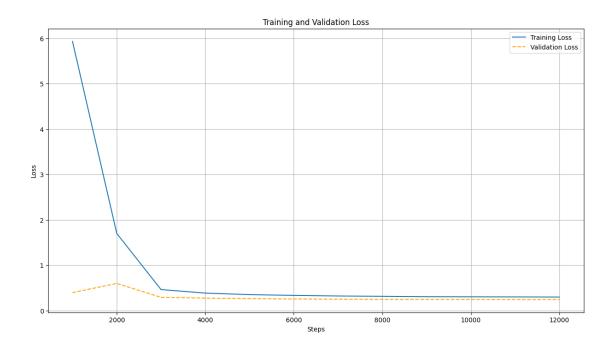
warnings.warn('Was asked to gather along dimension 0, but all '
/home/ahmed.aboeitta/.local/lib/python3.8/site-

packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather along dimension 0, but all input tensors were scalars; will instead unsqueeze and return a vector.

```
warnings.warn('Was asked to gather along dimension 0, but all '
    /home/ahmed.aboeitta/.local/lib/python3.8/site-
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    packages/torch/nn/parallel/_functions.py:68: UserWarning: Was asked to gather
    along dimension 0, but all input tensors were scalars; will instead unsqueeze
    and return a vector.
      warnings.warn('Was asked to gather along dimension 0, but all '
[]: TrainOutput(global_step=12320, training_loss=0.9058312131212903,
    metrics={'train_runtime': 7155.2974, 'train_samples_per_second': 27.545,
     'train_steps_per_second': 1.722, 'total_flos': 1.061593759429632e+17,
     'train_loss': 0.9058312131212903, 'epoch': 10.0})
[]: logs = trainer.state.log_history
     train_steps = [x['step'] for x in logs if 'loss' in x][1:]
     train_loss = [x['loss'] for x in logs if 'loss' in x][1:]
     eval_steps = [x['step'] for x in logs if 'eval_loss' in x]
     eval_loss = [x['eval_loss'] for x in logs if 'eval_loss' in x]
     plt.figure(figsize=(15, 8))
     plt.plot(train_steps, train_loss, label='Training Loss')
     plt.plot(eval_steps, eval_loss, label='Validation Loss', linestyle='--',u

¬color='orange')
     plt.xlabel('Steps')
     plt.ylabel('Loss')
     plt.legend()
     plt.title('Training and Validation Loss')
```

plt.grid(True)
plt.show()



```
[]:|device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
     def compute_bleu(model, dataset, tokenizer):
         reference_texts = []
         translated_texts = []
         for data in dataset:
             data = {key: val.to(device) for key, val in data.items()}
             reference_text = tokenizer.decode(data["labels"],__
      ⇔skip_special_tokens=True)
             reference_texts.append(reference_text)
             model.eval()
             with torch.no_grad():
                 output = model.generate(data["input_ids"].unsqueeze(0),_
      →attention_mask=data["attention_mask"].unsqueeze(0))
             translated_texts.append(tokenizer.decode(output[0],__
      ⇔skip_special_tokens=True))
         bleu_score = sacrebleu.corpus_bleu(translated_texts, [reference_texts])
         return bleu_score.score
     bleu = compute_bleu(model, val_dataset, tokenizer)
```

/l/users/ahmed.aboeitta/espnet/tools/anaconda/envs/espnet/lib/python3.8/site-packages/transformers/generation/utils.py:1369: UserWarning: Using `max_length`'s default (20) to control the generation length. This behaviour is

deprecated and will be removed from the config in v5 of Transformers -- we recommend using `max_new_tokens` to control the maximum length of the generation.

warnings.warn(

```
[]: print(f"Bleu Score: {bleu:.2f}")
```

Bleu Score: 6.66

Inference

2.6 Analysis:

Marian NMT seems to be the best suited for this translation task, given its consistently decreasing losses and high BLEU score. MBART, despite its potential, might require more careful fine-tuning or hyperparameter adjustments to achieve optimal results. MT5's performance suggests that not all models, regardless of their size or complexity, are equally suited for all tasks; the initial state of the model and its pretraining tasks play crucial roles in its fine-tuning performance.

The core advantage Marian NMT holds over the other two models in terms of architecture is its specialization. Every aspect of Marian, from its attention mechanisms to its tokenization strategy, has been refined and optimized exclusively for machine translation.

2.7 Why MARIAN Model is the Best:

• MARIAN:

- Marian NMT is specifically tailored for neural machine translation tasks. Its architecture, hyperparameters, and even the attention mechanisms are optimized for translation.
- The attention mechanisms in Marian NMT, such as self-attention, are fine-tuned to better understand the nuances of source and target languages in translation tasks. This focused design enables the model to achieve more accurate and coherent translations.
- The training and validation losses for Marian NMT tend to decrease over time indicating that the model is learning and generalizing well. The BLEU score is the highest among

the three models, suggesting very good translation quality.

• MBART:

- While MBART is also a sequence-to-sequence model like Marian, its design is more generalized. MBART is built to handle a variety of tasks, from translation to text summarization.
- MBART's unique pretraining approach involves reconstructing sentences with noise added. While this is useful for understanding context and generating coherent sequences, it might not always be as directly beneficial for translation as the specialized pretraining data Marian might use.
- MBART's training loss shows more fluctuations compared to Marian NMT, suggesting a less smooth learning process and possible overfitting scenarios or learning rate issues.

• MT5:

- MT5, derived from the T5 framework, is designed for various text-to-text transfer tasks.
 While this design offers flexibility, it may not be specialized enough for nuanced machine translation tasks.
- MT5 uses a unified SentencePiece tokenizer which, while powerful and capable of handling multiple languages, might not capture the intricacies of specific language pairs as effectively as a specialized system.
- MT5 starts with an alarmingly high training loss, which drastically drops later. This suggests that the model's pre-trained weights were initially not very conducive for the task at hand, but they adjusted considerably with more training.
- The massive gap in the training loss and the final BLEU score suggests that while MT5 is capable of adapting its weights for the task, its architecture or pretraining might not be as suited for this particular translation task.