

## Neural Machine Translation using Transformers

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# nightly version of tensorflow was used as they have more features available
!pip install -q tf-nightly > /dev/null 2>&1
!pip install -q tensorflow_text_nightly > /dev/null 2>&1
!pip install -q tensorflow_datasets

import os
import pathlib
import re
from nltk.translate.bleu_score import corpus_bleu
import numpy as np
import matplotlib.pyplot as plt
import tensorflow_datasets as tfds
import tensorflow_text as text
import tensorflow as tf
# from nightly
from tensorflow_text.tools.wordpiece_vocab import bert_vocab_from_dataset as bert_vocab

# to download the data-set, do not re-run if previously run
# dataset is already in lowercase and have space before and after punctuation.
tfds.disable_progress_bar()
builder = tfds.builder('ted_hrlr_translate/pt_to_en', data_dir=os.getcwd())
builder.download_and_prepare()

# loads the dataset
sets, info = tfds.load('ted_hrlr_translate/pt_to_en', data_dir=os.getcwd(),with_info=True, as_supervised=True, download=False)
train, val, test = sets['train'], sets['validation'], sets['test'] # 51785, 1193, 1803 examples in respective sets
for por_examples, eng_examples in test.batch(3).take(1):
    for pt in por_examples.numpy():
        print("Sample Portuguese: ", pt.decode('utf-8'))
    for en in eng_examples.numpy():
        print("Sample English: ", en.decode('utf-8'))

# Bert pre-trained language representation is used to feed vectors to the transformer model. It enhances the language understanding,
# by retaining context unlike word2vec or GloVe representation where each word only has one vector without context.
# Bert gives bidirectional context using encoder based on other words in the sequence giving more exploitation potential to the model.

# Bert wordpiece vocabulary of tensorflow is used, it uses Bert's splitting algorithm to split the text into words
# before generating the subword vocabulary on the pre-trained bert by Tensorflow team. Example vocabulary for hello: he###, hell##, #ello, etc.
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reserved_tokens = ["[START]", "[END]", "[PAD]", "[UNK]",
bert_vocab_args = dict(
    vocab_size = 5000,
    bert_tokenizer_params=dict(lower_case=True),
    reserved_tokens = reserved_tokens,
    learn_params = {}
)

eng_train = train.map(lambda pt, en:en)
por_train = train.map(lambda pt, en:pt)

# creating the vocabulary file
eng_vocab = bert_vocab.bert_vocab_from_dataset(eng_train.batch(1000).prefetch(2), **bert_vocab_args)
with open(os.path.join(os.getcwd(), 'eng_vocab.txt'), 'w') as f:
    for tok in eng_vocab:
        print(tok, file=f)
por_vocab = bert_vocab.bert_vocab_from_dataset(por_train.batch(1000).prefetch(2), **bert_vocab_args)
with open(os.path.join(os.getcwd(), 'por_vocab.txt'), 'w') as f:
    for tok in por_vocab:
        print(tok, file=f)

addons = ["[START]", "[END]", "[PAD]"]

def add_reserved_tokens(vector):
    count = vector.bounding_shape()[0]
    starts = tf.fill([count,1], tf.argmax(tf.constant(addons) == "[START]"))
    ends = tf.fill([count,1], tf.argmax(tf.constant(addons) == "[END]"))
    return tf.concat([starts, vector, ends], axis=1)

def post_process(words):
    remove_addons = "|".join([re.escape(token) for token in addons])
    result = tf.ragged.boolean_mask(words, ~tf.strings.regex_full_match(words, remove_addons))
    return tf.strings.reduce_join(result, separator=' ', axis=-1)

# The bert wordpiece vocabulary is used by BertTokenizer to convert text string to wordpiece tokenization.
class custom_Bert(tf.Module):
    def __init__(self, vocab_path):
        self.bert = text.BertTokenizer(vocab_path, lower_case=True)
        self.vocab_path = vocab_path
        self.vocab = tf.Variable(pathlib.Path(vocab_path).read_text().splitlines())

    # vectorize the given string to token ids, preprocess data, add start and end tokens
    def tokenize(self, strings):
        tokenized_string = self.bert.tokenize(strings) merge dims (-2 -1)

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tokenized_string = self.bert.tokenize(strings).merge_dims(-2, -1)
return add_reserved_tokens(tokenized_string)

# recreates the sentence using encoded tokens
def detokenize(self, tokens):
    return post_process(self.bert.detokenize(tokens))

# find the word from vocabulary using ids
def ids_to_word(self, ids):
    return tf.gather(self.vocab, ids)

def vocab_size(self):
    return tf.shape(self.vocab)[0]

bert_tokenizer = tf.Module()
bert_tokenizer.eng = custom_Bert(os.path.join(os.getcwd(), 'eng_vocab.txt'))
bert_tokenizer.por = custom_Bert(os.path.join(os.getcwd(), 'por_vocab.txt'))

# positional encoding layer using sin and cosines on alternate positions to get positional context.
def positional_encodings(position, embed_d):
    frequencies = np.arange(position).reshape(position,1)/(np.power(10000,(2*(np.arange(embed_d).reshape(1,embed_d)//2)/embed_d)))
    frequencies[:, 0::2] = np.sin(frequencies[:,0::2])
    frequencies[:, 1::2] = np.cos(frequencies[:,1::2])
    pos_enc = tf.cast(frequencies[np.newaxis, ...],tf.float32)
    return pos_enc

def feed_forward_network(embed_d, inner_d):
    ffn = tf.keras.Sequential(
        [
            tf.keras.layers.Dense(inner_d, activation='relu'),
            tf.keras.layers.Dense(embed_d)
        ]
    )
    return ffn

# attention to mask other values and only show seq which is being attended upon
def dot_product_attention(query, key, value, decode_mask):
    q_dot_k = tf.matmul(query,key,transpose_b=True)
    d = tf.cast(tf.shape(key)[-1], tf.float32)
    scaled_product = q_dot_k/tf.math.sqrt(d)
    if decode_mask is not None:
        scaled_product += (decode_mask * -1e9)
    attention_weights = tf.nn.softmax(scaled_product, axis=-1)
    scaled_attention = tf.matmul(attention_weights, value)

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return attention_weights, scaled_attention

# used to split heads and calculate attention which allows the model to jointly attend
# to the information from different representational dimensions.
class MultiHeadedAttention(tf.keras.layers.Layer):
    def __init__(self, embed_d, n_heads):
        super(MultiHeadedAttention, self).__init__()
        self.embed_d = embed_d
        self.n_heads = n_heads
        self.wq = tf.keras.layers.Dense(embed_d)
        self.wk = tf.keras.layers.Dense(embed_d)
        self.wv = tf.keras.layers.Dense(embed_d)
        self.depth = embed_d//self.n_heads
        self.dense = tf.keras.layers.Dense(embed_d)

    def splitting_heads(self, qkv, batch_size):
        qkv = tf.reshape(qkv, (batch_size, -1, self.n_heads, self.depth))
        return tf.transpose(qkv, perm=[0, 2, 1, 3])

    def call(self, v, k, q, mask):
        batch_size = tf.shape(q)[0]
        q = self.splitting_heads(self.wq(q), batch_size)
        k = self.splitting_heads(self.wk(k), batch_size)
        v = self.splitting_heads(self.wv(v), batch_size)

        attention_weights, scaled_attention = dot_product_attention(q, k, v, mask)
        scaled_attention = tf.transpose(scaled_attention, perm=[0,2,1,3])
        concated_attention = tf.reshape(scaled_attention, (batch_size, -1, self.embed_d))
        output = self.dense(concated_attention)
        return output, attention_weights

# Encoder architecture allows the self-attention where all of the keys, values and queries are same.
# hence attending to all positions in the previous step of layer.
class EncoderLayer(tf.keras.layers.Layer):
    def __init__(self, embed_d, n_heads, inner_d, drop_rate):
        super(EncoderLayer, self).__init__()
        self.multi_heads = MultiHeadedAttention(embed_d, n_heads)
        self.dropout_layer1 = tf.keras.layers.Dropout(drop_rate)
        self.layer_norm1 = tf.keras.layers.LayerNormalization(axis=-1, epsilon=1e-6)
        self.ffn = feed_forward_network(embed_d, inner_d)
        self.dropout_layer2 = tf.keras.layers.Dropout(drop_rate)
        self.layer_norm2 = tf.keras.layers.LayerNormalization(axis=-1, epsilon=1e-6)

    def call(self, v, mask, training):
        encoder_self_attention, encoder_attention_weights = self.multi_heads(v,v,v, mask)
        encoder_self_attention = self.dropout_layer1(encoder_self_attention, training)
        encoder_self_attention = self.layer_norm1(encoder_self_attention)
        encoder_self_attention = self.ffn(encoder_self_attention)
        encoder_self_attention = self.dropout_layer2(encoder_self_attention, training)
        encoder_self_attention = self.layer_norm2(encoder_self_attention)

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encoder_self_attention = self.dropout_layer1(encoder_self_attention, training=training)
normalized1 = self.layer_norm1(v+encoder_self_attention)
linear_transform = self.ffn(normalized1)
linear_transform = self.dropout_layer2(linear_transform, training=training)
normalized2 = self.layer_norm2(normalized1+linear_transform)
return normalized2

# this module includes embedding layers for input, positional encodings and output layer to feed into decoder
class Encoder(tf.keras.layers.Layer):
    def __init__(self, n_enc_layers, embed_d, n_heads, inner_d, vocab_size, max_pos, drop_rate):
        super(Encoder, self).__init__()
        self.embed_d = embed_d
        self.embedding_layer = tf.keras.layers.Embedding(vocab_size, embed_d)
        self.pos_encoding = positional_encodings(max_pos, self.embed_d)
        self.n_enc_layers = n_enc_layers
        self.enc_layers = [EncoderLayer(embed_d, n_heads, inner_d, drop_rate) for layer in range(n_enc_layers)]
        self.dropout_layer = tf.keras.layers.Dropout(drop_rate)

    def call(self, v, mask, training):
        input_seq_len = tf.shape(v)[1]
        v = self.embedding_layer(v)
        v *= tf.math.sqrt(tf.cast(self.embed_d, tf.float32))
        v += self.pos_encoding[:, :input_seq_len, :]
        v = self.dropout_layer(v, training=training)
        for layer in range(self.n_enc_layers):
            v = self.enc_layers[layer](v, mask, training)
        return v

class DecoderLayer(tf.keras.layers.Layer):
    def __init__(self, embed_d, n_heads, inner_d, drop_rate):
        super(DecoderLayer, self).__init__()
        self.masked_multi_heads = MultiHeadedAttention(embed_d, n_heads)
        self.dropout_layer1 = tf.keras.layers.Dropout(drop_rate)
        self.layer_norm1 = tf.keras.layers.LayerNormalization(axis=-1, epsilon=1e-6)
        self.multi_heads = MultiHeadedAttention(embed_d, n_heads)
        self.dropout_layer2 = tf.keras.layers.Dropout(drop_rate)
        self.layer_norm2 = tf.keras.layers.LayerNormalization(axis=-1, epsilon=1e-6)
        self.ffn = feed_forward_network(embed_d, inner_d)
        self.dropout_layer3 = tf.keras.layers.Dropout(drop_rate)
        self.layer_norm3 = tf.keras.layers.LayerNormalization(axis=-1, epsilon=1e-6)

    def call(self, v, look_ahead_mask, padding, training, encoder_output):
        decoder_self_attention, decoder_self_attn_wts = self.masked_multi_heads(v, v, v, look_ahead_mask)
        decoder_self_attention = self.dropout_layer1(decoder_self_attention, training=training)
        normalized1 = self.layer_norm1(decoder_self_attention + v)

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normalized2 = self.layer_norm2(dec_enc_attention + v)
dec_enc_attention, dec_enc_attn_wts = self.multi_heads(encoder_output, encoder_output, normalized1, padding)
dec_enc_attention = self.dropout_layer2(dec_enc_attention, training=training)
normalized2 = self.layer_norm2(dec_enc_attention + normalized1)
linear_transform = self.ffn(normalized2)
linear_transform = self.dropout_layer3(linear_transform, training=training)
normalized3 = self.layer_norm3(linear_transform + normalized2)
return normalized3, decoder_self_attn_wts, dec_enc_attn_wts

```

```

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

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```

    def __init__(self, n_dec_layers, embed_d, n_heads, inner_d, vocab_size, max_pos, drop_rate):

```

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        super(Decoder, self).__init__()

```

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        self.embed_d = embed_d

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        self.embedding_layer = tf.keras.layers.Embedding(vocab_size, embed_d)

```

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        self.pos_encoding = positional_encodings(max_pos, self.embed_d)

```

```

        self.n_dec_layers = n_dec_layers

```

```

        self.dec_layers = [DecoderLayer(embed_d, n_heads, inner_d, drop_rate) for layer in range(n_dec_layers)]

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        self.dropout_layer = tf.keras.layers.Dropout(drop_rate)

```

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    def call(self, v, look_ahead_mask, padding, training, encoder_output):

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        target_seq_len = tf.shape(v)[1]

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        v = self.embedding_layer(v)

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        v *= tf.math.sqrt(tf.cast(self.embed_d, tf.float32))

```

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        v += self.pos_encoding[:, :target_seq_len, :]

```

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        v = self.dropout_layer(v, training=training)

```

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        for layer in range(self.n_dec_layers):

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            v, decoder_self_attn_wts, dec_enc_attn_wts = self.dec_layers[layer](v, look_ahead_mask, padding, training, encoder_output)

```

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        return v, decoder_self_attn_wts, dec_enc_attn_wts

```

```

class NMT_Transformer(tf.keras.Model):

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```

    def __init__(self, n_layers, embed_d, n_heads, inner_d, inp_vocab_size, tar_vocab_size, max_pos, drop_rate):

```

```

        super(NMT_Transformer, self).__init__()

```

```

        self.encoder = Encoder(n_layers, embed_d, n_heads, inner_d, inp_vocab_size, max_pos, drop_rate)

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        self.decoder = Decoder(n_layers, embed_d, n_heads, inner_d, tar_vocab_size, max_pos, drop_rate)

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        self.linear = tf.keras.layers.Dense(tar_vocab_size)

```

```

    def call(self, enc_dec_mask, look_ahead_mask, input, target, training):

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        encoder_output = self.encoder(input, enc_dec_mask, training)

```

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        decoder_output, decoder_self_attn_wts, dec_enc_attn_wts = self.decoder(target, look_ahead_mask, enc_dec_mask, training, encoder_output)

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        linear_output = self.linear(decoder_output)

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        return linear_output, decoder_self_attn_wts, dec_enc_attn_wts

```

```

class AdaptiveLR(tf.keras.optimizers.schedules.LearningRateSchedule):

```

```

def __init__(self, embed_d, warmup_steps):
    super(AdaptiveLR, self).__init__()
    self.embed_d = tf.cast(embed_d, tf.float32)
    self.warmup_steps = warmup_steps

def __call__(self, schedule):
    variable_lr = tf.math.rsqrt(self.embed_d)*tf.math.minimum(tf.math.rsqrt(schedule), schedule*(self.warmup_steps**-1.5))
    return variable_lr

```

```

train_loss = tf.keras.metrics.Mean(name='train_loss')
train_accuracy = tf.keras.metrics.Mean(name='train_accuracy')

```

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def loss_func(predicted, true):
    sparse_cat_loss = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True, reduction='none')
    loss = sparse_cat_loss(true, predicted)
    pad_mask = tf.cast(tf.math.logical_not(tf.math.equal(true,0)), dtype=loss.dtype)
    return tf.reduce_sum(loss*pad_mask)/tf.reduce_sum(pad_mask)

```

```

def acc_func(predicted, true):
    acc = tf.equal(true, tf.argmax(predicted, axis=2))
    pad_mask = tf.math.logical_not(tf.math.equal(true,0))
    acc = tf.math.logical_and(pad_mask, acc)
    return tf.reduce_sum(tf.cast(acc, dtype=tf.float32))/tf.reduce_sum(tf.cast(pad_mask, dtype=tf.float32))

```

```

def masks(input, target):
    # padding masks will create a mask of 1's wherever there are 0's
    enc_dec_values = tf.cast(tf.math.equal(input, 0), tf.float32)
    enc_dec_mask = enc_dec_values[:, tf.newaxis, tf.newaxis, :]
    # look ahead mask is used to hide the future tokens from an index in decoder as that index needs to be predicted
    dec_look_ahead_mask = 1-tf.linalg.band_part(tf.ones((tf.shape(target)[1],tf.shape(target)[1])), -1, 0)
    dec_pad_values = tf.cast(tf.math.equal(target, 0), tf.float32)
    dec_target_mask = dec_pad_values[:, tf.newaxis, tf.newaxis, :]
    dec_masked = tf.maximum(dec_look_ahead_mask, dec_target_mask)
    return enc_dec_mask, dec_masked

```

```

def bert_mapping(pt, en):
    pt = bert_tokenizer.por.tokenize(pt).to_tensor()
    en = bert_tokenizer.eng.tokenize(en).to_tensor()
    return pt, en

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train_batch = train_cache().shuf512(10000).batch(64).map(bert_mapping, num_parallel_calls=tf.data.AUTOTUNE).prefetch(tf.data.AUTOTUNE)

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```

train_batch = train.cache().shuffle(10000).batch(64).map(bert_mapping, num_parallel_calls=tf.data.AUTOTUNE).prefetch(tf.data.AUTOTUNE)
val_batch = val.cache().shuffle(10000).batch(64).map(bert_mapping, num_parallel_calls=tf.data.AUTOTUNE).prefetch(tf.data.AUTOTUNE)
test_batch = test.cache().shuffle(10000).batch(64).map(bert_mapping, num_parallel_calls=tf.data.AUTOTUNE).prefetch(tf.data.AUTOTUNE)

nmt = NMT_Transformer(n_layers=2, embed_d=64, n_heads=2, inner_d=256, inp_vocab_size=bert_tokenizer.eng.vocab_size(), tar_vocab_size=bert_tokenizer.por.vocab_size())
lr = AdaptiveLR(embed_d=64, warmup_steps=1000)
optimizer = tf.keras.optimizers.Adam(lr, beta_1=0.9, beta_2=0.98, epsilon=1e-9)

train_signature = [tf.TensorSpec(shape=(None, None), dtype=tf.int64), tf.TensorSpec(shape=(None, None), dtype=tf.int64)]

@tf.function(input_signature=train_signature)
def training(input, target):
    # target input leaves last word in seq to predict
    target_input = target[:, :-1]
    # target input leaves first word in seq
    target_real = target[:, 1:]
    enc_dec_mask, dec_masked = masks(input, target_input)

    with tf.GradientTape() as tape:
        prediction, decoder_self_attn_wts, dec_enc_attn_wts = nmt(enc_dec_mask, dec_masked, input, target_input, training=True)
        loss = loss_func(prediction, target_real)

    grad = tape.gradient(loss, nmt.trainable_variables)
    optimizer.apply_gradients(zip(grad, nmt.trainable_variables))
    train_loss(loss)
    train_accuracy(acc_func(prediction, target_real))

    Sample Portuguese: depois , podem fazer-se e testar-se previsões .
    Sample Portuguese: forçou a parar múltiplos laboratórios que ofereciam testes brca .
    Sample Portuguese: as formigas são um exemplo clássico ; as operárias trabalham para as rainhas e vice-versa .
    Sample English: then , predictions can be made and tested .
    Sample English: it had forced multiple labs that were offering brca testing to stop .
    Sample English: ants are a classic example ; workers work for queens and queens work for workers .

epochs = 2
for epoch in range(epochs):
    train_loss.reset_states()
    train_accuracy.reset_states()
    for (batch, (por, eng)) in enumerate(train_batch):
        training(eng, por)
        if batch % 100 == 0:
            print(f'Epoch no. {epoch+1} Batch {batch} Loss {train_loss.result():.3f} Accuracy {train_accuracy.result():.3f}')
    print(f'Epoch no. {epoch + 1} Loss {train_loss.result():.3f} Accuracy {train_accuracy.result():.3f}')
nmt.save_weights(os.path.join(os.getcwd(), 'weights'))

def translate(sentence, max_seq_len=40):

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tokenized_input = bert_tokenizer.eng.tokenize(tf.convert_to_tensor([sentence])).to_tensor()
start_token, end_token = bert_tokenizer.por.tokenize([''])[0]
target = tf.expand_dims(tf.convert_to_tensor([start_token]),0)
for token in range(max_seq_len):
    enc_dec_mask, dec_masked = masks(tokenized_input, target)
    prediction, decoder_self_attn_wts, dec_enc_attn_wts = nmt(enc_dec_mask, dec_masked, tokenized_input, target, training=False)
    prediction_id = tf.argmax(prediction[:, -1:, :], axis=-1)
    target = tf.concat([target, prediction_id], axis=-1)
    if prediction_id == end_token:
        break

translated_text = bert_tokenizer.por.detokenize(target)[0]
translated_tokens = bert_tokenizer.por.ids_to_word(target)[0]
return translated_text, translated_tokens, decoder_self_attn_wts, dec_enc_attn_wts

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```

Epoch no. 1 Batch 0 Loss 8.506 Accuracy 0.000
Epoch no. 1 Batch 100 Loss 8.093 Accuracy 0.028
Epoch no. 1 Batch 200 Loss 7.349 Accuracy 0.044
Epoch no. 1 Batch 300 Loss 6.865 Accuracy 0.075
Epoch no. 1 Batch 400 Loss 6.507 Accuracy 0.100
Epoch no. 1 Batch 500 Loss 6.227 Accuracy 0.120
Epoch no. 1 Batch 600 Loss 6.000 Accuracy 0.137
Epoch no. 1 Batch 700 Loss 5.807 Accuracy 0.152
Epoch no. 1 Batch 800 Loss 5.639 Accuracy 0.165
Epoch no. 1 Loss 5.626 Accuracy 0.166
Epoch no. 2 Batch 0 Loss 4.378 Accuracy 0.267
Epoch no. 2 Batch 100 Loss 4.334 Accuracy 0.269
Epoch no. 2 Batch 200 Loss 4.276 Accuracy 0.275
Epoch no. 2 Batch 300 Loss 4.237 Accuracy 0.278
Epoch no. 2 Batch 400 Loss 4.190 Accuracy 0.283
Epoch no. 2 Batch 500 Loss 4.141 Accuracy 0.288
Epoch no. 2 Batch 600 Loss 4.095 Accuracy 0.293
Epoch no. 2 Batch 700 Loss 4.047 Accuracy 0.298
Epoch no. 2 Batch 800 Loss 4.003 Accuracy 0.303
Epoch no. 2 Loss 3.999 Accuracy 0.304

```

```

def test_bleu():
    test_input = []
    test_predicted = []
    test_truth = []
    bleu_scores = []
    for por_examples, eng_examples in test.batch(30).take(10):
        for pt in por_examples.numpy():
            test_truth.append(pt.decode('utf-8'))
        for en in eng_examples.numpy():
            test_input.append(en.decode('utf-8'))
            translated_text = translate(en.decode('utf-8'))

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```

translated_text, _, _ = translate(en.decode('utf-8'))
test_predicted.append(translated_text.numpy().decode("utf-8"))

bleu1 = corpus_bleu(test_truth, test_predicted, weights=(1.0, 0, 0, 0))
print('BLEU-1 results: {:.3f}'.format(bleu1))
bleu2 = corpus_bleu(test_truth, test_predicted, weights=(0.5, 0.5, 0, 0))
print('BLEU-2 results: {:.3f}'.format(bleu2))
bleu3 = corpus_bleu(test_truth, test_predicted, weights=(0.3, 0.3, 0.3, 0))
print('BLEU-3 results: {:.3f}'.format(bleu3))
bleu4 = corpus_bleu(test_truth, test_predicted, weights=(0.25, 0.25, 0.25, 0.25))
print('BLEU-4 results: {:.3f}'.format(bleu4))
bleu_scores = [bleu1, bleu2, bleu3, bleu4]
return test_input, test_predicted, test_truth, bleu_scores

print("Bleu scores computed on 300 examples from test set and sample results: ")
test_input, test_predicted, test_truth, bleu_scores = test_bleu()
for ind in range(6):
    print("Sample Input: ", test_input[ind])
    print("Sample Predicted: ", test_predicted[ind])
    print("Sample Truth: ", test_truth[ind])

    Bleu scores computed on 300 examples from test set and sample results:
    /usr/local/lib/python3.7/dist-packages/nltk/translate/bleu_score.py:490: UserWarning:
    Corpus/Sentence contains 0 counts of 2-gram overlaps.
    BLEU scores might be undesirable; use SmoothingFunction().
        warnings.warn(_msg)
    BLEU-1 results: 0.143
    BLEU-2 results: 0.378
    BLEU-3 results: 0.557
    BLEU-4 results: 0.615
    Sample Input:  then , predictions can be made and tested .
    Sample Predicted:  , exproventaveis .
    Sample Truth:  depois , podem fazer-se e testar-se previsões .
    Sample Input:  it had forced multiple labs that were offering brca testing to stop .
    Sample Predicted:
    Sample Truth:  forçou a parar múltiplos laboratórios que ofereciam testes brca .
    Sample Input:  ants are a classic example ; workers work for queens and queens work for workers .
    Sample Predicted:  um exemplo , os dias , os dias expeitos para os trabalhadores .
    Sample Truth:  as formigas são um exemplo clássico ; as operárias trabalham para as rainhas e vice-versa .
    Sample Input:  one of every hundred children born worldwide has some kind of heart disease .
    Sample Predicted:  de todos os miudos do mundo .
    Sample Truth:  uma em cada cem crianças no mundo nascem com uma doença cardíaca .
    Sample Input:  at this point in her life , she 's suffering with full-blown aids and had pneumonia .
    Sample Predicted:  o seu ponto de
    Sample Truth:  neste momento da sua vida , ela está a sofrer de sida no seu expoente máximo e tinha pneumonia .
    Sample Input:  where are economic networks ?
    Sample Predicted:  onde sao as redes sociais ?
    Sample Truth:  onde estão as redes económicas ?

```

```
sample_text = "where are we going after lunch, do you have any plans or we should make on our way?"
translated_text, _, _ = translate(sample_text)
print(translated_text.numpy().decode("utf-8"))
```

```
# truth: as formigas são um exemplo clássico ; as operárias trabalham para as rainhas e vice-versa .
sample_text3 = "ants are a classic example ; workers work for queens and queens work for workers."
translated_text, _, _ = translate(sample_text3)
print(translated_text.numpy().decode("utf-8"))
```

```
` `` `` ` ' ' ' onde nos vamos ter descordar ou os nossos estudos ? ' ' '
` `` `` ` ' ' ' ' um exemplo , os dias , os dias expeitos para os trabalhadores . ' ' '
```