Transformer_Jason_v1

July 13, 2020

1 Transformer

1.0.1 The original transform for NLP and Time Series problem

https://arxiv.org/abs/1706.03762 https://www.tensorflow.org/tutorials/text/transformer Pytorch version will come soon

```
In [2]: import tensorflow_datasets as tfds
        import tensorflow as tf

        import time
        import numpy as np
        import matplotlib.pyplot as plt
        import gc
```

```
In [18]: def get_angles(pos, i, d_model):
             angle_rates = 1 / np.power(10000, (2 * (i//2)) / np.float32(d_model))
             return pos * angle_rates

         def positional_encoding(position, d_model):
             angle_rads = get_angles(np.arange(position)[:, np.newaxis],
                                     np.arange(d_model)[np.newaxis, :],
                                     d_model)

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

             # apply cos to odd indices in the array; 2i+1
             angle_rads[:, 1::2] = np.cos(angle_rads[:, 1::2])
             pos_encoding = angle_rads[np.newaxis, ...]
             return tf.cast(pos_encoding, dtype=tf.float32)

         pos_encoding = positional_encoding(50, 512)
         print (pos_encoding.shape)
```

```
(1, 50, 512)
```

In [3]:
```python
# Calculate scaled dot product: q k v

def scaled_dot_product_attention(q, k, v, mask):
    matmul_qk = tf.matmul(q, k, transpose_b=True)
    dk = tf.cast(tf.shape(k)[-1], tf.float32)
    scaled_attention_logits = matmul_qk / tf.math.sqrt(dk)
    # add the mask to the scaled tensor.
    if mask is not None:
        scaled_attention_logits += (mask * -1e9)
    # calculate attention weight:
    attention_weights = tf.nn.softmax(scaled_attention_logits, axis=-1)
    # Attention (q.k.v)
    output = tf.matmul(attention_weights, v)
    return output, attention_weights



def print_out(q, k, v):
    temp_out, temp_attn = scaled_dot_product_attention(
      q, k, v, None)

    print ('Attention weights are:')
    print (temp_attn)
    print ('Output is:')
    print (temp_out)
```

In [10]:
```python
# some temporary weights:


 if True:
     np.set_printoptions(suppress=True)

     temp_k = tf.constant([[10,0,0],
                           [0,10,0],
                           [0,0,10],
                           [0,0,10]], dtype=tf.float32)  # (4, 3)

     temp_v = tf.constant([[   1,0],
                           [  10,0],
                           [ 100,5],
                           [1000,6]], dtype=tf.float32)  # (4, 2)
     temp_q = tf.constant([[0, 10, 0]], dtype=tf.float32)  # (1, 3)
     print_out(temp_q, temp_k, temp_v)
```

```
Attention weights are:
tf.Tensor([[0. 1. 0. 0.]], shape=(1, 4), dtype=float32)
Output is:
tf.Tensor([[10.  0.]], shape=(1, 2), dtype=float32)
```

Create a `MultiHeadAttention` layer to try out. At each location in the sequence, `y`, the `MultiHeadAttention` runs all 8 attention heads across all other locations in the sequence, returning a new vector of the same length at each location.

In [5]:
```
# Multi-head Attention:
class MultiHeadAttention(tf.keras.layers.Layer):
    def __init__(self, d_model, num_heads):

        # Always use Super to inheriatte and avoid extra code.
        super(MultiHeadAttention, self).__init__()
        self.num_heads = num_heads
        self.d_model = d_model
        # sanity check:
        assert d_model % self.num_heads == 0
        self.depth = d_model // self.num_heads
        # Q K W:
        self.wq = tf.keras.layers.Dense(d_model)
        self.wk = tf.keras.layers.Dense(d_model)
        self.wv = tf.keras.layers.Dense(d_model)

        self.dense = tf.keras.layers.Dense(d_model)
    def split_heads(self, x, batch_size):
        # Transpose the result such that the shape is (batch_size, num_heads, seq_len,
        x = tf.reshape(x, (batch_size, -1, self.num_heads, self.depth))
        return tf.transpose(x, perm=[0, 2, 1, 3])
    def call(self, v, k, q, mask):
        batch_size = tf.shape(q)[0]
        q = self.wq(q)  # (batch_size, seq_len, d_model)
        k = self.wk(k)  # (batch_size, seq_len, d_model)
        v = self.wv(v)  # (batch_size, seq_len, d_model)

        q = self.split_heads(q, batch_size)  # (batch_size, num_heads, seq_len_q, depth
        k = self.split_heads(k, batch_size)  # (batch_size, num_heads, seq_len_k, depth
        v = self.split_heads(v, batch_size)  # (batch_size, num_heads, seq_len_v, depth

        # scaled_attention.shape == (batch_size, num_heads, seq_len_q, depth)
        # attention_weights.shape == (batch_size, num_heads, seq_len_q, seq_len_k)

        scaled_attention, attention_weights = scaled_dot_product_attention(q, k, v, mas
        # https://www.tensorflow.org/api_docs/python/tf/transpose : perm
        scaled_attention = tf.transpose(scaled_attention, perm=[0, 2, 1, 3])  # (batch_
        concat_attention = tf.reshape(scaled_attention,
```

```
                                    (batch_size, -1, self.d_model))  # (batch_size, seq_
            output = self.dense(concat_attention)  # (batch_size, seq_len_q, d_model)
            return output, attention_weights




    # check our Multi-head attention:

    n_d_model=512
    temp_mha = MultiHeadAttention(d_model=n_d_model, num_heads=8)
    y = tf.random.uniform((1, 60, n_d_model))  # (batch_size, encoder_sequence, d_model)
    out, attn = temp_mha(y, k=y, q=y, mask=None)
    out.shape, attn.shape
```

```
Out[5]: (TensorShape([1, 60, 512]), TensorShape([1, 8, 60, 60]))
```

```
In [6]: # Point wise feed forward network consists of two fully-connected layers with a ReLU a
        def point_wise_feed_forward_network(d_model, dff):
            # Two FC layers:
            return tf.keras.Sequential([
              tf.keras.layers.Dense(dff, activation='relu'),  # (batch_size, seq_len, dff)
              tf.keras.layers.Dense(d_model)  # (batch_size, seq_len, d_model)
          ])
```

```
In [9]: sample_ffn = point_wise_feed_forward_network(512, 2048)
        sample_ffn(tf.random.uniform((64, 50, 512))).shape
```

```
Out[9]: TensorShape([64, 50, 512])
```

2 Encoder and Decoder:

2.0.1 Encoder layer

Each encoder layer consists of sublayers:

1. Multi-head attention (with padding mask)
2. Point wise feed forward networks.

Each of these sublayers has a residual connection around it followed by a layer normalization. Residual connections help in avoiding the vanishing gradient problem in deep networks.

The output of each sublayer is `LayerNorm(x + Sublayer(x))`. The normalization is done on the `d_model` (last) axis. There are N encoder layers in the transformer.

```
In [11]: class EncoderLayer(tf.keras.layers.Layer):
             # Here we use a 0.1 dropout rate as default
```

```
    def __init__(self, d_model, num_heads, dff, rate=0.1):
        super(EncoderLayer, self).__init__()
        self.mha = MultiHeadAttention(d_model, num_heads)
        self.ffn = point_wise_feed_forward_network(d_model, dff)

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

        self.dropout1 = tf.keras.layers.Dropout(rate)
        self.dropout2 = tf.keras.layers.Dropout(rate)

    def call(self, x, training, mask):
        attn_output, _ = self.mha(x, x, x, mask)  # (batch_size, input_seq_len, d_mod
        attn_output = self.dropout1(attn_output, training=training)

        out1 = self.layernorm1(x + attn_output)  # (batch_size, input_seq_len, d_mode
        ffn_output = self.ffn(out1)  # (batch_size, input_seq_len, d_model)
        ffn_output = self.dropout2(ffn_output, training=training)

        out2 = self.layernorm2(out1 + ffn_output)  # (batch_size, input_seq_len, d_mo

        return out2
```

```
In [13]: if True:
             sample_encoder_layer = EncoderLayer(512, 8, 2048)

             sample_encoder_layer_output = sample_encoder_layer(tf.random.uniform((64, 43, 512

             print(sample_encoder_layer_output.shape)  # (batch_size, input_seq_len, d_model)
```

```
(64, 43, 512)
```

2.0.2 Decoder layer

Each decoder layer consists of sublayers:

1. Masked multi-head attention (with look ahead mask and padding mask)
2. Multi-head attention (with padding mask). V (value) and K (key) receive the *encoder output* as inputs. Q (query) receives the *output from the masked multi-head attention sublayer.*
3. Point wise feed forward networks

Each of these sublayers has a residual connection around it followed by a layer normalization. The output of each sublayer is `LayerNorm(x + Sublayer(x))`. The normalization is done on the `d_model` (last) axis.

There are N decoder layers in the transformer.

As Q receives the output from decoder's first attention block, and K receives the encoder output, the attention weights represent the importance given to the decoder's input based on the encoder's output. In other words, the decoder predicts the next word by looking at the encoder output and self-attending to its own output. See the demonstration above in the scaled dot product attention section.

In [20]:
```
class DecoderLayer(tf.keras.layers.Layer):
    def __init__(self, d_model, num_heads, dff, rate=0.1):
        super(DecoderLayer, self).__init__()

        self.mha1 = MultiHeadAttention(d_model, num_heads)
        self.mha2 = MultiHeadAttention(d_model, num_heads)

        self.ffn = point_wise_feed_forward_network(d_model, dff)

        self.layernorm1 = tf.keras.layers.LayerNormalization(epsilon=1e-6)
        self.layernorm2 = tf.keras.layers.LayerNormalization(epsilon=1e-6)
        self.layernorm3 = tf.keras.layers.LayerNormalization(epsilon=1e-6)

        self.dropout1 = tf.keras.layers.Dropout(rate)
        self.dropout2 = tf.keras.layers.Dropout(rate)
        self.dropout3 = tf.keras.layers.Dropout(rate)

    def call(self, x, enc_output, training, look_ahead_mask, padding_mask):
        # enc_output.shape == (batch_size, input_seq_len, d_model)

        attn1, attn_weights_block1 = self.mha1(x, x, x, look_ahead_mask)  # (batch_si
        attn1 = self.dropout1(attn1, training=training)
        out1 = self.layernorm1(attn1 + x)

        attn2, attn_weights_block2 = self.mha2(
            enc_output, enc_output, out1, padding_mask)  # (batch_size, target_seq_le
        attn2 = self.dropout2(attn2, training=training)
        out2 = self.layernorm2(attn2 + out1)  # (batch_size, target_seq_len, d_model)

        ffn_output = self.ffn(out2)  # (batch_size, target_seq_len, d_model)
        ffn_output = self.dropout3(ffn_output, training=training)
        out3 = self.layernorm3(ffn_output + out2)  # (batch_size, target_seq_len, d_m

        return out3, attn_weights_block1, attn_weights_block2

sample_decoder_layer = DecoderLayer(512, 8, 2048)

sample_decoder_layer_output, _, _ = sample_decoder_layer(
    tf.random.uniform((64, 50, 512)), sample_encoder_layer_output,
    False, None, None)

sample_decoder_layer_output.shape  # (batch_size, target_seq_len, d_model)
```

Out[20]: TensorShape([64, 50, 512])

2.0.3 Encoder

The Encoder consists of: 1. Input Embedding 2. Positional Encoding 3. N encoder layers

The input is put through an embedding which is summed with the positional encoding. The output of this summation is the input to the encoder layers. The output of the encoder is the input to the decoder.

In [21]:
```
class Encoder(tf.keras.layers.Layer):
    def __init__(self, num_layers, d_model, num_heads, dff, input_vocab_size,
                 maximum_position_encoding, rate=0.1):
        super(Encoder, self).__init__()

        self.d_model = d_model
        self.num_layers = num_layers

        self.embedding = tf.keras.layers.Embedding(input_vocab_size, d_model)
        self.pos_encoding = positional_encoding(maximum_position_encoding,
                                                self.d_model)


        self.enc_layers = [EncoderLayer(d_model, num_heads, dff, rate)
                           for _ in range(num_layers)]

        self.dropout = tf.keras.layers.Dropout(rate)

    def call(self, x, training, mask):
        seq_len = tf.shape(x)[1]

        # adding embedding and position encoding.
        x = self.embedding(x)  # (batch_size, input_seq_len, d_model)
        x *= tf.math.sqrt(tf.cast(self.d_model, tf.float32))
        x += self.pos_encoding[:, :seq_len, :]

        x = self.dropout(x, training=training)

        for i in range(self.num_layers):
            x = self.enc_layers[i](x, training, mask)
        return x  # (batch_size, input_seq_len, d_model)


sample_encoder = Encoder(num_layers=2, d_model=512, num_heads=8,
                         dff=2048, input_vocab_size=8500,
                         maximum_position_encoding=10000)
temp_input = tf.random.uniform((64, 62), dtype=tf.int64, minval=0, maxval=200)
```

```
sample_encoder_output = sample_encoder(temp_input, training=False, mask=None)

print (sample_encoder_output.shape)  # (batch_size, input_seq_len, d_model)
```

```
(64, 62, 512)
```

2.0.4 decoder

The `Decoder` consists of: 1. Output Embedding 2. Positional Encoding 3. N decoder layers

The target is put through an embedding which is summed with the positional encoding. The output of this summation is the input to the decoder layers. The output of the decoder is the input to the final linear layer.

In [24]:
```
class Decoder(tf.keras.layers.Layer):
    def __init__(self, num_layers, d_model, num_heads, dff, target_vocab_size,
                 maximum_position_encoding, rate=0.1):
        super(Decoder, self).__init__()
        self.d_model = d_model
        self.num_layers = num_layers

        self.embedding = tf.keras.layers.Embedding(target_vocab_size, d_model)
        self.pos_encoding = positional_encoding(maximum_position_encoding, d_model)

        self.dec_layers = [DecoderLayer(d_model, num_heads, dff, rate)
                           for _ in range(num_layers)]
        self.dropout = tf.keras.layers.Dropout(rate)

    def call(self, x, enc_output, training, look_ahead_mask, padding_mask):
        seq_len = tf.shape(x)[1]
        attention_weights = {}

        x = self.embedding(x)  # (batch_size, target_seq_len, d_model)
        x *= tf.math.sqrt(tf.cast(self.d_model, tf.float32))
        x += self.pos_encoding[:, :seq_len, :]

        x = self.dropout(x, training=training)
        for i in range(self.num_layers):
            x, block1, block2 = self.dec_layers[i](x, enc_output, training,
                                                   look_ahead_mask, padding_mask)

            attention_weights['decoder_layer{}_block1'.format(i+1)] = block1
            attention_weights['decoder_layer{}_block2'.format(i+1)] = block2

        # x.shape == (batch_size, target_seq_len, d_model)
        return x, attention_weights
```

```
sample_decoder = Decoder(num_layers=2, d_model=512, num_heads=8,
                         dff=2048, target_vocab_size=8000,
                         maximum_position_encoding=5000)
temp_input = tf.random.uniform((64, 26), dtype=tf.int64, minval=0, maxval=200)

output, attn = sample_decoder(temp_input,
                              enc_output=sample_encoder_output,
                              training=False,
                              look_ahead_mask=None,
                              padding_mask=None)

output.shape, attn['decoder_layer2_block2'].shape
```

Out[24]: (TensorShape([64, 26, 512]), TensorShape([64, 8, 26, 62]))

2.1 Let's create Transformer

Transformer consists of the encoder, decoder and a final linear layer. The output of the decoder is the input to the linear layer and its output is returned.

```
In [25]: class Transformer(tf.keras.Model):
             def __init__(self, num_layers, d_model, num_heads, dff, input_vocab_size,
                          target_vocab_size, pe_input, pe_target, rate=0.1):
                 super(Transformer, self).__init__()

                 self.encoder = Encoder(num_layers, d_model, num_heads, dff,
                                        input_vocab_size, pe_input, rate)

                 self.decoder = Decoder(num_layers, d_model, num_heads, dff,
                                        target_vocab_size, pe_target, rate)

                 self.final_layer = tf.keras.layers.Dense(target_vocab_size)

             def call(self, inp, tar, training, enc_padding_mask,
                    look_ahead_mask, dec_padding_mask):
                 enc_output = self.encoder(inp, training, enc_padding_mask)  # (batch_size, in

                 # dec_output.shape == (batch_size, tar_seq_len, d_model)
                 dec_output, attention_weights = self.decoder(
                     tar, enc_output, training, look_ahead_mask, dec_padding_mask)

                 final_output = self.final_layer(dec_output)  # (batch_size, tar_seq_len, targ

                 return final_output, attention_weights
```

```
In [26]: sample_transformer = Transformer(
             num_layers=2, d_model=512, num_heads=8, dff=2048,
             input_vocab_size=8500, target_vocab_size=8000,
             pe_input=10000, pe_target=6000)
```

```
temp_input = tf.random.uniform((64, 38), dtype=tf.int64, minval=0, maxval=200)
temp_target = tf.random.uniform((64, 36), dtype=tf.int64, minval=0, maxval=200)

fn_out, _ = sample_transformer(temp_input, temp_target, training=False,
                               enc_padding_mask=None,
                               look_ahead_mask=None,
                               dec_padding_mask=None)

fn_out.shape  # (batch_size, tar_seq_len, target_vocab_size)
```

Out[26]: TensorShape([64, 36, 8000])

In [28]:
```
sample_transformer.summary()
```

```
Model: "transformer"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
encoder_1 (Encoder)          multiple                  10656768
_________________________________________________________________
decoder_4 (Decoder)          multiple                  12504064
_________________________________________________________________
dense_116 (Dense)            multiple                  4104000
=================================================================
Total params: 27,264,832
Trainable params: 27,264,832
Non-trainable params: 0
_________________________________________________________________
```

In [30]:
```
# Load data:
examples, metadata = tfds.load('ted_hrlr_translate/pt_to_en', with_info=True,
                               as_supervised=True)
train_examples, val_examples = examples['train'], examples['validation']


tokenizer_en = tfds.features.text.SubwordTextEncoder.build_from_corpus(
    (en.numpy() for pt, en in train_examples), target_vocab_size=2**13)

tokenizer_pt = tfds.features.text.SubwordTextEncoder.build_from_corpus(
    (pt.numpy() for pt, en in train_examples), target_vocab_size=2**13)

print("Finish loading data")
```

In [36]:
```
sample_string = 'Transformer is awesome.'

tokenized_string = tokenizer_en.encode(sample_string)
print ('Tokenized string is {}'.format(tokenized_string))
```

```
    original_string = tokenizer_en.decode(tokenized_string)
    print ('The original string: {}'.format(original_string))

    assert original_string == sample_string
```

```
Tokenized string is [7915, 1248, 7946, 7194, 13, 2799, 7877]
The original string: Transformer is awesome.
```

2.2 MASK:

Mask all the pad tokens in the batch of sequence. It ensures that the model does not treat padding as the input. The mask indicates where pad value `0` is present: it outputs a `1` at those locations, and a `0` otherwise.

```
In [65]: def create_padding_mask(seq):
             seq = tf.cast(tf.math.equal(seq, 0), tf.float32)

             # add extra dimensions to add the padding
             # to the attention logits.
             return seq[:, tf.newaxis, tf.newaxis, :]  # (batch_size, 1, 1, seq_len)

         x = tf.constant([[7, 6, 0, 0, 1], [1, 2, 3, 0, 0], [0, 0, 0, 4, 5]])
         create_padding_mask(x)
```

```
Out[65]: <tf.Tensor: shape=(3, 1, 1, 5), dtype=float32, numpy=
         array([[[[0., 0., 1., 1., 0.]]],


                [[[0., 0., 0., 1., 1.]]],


                [[[1., 1., 1., 0., 0.]]]], dtype=float32)>
```

```
In [67]: def create_look_ahead_mask(size):
             mask = 1 - tf.linalg.band_part(tf.ones((size, size)), -1, 0)
             return mask  # (seq_len, seq_len)

         x = tf.random.uniform((1, 3))
         temp = create_look_ahead_mask(x.shape[1])
         temp
```

```
Out[67]: <tf.Tensor: shape=(3, 3), dtype=float32, numpy=
         array([[0., 1., 1.],
                [0., 0., 1.],
                [0., 0., 0.]], dtype=float32)>
```

In [38]:
```python
def encode(lang1, lang2):
    lang1 = [tokenizer_pt.vocab_size] + tokenizer_pt.encode(
        lang1.numpy()) + [tokenizer_pt.vocab_size+1]

    lang2 = [tokenizer_en.vocab_size] + tokenizer_en.encode(
        lang2.numpy()) + [tokenizer_en.vocab_size+1]

    return lang1, lang2
```

In [39]:
```python
def tf_encode(pt, en):
    result_pt, result_en = tf.py_function(encode, [pt, en], [tf.int64, tf.int64])
    result_pt.set_shape([None])
    result_en.set_shape([None])

    return result_pt, result_en
```

In [40]:
```python
MAX_LENGTH = 40
def filter_max_length(x, y, max_length=MAX_LENGTH):
    return tf.logical_and(tf.size(x) <= max_length,
                          tf.size(y) <= max_length)
```

In [42]:
```python
BUFFER_SIZE = 20000
BATCH_SIZE = 64


train_dataset = train_examples.map(tf_encode)
train_dataset = train_dataset.filter(filter_max_length)
# cache the dataset to memory to get a speedup while reading from it.
train_dataset = train_dataset.cache()
train_dataset = train_dataset.shuffle(BUFFER_SIZE).padded_batch(BATCH_SIZE)
train_dataset = train_dataset.prefetch(tf.data.experimental.AUTOTUNE)


val_dataset = val_examples.map(tf_encode)
val_dataset = val_dataset.filter(filter_max_length).padded_batch(BATCH_SIZE)
```

In [43]:
```python
pt_batch, en_batch = next(iter(val_dataset))
pt_batch, en_batch
```

Out[43]:
```
(<tf.Tensor: shape=(64, 38), dtype=int64, numpy=
 array([[8214,  342, 3032, ...,    0,    0,    0],
        [8214,   95,  198, ...,    0,    0,    0],
        [8214, 4479, 7990, ...,    0,    0,    0],
        ...,
        [8214,  584,   12, ...,    0,    0,    0],
        [8214,   59, 1548, ...,    0,    0,    0],
        [8214,  118,   34, ...,    0,    0,    0]])>,
 <tf.Tensor: shape=(64, 40), dtype=int64, numpy=
 array([[8087,   98,   25, ...,    0,    0,    0],
```

```
       [8087,   12,   20, ...,    0,    0,    0],
       [8087,   12, 5453, ...,    0,    0,    0],
       ...,
       [8087,   18, 2059, ...,    0,    0,    0],
       [8087,   16, 1436, ...,    0,    0,    0],
       [8087,   15,   57, ...,    0,    0,    0]])>)
```

In [46]:
```
# Hyper parameteres:
num_layers = 4
d_model = 128
dff = 512
num_heads = 8

input_vocab_size = tokenizer_pt.vocab_size + 2
target_vocab_size = tokenizer_en.vocab_size + 2
dropout_rate = 0.1
```

2.3 Optimizer

Use the Adam optimizer with a custom learning rate scheduler according to the formula in the paper.

$$lrate = d_{model}^{-0.5} * min(step\_num^{-0.5}, step\_num * warmup\_steps^{-1.5})$$

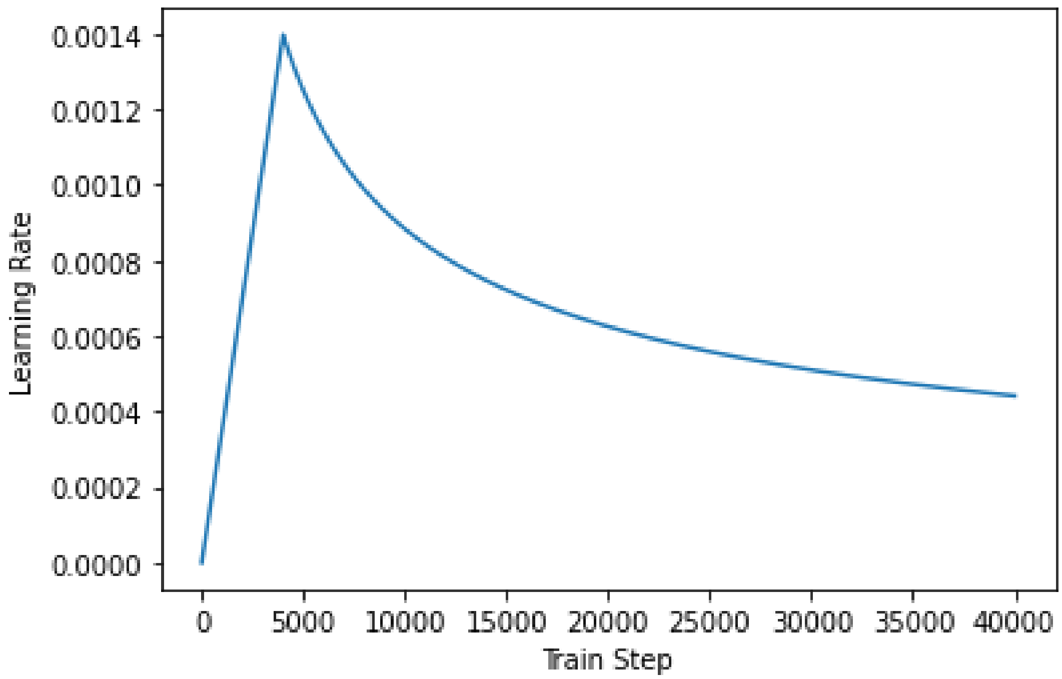
In [47]:
```
class CustomSchedule(tf.keras.optimizers.schedules.LearningRateSchedule):
    def __init__(self, d_model, warmup_steps=4000):
        super(CustomSchedule, self).__init__()

        self.d_model = d_model
        self.d_model = tf.cast(self.d_model, tf.float32)

        self.warmup_steps = warmup_steps

    def __call__(self, step):
        arg1 = tf.math.rsqrt(step)
        arg2 = step * (self.warmup_steps ** -1.5)

        return tf.math.rsqrt(self.d_model) * tf.math.minimum(arg1, arg2)
```

In [48]:
```
learning_rate = CustomSchedule(d_model)

optimizer = tf.keras.optimizers.Adam(learning_rate, beta_1=0.9, beta_2=0.98,
                                     epsilon=1e-9)
```

In [49]:
```
# Learning rate curve:
temp_learning_rate_schedule = CustomSchedule(d_model)
```

```
plt.plot(temp_learning_rate_schedule(tf.range(40000, dtype=tf.float32)))
plt.ylabel("Learning Rate")
plt.xlabel("Train Step")
```

Out[49]: Text(0.5, 0, 'Train Step')



2.4 Loss and metrics

Since the target sequences are padded, it is important to apply a padding mask when calculating the loss.

In [50]:
```
loss_object = tf.keras.losses.SparseCategoricalCrossentropy(
    from_logits=True, reduction='none')
```

In [51]:
```
def loss_function(real, pred):
    mask = tf.math.logical_not(tf.math.equal(real, 0))
    loss_ = loss_object(real, pred)

    mask = tf.cast(mask, dtype=loss_.dtype)
    loss_ *= mask

    return tf.reduce_sum(loss_)/tf.reduce_sum(mask)
```

In [52]:
```
train_loss = tf.keras.metrics.Mean(name='train_loss')
train_accuracy = tf.keras.metrics.SparseCategoricalAccuracy(
    name='train_accuracy')
```

2.5 Training and check points

In [69]:
```
transformer = Transformer(num_layers, d_model, num_heads, dff,
                          input_vocab_size, target_vocab_size,
                          pe_input=input_vocab_size,
                          pe_target=target_vocab_size,
                          rate=dropout_rate)
```

In [70]:
```
def create_masks(inp, tar):
    # Encoder padding mask
    enc_padding_mask = create_padding_mask(inp)

    # Used in the 2nd attention block in the decoder.
    # This padding mask is used to mask the encoder outputs.
    dec_padding_mask = create_padding_mask(inp)

    # Used in the 1st attention block in the decoder.
    # It is used to pad and mask future tokens in the input received by
    # the decoder.
    look_ahead_mask = create_look_ahead_mask(tf.shape(tar)[1])
    dec_target_padding_mask = create_padding_mask(tar)
    combined_mask = tf.maximum(dec_target_padding_mask, look_ahead_mask)

    return enc_padding_mask, combined_mask, dec_padding_mask
```

In [71]:
```
# check point
checkpoint_path = "./checkpoints/train"

ckpt = tf.train.Checkpoint(transformer=transformer,
                           optimizer=optimizer)

ckpt_manager = tf.train.CheckpointManager(ckpt, checkpoint_path, max_to_keep=5)

# if a checkpoint exists, restore the latest checkpoint.
if ckpt_manager.latest_checkpoint:
    ckpt.restore(ckpt_manager.latest_checkpoint)
    print ('Latest checkpoint restored!!')
```

```
Latest checkpoint restored!!
```

In [72]:
```
EPOCHS = 20


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

```
@tf.function(input_signature=train_step_signature)

def train_step(inp, tar):
    tar_inp = tar[:, :-1]
    tar_real = tar[:, 1:]

    enc_padding_mask, combined_mask, dec_padding_mask = create_masks(inp, tar_inp)
    with tf.GradientTape() as tape:
        predictions, _ = transformer(inp, tar_inp,
                                     True,
                                     enc_padding_mask,
                                     combined_mask,
                                     dec_padding_mask)
        loss = loss_function(tar_real, predictions)
    gradients = tape.gradient(loss, transformer.trainable_variables)
    optimizer.apply_gradients(zip(gradients, transformer.trainable_variables))

    train_loss(loss)
    train_accuracy(tar_real, predictions)
```

```
In [73]: for epoch in range(EPOCHS):
           start = time.time()

           train_loss.reset_states()
           train_accuracy.reset_states()

           # inp -> portuguese, tar -> english
           for (batch, (inp, tar)) in enumerate(train_dataset):
               train_step(inp, tar)

               if batch % 200 == 0:
                   print ('Epoch {} Batch {} Loss {:.4f} Accuracy {:.4f}'.format(epoch + 1, b
                                                                                   train_loss.r

           if (epoch + 1) % 5 == 0:
               ckpt_save_path = ckpt_manager.save()
               print ('Saving checkpoint for epoch {} at {}'.format(epoch+1,
                                                                    ckpt_save_path))

           print ('Epoch {} Loss {:.4f} Accuracy {:.4f}'.format(epoch + 1,
                                                               train_loss.result(),
                                                               train_accuracy.result()))

           print ('Time taken for 1 epoch: {} secs\n'.format(time.time() - start))
```

```
Epoch 1 Batch 0 Loss 0.3190 Accuracy 0.4421
Epoch 1 Batch 200 Loss 0.3193 Accuracy 0.4281
```

```
Epoch 1 Batch 400 Loss 0.3326 Accuracy 0.4269
Epoch 1 Batch 600 Loss 0.3438 Accuracy 0.4249
Epoch 1 Loss 0.3502 Accuracy 0.4247
Time taken for 1 epoch: 88.43562340736389 secs

Epoch 2 Batch 0 Loss 0.3196 Accuracy 0.4494
Epoch 2 Batch 200 Loss 0.3180 Accuracy 0.4270
Epoch 2 Batch 400 Loss 0.3301 Accuracy 0.4250
Epoch 2 Batch 600 Loss 0.3406 Accuracy 0.4253
Epoch 2 Loss 0.3453 Accuracy 0.4245
Time taken for 1 epoch: 62.07188296318054 secs

Epoch 3 Batch 0 Loss 0.2923 Accuracy 0.4787
Epoch 3 Batch 200 Loss 0.3197 Accuracy 0.4305
Epoch 3 Batch 400 Loss 0.3316 Accuracy 0.4272
Epoch 3 Batch 600 Loss 0.3414 Accuracy 0.4252
Epoch 3 Loss 0.3462 Accuracy 0.4246
Time taken for 1 epoch: 61.9879732131958 secs

Epoch 4 Batch 0 Loss 0.3229 Accuracy 0.4379
Epoch 4 Batch 200 Loss 0.3186 Accuracy 0.4265
Epoch 4 Batch 400 Loss 0.3299 Accuracy 0.4257
Epoch 4 Batch 600 Loss 0.3399 Accuracy 0.4253
Epoch 4 Loss 0.3449 Accuracy 0.4254
Time taken for 1 epoch: 62.00139260292053 secs

Epoch 5 Batch 0 Loss 0.3037 Accuracy 0.4333
Epoch 5 Batch 200 Loss 0.3177 Accuracy 0.4309
Epoch 5 Batch 400 Loss 0.3268 Accuracy 0.4271
Epoch 5 Batch 600 Loss 0.3367 Accuracy 0.4264
Saving checkpoint for epoch 5 at ./checkpoints/train/ckpt-25
Epoch 5 Loss 0.3420 Accuracy 0.4262
Time taken for 1 epoch: 63.04894161224365 secs

Epoch 6 Batch 0 Loss 0.2844 Accuracy 0.4661
Epoch 6 Batch 200 Loss 0.3151 Accuracy 0.4298
Epoch 6 Batch 400 Loss 0.3277 Accuracy 0.4245
Epoch 6 Batch 600 Loss 0.3376 Accuracy 0.4248
Epoch 6 Loss 0.3418 Accuracy 0.4246
Time taken for 1 epoch: 62.07981491088867 secs

Epoch 7 Batch 0 Loss 0.3179 Accuracy 0.4940
Epoch 7 Batch 200 Loss 0.3125 Accuracy 0.4313
Epoch 7 Batch 400 Loss 0.3217 Accuracy 0.4286
Epoch 7 Batch 600 Loss 0.3318 Accuracy 0.4271
Epoch 7 Loss 0.3368 Accuracy 0.4264
Time taken for 1 epoch: 61.96492052078247 secs
```

```
Epoch 8 Batch 0 Loss 0.2507 Accuracy 0.4050
Epoch 8 Batch 200 Loss 0.3121 Accuracy 0.4264
Epoch 8 Batch 400 Loss 0.3216 Accuracy 0.4268
Epoch 8 Batch 600 Loss 0.3321 Accuracy 0.4265
Epoch 8 Loss 0.3362 Accuracy 0.4263
Time taken for 1 epoch: 62.00608944892883 secs

Epoch 9 Batch 0 Loss 0.2597 Accuracy 0.4566
Epoch 9 Batch 200 Loss 0.3053 Accuracy 0.4273
Epoch 9 Batch 400 Loss 0.3197 Accuracy 0.4264
Epoch 9 Batch 600 Loss 0.3300 Accuracy 0.4251
Epoch 9 Loss 0.3355 Accuracy 0.4249
Time taken for 1 epoch: 62.099849224090576 secs

Epoch 10 Batch 0 Loss 0.2716 Accuracy 0.4143
Epoch 10 Batch 200 Loss 0.3077 Accuracy 0.4315
Epoch 10 Batch 400 Loss 0.3179 Accuracy 0.4288
Epoch 10 Batch 600 Loss 0.3288 Accuracy 0.4273
Saving checkpoint for epoch 10 at ./checkpoints/train/ckpt-26
Epoch 10 Loss 0.3339 Accuracy 0.4268
Time taken for 1 epoch: 62.95390582084656 secs

Epoch 11 Batch 0 Loss 0.2721 Accuracy 0.4412
Epoch 11 Batch 200 Loss 0.3071 Accuracy 0.4293
Epoch 11 Batch 400 Loss 0.3172 Accuracy 0.4280
Epoch 11 Batch 600 Loss 0.3270 Accuracy 0.4277
Epoch 11 Loss 0.3318 Accuracy 0.4270
Time taken for 1 epoch: 62.02247405052185 secs

Epoch 12 Batch 0 Loss 0.2817 Accuracy 0.3754
Epoch 12 Batch 200 Loss 0.3020 Accuracy 0.4270
Epoch 12 Batch 400 Loss 0.3134 Accuracy 0.4279
Epoch 12 Batch 600 Loss 0.3245 Accuracy 0.4271
Epoch 12 Loss 0.3302 Accuracy 0.4261
Time taken for 1 epoch: 62.048261404037476 secs

Epoch 13 Batch 0 Loss 0.2757 Accuracy 0.4646
Epoch 13 Batch 200 Loss 0.3042 Accuracy 0.4306
Epoch 13 Batch 400 Loss 0.3158 Accuracy 0.4300
Epoch 13 Batch 600 Loss 0.3239 Accuracy 0.4284
Epoch 13 Loss 0.3290 Accuracy 0.4279
Time taken for 1 epoch: 62.001415967941284 secs

Epoch 14 Batch 0 Loss 0.2988 Accuracy 0.4844
Epoch 14 Batch 200 Loss 0.3047 Accuracy 0.4311
Epoch 14 Batch 400 Loss 0.3133 Accuracy 0.4279
Epoch 14 Batch 600 Loss 0.3235 Accuracy 0.4284
Epoch 14 Loss 0.3282 Accuracy 0.4275
```

```
Time taken for 1 epoch: 62.05406928062439 secs

Epoch 15 Batch 0 Loss 0.2537 Accuracy 0.4770
Epoch 15 Batch 200 Loss 0.3008 Accuracy 0.4311
Epoch 15 Batch 400 Loss 0.3093 Accuracy 0.4299
Epoch 15 Batch 600 Loss 0.3207 Accuracy 0.4291
Saving checkpoint for epoch 15 at ./checkpoints/train/ckpt-27
Epoch 15 Loss 0.3261 Accuracy 0.4284
Time taken for 1 epoch: 62.9287645816803 secs

Epoch 16 Batch 0 Loss 0.3274 Accuracy 0.4038
Epoch 16 Batch 200 Loss 0.2976 Accuracy 0.4293
Epoch 16 Batch 400 Loss 0.3103 Accuracy 0.4289
Epoch 16 Batch 600 Loss 0.3206 Accuracy 0.4272
Epoch 16 Loss 0.3261 Accuracy 0.4267
Time taken for 1 epoch: 62.09530711174011 secs

Epoch 17 Batch 0 Loss 0.2953 Accuracy 0.4371
Epoch 17 Batch 200 Loss 0.2984 Accuracy 0.4302
Epoch 17 Batch 400 Loss 0.3087 Accuracy 0.4294
Epoch 17 Batch 600 Loss 0.3184 Accuracy 0.4283
Epoch 17 Loss 0.3245 Accuracy 0.4276
Time taken for 1 epoch: 62.016918659210205 secs

Epoch 18 Batch 0 Loss 0.3209 Accuracy 0.4288
Epoch 18 Batch 200 Loss 0.2977 Accuracy 0.4307
Epoch 18 Batch 400 Loss 0.3092 Accuracy 0.4291
Epoch 18 Batch 600 Loss 0.3180 Accuracy 0.4291
Epoch 18 Loss 0.3229 Accuracy 0.4282
Time taken for 1 epoch: 61.98962330818176 secs

Epoch 19 Batch 0 Loss 0.2535 Accuracy 0.4749
Epoch 19 Batch 200 Loss 0.2934 Accuracy 0.4321
Epoch 19 Batch 400 Loss 0.3061 Accuracy 0.4298
Epoch 19 Batch 600 Loss 0.3164 Accuracy 0.4286
Epoch 19 Loss 0.3208 Accuracy 0.4284
Time taken for 1 epoch: 61.987332820892334 secs

Epoch 20 Batch 0 Loss 0.2907 Accuracy 0.4401
Epoch 20 Batch 200 Loss 0.2948 Accuracy 0.4316
Epoch 20 Batch 400 Loss 0.3057 Accuracy 0.4302
Epoch 20 Batch 600 Loss 0.3148 Accuracy 0.4298
Saving checkpoint for epoch 20 at ./checkpoints/train/ckpt-28
Epoch 20 Loss 0.3188 Accuracy 0.4286
Time taken for 1 epoch: 63.266361474990845 secs
```

2.6 Evaluate:

The following steps are used for evaluation:

- Encode the input sentence using the Portuguese tokenizer (`tokenizer_pt`). Moreover, add the start and end token so the input is equivalent to what the model is trained with. This is the encoder input.
- The decoder input is the `start token == tokenizer_en.vocab_size`.
- Calculate the padding masks and the look ahead masks.
- The `decoder` then outputs the predictions by looking at the `encoder output` and its own output (self-attention).
- Select the last word and calculate the argmax of that.
- Concatentate the predicted word to the decoder input as pass it to the decoder.
- In this approach, the decoder predicts the next word based on the previous words it predicted.

Note: The model used here has less capacity to keep the example relatively faster so the predictions maybe less right. To reproduce the results in the paper, use the entire dataset and base transformer model or transformer XL, by changing the hyperparameters above.

```
In [74]: def evaluate(inp_sentence):
           start_token = [tokenizer_pt.vocab_size]
           end_token = [tokenizer_pt.vocab_size + 1]

           # inp sentence is portuguese, hence adding the start and end token
           inp_sentence = start_token + tokenizer_pt.encode(inp_sentence) + end_token
           encoder_input = tf.expand_dims(inp_sentence, 0)

           # as the target is english, the first word to the transformer should be the
           # english start token.
           decoder_input = [tokenizer_en.vocab_size]
           output = tf.expand_dims(decoder_input, 0)

           for i in range(MAX_LENGTH):
               enc_padding_mask, combined_mask, dec_padding_mask = create_masks(
               encoder_input, output)

               # predictions.shape == (batch_size, seq_len, vocab_size)
               predictions, attention_weights = transformer(encoder_input,
                                                            output,
                                                            False,
                                                            enc_padding_mask,
                                                            combined_mask,
                                                            dec_padding_mask)

               # select the last word from the seq_len dimension
               predictions = predictions[: ,-1:, :]  # (batch_size, 1, vocab_size)

               predicted_id = tf.cast(tf.argmax(predictions, axis=-1), tf.int32)
```

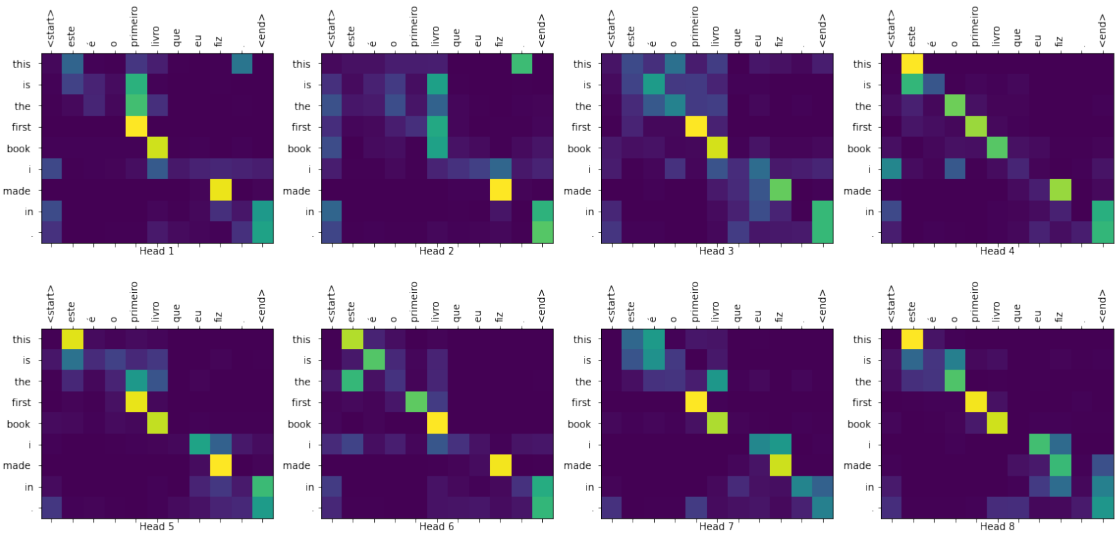
```
        # return the result if the predicted_id is equal to the end token
        if predicted_id == tokenizer_en.vocab_size+1:
            return tf.squeeze(output, axis=0), attention_weights

        # concatentate the predicted_id to the output which is given to the decoder a
        output = tf.concat([output, predicted_id], axis=-1)

    return tf.squeeze(output, axis=0), attention_weights
```

```
In [78]: def plot_attention_weights(attention, sentence, result, layer):
             fig = plt.figure(figsize=(16, 8))

             sentence = tokenizer_pt.encode(sentence)

             attention = tf.squeeze(attention[layer], axis=0)

             for head in range(attention.shape[0]):
                 ax = fig.add_subplot(2, 4, head+1)

                 # plot the attention weights
                 ax.matshow(attention[head][:-1, :], cmap='viridis')

                 fontdict = {'fontsize': 10}

                 ax.set_xticks(range(len(sentence)+2))
                 ax.set_yticks(range(len(result)))

                 ax.set_ylim(len(result)-1.5, -0.5)

                 ax.set_xticklabels(
                 ['<start>']+[tokenizer_pt.decode([i]) for i in sentence]+['<end>'],
                 fontdict=fontdict, rotation=90)

                 ax.set_yticklabels([tokenizer_en.decode([i]) for i in result
                                     if i < tokenizer_en.vocab_size],
                                    fontdict=fontdict)

                 ax.set_xlabel('Head {}'.format(head+1))

             plt.tight_layout()
             plt.show()

         def translate(sentence, plot=''):
             result, attention_weights = evaluate(sentence)
```

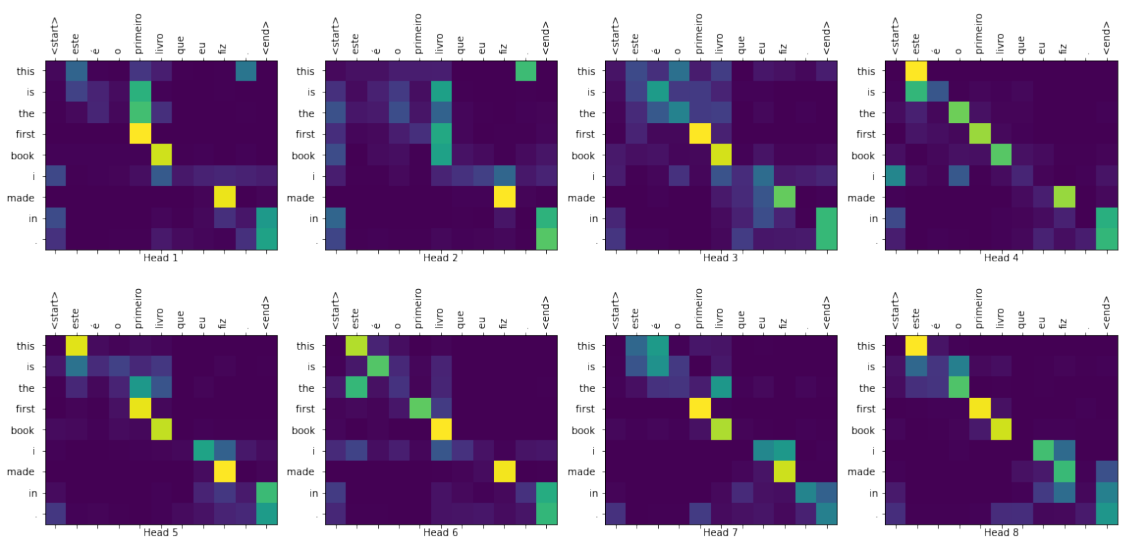
```python
            predicted_sentence = tokenizer_en.decode([i for i in result
                                                      if i < tokenizer_en.vocab_size])

            print('Input: {}'.format(sentence))
            print('Predicted translation: {}'.format(predicted_sentence))

            if plot:
                plot_attention_weights(attention_weights, sentence, result, plot)
```

In [79]:
```python
translate("este é um problema que temos que resolver.")
print ("Real translation: this is a problem we have to solve .")
translate("os meus vizinhos ouviram sobre esta ideia.")
print ("Real translation: and my neighboring homes heard about this idea .")
translate("vou então muito rapidamente partilhar convosco algumas histórias de algumas
print ("Real translation: so i 'll just share with you some stories very quickly of so
translate("este é o primeiro livro que eu fiz.", plot='decoder_layer4_block2')
print ("Real translation: this is the first book i've ever done.")


translate("este é o primeiro livro que eu fiz.", plot='decoder_layer4_block2')
print ("Real translation: this is the first book i've ever done.")
```

```
Input: este é um problema que temos que resolver.
Predicted translation: so this is a problem that we need to contain first better than our per l
Real translation: this is a problem we have to solve .
Input: os meus vizinhos ouviram sobre esta ideia.
Predicted translation: my neighbors heard about this idea of this united states .
Real translation: and my neighboring homes heard about this idea .
Input: vou então muito rapidamente partilhar convosco algumas histórias de algumas coisas mágic
Predicted translation: so i 'm going to share with you some of you some pretty strong things th
Real translation: so i 'll just share with you some stories very quickly of some magical things
Input: este é o primeiro livro que eu fiz.
Predicted translation: this is the first book i made in .
```




```
Real translation: this is the first book i've ever done.
Input: este é o primeiro livro que eu fiz.
Predicted translation: this is the first book i made in .
```




```
Real translation: this is the first book i've ever done.
```

In [87]:
```
transformer.summary()
```

```
Model: "transformer_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
encoder_3 (Encoder)          multiple                  1844736
_________________________________________________________________
decoder_6 (Decoder)          multiple                  2093696
_________________________________________________________________
dense_246 (Dense)            multiple                  1043481
=================================================================
Total params: 4,981,913
Trainable params: 4,981,913
Non-trainable params: 0
_________________________________________________________________
```

3 Time series problem:

Encode time series into a smaller dimension

In [ ]:

In [ ]: