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GENERATIVE AI LAB - 8

[TRANSFORMERS]

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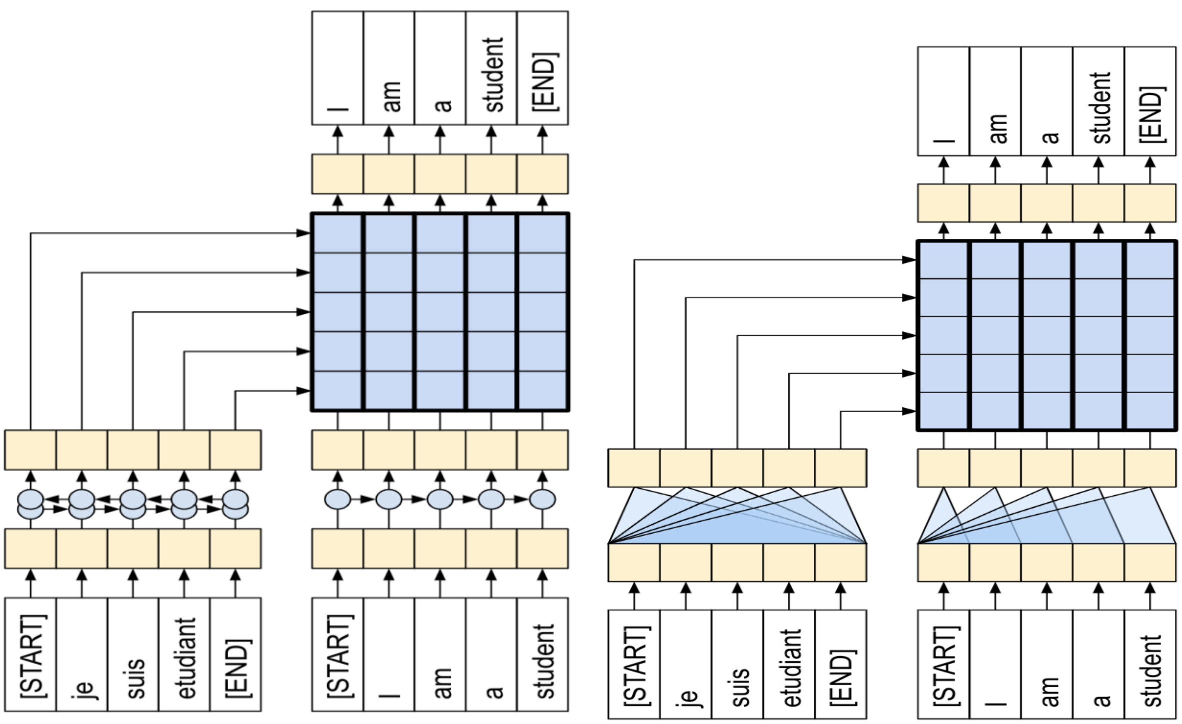
The purpose of lab sheet-8 is to learn the concepts of vanilla transformer. We will learn how to create and train a sequence-to-sequence Transformer model to translate Portuguese into English. The Transformer was originally proposed in "Attention is all you need" by Vaswani et al. (2017).

Transformers are deep neural networks that replace CNNs and RNNs with self-attention. Self attention allows Transformers to easily transmit information across the input sequences.

Neural networks for machine translation typically contain an encoder reading the input sentence and generating a representation of it. A decoder then generates the output sentence word by word while consulting the representation generated by the encoder. The Transformer starts by generating initial representations, or embeddings, for each word, then, using self-attention, it aggregates information from all of the other words, generating a new representation per word informed by the entire context. This step is then repeated multiple times in parallel for all words, successively generating new representations.

A single-layer Transformer takes a little more code to write, but is almost identical to the encoder-decoder RNN model. The only difference is that the RNN layers are replaced with self attention layers. We will build a 4-layer Transformer which is larger and more powerful, but not fundamentally more complex.



Difference in RNN and transformer layer

Implementation:-

We will follow the following steps to implement this transformer:

- Prepare the data.
- Implement necessary components:
  - Positional embeddings.
  - Attention layers.
  - The encoder and decoder.
- Build & train the Transformer.
- Generate translations.

Begin by installing TensorFlow Datasets for loading the dataset and TensorFlow Text for text preprocessing:

```
# Install the most re version of TensorFlow to use the improved

# masking support for `tf.keras.layers.MultiHeadAttention`.

!apt install --allow-change-held-packages libcudnn8=8.1.0.77-1+cuda11.2

!pip uninstall -y -q tensorflow keras tensorflow-estimator tensorflow-text

!pip install protobuf~=3.20.3

!pip install -q tensorflow_datasets

!pip install -q -U tensorflow-text tensorflow
```

Import the necessary modules:

```
import logging

import time

import numpy as np

import matplotlib.pyplot as plt

import tensorflow_datasets as tfds

import tensorflow as tf

import tensorflow_text
```

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Data handling

Download the dataset and the subword tokenizer, then wrap it all up in a `tf.data.Dataset` for training.

Download the dataset

Use TensorFlow Datasets to load the Portuguese-English translation dataset. This dataset contains approximately 52,000 training, 1,200 validation and 1,800 test examples.

```
examples, metadata = tfds.load('ted_hrlr_translate/pt_to_en',
                               with_info=True,
                               as_supervised=True)

train_examples, val_examples =  # TODO: Use appropriate fields from examples
```

The `tf.data.Dataset` object returned by TensorFlow Datasets yields pairs of text examples:

```
for pt_examples, en_examples in train_examples.batch(3).take(1):
 print('> Examples in Portuguese:')
 for pt in pt_examples.numpy():
   print(pt.decode('utf-8'))
 print()
 print('> Examples in English:')
 for en in en_examples.numpy():
   print(en.decode('utf-8'))
```

Set up the tokenizer

Now that you have loaded the dataset, you need to tokenize the text, so that each element is represented as a token or token ID (a numeric representation).

Tokenization is the process of breaking up text into "tokens". Depending on the tokenizer, these tokens can represent sentence-pieces, words, subwords, or characters.

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We will use the tokenizers built in the subword tokenizer. It optimizes two `text.BertTokenizer` objects (one for English, one for Portuguese) for **this dataset**.

Download, extract, and import the `saved_model`:

```
model_name = 'ted_hrlr_translate_pt_en_converter'
tf.keras.utils.get_file(
   f'{model_name}.zip',
f'https://storage.googleapis.com/download.tensorflow.org/models/{model_nam
e}.zip',
   cache_dir='.', cache_subdir='', extract=True
)
tokenizers = tf.saved_model.load(model_name)
```

The `tf.saved_model` contains two text tokenizers, one for English and one for Portuguese. Both have the same methods:

```
[item for item in dir(tokenizers.en) if not item.startswith('_')]
```

The `tokenize` method converts a batch of strings to a padded-batch of token IDs. This method splits punctuation, lowercases and unicode-normalizes the input before tokenizing. That standardization is not visible here because the input data is already standardized.

```
print('> This is a batch of strings:')
for en in en_examples.numpy():
 print(en.decode('utf-8'))

encoded = tokenizers.en.tokenize(en_examples)

print('> This is a padded-batch of token IDs:')
for row in encoded.to_list():
 print(row)
```

The `detokenize` method attempts to convert these token IDs back to human-readable text:

```
round_trip = tokenizers.en.detokenize(encoded)

print('> This is human-readable text:')
```

```
for line in round_trip.numpy():
 print(line.decode('utf-8'))
```

The lower level `lookup` method converts from token-IDs to token text:

```
print('> This is the text split into tokens:')
tokens = tokenizers.en.lookup(encoded)
tokens
```

The output demonstrates the "subword" aspect of the subword tokenization.

For example, the word `'searchability'` is decomposed into `'search'` and `'##ability'`, and the word `'serendipity'` into `'s'`, `'##ere'`, `'##nd'`, `'##ip'` and `'##ity'`.

Note that the tokenized text includes `'[START]'` and `'[END]'` tokens.

The distribution of tokens per example in the dataset is as follows:

```
lengths = []

for pt_examples, en_examples in train_examples.batch(1024):
 pt_tokens = # TODO: Use tokenizers to tokenize pt_examples appropriately
 lengths.append(pt_tokens.row_lengths())
  en_tokens = # TODO: Use tokenizers appropriately
 lengths.append(en_tokens.row_lengths())
 print('.', end='', flush=True)


all_lengths = np.concatenate(lengths)

plt.hist(all_lengths, np.linspace(0, 500, 101))
plt.ylim(plt.ylim())
max_length = max(all_lengths)
plt.plot([max_length, max_length], plt.ylim())
plt.title(f'Maximum tokens per example: {max_length}');
```

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Set up a data pipeline with `tf.data`

The following function takes batches of text as input, and converts them to a format suitable for training.

1. It tokenizes them into ragged batches.
2. trims each to be no longer than `MAX_TOKENS`.
3. splits the target (English) tokens into inputs and labels. These are shifted by one step so that at each input location the `label` is the id of the next token.
4. converts the `RaggedTensor`s to padded dense `Tensor`s.
5. returns an `(inputs, labels)` pair.

```
MAX_TOKENS=128
def prepare_batch(pt, en):
   pt = tokenizers.pt.tokenize(pt)       # Output is ragged.
   pt = ...   #TODO  # Trim to MAX_TOKENS.
   pt = pt.to_tensor()  # Convert to 0-padded dense Tensor

   en = tokenizers.en.tokenize(en)
   en = en[:, :(MAX_TOKENS+1)]
   en_inputs = en[...].to_tensor() #TODO  # Drop the [END] tokens
   en_labels = en[...].to_tensor() #TODO  # Drop the [START] tokens

   return (pt, en_inputs), en_labels
```

The function below converts a dataset of text examples into data of batches for training.

1. It tokenizes the text, and filters out the sequences that are too long. (The `batch`/`unbatch` is included because the tokenizer is much more efficient on large batches).
2. The `cache` method ensures that that work is only executed once.
3. Then `shuffle` and, `dense_to_ragged_batch` randomize the order and assemble batches of examples.
4. Finally `prefetch` runs the dataset in parallel with the model to ensure that data is available when needed.

```
BUFFER_SIZE = 20000
BATCH_SIZE = 64
def make_batches(ds):
 return (ds
      .shuffle(BUFFER_SIZE)
      .batch(BATCH_SIZE)
      .map(prepare_batch, tf.data.AUTOTUNE)
      .prefetch(buffer_size=tf.data.AUTOTUNE))
```

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Test the Dataset

```
# Create training and validation set batches.
train_batches = make_batches(train_examples)
val_batches = make_batches(val_examples)
```

The resulting `tf.data.Dataset` objects are setup for training with Keras. Keras `Model.fit` training expects `(inputs, labels)` pairs. The `inputs` are pairs of tokenized Portuguese and English sequences, `(pt, en)`. The `labels` are the same English sequences shifted by 1. This shift is so that at each location input `en` sequence, the `label` in the next token.regardless of the model's output at each timestep, it gets the true value as input for the next timestep. This is a simple and efficient way to train a text generation model. It's efficient because you don't need to run the model sequentially, the outputs at the different sequence locations can be computed in parallel.

You might have expected the `input,output`, pairs to simply be the `Portuguese,English` sequences. Given a Portuguese sequence, the model would try to generate an English sequence.

It's possible to train a model that way. You'd need to write out the inference loop and pass the model's output back to the input. It's slower (time steps can't run in parallel), and a harder task to learn (the model can't get the end of a sentence right until it gets the beginning right), but it can give a more stable model because the model has to learn to correct its own errors during training.

```
for (pt, en), en_labels in train_batches.take(1):
 break

print(pt.shape)
print(en.shape)
print(en_labels.shape)
```

Define the components

There's a lot going on inside a Transformer. The important things to remember are:

1. It follows the same general pattern as a standard sequence-to-sequence model with an encoder and a decoder.
2. If you work through it step by step it will all make sense.

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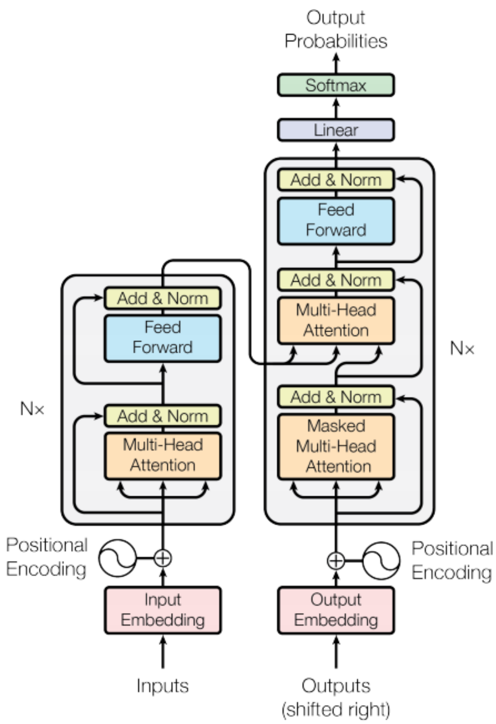

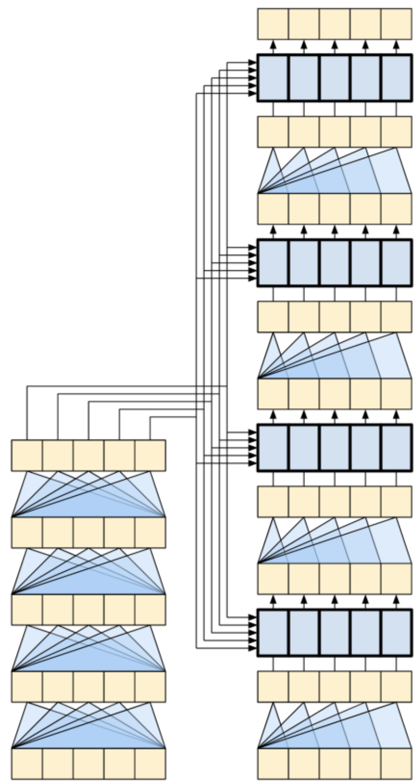

Each of the components in these two diagrams(original transformer & rep. of 4-layer transformer) will be explained as you progress through the labsheet.

The embedding and positional encoding layer

The inputs to both the encoder and decoder use the same embedding and positional encoding logic.

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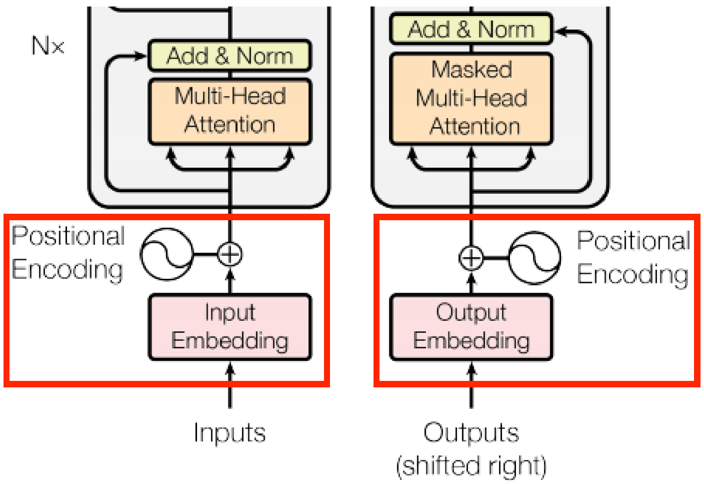

Given a sequence of tokens, both the input tokens (Portuguese) and target tokens (English) have to be converted to vectors using a `tf.keras.layers.Embedding` layer.

The attention layers used throughout the model see their input as a set of vectors, with no order. Since the model doesn't contain any recurrent or convolutional layers. It needs some way to identify word order, otherwise it would see the input sequence as a bag of words instance, `how are you`, `how you are`, `you how are`, and so on, are indistinguishable.

A Transformer adds a "Positional Encoding" to the embedding vectors. It uses a set of sines and cosines at different frequencies (across the sequence). By definition nearby elements will have similar position encodings.

The formula for calculating the positional encoding (implemented in Python below) is as follows:

```
 Large{PE_{(pos, 2i)} = \sin(pos / 10000^{2i / d_{model}}

Large{PE_{(pos, 2i+1)} = \cos(pos / 10000^{2i / d_{model}}
```

```
def positional_encoding(length, depth):
 depth = depth/2
 positions = np.arange(length)[...]      #TODO # (seq, 1)
 depths = np.arange(depth)[np.newaxis, :]/depth    # (1, depth)
  angle_rates = 1 / (10000**depths)          # (1, depth)
 angle_rads = positions * angle_rates       # (pos, depth)
 pos_encoding = np.concatenate(
     [np.sin(angle_rads), np.cos(angle_rads)],
     axis=-1)
 return tf.cast(pos_encoding, dtype=tf.float32)
```

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The position encoding function is a stack of sines and cosines that vibrate at different frequencies depending on their location along the depth of the embedding vector. They vibrate across the position axis.

```
pos_encoding = positional_encoding(length=2048, depth=512)
# Check the shape.
print(pos_encoding.shape)
# Plot the dimensions.
plt.pcolormesh(pos_encoding.numpy().T, cmap='RdBu')
plt.ylabel('Depth')
plt.xlabel('Position')
plt.colorbar()
plt.show()
```

By definition these vectors align well with nearby vectors along the position axis. Below the position encoding vectors are normalized and the vector from position `1000` is compared, by dot-product, to all the others:

```
#@title
pos_encoding/=tf.norm(pos_encoding, axis=1, keepdims=True)
p = pos_encoding[1000]
dots = tf.einsum('pd,d -> p', pos_encoding, p)
plt.subplot(2,1,1)
plt.plot(dots)
plt.ylim([0,1])
plt.plot([950, 950, float('nan'), 1050, 1050],
        [0,1,float('nan'),0,1], color='k', label='Zoom')
plt.legend()
plt.subplot(2,1,2)
plt.plot(dots)
plt.xlim([950, 1050])
plt.ylim([0,1])
```

So use this to create a `PositionEmbedding` layer that looks-up a token's embedding vector and adds the position vector:

```
class PositionalEmbedding(tf.keras.layers.Layer):
 def __init__(self, vocab_size, d_model):
   super().__init__()
   self.d_model = d_model
```

```
    self.embedding = ... # TODO: tf.keras appropriate frame
    self.pos_encoding = positional_encoding(length=2048, depth=d_model)

  def compute_mask(self, *args, **kwargs):
    return self.embedding.compute_mask(*args, **kwargs)

  def call(self, x):
    length = tf.shape(x)[1]
    x = self.embedding(x)
    # This factor sets the relative scale of the embedding and positonal_encoding.
    x *= tf.math.sqrt(tf.cast(self.d_model, tf.float32))
    x = x + self.pos_encoding[tf.newaxis, :length, :]
```

embed_pt = PositionalEmbedding(vocab_size=..., d_model=512)
embed_en = PositionalEmbedding(vocab_size=…, d_model=512)
pt_emb = embed_pt(pt) en_emb = embed_en(en)

en_emb._keras_mask

Add and normalize

These "Add & Norm" blocks are scattered throughout the model. Each one joins a residual connection and runs the result through a `LayerNormalization` layer.

The easiest way to organize the code is around these residual blocks. The following sections will define custom layer classes for each.

The residual "Add & Norm" blocks are included so that training is efficient. The residual connection provides a direct path for the gradient (and ensures that vectors are **updated** by the attention layers instead of **replaced**), while the normalization maintains a reasonable scale for the outputs.

Note: The implementations, below, use the `Add` layer to ensure that Keras masks are propagated (the `+` operator does not).

The base attention layer

Attention layers are used throughout the model. These are all identical except for how the attention is configured. Each one contains a `layers.MultiHeadAttention`, a `layers.LayerNormalization` and a `layers.Add`.

To implement the attention layers, start with a simple base class that just contains the component layers. Each use-case will be implemented as a subclass.

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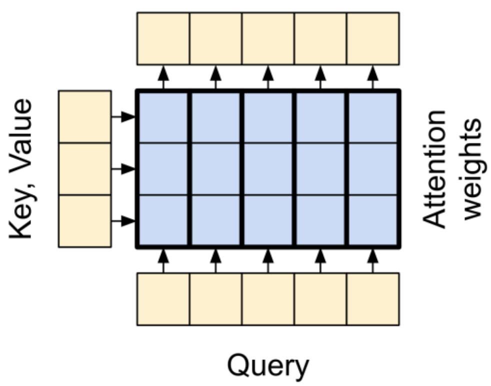
```python
class BaseAttention(tf.keras.layers.Layer):
 def __init__(self, **kwargs):
   super().__init__()
   self.mha = tf.keras.layers.MultiHeadAttention(**kwargs)
   self.layernorm = ... #TODO: Normalization
   self.add = tf.keras.layers.Add()
```

Attention

Before you get into the specifics of each usage, here is a quick refresher on how attention works:



There are two inputs:

1. The query sequence; the sequence being processed; the sequence doing the attending (bottom).
2. The context sequence; the sequence being attended to (left).

The output has the same shape as the query-sequence.

The common comparison is that this operation is like a dictionary lookup. A **fuzzy**, **differentiable**, **vectorized** dictionary lookup.

Here's a regular python dictionary, with 3 keys and 3 values being passed a single query.

d = {'color': 'blue', 'age': 22, 'type': 'pickup'}
result = d['color']

- The `query`s is what you're trying to find.
- The `key`s what sort of information the dictionary has.

- The `value` is that information.

When you look up a `query` in a regular dictionary, the dictionary finds the matching `key`, and returns its associated `value`. The `query` either has a matching `key` or it doesn't. You can imagine a **fuzzy** dictionary where the keys don't have to match perfectly. If you looked up `d["species"]` in the dictionary above, maybe you'd want it to return `"pickup"` since that's the best match for the query.

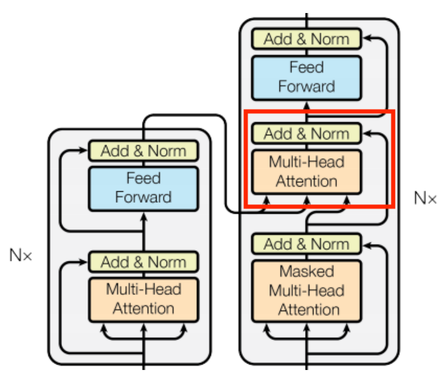
An attention layer does a fuzzy lookup like this, but it's not just looking for the best key. It combines the `values` based on how well the `query` matches each `key`.

How does that work? In an attention layer the `query`, `key`, and `value` are each vectors. Instead of doing a hash lookup the attention layer combines the `query` and `key` vectors to determine how well they match, the "attention score". The layer returns the average across all the `values`, weighted by the "attention scores".

Each location the query-sequence provides a `query` vector. The context sequence acts as the dictionary. At each location in the context sequence provides a `key` and `value` vector. The input vectors are not used directly, the `layers.MultiHeadAttention` layer includes `layers.Dense` layers to project the input vectors before using them.

The cross attention layer

At the literal center of the Transformer is the cross-attention layer. This layer connects the encoder and decoder. This layer is the most straight-forward use of attention in the model



To implement this you pass the target sequence `x` as the `query` and the `context` sequence as the `key/value` when calling the `mha` layer:

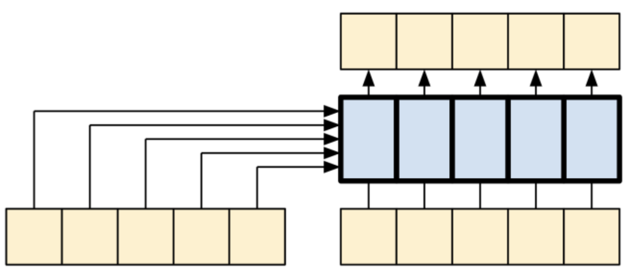
```
class CrossAttention(BaseAttention):
 def call(self, x, context):
   attn_output, attn_scores = self.mha(
       query=x,
       key=context,
```

```
        value=context,
        return_attention_scores=True)
# Cache the attention scores for plotting later.
    self.last_attn_scores = attn_scores
    x = self.add([...]) #TODO
    x = self.layernorm(x)

    return x
```

The caricature below shows how information flows through this layer. The columns represent the weighted sum over the context sequence.There's no need to draw the entire "Attention weights" matrix. The point is that each `query` location can see all the `key/value` pairs in the context, but no information is exchanged between the queries.

Each query sees the whole context.



Test run it on sample inputs:

```
sample_ca = CrossAttention(num_heads=2, key_dim=512)

print(pt_emb.shape)
print(en_emb.shape)
print(sample_ca(en_emb, pt_emb).shape)
```

The global self attention layer

This layer is responsible for processing the context sequence, and propagating information along its length

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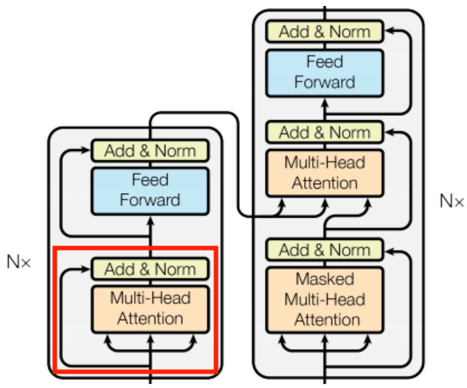

To implement this layer you just need to pass the target sequence, `x`, as both the `query`, and `value` arguments to the `mha` layer:

```
class GlobalSelfAttention(BaseAttention):
 def call(self, x):
   attn_output = self.mha(
       query=x,
       value=x,
       key=x)
   x = self.add([...]) #TODO
   x = self.layernorm(x)
   return x

sample_gsa = GlobalSelfAttention(num_heads=2, key_dim=512)

print(pt_emb.shape)
print(sample_gsa(pt_emb).shape)
```

The causal self attention layer

This layer does a similar job as the global self attention layer, for the output sequence:

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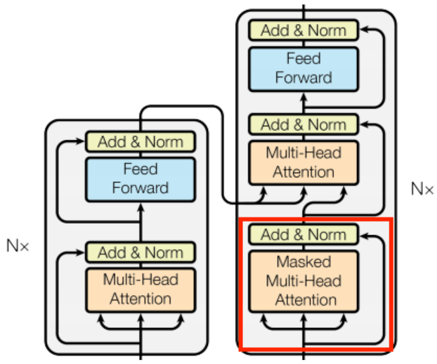

A causal model is efficient in two ways:

1. In training, it lets you compute loss for every location in the output sequence while executing the model just once.
2. During inference, for each new token generated you only need to calculate its outputs, the outputs for the previous sequence elements can be reused.

This is taken care of automatically if you pass `use_causal_mask = True` to the `MultiHeadAttention` layer when you call it:

```
class CausalSelfAttention(BaseAttention):
 def call(self, x):
   attn_output = self.mha(
       query=x,
       value=x,
       key=x,
       use_causal_mask = True)
   x = self.add([x, attn_output])
   x = self.layernorm(x)
   return x
```

The causal mask ensures that each location only has access to the locations that come before it:

Test out the layer:

```
sample_csa = ...(num_heads=2, key_dim=512) #TODO: CausalSelfAttention

print(en_emb.shape)
print(sample_csa(en_emb).shape)
```

The output for early sequence elements doesn't depend on later elements, so it shouldn't matter if you trim elements before or after applying the layer:

```
out1 = sample_csa(embed_en(en[:, :3]))
out2 = sample_csa(embed_en(en))[:, :3]

tf.reduce_max(abs(out1 - out2)).numpy()
```

The feed forward network

The transformer also includes this point-wise feed-forward network in both the encoder and decoder:

The network consists of two linear layers (`tf.keras.layers.Dense`) with a ReLU activation in-between, and a dropout layer. As with the attention layers the code here also includes the residual connection and normalization:

```
class FeedForward(tf.keras.layers.Layer):
 def __init__(self, d_model, dff, dropout_rate=0.1):
   super().__init__()
   self.seq = tf.keras.Sequential([
     tf.keras.layers.Dense(dff, activation='relu'),
     tf.keras.layers.Dense(d_model),
     tf.keras.layers.Dropout(dropout_rate)
   ])
   self.add = tf.keras.layers.Add()
   self.layer_norm = tf.keras.layers.LayerNormalization()

 def call(self, x):
   x = self.add([x, self.seq(x)])
   x = self.layer_norm(x)
   return X
```

Test the layer, the output is the same shape as the input:

```
sample_ffn = FeedForward(512, 2048)
print(en_emb.shape)
print(sample_ffn(en_emb).shape)
```

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The encoder layer

The encoder contains a stack of `N` encoder layers. Where each `EncoderLayer` contains a `GlobalSelfAttention` and `FeedForward` layer:

Here is the definition of the `EncoderLayer`:

```
class EncoderLayer(tf.keras.layers.Layer):
 def __init__(self,*, d_model, num_heads, dff, dropout_rate=0.1):
   super().__init__()
   self.self_attention = GlobalSelfAttention(
       num_heads=num_heads,
       key_dim=d_model,
       dropout=dropout_rate)

   self.ffn = FeedForward(d_model, dff)

 def call(self, x):
   x = self.self_attention(x)
   x = self.ffn(x)
   return x
```

And a quick test, the output will have the same shape as the input:

```
sample_encoder_layer = ...(d_model=512, num_heads=8, dff=2048) #TODO:

print(pt_emb.shape)
print(sample_encoder_layer(pt_emb).shape)
```

The encoder

The encoder consists of:

- A `PositionalEmbedding` layer at the input.
- A stack of `EncoderLayer` layers.

```
class EncoderLayer(tf.keras.layers.Layer):
 def __init__(self,*, d_model, num_heads, dff, dropout_rate=0.1):
   super().__init__()

   self.self_attention = GlobalSelfAttention(
```

```
        num_heads=num_heads,
        key_dim=d_model,
        dropout=dropout_rate)

    self.ffn = ... #TODO: Appropriate call to function

  def call(self, x):
    x = self.self_attention(x)
    x = self.ffn(x)
    return x
```

Test the encoder:

```
sample_encoder_layer = ...(d_model=512, num_heads=8, dff=2048) #TODO

print(pt_emb.shape)
print(sample_encoder_layer(pt_emb).shape)
```

The decoder layer

The decoder's stack is slightly more complex, with each `DecoderLayer` containing a `CausalSelfAttention`, a `CrossAttention`, and a `FeedForward` layer:

```
class DecoderLayer(tf.keras.layers.Layer):
  def __init__(self,
               *,
               d_model,
               num_heads,
               dff,
               dropout_rate=0.1):
    super(DecoderLayer, self).__init__()

    self.causal_self_attention = ...(
        num_heads=num_heads,
        key_dim=d_model,
        dropout=dropout_rate)

    self.cross_attention = ...( #TODO: Cross Attention
```

```
        num_heads=num_heads,
        key_dim=d_model,
        dropout=dropout_rate)

    self.ffn = FeedForward(d_model, dff)

  def call(self, x, context):
    x = self.causal_self_attention(x=x)
    x = self.cross_attention(x=x, context=context)

    # Cache the last attention scores for plotting later
    self.last_attn_scores = self.cross_attention.last_attn_scores

    x = self.ffn(x)  # Shape `(batch_size, seq_len, d_model)`.
    return x
```

Test the decoder layer:

```
sample_decoder_layer = DecoderLayer(d_model=512, num_heads=8, dff=2048)

sample_decoder_layer_output = ...( #TODO
    x=en_emb, context=pt_emb)
print(en_emb.shape)
print(pt_emb.shape)
print(sample_decoder_layer_output.shape)  # `(batch_size, seq_len, d_model)`
```

The decoder

Similar to the `Encoder`, the `Decoder` consists of a `PositionalEmbedding`, and a stack of `DecoderLayer`s:

Define the decoder by extending `tf.keras.layers.Layer`:

```
class Decoder(tf.keras.layers.Layer):
  def __init__(self, *, num_layers, d_model, num_heads, dff, vocab_size,
               dropout_rate=0.1):
    super(Decoder, self).__init__()
```

```
    self.d_model = d_model
    self.num_layers = num_layers

    self.pos_embedding = ...(vocab_size=vocab_size, #TODO
                                             d_model=d_model)
    self.dropout = tf.keras.layers.Dropout(dropout_rate)
    self.dec_layers = [
        DecoderLayer(d_model=d_model, num_heads=num_heads,
                     dff=dff, dropout_rate=dropout_rate)
        for _ in range(num_layers)]

    self.last_attn_scores = None

  def call(self, x, context):
    # `x` is token-IDs shape (batch, target_seq_len)
    x = self.pos_embedding(x)  # (batch_size, target_seq_len, d_model)

    x = self.dropout(x)

    for i in range(self.num_layers):
      x  = self.dec_layers[i](x, context)

    self.last_attn_scores = ... #TODO Use .last_attn_scores appropriately

    # The shape of x is (batch_size, target_seq_len, d_model).
    return x
```

Test the decoder:

```
# Instantiate the decoder.
sample_decoder = Decoder(num_layers=4,
                         d_model=512,
                         num_heads=8,
                         dff=2048,
                         vocab_size=8000)

output = ...( # TODO
```

```
   x=en,
   context=pt_emb)

# Print the shapes.
print(en.shape)
print(pt_emb.shape)
print(output.shape)
```

sample_decoder.last_attn_scores.shape # (batch, heads, target_seq, input_seq)

Having created the Transformer encoder and decoder, now build the Transformer model and train it.

The Transformer

You now have `Encoder` and `Decoder`. To complete the `Transformer` model, you need to put them together and add a final linear (`Dense`) layer which converts the resulting vector at each location into output token probabilities.

The output of the decoder is the input to this final linear layer.

Create the `Transformer` by extending `tf.keras.Model`:

```
class Transformer(tf.keras.Model):
 def __init__(self, *, num_layers, d_model, num_heads, dff,
             input_vocab_size, target_vocab_size, dropout_rate=0.1):
   super().__init__()
   self.encoder = Encoder(num_layers=num_layers, d_model=d_model,
                          num_heads=num_heads, dff=dff,
                          vocab_size=input_vocab_size,
                          dropout_rate=dropout_rate)

   self.decoder = Decoder(num_layers=num_layers, d_model=d_model,
                          num_heads=num_heads, dff=dff,
                          vocab_size=target_vocab_size,
                          dropout_rate=dropout_rate)

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

 def call(self, inputs):
   # To use a Keras model with `.fit` you must pass all your inputs in
```

```
the
    # first argument.
    context, x  = inputs

    context  =  self.encoder(context)    #  (batch_size,  context_len,
d_model)

    x = self.decoder(x, context)  # (batch_size, target_len, d_model)

    # Final linear layer output.
    logits   =   self.final_layer(x)      #   (batch_size,   target_len,
target_vocab_size)
    try:
      # Drop the keras mask, so it doesn't scale the losses/metrics.
      # b/250038731
      del logits._keras_mask
    except AttributeError:
      pass

    # Return the final output and the attention weights.
    return logits
```

Hyperparameters

To keep this example small and relatively fast, the number of layers (`num_layers`), the dimensionality of the embeddings (`d_model`), and the internal dimensionality of the `FeedForward` layer (`dff`) have been reduced.

The base model described in the original Transformer paper used `num_layers=6`, `d_model=512`, and `dff=2048`.

The number of self-attention heads remains the same (`num_heads=8`).

num_layers = 4 d_model = 128 dff = 512 num_heads = 8 dropout_rate = 0.1

Try it out

Instantiate the `Transformer` model:

```
transformer = Transformer(
```

```
    num_layers=num_layers,
    d_model=d_model,
    num_heads=num_heads,
    dff=dff,
    input_vocab_size=tokenizers.pt.get_vocab_size().numpy(),
    target_vocab_size=tokenizers.en.get_vocab_size().numpy(),
    dropout_rate=dropout_rate)
```

Test it:

```
output = transformer((pt, en))

print(en.shape)
print(pt.shape)
print(output.shape)


attn_scores = transformer.decoder.dec_layers[-1].last_attn_scores

print(attn_scores.shape)  # (batch, heads, target_seq, input_seq)
```

Print the summary of the model:

```
transformer.summary()
```

Training

It's time to prepare the model and start training it.

Set up the optimizer

Use the Adam optimizer with a custom learning rate scheduler

```
class CustomSchedule(tf.keras.optimizers.schedules.LearningRateSchedule):
 def __init__(self, d_model, warmup_steps=4000):
    super().__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):
    step = tf.cast(step, dtype=tf.float32)
    arg1 = tf.math.rsqrt(step)
    arg2 = step * (self.warmup_steps ** -1.5)

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

Instantiate the optimizer (in this example it's `tf.keras.optimizers.Adam`):

learning_rate = CustomSchedule(d_model)

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

Test the custom learning rate scheduler:

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

Set up the loss and metrics

Since the target sequences are padded, it is important to apply a padding mask when calculating the loss.Use the cross-entropy loss function (`tf.keras.losses.SparseCategoricalCrossentropy`):

```
def masked_loss(label, pred):
  mask = label != 0
  loss_object = tf.keras.losses.SparseCategoricalCrossentropy(
    from_logits=True, reduction='none')
  loss = loss_object(label, pred)
  mask = tf.cast(mask, dtype=loss.dtype)
  loss *= mask
  loss = tf.reduce_sum(loss)/tf.reduce_sum(mask)
  return loss


def masked_accuracy(label, pred):
```

```
pred = tf.argmax(pred, axis=2)
label = tf.cast(label, pred.dtype)
match = label == pred

mask = label != 0
match = match & mask
match = tf.cast(match, dtype=tf.float32)
mask = tf.cast(mask, dtype=tf.float32)
return tf.reduce_sum(match)/tf.reduce_sum(mask)
```

Train the model

With all the components ready, configure the training procedure using `model.compile`, and then run it with `model.fit`:

transformer.compile(loss=masked_loss, optimizer=optimizer, metrics=[masked_accuracy])

transformer.fit(train_batches, epochs=1, validation_data=val_batches)

Run inference

You can now test the model by performing a translation. The following steps are used for inference:

- Encode the input sentence using the Portuguese tokenizer (`tokenizers.pt`). This is the encoder input.
- The decoder input is initialized to the `[START]` token.
- 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).
- Concatenate the predicted token to the decoder input and pass it to the decoder.
- In this approach, the decoder predicts the next token based on the previous tokens it predicted.

Note: The model is optimized for *efficient training* and makes a next-token prediction for each token in the output simultaneously. This is redundant during inference, and only the last prediction is used. This model can be made more efficient for inference if you only calculate the last prediction when running in inference mode (`training=False`).

Define the `Translator` class by subclassing `tf.Module`:

```
class Translator(tf.Module):
 def __init__(self, tokenizers, transformer):
```

```
    self.tokenizers = tokenizers
    self.transformer = transformer

  def __call__(self, sentence, max_length=MAX_TOKENS):
    # The input sentence is Portuguese, hence adding the `[START]` and `[END]`
tokens.
    assert isinstance(sentence, tf.Tensor)
    if len(sentence.shape) == 0:
      sentence = sentence[tf.newaxis]

    sentence = self.tokenizers.pt.tokenize(sentence).to_tensor()

    encoder_input = sentence

    # As the output language is English, initialize the output with the
    # English `[START]` token.
    start_end = self.tokenizers.en.tokenize([''])[0]
    start = start_end[0][tf.newaxis]
    end = start_end[1][tf.newaxis]
# `tf.TensorArray`is required here (instead of a Python list), so that the
    # dynamic-loop can be traced by `tf.function`.
    output_array = tf.TensorArray(dtype=tf.int64, size=0, dynamic_size=True)
    output_array = output_array.write(0, start)

    for i in tf.range(max_length):
      output = tf.transpose(output_array.stack())
      predictions      =      self.transformer([encoder_input,      output],
training=False)

      # Select the last token from the `seq_len` dimension.
      predictions  =  predictions[:,  -1:,  :]   #  Shape  `(batch_size,  1,
vocab_size)`.

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

      # Concatenate the `predicted_id` to the output which is given to the
```

```
      # decoder as its input.
      output_array = output_array.write(i+1, predicted_id[0])

      if predicted_id == end:
        break

    output = tf.transpose(output_array.stack())
    # The output shape is `(1, tokens)`.
    text = tokenizers.en.detokenize(output)[0]  # Shape: `()`.

    tokens = tokenizers.en.lookup(output)[0]

    # `tf.function` prevents us from using the attention_weights that were
    # calculated on the last iteration of the loop.
    # So, recalculate them outside the loop.
    self.transformer([encoder_input, output[:,:-1]], training=False)
    attention_weights = self.transformer.decoder.last_attn_scores

    return text, tokens, attention_weights
```

Create an instance of this `Translator` class, and try it out a few times:

```
translator = Translator(tokenizers, transformer)
def print_translation(sentence, tokens, ground_truth):
 print(f'{"Input:":15s}: {sentence}')
 print(f'{"Prediction":15s}: {tokens.numpy().decode("utf-8")}')
 print(f'{"Ground truth":15s}: {ground_truth}')
```

Example 1:
sentence = 'este é um problema que temos que resolver.'
ground_truth = 'this is a problem we have to solve .'
translated_text, translated_tokens, attention_weights = translator(tf.constant(sentence))
print_translation(sentence, translated_text, ground_truth)

Example 2:
sentence = 'os meus vizinhos ouviram sobre esta ideia.'
ground_truth = 'and my neighboring homes heard about this idea .'
translated_text, translated_tokens, attention_weights = translator(tf.constant(sentence))
print_translation(sentence, translated_text, ground_truth)

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GENERATIVE AI LAB - 8

[TRANSFORMERS]

TIME: 02 Hours

Create attention plots

The `Translator` class you created in the previous section returns a dictionary of attention heatmaps you can use to visualize the internal working of the model.

For example:

sentence = 'este é o primeiro livro que eu fiz.'
ground_truth = "this is the first book i've ever done."
translated_text, translated_tokens, attention_weights = translator(tf.constant(sentence))
print_translation(sentence, translated_text, ground_truth)

Create a function that plots the attention when a token is generated:

```
def plot_attention_head(in_tokens, translated_tokens, attention):
 # The model didn't generate `<START>` in the output. Skip it.
 translated_tokens = translated_tokens[1:]
 ax = plt.gca()
 ax.matshow(attention)
 ax.set_xticks(range(len(in_tokens)))
 ax.set_yticks(range(len(translated_tokens)))

 labels = [label.decode('utf-8') for label in in_tokens.numpy()]
 ax.set_xticklabels(
     labels, rotation=90)

 labels = [label.decode('utf-8') for label in translated_tokens.numpy()]
 ax.set_yticklabels(labels)
head = 0
# Shape: `(batch=1, num_heads, seq_len_q, seq_len_k)`.
attention_heads = tf.squeeze(attention_weights, 0)
attention = attention_heads[head]
attention.shape
```

These are the input (Portuguese) tokens:

```
in_tokens = tf.convert_to_tensor([sentence])
in_tokens = tokenizers.pt.tokenize(in_tokens).to_tensor()
in_tokens = tokenizers.pt.lookup(in_tokens)[0]
in_tokens
```

And these are the output (English translation) tokens:

translated_tokens

plot_attention_head(in_tokens, translated_tokens, attention)

```
def plot_attention_weights(sentence, translated_tokens, attention_heads):
 in_tokens = tf.convert_to_tensor([sentence])
 in_tokens = tokenizers.pt.tokenize(in_tokens).to_tensor()
 in_tokens = tokenizers.pt.lookup(in_tokens)[0]

 fig = plt.figure(figsize=(16, 8))

 for h, head in enumerate(attention_heads):
   ax = fig.add_subplot(2, 4, h+1)

   plot_attention_head(in_tokens, translated_tokens, head)

   ax.set_xlabel(f'Head {h+1}')

 plt.tight_layout()
 plt.show()
```

plot_attention_weights(sentence, translated_tokens, attention_weights[0])

The model can handle unfamiliar words. Neither `'triceratops'` nor `'encyclopédia'` are in the input dataset, and the model attempts to transliterate them even without a shared vocabulary. For example:

```
sentence = 'Eu li sobre triceratops na enciclopédia.'
ground_truth = 'I read about triceratops in the encyclopedia.'

translated_text, translated_tokens, attention_weights = translator(
   tf.constant(sentence))
print_translation(sentence, translated_text, ground_truth)

plot_attention_weights(sentence, translated_tokens, attention_weights[0])
```

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[TRANSFORMERS]

TIME: 02 Hours

Exercise:

1. Complete all the TODOs given in the labsheet
2. For 5 different set of hyperparameters, generate a table showing the loss and evaluation metrics