[TensorFlow Transformer Tutorial (https://www.tensorflow.org/text/tutorials/transformer)](https://www.tensorflow.org/text/tutorials/transformer)

The link in the title is to an *excellent* tutorial on the Transformer

- more in-depth than this notebook
- background

It is recommended especially for those readers without a background in Transformers from the Intro course.

We will take a look at the actual code of a Transformer.

There are many pieces, which we will examine individually.

We will proceed starting with a high level view and descend to a lower level

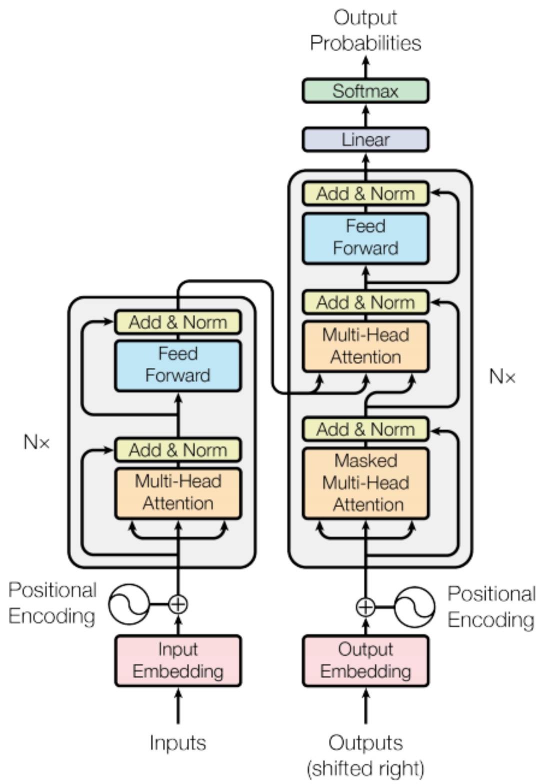
- means reading the code from bottom to top

There are many subtle points which we will highlight with the tag **SUBTLETY**

One of the key components of a Transformer is the Attention mechanism.

In the code we examine, the base Attention class is via a `MultiHeadAttention` layer type

- we will study this layer separately
- so as not to distract from the other details of the Transformer architecture



Output Probabilities
Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Nx
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Nx
Positional Encoding
Positional Encoding
Input Embedding
Output Embedding
Inputs
Outputs (shifted right)

[The Model: Transformer (https://www.tensorflow.org/text/tutorials/transformer#the_transformer)](https://www.tensorflow.org/text/tutorials/transformer#the_transformer)

- The Transformer is a Model: a subclass of `tf.keras.Model`
- The initializer creates
    - An Encoder
    - A Decoder
    - a `final_layer` which converts the vector at each position into logits over the distribution of tokens

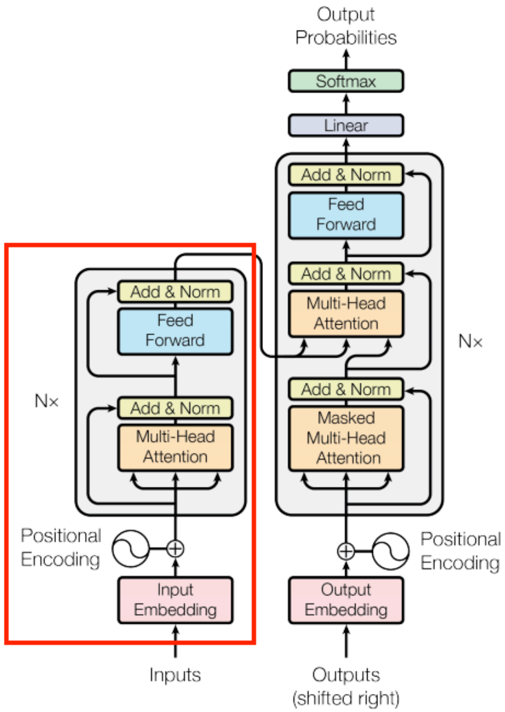
```
class Transformer(tf.keras.Model):
  def __init__(self, *, num_layers, d_model, num_heads, dff,
               input_vocab_size, target_vocab_size, dropout_rate=0.1):
    super().__init__()
    self.encoder = Encoder(num_layers=num_layers, d_model=d_model,
                           num_heads=num_heads,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

The model overrides the `call` method

- defines what happens when we pass an input to the Transformer
- passes the `context`input to the Encoder
- the Encoder output is passed to the Decoder
- the Decoder output (logits) is passed through a layer to produce a logit (at each position)

```
      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_s
ize)

        try:
          # Drop the keras mask, so it doesn't scale the losses/metrics.
          # b/250038731
          del logits._keras_mask
        except AttributeError:
          pass
```

The Encoder (https://www.tensorflow.org/text/tutorials/transformer#the_encoder_layer)



Confusion warning

The Encoder is a stack of N "blocks"

- that is what the "Nx" in the diagram refers to

Each block is implemented by the class `EncoderLayer.

The `Encoder` object is the *stack* of encoder blocks (`EncoderLayer` 's)

The `Encoder` is a Layer: sub-class of `tf.keras.layers.Layer`)

- The initializer creates the sub-components of the Encoder
    - Positional Embedding
    - A sub-component (`enc_layers`) which is an **array** of blocks whose elements are objects containing
        - Self-Attention
        - Feed-forward network
    - This array (of length `num_layers`) is the *stack* of blocks

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

    self.d_model = d_model
    self.num_layers = num_layers

    self.pos_embedding = PositionalEmbedding(
        vocab_size=vocab_size, d_model=d_model)

    self.enc_layers = [
        EncoderLayer(d_model=d_model,
                     num_heads=num_heads,
                     dff=dff,
                     dropout_rate=dropout_rate)
        for _ in range(num_layers)]
    self.dropout = tf.keras.layers.Dropout(dropout_rate)
```

The `call` method defines how the layer behaves when presented with input

- calls the Positional Embedding on the Encoder input
- passes the result through each block in the stacked `EncoderLayer`'s
    - Self-Attention followed by Feed Forward

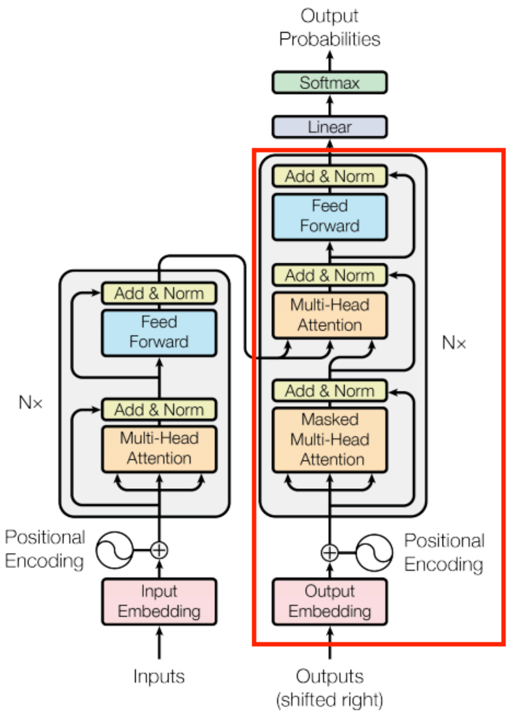
```
def call(self, x):
  # `x` is token-IDs shape: (batch, seq_len)
  x = self.pos_embedding(x)  # Shape `(batch_size, seq_len, d_model)`.

  # Add dropout.
  x = self.dropout(x)

  for i in range(self.num_layers):
    x = self.enc_layers[i](x)

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

The `EncoderLayer` (one block) class has

- an initializer that creates sub-components
- a `call` method is over-ridden to pass inputs through the sub-components

```
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
```

[The Decoder (https://www.tensorflow.org/text/tutorials/transformer#the_decoder)](https://www.tensorflow.org/text/tutorials/transformer#the_decoder)



Confusion warning

The `Decoder` object is the *stack* of decoder blocks (which are called `DecoderLayer` 's)

The `Decoder` is a Layer: sub-class of `tf.keras.layers.Layer`)

- The initializer creates the sub-components of the Decoder
    - Positional Embedding
    - A sub-component (confusingly named `DecoderLayer`) which is an **array** of blocks whose elements are objects containing
        - Self-Attention
        - Cross-Attention
        - Feed-forward network
    - This array (of length `num_layers`) is the *stack* of blocks

```
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 = PositionalEmbedding(vocab_size=vocab_size,
                                             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
```

The `call` method defines how the layer behaves when presented with input

- calls the Positional Embedding on the Decoder input
- passes the result to the stacked `DecoderLayer`'s
    - *Causal* Self-Attention followed by
    - Cross-Attention followed by Feed Forward

```
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 = self.dec_layers[-1].last_attn_scores

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

The `DecoderLayer`

- initializer creates sub-components

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

    self.cross_attention = CrossAttention(
        num_heads=num_heads,
        key_dim=d_model,
        dropout=dropout_rate)

    self.ffn = FeedForward(d_model, dff)
```

The `call` method is over-ridden to pass inputs through the sub-components

```
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
```

Let us focus on the two forms of Attention

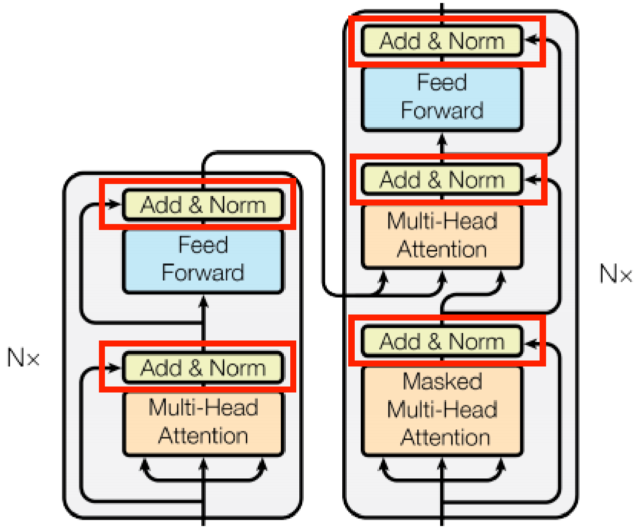
- `context` is the Encoder output
- `x` is the Decoder input

The *Causal* Self-Attention uses query `x` (at each position) to attend to entire sequence `x`.

- the attention is *causual*: for each position, future positions *may not* be attended to

The Cross-Attention uses query `x` (at each position) to attend to Encoder output `context`

[Add and Normalize (https://www.tensorflow.org/text/tutorials/transformer#add_and_normalize)](https://www.tensorflow.org/text/tutorials/transformer#add_and_normalize)



Review: Layer Normalization

- The variance of outputs tends to grow from layer to layer
- Large variance causes gradient updates to become unstable
- Layer Normalization (https://proceedings.neurips.cc/paper_files/paper/2019/file/2f4fe03d77724a7217(Paper.pdf) reduces the variance of the input distribution to unit variance

SUBTLETY

The output of Attention layers (both Self Attention and Cross Attention) are feed into an `Add & Norm` block.

In what seems to be a "coding convenience"

- the code creates a common base class `BaseAttention`
    - for both Self Attention and Cross Attention
    - that is partially responsible for **both**
        - Attention
        - Add & Norm

This is much more subtle than "coding convenience" !

The initializer of `BaseAttention` creates sub-components

- Attention
- Layer Normalization
- Add

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

but doesn't actually perform the normalization or addition.

- there is no `call` method of the base class
- these are left to the child (Attention) classes

The *child* sub-class (`GlobalSelfAttention` or `CrossAttention`)

- **uses** the components of its parent class
    - `self.mha`: to implement the attention call
    - `'self.layernorm`, `self.add`: to implement the Add & Norm

To illustrate, here is the code for the `CrossAttention` sub-class

- note the arguments to `mha`
    - query is `x` ; key and value are both `context` (the Encoder output)

      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([x, attn_output])
  x = self.layernorm(x)

  return x
```

What is the purpose of `Add & Norm`

The "obvious" purpose is to normalize the Attention outputs

- using a `tf.keras.layers.LayerNormalization` layer
- that is the `Norm` part of `Add & Norm`

It is *easy to miss* the role of the `Add` part.

Mechanically: the `Add` is uninteresting.

The `Add` part adds the block's two inputs (i.e, Attention input and Attention output)

- before Normalization
- In both the Self-Attention and Cross Attention children, the `call` method performs the `Add` and `Norm` via statements

```
x = self.add([x, attn_output])
x = self.layernorm(x)
```

- where `x` is the Attention input and `attn_output` is the Attention output.

But what is the **purpose** of adding Attention input and Attention output ?

This creates a *residual* or *skip* connection

- on the forward pass, the input to Attention can "skip over" the Attention block
- more importantly: on the backward pass: the loss gradient can skip over the Attention block

[Review: Residual connections (RNN_Residual_Networks.ipynb#Residual-connections:-a-gradient-highway)](RNN_Residual_Networks.ipynb#Residual-connections:-a-gradient-highway)

- Gradients can vanish or explode as they traverse an increasing number of layers during back propagation
- A zero gradient causes the Gradient update step to leave weights unchanged
    - the model can't "learn"
- The skip connection prevents gradients from vanishing or exploding by allowing them to by-pass one or more layers in the backward pass

So `Add & Norm` is much more than "good coding"

- observing that Attention outputs are always fed into common blocks

It is also the mechanism by which the residual connections are implemented.

Attention

The Self Attention (the class is called `GlobalSelfAttention`) and Cross Attention blocks are both derived from `BaseAttention`

- which we explained in the section on "Add and Norm".

The sub-components (including the class `MultiHeadAttention` that implements Attention) are created by the parent class.

The child classes mainly implement the `call` method

- that invokes the sub-components in sequence
- and implement the residual connection

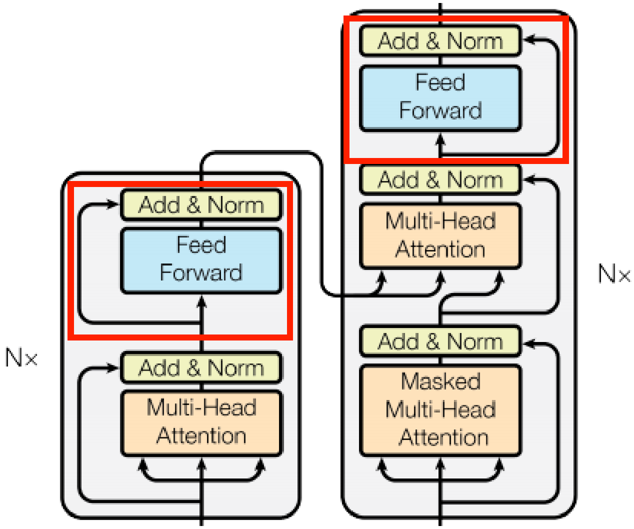
We already saw the `call` for `CrossAttention` above.

For Self-Attention, the `call` follows note the arguments to `mha`

```
- query, key and value are identical and equal to `x` (the Decoder input)
```

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

[Feed forward (https://www.tensorflow.org/text/tutorials/transformer#the_feed_forward_network)](https://www.tensorflow.org/text/tutorials/transformer#the_feed_forward_network)



The purpose of the Feed Forward block

- is to transform the Decoder Cross Attention output at each position into a "prediction"
    - of the next token (that is the Language Model objective

This is also where it is believed that "world knowledge" encountered during training is stored.

The typical Feed Forward network is two `Dense` layers

- the first has d_{ff} units
    - creating d_{ff} synthetic features from the d_{model} features of the Attention output
- the second has d_{model} units
    - re-sizing the output to the standard d_{model} output size of all blocks in a Transformer through two `Dense` layers.

In the original paper
$$d_{\text{ff}} = 4 * d_{\text{model}}$$
and this seems to have become a common choice.

Here is the code:

```
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
```

SUBTLETY

The Feed Forward output is passed to an `Add & Norm` block

- which has **two inputs**
  - Feed Forward output and Feed Forward input
  - the Feed Forward input is a residual connection
- similar to the residual connection we saw in the "Add and Normalize" section.

The residual connection is implemented in the `call` via the statements

```
x = self.add([x, self.seq(x)])
x = self.layer_norm(x)
```

where

- `x` is the input to the Feed Forward block
- `self.seq(x)` is the output of the Feed Forward block
    - the input passed through the two `Dense`layers, implemented as a `Sequential` model

[Training (https://www.tensorflow.org/text/tutorials/transformer#training)](https://www.tensorflow.org/text/tutorials/transformer#training)

Teacher forcing

SUBTLETY

A Generative task (like the LLM objective) exhibits Autoregressive behavior

- the Decoder output $\hat{\mathbf{y}}_{(t-1)}$ at position $(t-1)$ is fed back as *input* for position t.

In the Transformer, the position $(t-1)$ output is appended to all previous outputs.

Thus, at *inference* time: the input for position t is $\hat{\mathbf{y}}_{([1:t-1])}$

But, this **exact** behavior is not conducive to *training*

- Suppose $\hat{\mathbf{y}}_{(t-1)}$ is incorrect and not equal to correct label $\mathbf{y}_{(t-1)}$
- this error cascades into the prediction of all subsequent positions $\hat{\mathbf{y}}_{([t:])}$

So, during **training** time: the input for position t is $\mathbf{y}_{(1:t-1)}$

- the *correct* sequence
- rather than the *predicted* sequence

This is why **causal masking** is necessary for the Decoder

- **Masked** Self-Attention
- don't want to look into the future
    - i.e., at positions $t' \geq t$ when the decoder is producing $\hat{\mathbf{y}}_{(t)}$

Feeding the *correct target* (rather than the actual *predicted target*) as the next input at training time

- is called *Teacher Forcing*
- does *not* occur at inference time
    - *predicted target* is used

It's very easy to *not notice* Teacher Forcing when it occurs because it is subtle.

Can you see where it occurs ?

It is in the *construction* of the Training examples

- the input for position t are the features of example t: $\mathbf{y}_{([1:t-1])}$
    - *not* the Autoregressive constructed $\hat{\mathbf{y}}_{([t:])}$

i	$\mathbf{x^{(i)}}$	$\mathbf{y^{(i)}}$
1	$\mathbf{y}_{(0)}$	$\mathbf{y}_{(1)}$
2	$\mathbf{y}_{([0:1])}$	$\mathbf{y}_{(2)}$
$\vdots$		
t	$\mathbf{y}_{([1:t-1])}$	$\mathbf{y}_{(t)}$
$\vdots$		
T	$\mathbf{y}_{([1:T-1])}$	$\mathbf{y}_{(T)}$

During training, each example trains for one "step"

- so we don't see the effect of $\hat{\mathbf{y}}_{(t-1)}$ being fed back to the input for the next step t

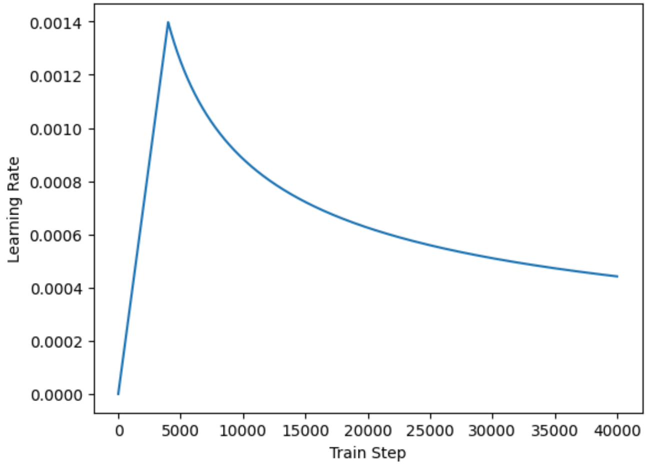
Custom Learning Rate Schedule

A custom learning rate schedule (subclassed from `tf.keras.optimizers.schedules.LearningRateSchedule`) is created

- varies learning rate α of Gradient update by epoch

$$\mathbf{W}_{(\text{epoch}+1)} = \mathbf{W}_{(\text{epoch})} - \alpha * \frac{\partial \mathcal{L}_{(\text{epoch})}}{\partial \mathbf{W}_{(\text{epoch})}}$$

  - a warm-up period where α increases
  - a post-warm-up period where α decays



[Loss and metrics (https://www.tensorflow.org/text/tutorials/transformer#set_up_the_loss_and_metrics)](https://www.tensorflow.org/text/tutorials/transformer#set_up_the_loss_and_metrics)

Since the targets are Categorical values, Cross Entropy is used as a loss.

But: the target is a sequence with *padding*

- the padding should not figure into the Loss
- so the loss is "masked" whenever the target `label` is a padding token (0)

Similarly the Accuracy metric is modified so that padding characters don't participate in the calculation.

```
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
```

Where do all the weights come from ?

Ignoring the weights associated with the various embeddings, the weights come from

- Attention
- Feed forward Network

This is for *each* Transformer block

- we will stack n_{layer} such blocks

For Attention, the weights/parameters are in the matrices $\mathbf{W}_Q$, $\mathbf{W}_K$, $\mathbf{W}_V$ and $\mathbf{W}_O$

- all of size $\mathcal{O}\left(d^2_{\text{model}}\right)$, total:
$$4 * \mathcal{O}\left(d^2_{\text{model}}\right)$$

For the Feed forward network, there are two `Dense` layers

- the first mapping attention output of size d_{model} to size d_{ff}
- the second mapping size d_{ff} to standard output size d_{model}
- total Feed forward weights are $2 * (d_{\text{model}} * d_{\text{ff}})$

Using the standard

$$d_{\text{ff}} = 4 * d_{\text{model}}$$

total Feed forward weights per block

$$2 * (d_{\text{model}} * 4 * d_{\text{model}}) = 8 * \mathcal{O}\left(d_{\text{model}}^2\right)$$

Notice

- that $\frac{1}{3}$ of the total weights
- come from *linear* projections
    - the matrices associated with Attention
- rather than non-linearities
    - confined to Feed forward network

Thus the total weights *per Transformer block is $$ 12* \OrderOf{d_\text{model}^2} $$

This gets multiplied by the number n_{layer} stacked blocks..

For GPT-3

- $n_{\text{layer}} = 96$
- $d_{\text{model}} = 12 * 1024$

Total Transformer (non-embedding) weights

$$96 * 12 * (12 * 1024)^2 = 174 \text{ billion}$$

Second example: Mini-GPT (https://keras.io/examples/generative/text_generation_with_miniature_gpt/)

We will examine a notebook that builds a miniature version of GPT: tutorial view (https://keras.io/examples/generative/text_generation_with_miniature_gpt/)

- Colab notebook (https://colab.research.google.com/github/keras-team/keras-io/blob/master/examples/generative/ipynb/text_generation_with_miniature_gpt.ipy

We first see a definition of the constants:

```
vocab_size = 20000  # Only consider the top 20k words
maxlen = 80  # Max sequence size
embed_dim = 256  # Embedding size for each token
num_heads = 2  # Number of attention heads
feed_forward_dim = 256  # Hidden layer size in feed forward network inside tran
sformer
```

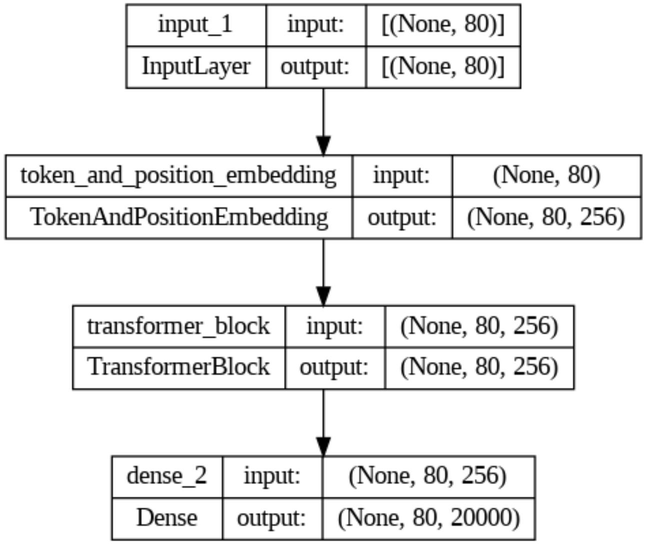
Relating the variable names to our notation

Notation	**variable**	**value**
d_{model}	embed_dim	256
T	max_len	80
n_{heads}	num_heads	2
	vocab_size	20,000

And the Decoder model:

```
def create_model():
    inputs = layers.Input(shape=(maxlen,), dtype=tf.int32)
    embedding_layer = TokenAndPositionEmbedding(maxlen, vocab_size, embed_dim)
    x = embedding_layer(inputs)
    transformer_block = TransformerBlock(embed_dim, num_heads, feed_forward_di
m)
    x = transformer_block(x)
    outputs = layers.Dense(vocab_size)(x)
    model = keras.Model(inputs=inputs, outputs=[outputs, x])
    loss_fn = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)
    model.compile(
        "adam", loss=[loss_fn, None],
    )  # No loss and optimization based on word embeddings from transformer blo
ck
    return model
```

Here is the plot:



Examining each layer

- `Input`
    - sequence (length $T = 80$) of integers (index of a character within vocabulary) $\mathbf{y}_{(1:T)}$
- `TokenAndPositionEmbedding`
    - maps sequence (length $T = 80$) of integers (index of character)
    - into sequence (length $T = 80$) of $d_{\text{model}} = 256$ size representations
- `TransformerBlock`
    - maps sequence (length $T = 80$) into sequence of latents $\mathbf{h}_{(1:T)}$
        - one latent per position in input

- `Dense`
    - Classifier layer
    - maps sequence of latents
    - to sequence of probability vectors
        - each position is a probability vector of length `vocab_size` $= 20000$
        - position i: probability that output is element i of vocabulary
        - sum across positions in each vector is 100%

Loss function

The `create_model` method also defines the Loss Function

```
loss_fn = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)
```

as Cross Entropy, as is common for a Classifier

Notice that the `SparseCategoricalCrossentropy` takes a vector (of length `vocab_size`) of **logits** rather than **probabilities**.

TransformerBlock

Let's examine the [TransformerBlock (https://colab.research.google.com/github/keras-team/keras-io/blob/master/examples/generative/ipynb/text_generation_with_miniature_gpt.ipynb#scrb)](https://colab.research.google.com/github/keras-team/keras-io/blob/master/examples/generative/ipynb/text_generation_with_miniature_gpt.ipynb#scrb) in more detail

---

```
class TransformerBlock(layers.Layer):
    def __init__(self, embed_dim, num_heads, ff_dim, rate=0.1):
        super().__init__()
        self.att = layers.MultiHeadAttention(num_heads, embed_dim)
        self.ffn = keras.Sequential(
            [layers.Dense(ff_dim, activation="relu"), layers.Dense(embed_dim),]
        )
        self.layernorm1 = layers.LayerNormalization(epsilon=1e-6)
        self.layernorm2 = layers.LayerNormalization(epsilon=1e-6)
        self.dropout1 = layers.Dropout(rate)
        self.dropout2 = layers.Dropout(rate)

    def call(self, inputs):
        input_shape = tf.shape(inputs)
        batch_size = input_shape[0]
        seq_len = input_shape[1]
        causal_mask = causal_attention_mask(batch_size, seq_len, seq_len, tf.bo
ol)
        attention_output = self.att(inputs, inputs, attention_mask=causal_mask)
        attention_output = self.dropout1(attention_output)
```

We can see that the TransformerBlock is implemented as a Layer (`layers.Layer`)

- so it will translate its input into output via a `call` method

The class `__init__` method defines the components of the Transformer

- stores them in instance variables:
    - Attention: `self.att`
    - Feed Forward Network FFN: `self.ffn`
    - Other: Layer Norms, Dropouts

The `call` method does the actual work

- Masked self-attention to $\mathbf{y}_{(1:T)}$
    - Creates casual mask `causal_mask` to prevent peeking ahead at not-yet-generated output
        - `seq_len` is current length t of $\mathbf{y}_{1:t)}$
    - Attention block `self.att` applied to causally-masked input

      ```
      attention_output = self.att(inputs, inputs, attention_mask=causal_mask)
      ```
- Dropout `self.dropout1` and LayerNorm `layernorm1` applied to attention output
- Result passed through Feed Forward Network `self.ffn`

TokenAndPositionEmbedding

Let's examine the [TokenAndPositionEmbedding (https://colab.research.google.com/github/keras-team/keras-io/blob/master/examples/generative/ipynb/text_generation_with_miniature_gpt.ipynb#scrc)](https://colab.research.google.com/github/keras-team/keras-io/blob/master/examples/generative/ipynb/text_generation_with_miniature_gpt.ipynb#scrc)

```
class TokenAndPositionEmbedding(layers.Layer):
    def __init__(self, maxlen, vocab_size, embed_dim):
        super().__init__()
        self.token_emb = layers.Embedding(input_dim=vocab_size, output_dim=embe
d_dim)
        self.pos_emb = layers.Embedding(input_dim=maxlen, output_dim=embed_dim)

    def call(self, x):
        maxlen = tf.shape(x)[-1]
        positions = tf.range(start=0, limit=maxlen, delta=1)
        positions = self.pos_emb(positions)
        x = self.token_emb(x)
        return x + positions
```

We can see that it too is implemented as a Layer.

The `call` method

- translates the input sequence
    - each position in the sequence is an integer index within the vocabulary

- into a sequence of pairs

    - first element: token embedding

      ```
      x = self.token_emb(x)
      ```

    - second element: position embedding

      ```
      positions = tf.range(start=0, limit=maxlen, delta=1)
      positions = self.pos_emb(positions)
      ```

As explained [in a prior module (Transformer_PositionalEmbedding.ipynb#Representing-the-combined-token-and-positional-encoding)](Transformer_PositionalEmbedding.ipynb#Representing-the-combined-token-and-positional-encoding)

- The output is not actually a sequence of *pairs*
    - it is a sequence of numbers
    - the token and positional emeddings are *added* not concatenated
        - concatenation would double the length
        - all layers in Transformer preserve output length equal input length = d_{model}
- See the module's explanation as to why addition works

Dense (Feed Forward Network)

We can see that the Feed Forward Network are two Dense layers

```
self.ffn = keras.Sequential(
            [layers.Dense(ff_dim, activation="relu"), layers.Dense(embed_dim),]
        )
```

We may have been expecting the final layer of `TransformerBlock` to be outputting a probability vector (over the Vocabulary)

- a vector of length `vocab_size`
    - position i is probability that output is element i of the Vocabulary
- using a `softmax` activation
    - to make sure sum (across the `vocab_size` elements of the vector) of probabilities is `00%

But we see that the output is

- a singleton (not a vector)
- of size equal to `embed_dim` = d_{model}

That is:

- the `Dense` component of the `TransformerBlock` is outputing the embedding of $\hat{\mathbf{y}}_{(t)}$ rather than a probability vector

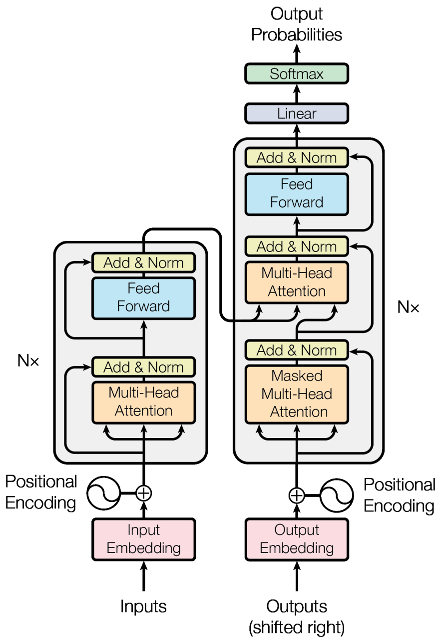
As we will see

- there is a layer in the Model *after* the `TransformerBlock`
- that produces the probability vector

Skip connections

Here is a more detailed view of the Transformer

Transformer (Encoder/Decoder)



In particular, please focus on the arrows *into the "Add & Norm" layers*.

These are *skip connections* that bypass the Attention layers.

- *Residual Networks*

Where is this reflected in the code ?

It is a little subtle and easy to miss.

With the `call` method of the `TransformerBlock` please notice the statement

```
out1 = self.layernorm1(inputs + attention_output)
```

- `inputs` is the input to the Attention layer

  attention_output = self.att(inputs, inputs, attention_mask=causal_mask)

So the addition

```
inputs + attention_output
```

is joining (via addition)

- the output of the Attetnion layer
- the input of the Attention layer

This is the skip connection !

Similar code appears

```
ffn_output = self.ffn(out1)
ffn_output = self.dropout2(ffn_output)
return self.layernorm2(out1 + ffn_output)
```

where

- the input to the FFN (i.e., `out1`)
- is joined (via addition) to the output of the FFN (i.e., `ffn_output`)

```
out1 + ffn_output
```

Model

By examining the `create_model` function, we see that the output of the `TransformerBlock`

- is fed into a `Dense` layer
- which outputs a vector of length `vocab_size` (the correct length of a probability vector)
- and the output of this `Dense` layer is the output of the **model**
    - not the output of the `TransformerBlock`

    ```
    outputs = layers.Dense(vocab_size)(x)
    model = keras.Model(inputs=inputs, outputs=[outputs, x])
    ```

- Technically: the output vector is of *un-normalized logits* rather than probabilities

- the logit vector can be turned into a probability vector via a `softmax`

Thus, the Model outputs a vector of logits.

We can see how a token is sampled

- by converting the logit vector into a probability vector
- with the `sample_from` method of the `TextGenerator` callback

  def sample_from(self, logits):

  ```
  logits, indices = tf.math.top_k(logits, k=self.k, sorted=True)
  indices = np.asarray(indices).astype("int32")
  preds = keras.activations.softmax(tf.expand_dims(logits, 0))[0]
  preds = np.asarray(preds).astype("float32")
  return np.random.choice(indices, p=preds)
  ```

Rather than outputting a probability vector

- which would require the user choosing one element from the vector (a word in the vocabulary)
- what is output is the *embedding* of the chosen word in the vocabulary

Since this output is compared against the correct label (i.e, $\mathbf{y}_{(t+1)}$ for position t)

- we should also see that the *labels* used are embeddings

Training

A `TextGenerator` [(https://colab.research.google.com/github/keras-team/keras-io/blob/master/examples/generative/ipynb/text_generation_with_miniature_gpt.ipynb#scrollTo=...f)](https://colab.research.google.com/github/keras-team/keras-io/blob/master/examples/generative/ipynb/text_generation_with_miniature_gpt.ipynb) call-back is used during training

- at the end every `self.print_every` epochs
- a sample of $\hat{\mathbf{y}}_{(1:T)}$ will be drawn
- to illustrate what the model output would be up to that point in training

The heart of the call-back

```
while num_tokens_generated <= self.max_tokens:
    ...
    y, _ = self.model.predict(x)
    sample_token = self.sample_from(y[0][sample_index])
    ...
```

- is a loop over positions t
- that extends a fixed input (prefix of text) `start_tokens`
- to full length T
- by sampling a token from the output for position t

This is useful

- to see whether our model is learning as epochs advance
- to confirm the shape and type of the model output is a vector of logits
    - the model output for position t: `y, _ = self.model.predict(x)`
    - is passed to `sample_from`
    - which samples from the probability distribution derived from the logits (model output)

In [2]:

```
print("Done")
```

Done