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

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

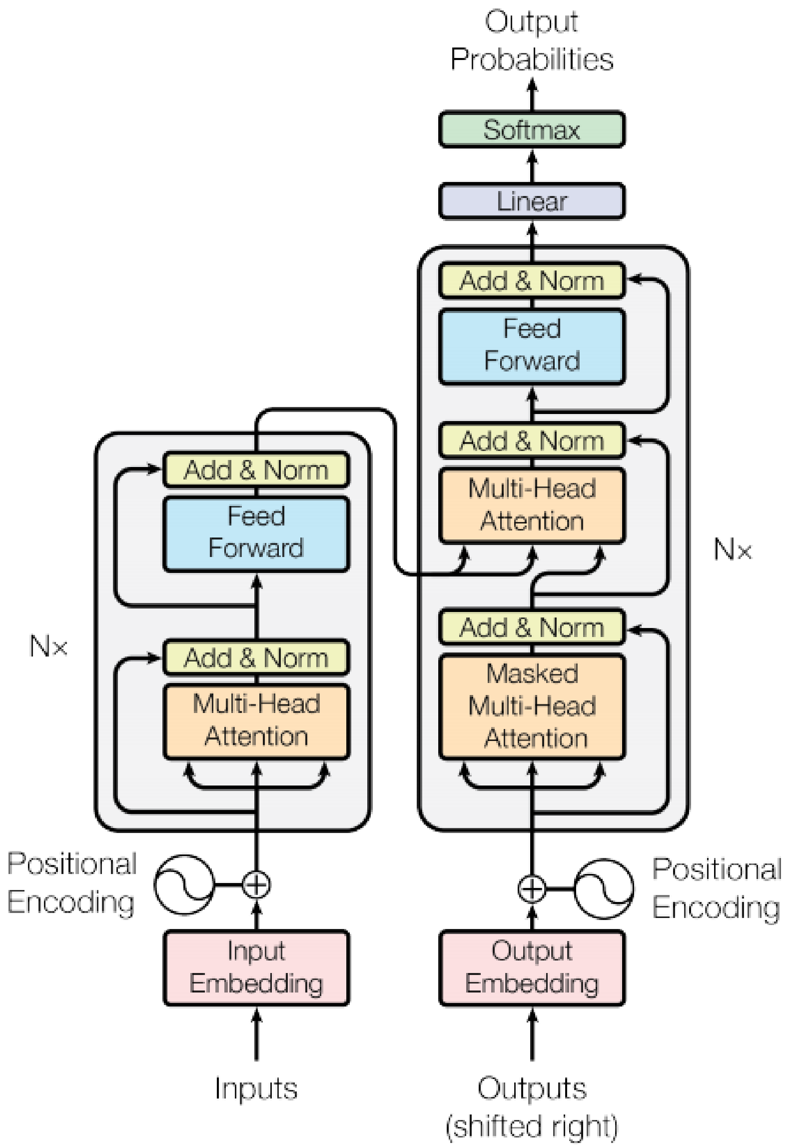
- means reading the code from bottom to top

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

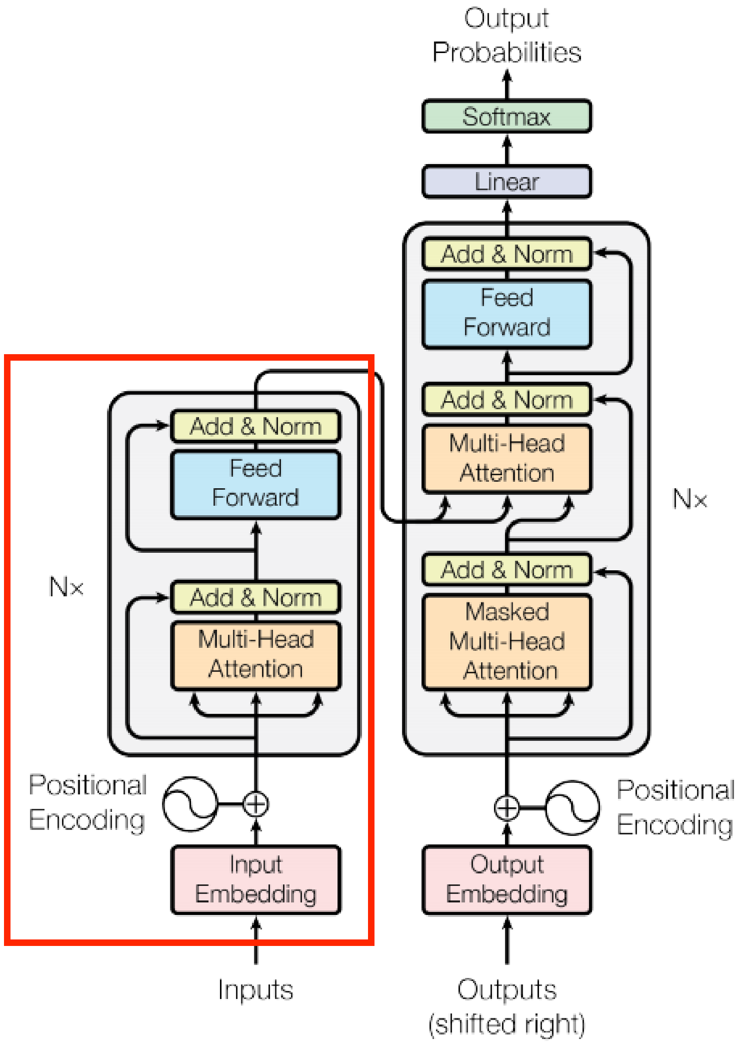
```python
class Transformer(tf.keras.Model):
  def __init__(self, *, num_layers, d_model, num_heads, dff,
               input_vocab_size, target_vocab_size, dropout_rate=0.1):
    super().__init__()
    self.encoder = Encoder(num_layers=num_layers, d_model=d_model,
                           num_heads=num_heads, 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)](https://www.tensorflow.org/text/tutorials/transformer#the_encoder_layer)



Confusion warning

The `Encoder` object is the *stack* of encoder blocks (which are called `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 (confusingly named `EncoderLayer`) 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 to the stacked `EncoderLayer`'s
    - Self-Attention followed by Feed Forward

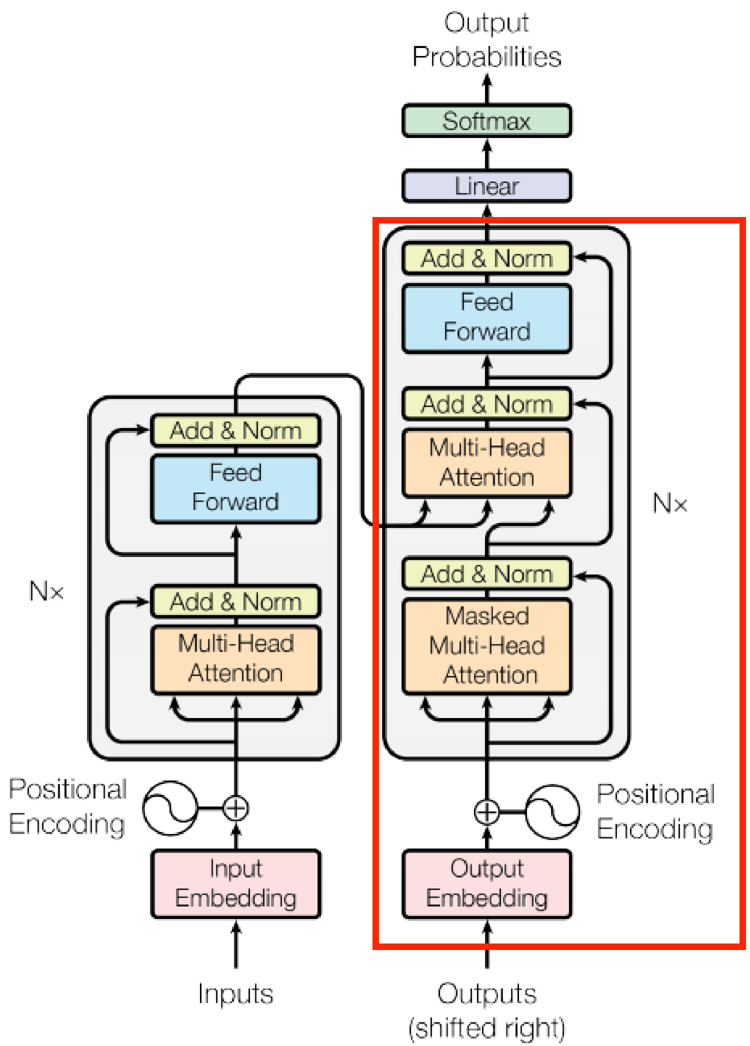
```
def call(self, x):
  # `x` is token-IDs shape: (batch, seq_len)
  x = self.pos_embedding(x)  # Shape `(batch_size, seq_len, d_model)`.

  # 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`

- initializer creates sub-components
- the `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

```python
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

```python
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

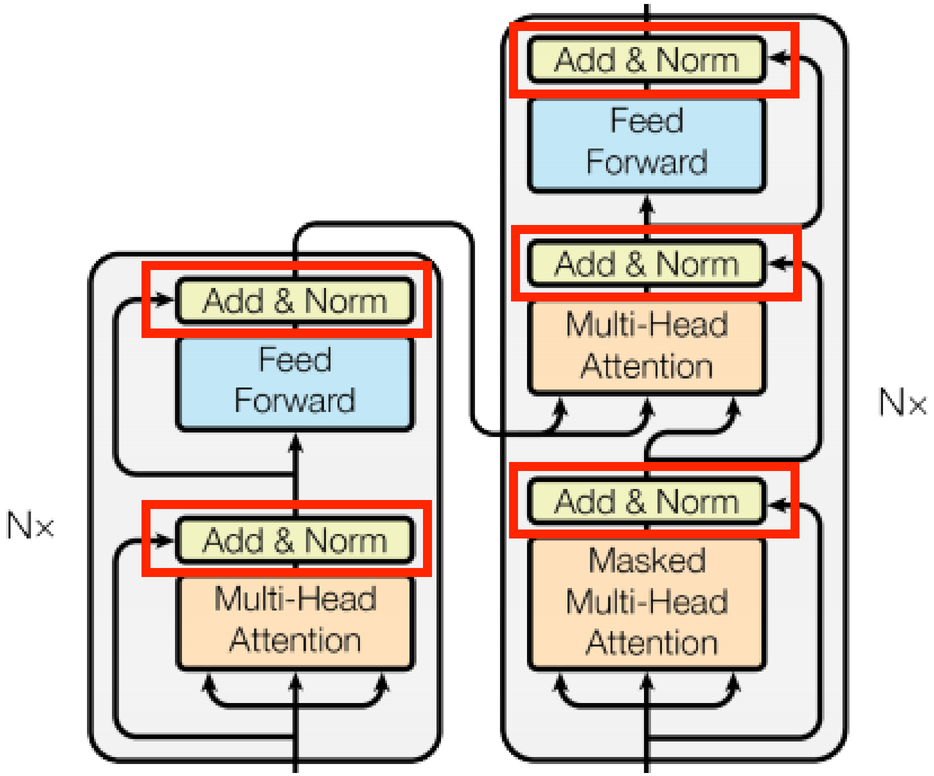
- `context` is the Encoder output
- `x` is the Decoder input

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)



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
- which facilitates the processing of Attention output through an `Add & Norm` block.

This is much more subtle than "coding convenience" !

The initializer 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

Before we examine the child classes, let's examine the **purpose** of the `Add & Norm` block.

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)

- 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

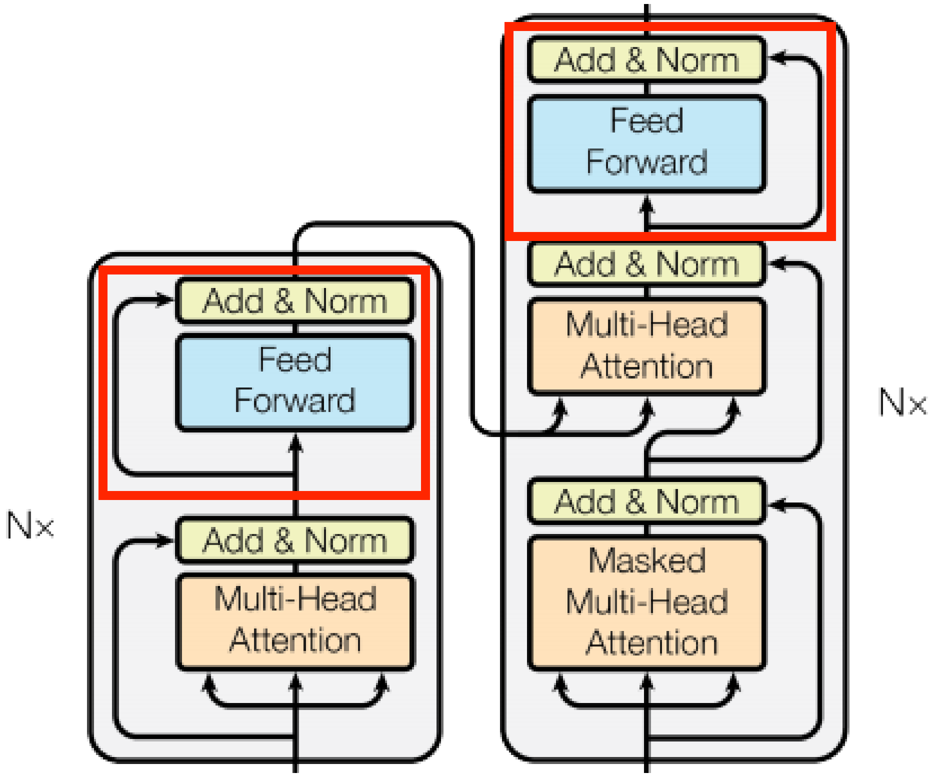
For Self-Attention, the `call` is

```
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
```

For Cross Attention, the `call` is

```
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
```

[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

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) is 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 learning.

- 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 called *Teacher Forcing* at training time

- but *not* at inference time

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

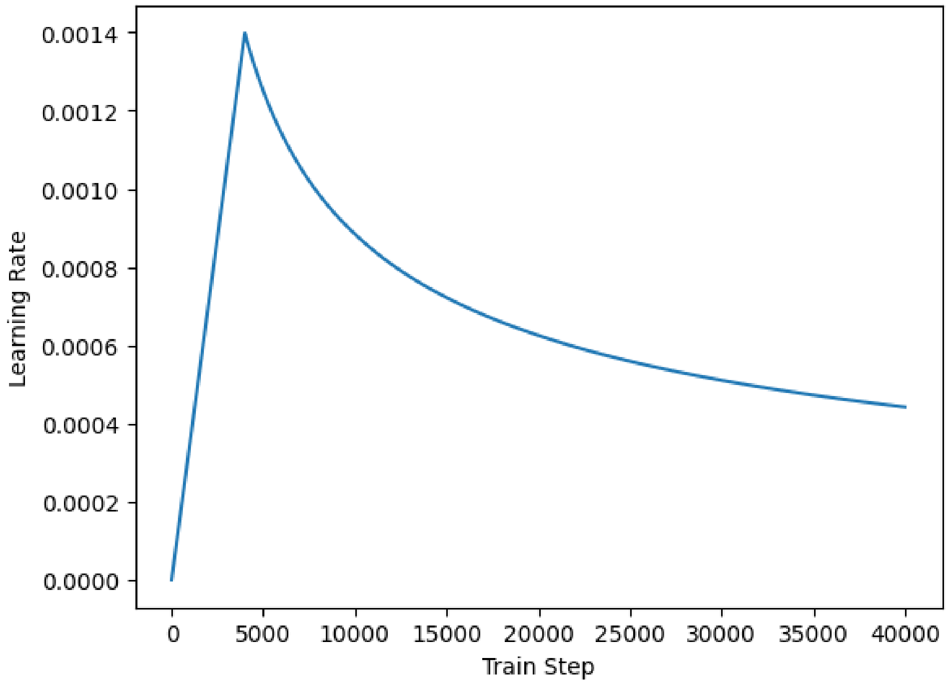
Custom Learning Rate Schedule

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 $\mathcal{O}\left(d_{\text{model}}^2\right)$, total:
$$4 * \mathcal{O}\left(d_{\text{model}}^2\right)$$

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
```

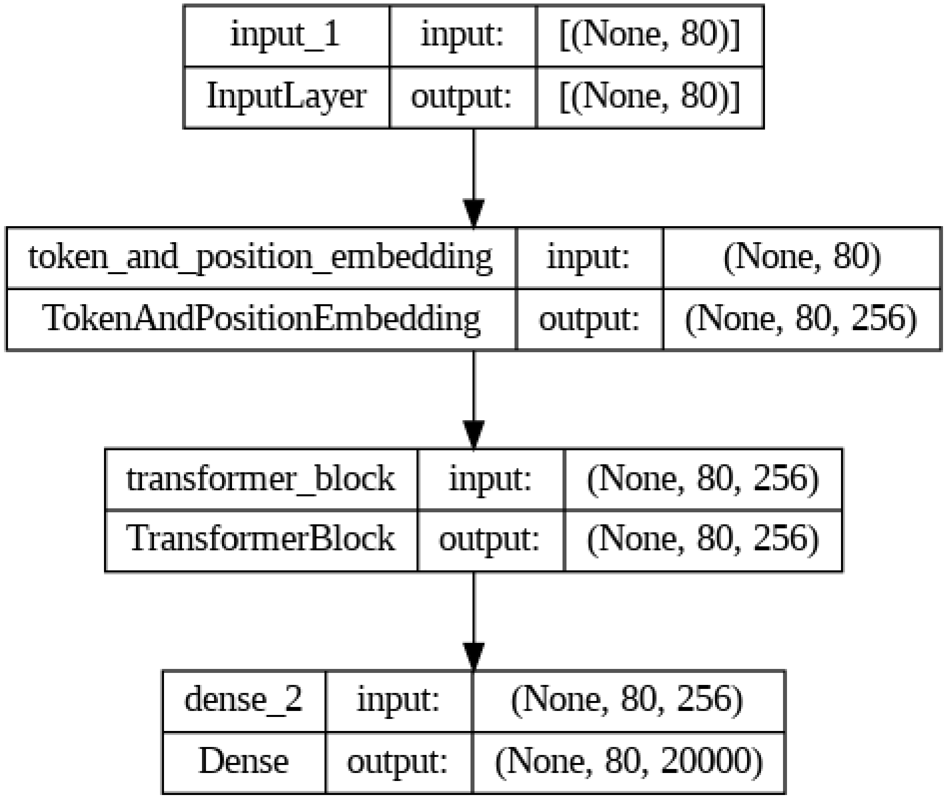
Relating the variable names to our notation

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) 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

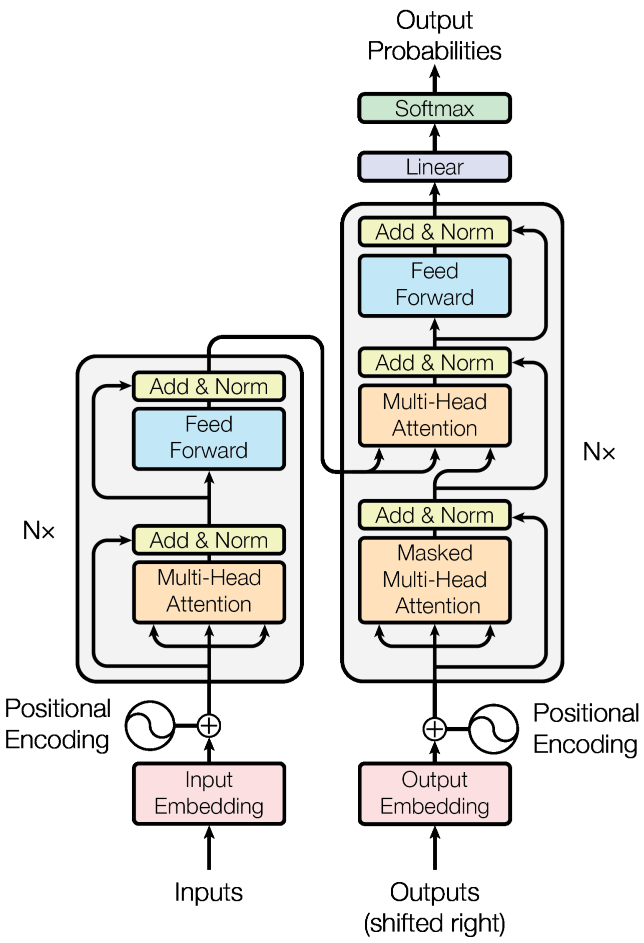
As we will see

- 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]:

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

```
Done
```