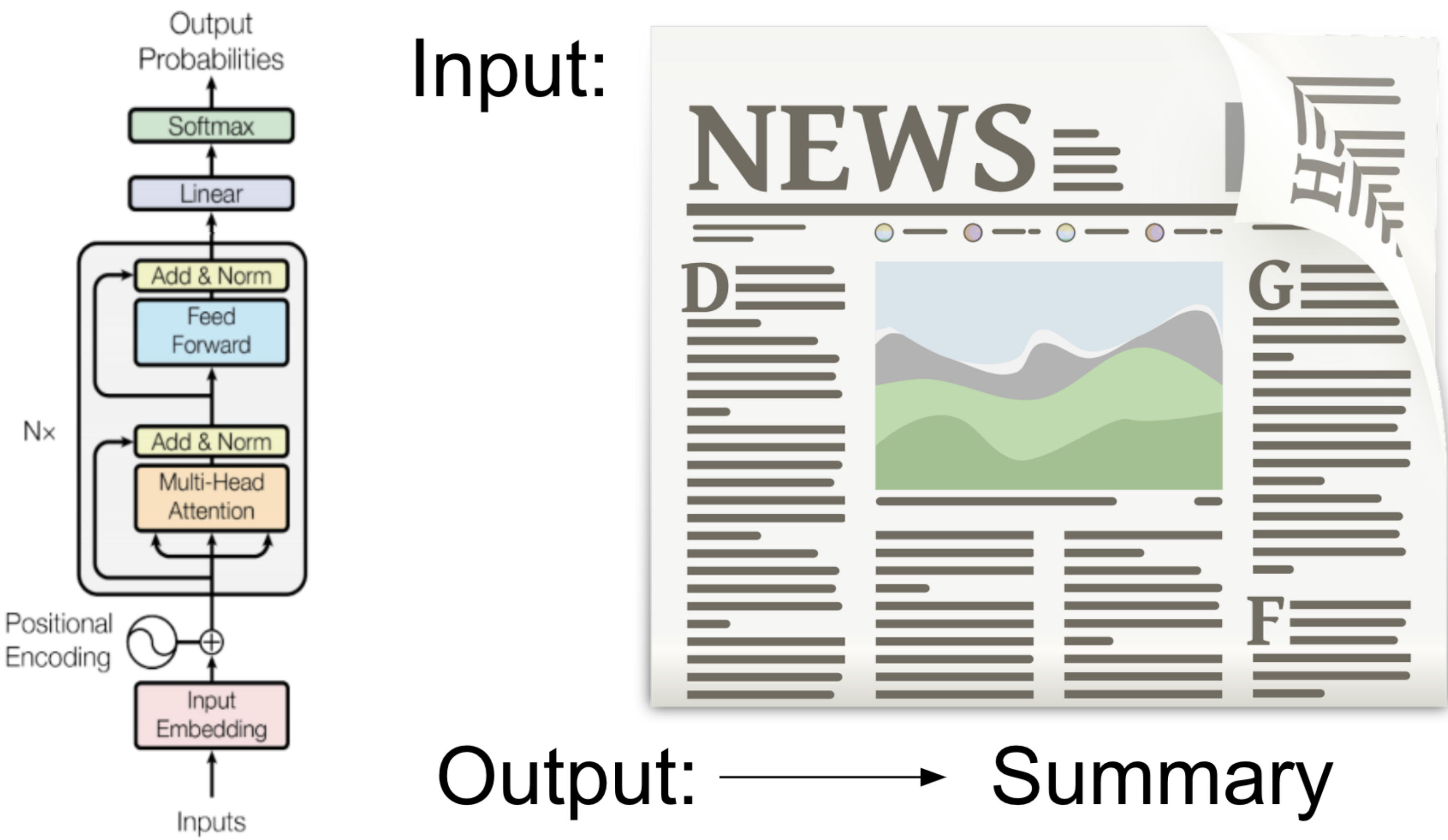
Assignment 2: Transformer Summarizer

Welcome to the second assignment of course 4. In this assignment you will explore summarization using the transformer model. Yes, you will implement the transformer decoder from scratch, but we will slowly walk you through it. There are many hints in this notebook so feel free to use them as needed.



Outline

Introduction

Summarization is an important task in natural language processing and could be useful for a consumer enterprise. For example, bots can be used to scrape articles, summarize them, and then you can use sentiment analysis to identify the sentiment about certain stocks. Anyways who wants to read an article or a long email today, when you can build a transformer to summarize text for you. Let's get started, by completing this assignment you will learn to:

- Use built-in functions to preprocess your data
- Implement DotProductAttention
- Implement Causal Attention
- Understand how attention works
- Build the transformer model
- Evaluate your model
- Summarize an article

As you can tell, this model is slightly different than the ones you have already implemented. This is heavily based on attention and does not rely on sequences, which allows for parallel computing.

In [56]:
```
import sys
import os

import numpy as np

import textwrap
wrapper = textwrap.TextWrapper(width=70)

import trax
from trax import layers as tl
from trax.fastmath import numpy as jnp

# to print the entire np array
np.set_printoptions(threshold=sys.maxsize)
```

Part 1: Importing the dataset

Trax makes it easy to work with Tensorflow's datasets:

In [57]:
```
# This will download the dataset if no data_dir is specified.
# Downloading and processing can take bit of time,
# so we have the data already in 'data/' for you

# Importing CNN/DailyMail articles dataset
train_stream_fn = trax.data.TFDS('cnn_dailymail',
                                 data_dir='data/',
                                 keys=('article', 'highlights'),
                                 train=True)

# This should be much faster as the data is downloaded already.
eval_stream_fn = trax.data.TFDS('cnn_dailymail',
                                data_dir='data/',
                                keys=('article', 'highlights'),
                                train=False)
```

1.1 Tokenize & Detokenize helper functions

Just like in the previous assignment, the cell above loads in the encoder for you. Given any data set, you have to be able to map words to their indices, and indices to their words. The inputs and outputs to your [Trax (https://github.com/google/trax)](https://github.com/google/trax) models are usually tensors of numbers where each number corresponds to a word. If you were to process your data manually, you would have to make use of the following:

- word2Ind: a dictionary mapping the word to its index.
- ind2Word: a dictionary mapping the index to its word.
- word2Count: a dictionary mapping the word to the number of times it appears.
- num_words: total number of words that have appeared.

Since you have already implemented these in previous assignments of the specialization, we will provide you with helper functions that will do this for you. Run the cell below to get the following functions:

- tokenize: converts a text sentence to its corresponding token list (i.e. list of indices). Also converts words to subwords.
- detokenize: converts a token list to its corresponding sentence (i.e. string).

In [58]:
```
def tokenize(input_str, EOS=1):
    """Input str to features dict, ready for inference"""

    # Use the trax.data.tokenize method. It takes streams and returns streams,
    # we get around it by making a 1-element stream with `iter`.
    inputs =  next(trax.data.tokenize(iter([input_str]),
                                      vocab_dir='vocab_dir/',
                                      vocab_file='summarize32k.subword.subwords'))

    # Mark the end of the sentence with EOS
    return list(inputs) + [EOS]

def detokenize(integers):
    """List of ints to str"""

    s = trax.data.detokenize(integers,
                             vocab_dir='vocab_dir/',
                             vocab_file='summarize32k.subword.subwords')

    return wrapper.fill(s)
```

1.2 Preprocessing for Language Models: Concatenate It!

This week you will use a language model -- Transformer Decoder -- to solve an input-output problem. As you know, language models only predict the next word, they have no notion of inputs. To create a single input suitable for a language model, we concatenate inputs with targets putting a separator in between. We also need to create a mask -- with 0s at inputs and 1s at targets -- so that the model is not penalized for mis-predicting the article and only focuses on the summary. See the preprocess function below for how this is done.

In [59]:
```python
# Special tokens
SEP = 0 # Padding or separator token
EOS = 1 # End of sentence token

# Concatenate tokenized inputs and targets using 0 as separator.
def preprocess(stream):
    for (article, summary) in stream:
        joint = np.array(list(article) + [EOS, SEP] + list(summary) + [EOS])
        mask = [0] * (len(list(article)) + 2) + [1] * (len(list(summary)) + 1) # Accounting for EOS and SEP
        yield joint, joint, np.array(mask)

# You can combine a few data preprocessing steps into a pipeline like this.
input_pipeline = trax.data.Serial(
    # Tokenizes
    trax.data.Tokenize(vocab_dir='vocab_dir/',
                       vocab_file='summarize32k.subword.subwords'),
    # Uses function defined above
    preprocess,
    # Filters out examples longer than 2048
    trax.data.FilterByLength(2048)
)

# Apply preprocessing to data streams.
train_stream = input_pipeline(train_stream_fn())
eval_stream = input_pipeline(eval_stream_fn())

train_input, train_target, train_mask = next(train_stream)

assert sum((train_input - train_target)**2) == 0  # They are the same in Language Model (LM).
```

In [ ]:
```python
# prints mask, 0s on article, 1s on summary
print(f'Single example mask:\n\n {train_mask}')
```

In [ ]:
```python
# prints: [Example][<EOS>][<pad>][Example Summary][<EOS>]
print(f'Single example:\n\n {detokenize(train_input)}')
```

1.3 Batching with bucketing

As in the previous week, we use bucketing to create batches of data.

In [60]:
```
# Bucketing to create batched generators.

# Buckets are defined in terms of boundaries and batch sizes.
# Batch_sizes[i] determines the batch size for items with length < boundaries[i]
# So below, we'll take a batch of 16 sentences of length < 128 , 8 of length < 256,
# 4 of length < 512. And so on.
boundaries =  [128, 256,  512, 1024]
batch_sizes = [16,    8,    4,    2, 1]

# Create the streams.
train_batch_stream = trax.data.BucketByLength(
    boundaries, batch_sizes)(train_stream)

eval_batch_stream = trax.data.BucketByLength(
    boundaries, batch_sizes)(eval_stream)
```

In [61]:
```
# Every execution will result in generation of a different article
# Try running this cell multiple times to see how the length of the examples affects the batch size
input_batch, _, mask_batch = next(train_batch_stream)

# Shape of the input_batch
input_batch.shape
```

Out[61]:
```
(1, 1201)
```

In [ ]:
```
# print corresponding integer values
print(input_batch[0])
```

Things to notice:

- First we see the corresponding values of the words.
- The first 1, which represents the `<EOS>` tag of the article.
- Followed by a 0, which represents a `<pad>` tag.
- After the first 0 (`<pad>` tag) the corresponding values are of the words that are used for the summary of the article.
- The second 1 represents the `<EOS>` tag for the summary.
- All the trailing 0s represent `<pad>` tags which are appended to maintain consistent length (If you don't see them then it would mean it is already of max length)

In [10]:

```
# print the article and its summary
print('Article:\n\n', detokenize(input_batch[0]))
```

Article:

Gordon Brown gave Labour rising star Chuka Umunna ‘the hairdryer treatment’ in a blistering phone call after the shadow business secretary publicly blamed him for Labour’s struggles on the economy. Mr Brown attacked the shadow cabinet minister for an interview he gave criticising the former Labour leader’s failure to confront Britain’s ballooning deficit in the run up to the 2010 election. Mr Umunna said Mr Brown’s refusal to even talk about Government ‘cuts’ was still costing Labour support, because it made the party look like it did not care about the deficit. Labour are currently 25 points behind the Tories on which party is best for the economy. Scroll down for video . Shadow business secretary Chuka Umunna (left) and Gordon Brown (right) clashed on the phone over Labour's record on the economy . But the remarks sparked a furious response from Mr Brown, MailOnline has learnt. The former Prime Minister told Mr Umunna that he should not accept Tory claims that Labour was spending too much before the last general election, a senior Labour source revealed. The source said: ‘He still cannot accept Labour was running a structural deficit. Even after all this time he won’t accept that he was wrong – it’s unbelievable.’ The deficit – the difference between Government spending and how much it raises in taxes each year – was more than £160 billion in 2010. Labour blamed the huge borrowing splurge on the global recession – because the Government was forced to withstand a huge hit on tax revenue as people lost their jobs, while at the same time increasing spending on benefits. But analysis has since revealed that the ‘structural deficit’ – the amount of borrowing needed even when the economy is growing normally – had grown to more than £100 billion in the last year of the Labour government. In an interview with GQ magazine, published this month, Mr Umunna said Mr Brown’s refusal to face up to the deficit was still hurting the Labour Party. He said: ‘My view is that the seeds were sown under the last government and Gordon - for whom I have a lot of respect - his refusal to use the word “cuts” in trying to frame the economic debate as investment versus cuts gave the impression we didn't understand that debt and deficit would have to be dealt with.’ Shadow chancellor Ed Balls (left) and the Labour leader Ed Miliband (right), who were both Treasury aides under Gordon Brown, have defended the party's record controlling Government spending . A source close to Mr Umunna confirmed the pair spoke in a telephone call after the interview was published earlier this month. The source said: ‘It is something they disagree on. ‘Chuka’s argument has always been that pursuing the line that it was Labour spending versus Tory cuts allowed Osborne to make the whole election debate about deficit reduction. They spoke and that is definitely still his view.’ A spokesman for Mr Umunna said: 'Chuka and Gordon are both members of the PLP - or course they speak to each other on a range of issues. Chuka has great respect for Gordon.' It is

```
understood that on this occasion Mr Umunna initiated the call.
Conservative MP Henry Smith said the confrontation between Mr Brown
and Mr Umunna revealed a 'divided' Labour Party. He said: 'This shows
a Labour party still in denial about the record deficit they left
behind and with no plan to deal with our debts and ensure a more
financially secure future for Britain. 'Brown’s intervention begs the
question who’s in charge of a clearly split and infighting Labour
leadership team.'<EOS><pad>EXCLUSIVE: Source reveals extraordinary
call by ex Prime Minister . Mr Umunna blamed former PM for Labour's
economic credibility problem . He said Mr Brown 'gave impression we
didn't understand debt and deficit' Former Labour leader confronted Mr
Umunna in an angry call afterwards .<EOS><pad><pad><pad><pad><pad><pad
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```

You can see that the data has the following structure:

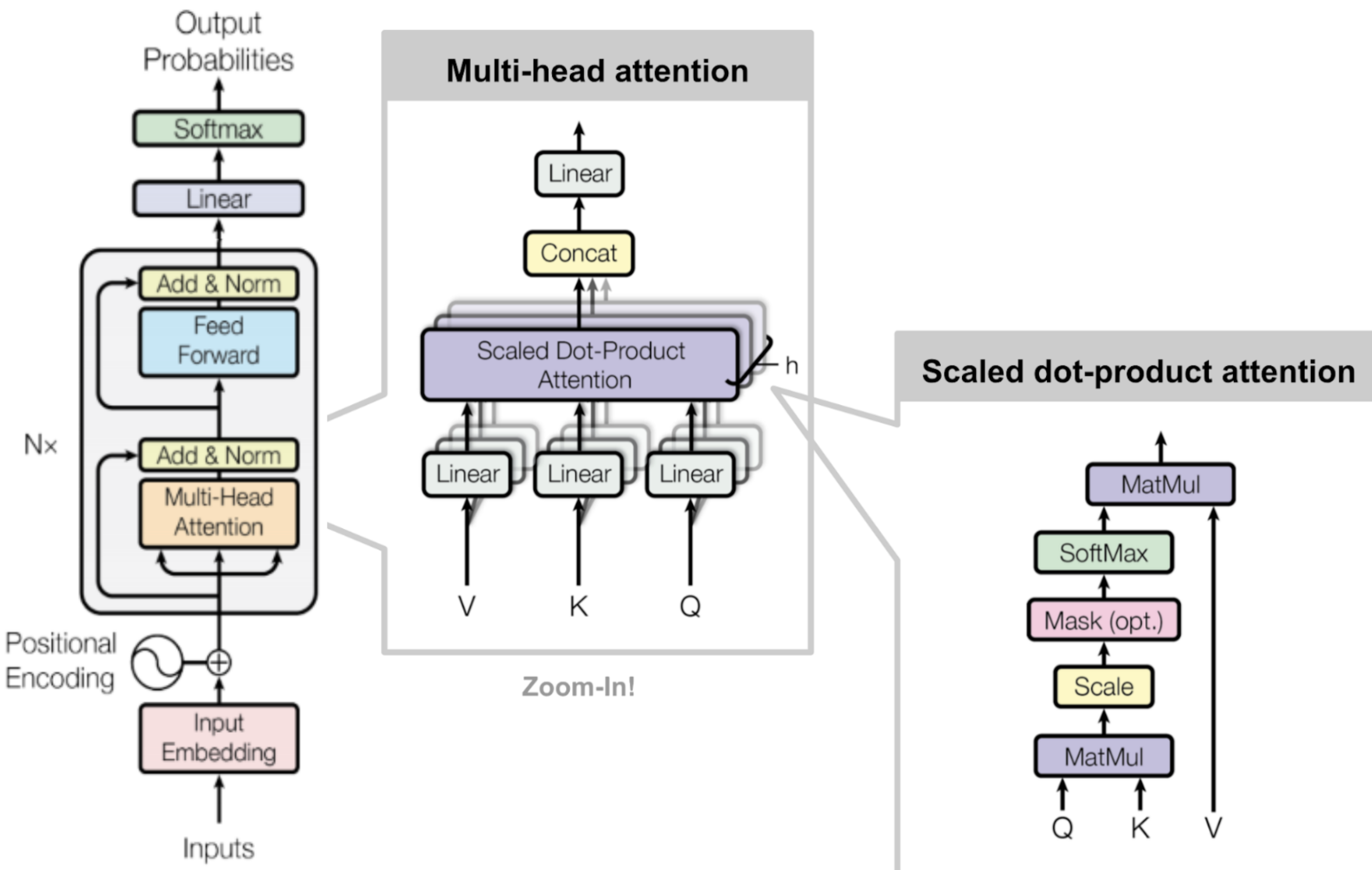
- [Article] -> `<EOS>` -> `<pad>` -> [Article Summary] -> `<EOS>` -> (possibly) multiple `<pad>`

The loss is taken only on the summary using cross_entropy as loss function.

Part 2: Summarization with transformer

Now that we have given you the data generator and have handled the preprocessing for you, it is time for you to build your own model. We saved you some time because we know you have already preprocessed data before in this specialization, so we would rather you spend your time doing the next steps.

You will be implementing the attention from scratch and then using it in your transformer model. Concretely, you will understand how attention works, how you use it to connect the encoder and the decoder.



2.1 Dot product attention

Now you will implement dot product attention which takes in a query, key, value, and a mask. It returns the output.

Here are some helper functions that will help you create tensors and display useful information:

- `create_tensor` creates a `jax numpy array` from a list of lists.
- `display_tensor` prints out the shape and the actual tensor.

In [11]:
```python
def create_tensor(t):
    """Create tensor from list of lists"""
    return jnp.array(t)


def display_tensor(t, name):
    """Display shape and tensor"""
    print(f'{name} shape: {t.shape}\n')
    print(f'{t}\n')
```

Before implementing it yourself, you can play around with a toy example of `dot product attention` without the softmax operation. Technically it would not be `dot product attention` without the softmax but this is done to avoid giving away too much of the answer and the idea is to display these tensors to give you a sense of how they look like.

The formula for attention is this one:

$$\text{Attention}\left(Q, K, V\right) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}} + M\right)V \tag{1}$$

d_k stands for the dimension of queries and keys.

The `query` , `key` , `value` and `mask` vectors are provided for this example.

Notice that the masking is done using very negative values that will yield a similar effect to using $-\infty$.

In [12]:
```python
q = create_tensor([[1, 0, 0], [0, 1, 0]])
display_tensor(q, 'query')
k = create_tensor([[1, 2, 3], [4, 5, 6]])
display_tensor(k, 'key')
v = create_tensor([[0, 1, 0], [1, 0, 1]])
display_tensor(v, 'value')
m = create_tensor([[0, 0], [-1e9, 0]])
display_tensor(m, 'mask')
```

```
query shape: (2, 3)

[[1 0 0]
 [0 1 0]]

key shape: (2, 3)

[[1 2 3]
 [4 5 6]]

value shape: (2, 3)

[[0 1 0]
 [1 0 1]]

mask shape: (2, 2)

[[ 0.e+00  0.e+00]
 [-1.e+09  0.e+00]]
```

Expected Output:

```
query shape: (2, 3)

[[1 0 0]
 [0 1 0]]

key shape: (2, 3)

[[1 2 3]
 [4 5 6]]

value shape: (2, 3)

[[0 1 0]
 [1 0 1]]

mask shape: (2, 2)

[[ 0.e+00  0.e+00]
 [-1.e+09  0.e+00]]
```

In [13]:
```python
q_dot_k = q @ k.T / jnp.sqrt(3)
display_tensor(q_dot_k, 'query dot key')
```

```
query dot key shape: (2, 2)

[[0.57735026 2.309401  ]
 [1.1547005  2.8867514 ]]
```

Expected Output:

```
query dot key shape: (2, 2)

[[0.57735026 2.309401  ]
 [1.1547005  2.8867514 ]]
```

In [14]:
```python
masked = q_dot_k + m
display_tensor(masked, 'masked query dot key')
```

```
masked query dot key shape: (2, 2)

[[ 5.7735026e-01  2.3094010e+00]
 [-1.0000000e+09  2.8867514e+00]]
```

Expected Output:

```
masked query dot key shape: (2, 2)

[[ 5.7735026e-01  2.3094010e+00]
 [-1.0000000e+09  2.8867514e+00]]
```

In [15]:
```python
display_tensor(masked @ v, 'masked query dot key dot value')
```

```
masked query dot key dot value shape: (2, 3)

[[ 2.3094010e+00  5.7735026e-01  2.3094010e+00]
 [ 2.8867514e+00 -1.0000000e+09  2.8867514e+00]]
```

Expected Output:

```
masked query dot key dot value shape: (2, 3)

[[ 2.3094010e+00  5.7735026e-01  2.3094010e+00]
 [ 2.8867514e+00 -1.0000000e+09  2.8867514e+00]]
```

In order to use the previous dummy tensors to test some of the graded functions, a batch dimension should be added to them so they mimic the shape of real-life examples. The mask is also replaced by a version of it that resembles the one that is used by trax:

In [16]:
```
q_with_batch = q[None,:]
display_tensor(q_with_batch, 'query with batch dim')
k_with_batch = k[None,:]
display_tensor(k_with_batch, 'key with batch dim')
v_with_batch = v[None,:]
display_tensor(v_with_batch, 'value with batch dim')
m_bool = create_tensor([[True, True], [False, True]])
display_tensor(m_bool, 'boolean mask')
```

```
query with batch dim shape: (1, 2, 3)

[[[1 0 0]
  [0 1 0]]]

key with batch dim shape: (1, 2, 3)

[[[1 2 3]
  [4 5 6]]]

value with batch dim shape: (1, 2, 3)

[[[0 1 0]
  [1 0 1]]]

boolean mask shape: (2, 2)

[[ True  True]
 [False  True]]
```

Expected Output:

```
query with batch dim shape: (1, 2, 3)

[[[1 0 0]
  [0 1 0]]]

key with batch dim shape: (1, 2, 3)

[[[1 2 3]
  [4 5 6]]]

value with batch dim shape: (1, 2, 3)

[[[0 1 0]
  [1 0 1]]]

boolean mask shape: (2, 2)

[[ True  True]
 [False  True]]
```

Exercise 01

Instructions: Implement the dot product attention. Concretely, implement the following equation

$$\text{Attention}\left(Q, K, V\right) = \text{softmax}\left(\frac{QK^{T}}{\sqrt{d_{k}}} + M\right)V \tag{1}$$

Q - query, K - key, V - values, M - mask, d_k - depth/dimension of the queries and keys (used for scaling down)

You can implement this formula either by `trax` numpy (trax.math.numpy) or regular `numpy` but it is recommended to use `jnp`.

Something to take into consideration is that within trax, the masks are tensors of `True/False` values not 0's and $-\infty$ as in the previous example. Within the graded function don't think of applying the mask by summing up matrices, instead use `jnp.where()` and treat the **mask as a tensor of boolean values with `False` for values that need to be masked and True for the ones that don't.**

Also take into account that the real tensors are far more complex than the toy ones you just played with. Because of this avoid using shortened operations such as `@` for dot product or `.T` for transposing. Use `jnp.matmul()` and `jnp.swapaxes()` instead.

This is the self-attention block for the transformer decoder. Good luck!

In [17]:

```python
# UNQ_C1
# GRADED FUNCTION: DotProductAttention
def DotProductAttention(query, key, value, mask):
    """Dot product self-attention.
    Args:
        query (jax.interpreters.xla.DeviceArray): array of query representations with shape (L_q by d)
        key (jax.interpreters.xla.DeviceArray): array of key representations with shape (L_k by d)
        value (jax.interpreters.xla.DeviceArray): array of value representations with shape (L_k by d) where L_v = L_k
        mask (jax.interpreters.xla.DeviceArray): attention-mask, gates attention with shape (L_q by L_k)

    Returns:
        jax.interpreters.xla.DeviceArray: Self-attention array for q, k, v arrays. (L_q by L_k)
    """

    assert query.shape[-1] == key.shape[-1] == value.shape[-1], "Embedding dimensions of q, k, v aren't all the same"

    ### START CODE HERE (REPLACE INSTANCES OF 'None' with your code) ###
    # Save depth/dimension of the query embedding for scaling down the dot product
    depth = query.shape[-1]

    # Calculate scaled query key dot product according to formula above
    dots = jnp.matmul(query, jnp.swapaxes(key, -1, -2)) / jnp.sqrt(depth)

    # Apply the mask
    if mask is not None: # The 'None' in this line does not need to be replaced
        dots = jnp.where(mask, dots, jnp.full_like(dots, -1e9))

    # Softmax formula implementation
    # Use trax.fastmath.logsumexp of dots to avoid underflow by division by large numbers
    # Hint: Last axis should be used and keepdims should be True
    # Note: softmax = e^(dots - logsumexp(dots)) = E^dots / sumexp(dots)
    logsumexp = trax.fastmath.logsumexp(dots, axis=-1, keepdims=True)

    # Take exponential of dots minus logsumexp to get softmax
    # Use jnp.exp()
    dots = jnp.exp(dots - logsumexp)

    # Multiply dots by value to get self-attention
    # Use jnp.matmul()
    attention = jnp.matmul(dots, value)

    ## END CODE HERE ###

    return attention
```

In [18]:
```
DotProductAttention(q_with_batch, k_with_batch, v_with_batch, m_bool)
```

Out[18]:
```
DeviceArray([[[0.8496746 , 0.15032545, 0.8496746 ],
              [1.        , 0.        , 1.        ]]], dtype=float32)
```

Expected Output:

```
DeviceArray([[[0.8496746 , 0.15032545, 0.8496746 ],
              [1.        , 0.        , 1.        ]]], dtype=float32)
```

2.2 Causal Attention

Now you are going to implement causal attention: multi-headed attention with a mask to attend only to words that occurred before.

In the image above, a word can see everything that is before it, but not what is after it. To implement causal attention, you will have to transform vectors and do many reshapes. You will need to implement the functions below.

Exercise 02

Implement the following functions that will be needed for Causal Attention:

- compute_attention_heads : Gets an input x of dimension (batch_size, seqlen, n_heads $\times$ d_head) and splits the last (depth) dimension and stacks it to the zeroth dimension to allow matrix multiplication (batch_size $\times$ n_heads, seqlen, d_head).
- dot_product_self_attention : Creates a mask matrix with `False` values above the diagonal and `True` values below and calls DotProductAttention which implements dot product self attention.
- compute_attention_output : Undoes compute_attention_heads by splitting first (vertical) dimension and stacking in the last (depth) dimension (batch_size, seqlen, n_heads $\times$ d_head). These operations concatenate (stack/merge) the heads.

Next there are some toy tensors which may serve to give you an idea of the data shapes and opperations involved in Causal Attention. They are also useful to test out your functions!

In [19]:
```
tensor2d = create_tensor(q)
display_tensor(tensor2d, 'query matrix (2D tensor)')

tensor4d2b = create_tensor([[q, q], [q, q]])
display_tensor(tensor4d2b, 'batch of two (multi-head) collections of query matrices (4D tensor)')

tensor3dc = create_tensor([jnp.concatenate([q, q], axis = -1)])
display_tensor(tensor3dc, 'one batch of concatenated heads of query matrices (3d tensor)')

tensor3dc3b = create_tensor([jnp.concatenate([q, q], axis = -1), jnp.concatenate([q, q], axis = -1), jnp.concatenate([q
, q], axis = -1)])
display_tensor(tensor3dc3b, 'three batches of concatenated heads of query matrices (3d tensor)')
```

```
query matrix (2D tensor) shape: (2, 3)

[[1 0 0]
 [0 1 0]]

batch of two (multi-head) collections of query matrices (4D tensor) shape: (2, 2, 2, 3)

[[[[1 0 0]
   [0 1 0]]

  [[1 0 0]
   [0 1 0]]]


 [[[1 0 0]
   [0 1 0]]

  [[1 0 0]
   [0 1 0]]]]

one batch of concatenated heads of query matrices (3d tensor) shape: (1, 2, 6)

[[[1 0 0 1 0 0]
  [0 1 0 0 1 0]]]

three batches of concatenated heads of query matrices (3d tensor) shape: (3, 2, 6)

[[[1 0 0 1 0 0]
  [0 1 0 0 1 0]]

 [[1 0 0 1 0 0]
  [0 1 0 0 1 0]]

 [[1 0 0 1 0 0]
  [0 1 0 0 1 0]]]
```

It is important to know that the following 3 functions would normally be defined within the `CausalAttention` function further below.

However this makes these functions harder to test. Because of this, these functions are shown individually using a `closure` (when necessary) that simulates them being inside of the `CausalAttention` function. This is done because they rely on some variables that can be accessed from within `CausalAttention`.

Support Functions

compute_attention_heads : Gets an input x of dimension (batch_size, seqlen, n_heads $\times$ d_head) and splits the last (depth) dimension and stacks it to the zeroth dimension to allow matrix multiplication (batch_size $\times$ n_heads, seqlen, d_head).

For the closures you only have to fill the inner function.

In [20]:

```python
# UNQ_C2
# GRADED FUNCTION: compute_attention_heads_closure
def compute_attention_heads_closure(n_heads, d_head):
    """ Function that simulates environment inside CausalAttention function.
    Args:
        d_head (int):  dimensionality of heads.
        n_heads (int): number of attention heads.
    Returns:
        function: compute_attention_heads function
    """

    def compute_attention_heads(x):
        """ Compute the attention heads.
        Args:
            x (jax.interpreters.xla.DeviceArray): tensor with shape (batch_size, seqlen, n_heads X d_head).
        Returns:
            jax.interpreters.xla.DeviceArray: reshaped tensor with shape (batch_size X n_heads, seqlen, d_head).
        """
        ### START CODE HERE (REPLACE INSTANCES OF 'None' with your code) ###

        # Size of the x's batch dimension
        batch_size = x.shape[0]
        # Length of the sequence
        # Should be size of x's first dimension without counting the batch dim
        seqlen = x.shape[1]
        # Reshape x using jnp.reshape()
        # batch_size, seqlen, n_heads*d_head -> batch_size, seqlen, n_heads, d_head
        x = jnp.reshape(x, (batch_size, seqlen, n_heads, -1))
        # Transpose x using jnp.transpose()
        # batch_size, seqlen, n_heads, d_head -> batch_size, n_heads, seqlen, d_head
        # Note that the values within the tuple are the indexes of the dimensions of x and you must rearrange them
        x = jnp.transpose(x, (0, 2, 1, 3))
        # Reshape x using jnp.reshape()
        # batch_size, n_heads, seqlen, d_head -> batch_size*n_heads, seqlen, d_head
        x = jnp.reshape(x, (batch_size*n_heads, seqlen, d_head))

        ### END CODE HERE ###

        return x

    return compute_attention_heads
```

In [21]:
```
display_tensor(tensor3dc3b, "input tensor")
result_cah = compute_attention_heads_closure(2,3)(tensor3dc3b)
display_tensor(result_cah, "output tensor")
```

```
input tensor shape: (3, 2, 6)

[[[1 0 0 1 0 0]
  [0 1 0 0 1 0]]

 [[1 0 0 1 0 0]
  [0 1 0 0 1 0]]

 [[1 0 0 1 0 0]
  [0 1 0 0 1 0]]]

output tensor shape: (6, 2, 3)

[[[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]]
```

Expected Output:

```
input tensor shape: (3, 2, 6)

[[[1 0 0 1 0 0]
  [0 1 0 0 1 0]]

 [[1 0 0 1 0 0]
  [0 1 0 0 1 0]]

 [[1 0 0 1 0 0]
  [0 1 0 0 1 0]]]

output tensor shape: (6, 2, 3)

[[[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]]
```

dot_product_self_attention : Creates a mask matrix with `False` values above the diagonal and `True` values below and calls DotProductAttention which implements dot product self attention.

In [22]:
```
# UNQ_C3
# GRADED FUNCTION: dot_product_self_attention
def dot_product_self_attention(q, k, v):
    """ Masked dot product self attention.
    Args:
        q (jax.interpreters.xla.DeviceArray): queries.
        k (jax.interpreters.xla.DeviceArray): keys.
        v (jax.interpreters.xla.DeviceArray): values.
    Returns:
        jax.interpreters.xla.DeviceArray: masked dot product self attention tensor.
    """
    ### START CODE HERE (REPLACE INSTANCES OF 'None' with your code) ###

    # Hint: mask size should be equal to L_q. Remember that q has shape (batch_size, L_q, d)
    mask_size = q.shape[1]

    # Creates a matrix with ones below the diagonal and 0s above. It should have shape (1, mask_size, mask_size)
    # Notice that 1's and 0's get casted to True/False by setting dtype to jnp.bool_
    # Use jnp.tril() - Lower triangle of an array and jnp.ones()
    mask = jnp.tril(jnp.ones((1, mask_size, mask_size), dtype=jnp.bool_), k=0)

    ### END CODE HERE ###

    return DotProductAttention(q, k, v, mask)
```

In [23]:
```
dot_product_self_attention(q_with_batch, k_with_batch, v_with_batch)
```

Out[23]:
```
DeviceArray([[[0.        , 1.        , 0.        ],
              [0.8496746 , 0.15032543, 0.8496746 ]]], dtype=float32)
```

Expected Output:

```
DeviceArray([[[0.        , 1.        , 0.        ],
              [0.8496746 , 0.15032543, 0.8496746 ]]], dtype=float32)
```

compute_attention_output : Undoes compute_attention_heads by splitting first (vertical) dimension and stacking in the last (depth) dimension (batch_size, seqlen, n_heads × d_head). These operations concatenate (stack/merge) the heads.

In [24]:
```
# UNQ_C4
# GRADED FUNCTION: compute_attention_output_closure
def compute_attention_output_closure(n_heads, d_head):
    """ Function that simulates environment inside CausalAttention function.
    Args:
        d_head (int):  dimensionality of heads.
        n_heads (int): number of attention heads.
    Returns:
        function: compute_attention_output function
    """

    def compute_attention_output(x):
        """ Compute the attention output.
        Args:
            x (jax.interpreters.xla.DeviceArray): tensor with shape (batch_size X n_heads, seqlen, d_head).
        Returns:
            jax.interpreters.xla.DeviceArray: reshaped tensor with shape (batch_size, seqlen, n_heads X d_head).
        """
        ### START CODE HERE (REPLACE INSTANCES OF 'None' with your code) ###

        # Length of the sequence
        # Should be size of x's first dimension without counting the batch dim
        seqlen = x.shape[1]
        # Reshape x using jnp.reshape() to shape (batch_size, n_heads, seqlen, d_head)
        x = jnp.reshape(x, (-1, n_heads, seqlen, d_head))
        # Transpose x using jnp.transpose() to shape (batch_size, seqlen, n_heads, d_head)
        x = jnp.transpose(x, (0, 2, 1, 3))

        ### END CODE HERE ###

        # Reshape to allow to concatenate the heads
        return jnp.reshape(x, (-1, seqlen, n_heads * d_head))

    return compute_attention_output
```

In [25]:
```
display_tensor(result_cah, "input tensor")
result_cao = compute_attention_output_closure(2,3)(result_cah)
display_tensor(result_cao, "output tensor")
```

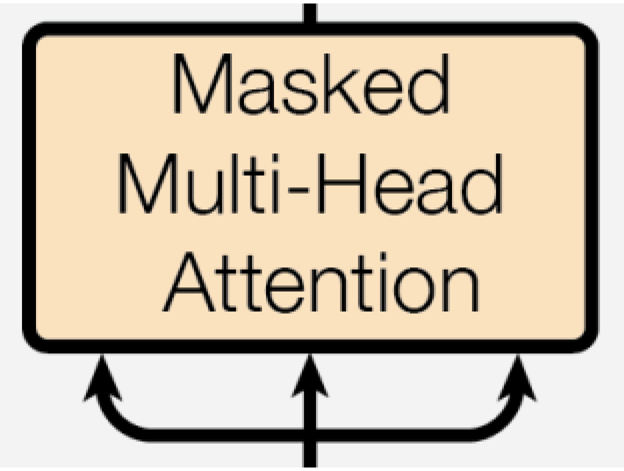
```
input tensor shape: (6, 2, 3)

[[[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]]

output tensor shape: (3, 2, 6)

[[[1 0 0 1 0 0]
  [0 1 0 0 1 0]]

 [[1 0 0 1 0 0]
  [0 1 0 0 1 0]]

 [[1 0 0 1 0 0]
  [0 1 0 0 1 0]]]
```

Expected Output:

```
input tensor shape: (6, 2, 3)

[[[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]

 [[1 0 0]
  [0 1 0]]]

output tensor shape: (3, 2, 6)

[[[1 0 0 1 0 0]
  [0 1 0 0 1 0]]

 [[1 0 0 1 0 0]
  [0 1 0 0 1 0]]

 [[1 0 0 1 0 0]
  [0 1 0 0 1 0]]]
```

Causal Attention Function

Now it is time for you to put everything together within the `CausalAttention` or Masked multi-head attention function:



Instructions: Implement the causal attention. Your model returns the causal attention through a $tl.Serial$ with the following:

- [tl.Branch](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.combinators.Branch) : consisting of 3 [tl.Dense(d_feature), ComputeAttentionHeads] to account for the queries, keys, and values.
- [tl.Fn](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.base.Fn): Takes in dot_product_self_attention function and uses it to compute the dot product using Q, K, V.
- [tl.Fn](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.base.Fn): Takes in compute_attention_output_closure to allow for parallel computing.
- [tl.Dense](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.core.Dense): Final Dense layer, with dimension `d_feature` .

Remember that in order for trax to properly handle the functions you just defined, they need to be added as layers using the [`tl.Fn()` (https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.base.Fn)](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.base.Fn) function.

In [75]:
```python
# UNQ_C5
# GRADED FUNCTION: CausalAttention
def CausalAttention(d_feature,
                    n_heads,
                    compute_attention_heads_closure=compute_attention_heads_closure,
                    dot_product_self_attention=dot_product_self_attention,
                    compute_attention_output_closure=compute_attention_output_closure,
                    mode='train'):
    """Transformer-style multi-headed causal attention.

    Args:
        d_feature (int):  dimensionality of feature embedding.
        n_heads (int): number of attention heads.
        compute_attention_heads_closure (function): Closure around compute_attention heads.
        dot_product_self_attention (function): dot_product_self_attention function.
        compute_attention_output_closure (function): Closure around compute_attention_output.
        mode (str): 'train' or 'eval'.

    Returns:
        trax.layers.combinators.Serial: Multi-headed self-attention model.
    """

    assert d_feature % n_heads == 0
    d_head = d_feature // n_heads

    ### START CODE HERE (REPLACE INSTANCES OF 'None' with your code) ###

    # HINT: The second argument to tl.Fn() is an uncalled function (without the parentheses)
    # Since you are dealing with closures you might need to call the outer
    # function with the correct parameters to get the actual uncalled function.
    ComputeAttentionHeads = tl.Fn('AttnHeads', compute_attention_heads_closure(n_heads, d_head), n_out=1)


    return tl.Serial(
        tl.Branch( # creates three towers for one input, takes activations and creates queries keys and values
            [tl.Dense(d_feature), ComputeAttentionHeads], # queries
            [tl.Dense(d_feature), ComputeAttentionHeads], # keys
            [tl.Dense(d_feature), ComputeAttentionHeads], # values
        ),

        tl.Fn('DotProductAttn', dot_product_self_attention, n_out=1), # takes QKV
        # HINT: The second argument to tl.Fn() is an uncalled function
        # Since you are dealing with closures you might need to call the outer
        # function with the correct parameters to get the actual uncalled function.
        tl.Fn('AttnOutput', compute_attention_output_closure(n_heads, d_head), n_out=1), # to allow for parallel
        tl.Dense(d_feature) # Final dense layer
    )
```

```python
    ### END CODE HERE ###
```

In [76]:
```python
# Take a look at the causal attention model
print(CausalAttention(d_feature=512, n_heads=8))
```

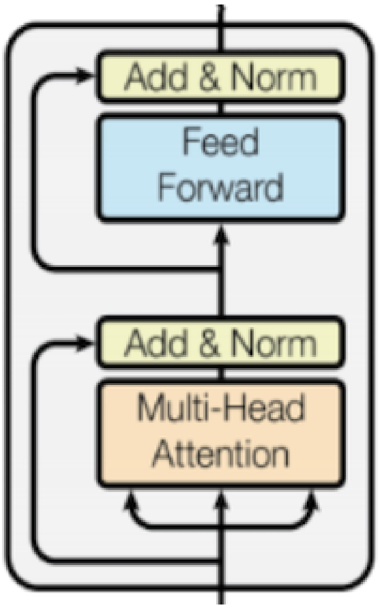
```
Serial[
  Branch_out3[
    [Dense_512, AttnHeads]
    [Dense_512, AttnHeads]
    [Dense_512, AttnHeads]
  ]
  DotProductAttn_in3
  AttnOutput
  Dense_512
]
```

Expected Output:

```
Serial[
  Branch_out3[
    [Dense_512, AttnHeads]
    [Dense_512, AttnHeads]
    [Dense_512, AttnHeads]
  ]
  DotProductAttn_in3
  AttnOutput
  Dense_512
]
```

2.3 Transformer decoder block

Now that you have implemented the causal part of the transformer, you will implement the transformer decoder block. Concretely you will be implementing this image now.



To implement this function, you will have to call the `CausalAttention` or Masked multi-head attention function you implemented above. You will have to add a feedforward which consists of:

- [tl.LayerNorm](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.normalization.LayerNorm) : used to layer normalize
- [tl.Dense](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.core.Dense) : the dense layer
- [ff_activation](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.activation_fns.Relu) : feed forward activation (we use ReLu) here.
- [tl.Dropout](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.core.Dropout) : dropout layer
- [tl.Dense](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.core.Dense) : dense layer
- [tl.Dropout](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.core.Dropout) : dropout layer

Finally once you implement the feedforward, you can go ahead and implement the entire block using:

- [tl.Residual](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.combinators.Residual) : takes in the tl.LayerNorm(), causal attention block, tl.dropout.
- [tl.Residual](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.combinators.Residual) : takes in the feedforward block you will implement.

Exercise 03

Instructions: Implement the transformer decoder block. Good luck!

In [83]:

```python
# UNQ_C6
# GRADED FUNCTION: DecoderBlock
def DecoderBlock(d_model, d_ff, n_heads,
                 dropout, mode, ff_activation):
    """Returns a list of layers that implements a Transformer decoder block.

    The input is an activation tensor.

    Args:
        d_model (int):  depth of embedding.
        d_ff (int): depth of feed-forward layer.
        n_heads (int): number of attention heads.
        dropout (float): dropout rate (how much to drop out).
        mode (str): 'train' or 'eval'.
        ff_activation (function): the non-linearity in feed-forward layer.

    Returns:
        list: list of trax.layers.combinators.Serial that maps an activation tensor to an activation tensor.
    """

    ### START CODE HERE (REPLACE INSTANCES OF 'None' with your code) ###

    # Create masked multi-head attention block using CausalAttention function
    causal_attention = CausalAttention(
                        d_model,
                        n_heads=n_heads,
                        mode=mode
                        )

    # Create feed-forward block (list) with two dense layers with dropout and input normalized
    feed_forward = [
        # Normalize layer inputs
        tl.LayerNorm(),
        # Add first feed forward (dense) layer (don't forget to set the correct value for n_units)
        tl.Dense(d_ff),
        # Add activation function passed in as a parameter (you need to call it!)
        ff_activation(), # Generally ReLU
        # Add dropout with rate and mode specified (i.e., don't use dropout during evaluation)
        tl.Dropout(dropout, mode=mode),
        # Add second feed forward layer (don't forget to set the correct value for n_units)
        tl.Dense(d_model),
        # Add dropout with rate and mode specified (i.e., don't use dropout during evaluation)
        tl.Dropout(dropout, mode=mode)
    ]

    # Add list of two Residual blocks: the attention with normalization and dropout and feed-forward blocks
    return [
```

```
        tl.Residual(
            # Normalize layer input
            tl.LayerNorm(),
            # Add causal attention block previously defined (without parentheses)
            causal_attention,
            # Add dropout with rate and mode specified
            tl.Dropout(dropout, mode=mode)
          ),
        tl.Residual(
            # Add feed forward block (without parentheses)
            feed_forward
          ),
        ]
    ### END CODE HERE ###
```

In [84]:
```python
# Take a look at the decoder block
print(DecoderBlock(d_model=512, d_ff=2048, n_heads=8, dropout=0.1, mode='train', ff_activation=tl.Relu))
```

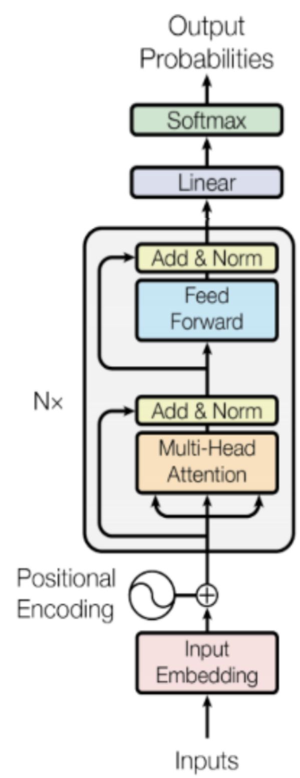
```
[Serial[
  Branch_out2[
    None
    Serial[
      LayerNorm
      Serial[
        Branch_out3[
          [Dense_512, AttnHeads]
          [Dense_512, AttnHeads]
          [Dense_512, AttnHeads]
        ]
        DotProductAttn_in3
        AttnOutput
        Dense_512
      ]
      Dropout
    ]
  ]
  Add_in2
], Serial[
  Branch_out2[
    None
    Serial[
      LayerNorm
      Dense_2048
      Relu
      Dropout
      Dense_512
      Dropout
    ]
  ]
  Add_in2
]]
```

Expected Output:

```
[Serial[
  Branch_out2[
    None
    Serial[
      LayerNorm
      Serial[
        Branch_out3[
          [Dense_512, AttnHeads]
          [Dense_512, AttnHeads]
          [Dense_512, AttnHeads]
        ]
        DotProductAttn_in3
        AttnOutput
        Dense_512
      ]
      Dropout
    ]
  ]
  Add_in2
], Serial[
  Branch_out2[
    None
    Serial[
      LayerNorm
      Dense_2048
      Relu
      Dropout
      Dense_512
      Dropout
    ]
  ]
  Add_in2
]]
```

2.4 Transformer Language Model

You will now bring it all together. In this part you will use all the subcomponents you previously built to make the final model. Concretely, here is the image you will be implementing.



Exercise 04

Instructions: Previously you coded the decoder block. Now you will code the transformer language model. Here is what you will need.

- positional_enconder - a list containing the following layers:
  - tl.Embedding (https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.core.Embedding)
  - tl.Dropout (https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.core.Dropout)
  - tl.PositionalEncoding (https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.attention.PositionalEncoding)
- A list of `n_layers` decoder blocks.
- [tl.Serial](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.combinators.Serial): takes in the following layers or lists of layers:
  - [tl.ShiftRight](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.attention.ShiftRight): : shift the tensor to the right by padding on axis 1.
  - positional_encoder : encodes the text positions.
  - decoder_blocks : the ones you created.

- [tl.LayerNorm](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.normalization.LayerNorm) : a layer norm.
- [tl.Dense](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.core.Dense) : takes in the vocab_size.
- [tl.LogSoftmax](https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.core.LogSoftmax) : to predict.

Go go go!! You can do it :)

In [85]:

```python
# UNQ_C7
# GRADED FUNCTION: TransformerLM
def TransformerLM(vocab_size=33300,
                  d_model=512,
                  d_ff=2048,
                  n_layers=6,
                  n_heads=8,
                  dropout=0.1,
                  max_len=4096,
                  mode='train',
                  ff_activation=tl.Relu):
    """Returns a Transformer language model.

    The input to the model is a tensor of tokens. (This model uses only the
    decoder part of the overall Transformer.)

    Args:
        vocab_size (int): vocab size.
        d_model (int):  depth of embedding.
        d_ff (int): depth of feed-forward layer.
        n_layers (int): number of decoder layers.
        n_heads (int): number of attention heads.
        dropout (float): dropout rate (how much to drop out).
        max_len (int): maximum symbol length for positional encoding.
        mode (str): 'train', 'eval' or 'predict', predict mode is for fast inference.
        ff_activation (function): the non-linearity in feed-forward layer.

    Returns:
        trax.layers.combinators.Serial: A Transformer language model as a layer that maps from a tensor of tokens
        to activations over a vocab set.
    """

    ### START CODE HERE (REPLACE INSTANCES OF 'None' with your code) ###

    # Embedding inputs and positional encoder
    positional_encoder = [
        # Add embedding layer of dimension (vocab_size, d_model)
        tl.Embedding(vocab_size, d_model),
        # Use dropout with rate and mode specified
        tl.Dropout(dropout, mode=mode),
        # Add positional encoding layer with maximum input length and mode specified
        tl.PositionalEncoding(max_len, mode=mode)]

    # Create stack (list) of decoder blocks with n_layers with necessary parameters
    decoder_blocks = [
        DecoderBlock(d_model, d_ff, n_heads, dropout, mode, ff_activation) for _ in range(n_layers)]
```

```
    # Create the complete model as written in the figure
    return tl.Serial(
        # Use teacher forcing (feed output of previous step to current step)
        tl.ShiftRight(mode=mode), # Specify the mode!
        # Add positional encoder
        positional_encoder,
        # Add decoder blocks
        decoder_blocks,
        # Normalize layer
        tl.LayerNorm(),

        # Add dense layer of vocab_size (since need to select a word to translate to)
        # (a.k.a., logits layer. Note: activation already set by ff_activation)
        tl.Dense(vocab_size),
        # Get probabilities with Logsoftmax
        tl.LogSoftmax()
    )

    ### END CODE HERE ###
```

In [86]:
```python
# Take a look at the Transformer
print(TransformerLM(n_layers=1))
```

```
Serial[
  ShiftRight(1)
  Embedding_33300_512
  Dropout
  PositionalEncoding
  Serial[
    Branch_out2[
      None
      Serial[
        LayerNorm
        Serial[
          Branch_out3[
            [Dense_512, AttnHeads]
            [Dense_512, AttnHeads]
            [Dense_512, AttnHeads]
          ]
          DotProductAttn_in3
          AttnOutput
          Dense_512
        ]
        Dropout
      ]
    ]
    Add_in2
  ]
  Serial[
    Branch_out2[
      None
      Serial[
        LayerNorm
        Dense_2048
        Relu
        Dropout
        Dense_512
        Dropout
      ]
    ]
    Add_in2
  ]
  LayerNorm
  Dense_33300
  LogSoftmax
]
```

Expected Output:

```
Serial[
  ShiftRight(1)
  Embedding_33300_512
  Dropout
  PositionalEncoding
  Serial[
    Branch_out2[
      None
      Serial[
        LayerNorm
        Serial[
          Branch_out3[
            [Dense_512, AttnHeads]
            [Dense_512, AttnHeads]
            [Dense_512, AttnHeads]
          ]
          DotProductAttn_in3
          AttnOutput
          Dense_512
        ]
        Dropout
      ]
    ]
    Add_in2
  ]
  Serial[
    Branch_out2[
      None
      Serial[
        LayerNorm
        Dense_2048
        Relu
        Dropout
        Dense_512
        Dropout
      ]
    ]
    Add_in2
  ]
  LayerNorm
```

```
  Dense_33300
  LogSoftmax
]
```

Part 3: Training

Now you are going to train your model. As usual, you have to define the cost function, the optimizer, and decide whether you will be training it on a `gpu` or `cpu`. In this case, you will train your model on a cpu for a few steps and we will load in a pre-trained model that you can use to predict with your own words.

3.1 Training the model

You will now write a function that takes in your model and trains it. To train your model you have to decide how many times you want to iterate over the entire data set. Each iteration is defined as an `epoch`. For each epoch, you have to go over all the data, using your training iterator.

Exercise 05

Instructions: Implement the `train_model` program below to train the neural network above. Here is a list of things you should do:

- Create the train task by calling `trax.supervised.training.TrainTask` (https://trax-ml.readthedocs.io/en/latest/trax.supervised.html#trax.supervised.training.TrainTask) and pass in the following:
  - labeled_data = train_gen
  - loss_fn = tl.CrossEntropyLoss() (https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.metrics.CrossEntropyLoss)
  - optimizer = trax.optimizers.Adam(0.01) (https://trax-ml.readthedocs.io/en/latest/trax.optimizers.html#trax.optimizers.adam.Adam)
  - lr_schedule = lr_schedule (https://trax-ml.readthedocs.io/en/latest/trax.supervised.html#trax.supervised.lr_schedules.warmup_and_rsqrt_decay)
- Create the eval task by calling `trax.supervised.training.EvalTask` (https://trax-ml.readthedocs.io/en/latest/trax.supervised.html#trax.supervised.training.EvalTask) and pass in the following:
  - labeled_data = eval_gen
  - metrics = tl.CrossEntropyLoss() and tl.Accuracy() (https://trax-ml.readthedocs.io/en/latest/trax.layers.html#trax.layers.metrics.Accuracy)
- Create the training loop by calling `trax.supervised.Training.Loop` (https://trax-ml.readthedocs.io/en/latest/trax.supervised.html#trax.supervised.training.Loop) and pass in the following:
  - TransformerLM
  - train_task
  - eval_task = [eval_task]
  - output_dir = output_dir

You will be using a cross entropy loss, with Adam optimizer. Please read the Trax (https://trax-ml.readthedocs.io/en/latest/index.html) documentation to get a full understanding.

The training loop that this function returns can be runned using the `run()` method by passing in the desired number of steps.

In [87]:

```python
from trax.supervised import training

# UNQ_C8
# GRADED FUNCTION: train_model
def training_loop(TransformerLM, train_gen, eval_gen, output_dir = "~/model"):
    '''
    Input:
        TransformerLM (trax.layers.combinators.Serial): The model you are building.
        train_gen (generator): Training stream of data.
        eval_gen (generator): Evaluation stream of data.
        output_dir (str): folder to save your file.

    Returns:
        trax.supervised.training.Loop: Training loop.
    '''
    output_dir = os.path.expanduser(output_dir)  # trainer is an object
    lr_schedule = trax.lr.warmup_and_rsqrt_decay(n_warmup_steps=1000, max_value=0.01)

    ### START CODE HERE (REPLACE INSTANCES OF 'None' with your code) ###
    train_task = training.TrainTask(
      labeled_data=train_gen, # The training generator
      loss_layer=tl.CrossEntropyLoss(), # Loss function
      optimizer=trax.optimizers.Adam(0.01), # Optimizer (Don't forget to set LR to 0.01)
      lr_schedule=lr_schedule,
      n_steps_per_checkpoint=10
    )

    eval_task = training.EvalTask(
      labeled_data=eval_gen, # The evaluation generator
      metrics=[tl.CrossEntropyLoss(), tl.Accuracy()] # CrossEntropyLoss and Accuracy
    )

    ### END CODE HERE ###

    loop = training.Loop(TransformerLM(d_model=4,
                                       d_ff=16,
                                       n_layers=1,
                                       n_heads=2,
                                       mode='train'),
                         train_task,
                         eval_tasks=[eval_task],
                         output_dir=output_dir)

    return loop
```

Notice that the model will be trained for only 10 steps.

Even with this constraint the model with the original default arguments took a very long time to finish. Because of this some parameters are changed when defining the model that is fed into the training loop in the function above.

In [88]:
```
# Should take around 1.5 minutes
!rm -f ~/model/model.pkl.gz
loop = training_loop(TransformerLM, train_batch_stream, eval_batch_stream)
loop.run(10)
```

```
Step      1: Ran 1 train steps in 8.17 secs
Step      1: train CrossEntropyLoss |  10.41125202
Step      1: eval  CrossEntropyLoss |  10.41141319
Step      1: eval          Accuracy |  0.00000000

Step     10: Ran 9 train steps in 74.17 secs
Step     10: train CrossEntropyLoss |  10.41234207
Step     10: eval  CrossEntropyLoss |  10.41357613
Step     10: eval          Accuracy |  0.00000000
```

Part 4: Evaluation

4.1 Loading in a trained model

In this part you will evaluate by loading in an almost exact version of the model you coded, but we trained it for you to save you time. Please run the cell below to load in the model.

As you may have already noticed the model that you trained and the pretrained model share the same overall architecture but they have different values for some of the parameters:

```
Original (pretrained) model:

   TransformerLM(vocab_size=33300, d_model=512, d_ff=2048, n_layers=6, n_heads=8,
                 dropout=0.1, max_len=4096, ff_activation=tl.Relu)
```

```
Your model:

   TransformerLM(d_model=4, d_ff=16, n_layers=1, n_heads=2)
```

Only the parameters shown for your model were changed. The others stayed the same.

In [89]:
```
# Get the model architecture
model = TransformerLM(mode='eval')

# Load the pre-trained weights
model.init_from_file('model.pkl.gz', weights_only=True)
```

Part 5: Testing with your own input

You will now test your input. You are going to implement greedy decoding. This consists of two functions. The first one allows you to identify the next symbol. It gets the argmax of the output of your model and then returns that index.

Exercise 06

Instructions: Implement the next symbol function that takes in the cur_output_tokens and the trained model to return the index of the next word.

In [90]:

```python
# UNQ_C9
def next_symbol(cur_output_tokens, model):
    """Returns the next symbol for a given sentence.

    Args:
        cur_output_tokens (list): tokenized sentence with EOS and PAD tokens at the end.
        model (trax.layers.combinators.Serial): The transformer model.

    Returns:
        int: tokenized symbol.
    """
    ### START CODE HERE (REPLACE INSTANCES OF 'None' with your code) ###

    # current output tokens length
    token_length = len(cur_output_tokens)
    # calculate the minimum power of 2 big enough to store token_length
    # HINT: use np.ceil() and np.log2()
    # add 1 to token_length so np.log2() doesn't receive 0 when token_length is 0
    padded_length = 2**int(np.ceil(np.log2(token_length + 1)))

    # Fill cur_output_tokens with 0's until it reaches padded_length
    padded = cur_output_tokens + [0] * (padded_length - token_length)
    padded_with_batch = np.array(padded)[None, :] # Don't replace this 'None'! This is a way of setting the batch dim

    # model expects a tuple containing two padded tensors (with batch)
    output, _ = model((padded_with_batch, padded_with_batch))
    # HINT: output has shape (1, padded_length, vocab_size)
    # To get log_probs you need to index output with 0 in the first dim
    # token_length in the second dim and all of the entries for the last dim.
    log_probs = output[0, token_length, :]

    ### END CODE HERE ###

    return int(np.argmax(log_probs))
```

In [91]:

```python
# Test it out!
sentence_test_nxt_symbl = "I want to fly in the sky."
detokenize([next_symbol(tokenize(sentence_test_nxt_symbl)+[0], model)])
```

Out[91]: 'The'

Expected Output:

'The'

5.1 Greedy decoding

Now you will implement the greedy_decode algorithm that will call the `next_symbol` function. It takes in the input_sentence, the trained model and returns the decoded sentence.

Exercise 07

Instructions: Implement the greedy_decode algorithm.

In [94]:
```
# UNQ_C10
# Decoding functions.
def greedy_decode(input_sentence, model):
    """Greedy decode function.

    Args:
        input_sentence (string): a sentence or article.
        model (trax.layers.combinators.Serial): Transformer model.

    Returns:
        string: summary of the input.
    """

    ### START CODE HERE (REPLACE INSTANCES OF 'None' with your code) ###
    # Use tokenize()
    cur_output_tokens = tokenize(input_sentence) + [0]
    generated_output = []
    cur_output = 0
    EOS = 1

    while cur_output != EOS:
        # Get next symbol
        cur_output = next_symbol(cur_output_tokens, model)
        # Append next symbol to original sentence
        cur_output_tokens.append(cur_output)
        # Append next symbol to generated sentence
        generated_output.append(cur_output)
        print(detokenize(generated_output))

    ### END CODE HERE ###

    return detokenize(generated_output)
```

In [95]:
```python
# Test it out on a sentence!
test_sentence = "It was a sunny day when I went to the market to buy some flowers. But I only found roses, not tulips."
print(wrapper.fill(test_sentence), '\n')
print(greedy_decode(test_sentence, model))
```

```
It was a sunny day when I went to the market to buy some flowers. But
I only found roses, not tulips.

:
: I
: I just
: I just found
: I just found ros
: I just found roses
: I just found roses,
: I just found roses, not
: I just found roses, not tu
: I just found roses, not tulips
: I just found roses, not tulips
: I just found roses, not tulips.
: I just found roses, not tulips.<EOS>
: I just found roses, not tulips.<EOS>
```

Expected Output:

```
:
: I
: I just
: I just found
: I just found ros
: I just found roses
: I just found roses,
: I just found roses, not
: I just found roses, not tu
: I just found roses, not tulips
: I just found roses, not tulips
: I just found roses, not tulips.
: I just found roses, not tulips.<EOS>
: I just found roses, not tulips.<EOS>
```

In [ ]:

```python
# Test it out with a whole article!
article = "It’s the posing craze sweeping the U.S. after being brought to fame by skier Lindsey Vonn, soccer star Omar Cummings, baseball player Albert Pujols - and even Republican politician Rick Perry. But now four students at Riverhead High School on Long Island, New York, have been suspended for dropping to a knee and taking up a prayer pose to mimic Denver Broncos quarterback Tim Tebow. Jordan Fulcoly, Wayne Drexel, Tyler Carroll and Connor Carroll were all suspended for one day because the ‘Tebowing’ craze was blocking the hallway and presenting a safety hazard to students. Scroll down for video. Banned: Jordan Fulcoly, Wayne Drexel, Tyler Carroll and Connor Carroll (all pictured left) were all suspended for one day by Riverhead High School on Long Island, New York, for their tribute to Broncos quarterback Tim Tebow. Issue: Four of the pupils were suspended for one day because they allegedly did not heed to warnings that the 'Tebowing' craze at the school was blocking the hallway and presenting a safety hazard to students."
print(wrapper.fill(article), '\n')
print(greedy_decode(article, model))
```

Expected Output:

```
Jordan
Jordan Ful
Jordan Fulcol
Jordan Fulcoly
Jordan Fulcoly,
Jordan Fulcoly, Wayne
Jordan Fulcoly, Wayne Dre
Jordan Fulcoly, Wayne Drexe
Jordan Fulcoly, Wayne Drexel
Jordan Fulcoly, Wayne Drexel,
.
.
.

Final summary:

Jordan Fulcoly, Wayne Drexel, Tyler Carroll and Connor Carroll were
suspended for one day. Four students were suspended for one day
because they allegedly did not heed to warnings that the 'Tebowing'
craze was blocking the hallway and presenting a safety hazard to
students.<EOS>
```

Congratulations on finishing this week's assignment! You did a lot of work and now you should have a better understanding of the encoder part of Transformers and how Transformers can be used for text summarization.

Keep it up!