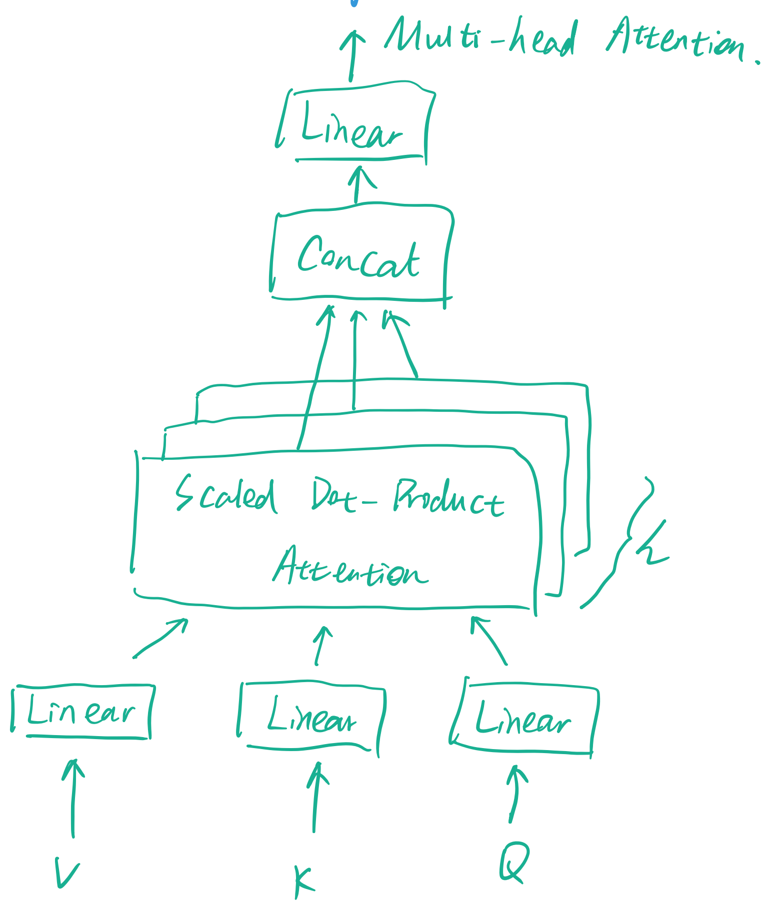
Paper:

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

Q: Query. K: keys. V: Values

$\frac{QK^T}{\sqrt{d_k}}$: a scaling divided by square root of embedding size for numerical stability.



Coding.

Self attention:

```
class SelfAttention(nn.Module):
    def __init__(self, embed_size, heads):
        super(SelfAttention, self).__init__()
        self.embed_size = embed_size
        self.heads = heads.
        self.head_dim = embed_size // heads.
        assert(self.head_dim * heads == embed_size),
            "Embed size needs to be div by heads"


        self.values = nn.Linear(self.head_dim, self.head_dim,
                bias = False)
        self.keys = nn.Linear(self.head_dim, self.head_dim,
                bias = False)
        self.queries = nn.Linear(self.head_dim, self.head_dim,
                bias = False)
```

self.fc_out = nn.Linear(heads * self.head_dim, embed_size)

Concatenation.

def forward(self, values, keys, query, mask):

N = query.shape[0] how many examples we send in for each time.

value_len, key_len, query_len = value.shape[1],
keys.shape[1],
query.shape[1]

source sentence length

target sentence length.

split embedding into self.head pieces:

values = values.reshape(N, value_len, self.heads, self.head_dim)

keys = keys.reshape(N, key_len, self.heads, self.head_dim)

queries = query.reshape(N, query_len, self.heads, self.head_dim).

values = self.values(values)
keys = self.keys(keys)

queries = self.queries(queries).

energy = torch.einsum("nqhd,nkhd->nhqk", [queries, keys])

queries shape: (N, query_len, heads, heads_dim)

keys shape: (N, key_len, heads, heads_dim) we want energy shape: (N, heads, query_len, key_len)

query_len is the target sentence,

key_len is the source sentence

for each word in the target, how much should we pay attention to each word in the input.

```
if mask is not None:
    energy = energy.masked_fill(mask == 0, float("-1e20"))
```

```
attention = torch.softmax(energy / (self.embed_size ** (1/2)),
    dim=3)
```

normalize the attention for the source sentence

```
out = torch.einsum("nhql,nlhd->nqhd", [attention, values]).
        reshape(N, query_len, self.heads * self.head_dim)
```

attention shape: (N, heads, query_len, key_len)

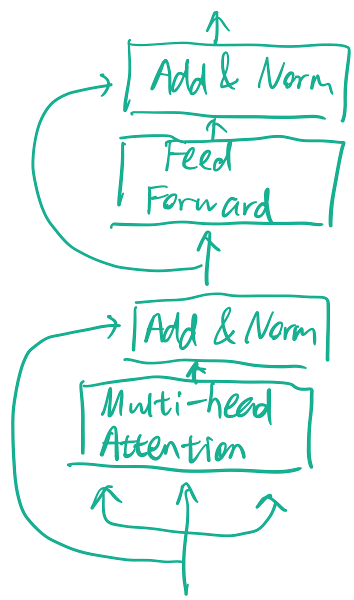
values shape: (N, value_len, heads, heads_dim)

Output dim: (N, query_len, heads, head_dim)

then reshape flattens the last two dimensions.

```
out = self.fc_out(out)

return out.
```




```
class TransformerBlock(nn.Module):

  def __init__(self, embed_size,
        heads, dropout,
        forward_expansion):

    super(TransformerBlock, self).__init__()

    self.attention = SelfAttention(embed_size, heads)

    self.norm1 = nn.LayerNorm(embed_size)
```

BatchNorm takes the average accross the batch, and then normalize.

LayerNorm takes average for every example.

```
self.norm2 = nn.LayerNorm(embed_size)


self.feed_forward = nn.Sequential(
    nn.Linear(embed_size, forward_expansion * embed_size),
    nn.ReLU(),
    nn.Linear(forward_expansion * embed_size, embed_size)
)

self.dropout = nn.Dropout(dropout)


def forward(self, value, key, query, mask):
    attention = self.attention(value, key, query, mask)
    x = self.dropout(self.norm1(attention + query))
```

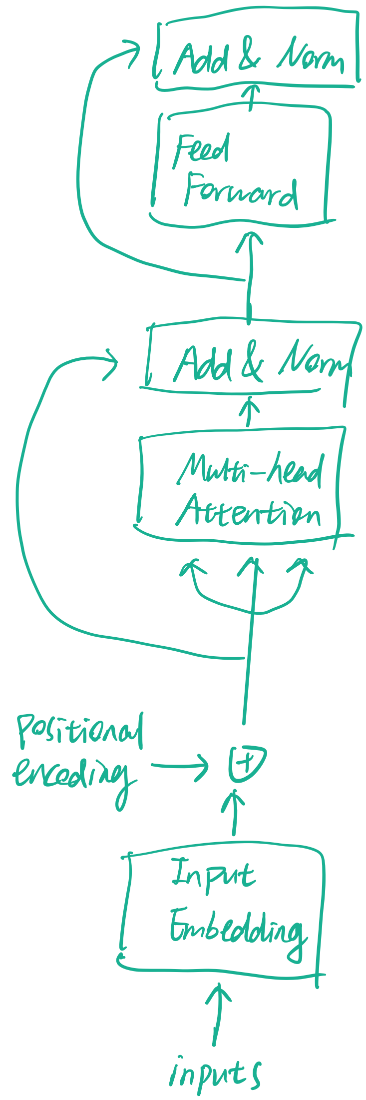
skip connection

```
    forward = self.feed_forward(x)
    out = self.dropout(self.norm2(forward + x))
```

```
return out


class Encoder(nn.Module):
    def __init__(self,
            src_vocab_size,
            embed_size,
            num_layers,
            heads,
            device,
            forward_expansion,
            dropout,
            max_length,
    ):
```

to keep the train data size limited e.g. 100.




```
        super(Encoder, self).__init__()
        self.embed_size = embed_size
        self.device = device.
```

```
self.word_embedding = nn.Embedding(src_vocab_size, embed_size)

self.position_embedding = nn.Embedding(max_length, embed_size)

self.layers = nn.ModuleList(
  [
      TransformerBlock(
          embed_size,
          heads,
          dropout=dropout,
          forward_expansion=forward_expansion,
      )
      for _ in range(num_layers)]
)

self.dropout = nn.Dropout(dropout)


def forward(self, x, mask):

    N, seq_length = x.shape

    positions = torch.arange(0, seq_length).expand(N, seq_length).
        to(self.device)
```

this learns the order of words

```
    out = self.dropout(self.word_embedding(x)
                       + self.position_embedding(positions))
```

```
for layer in self.layers:
    out = layer(out, out, out, mask)
```

all inputs are same in Encoder

```
return out
```

```
class DecoderBlock(nn.Module):
    def __init__(self, embed_size, heads, forward_expansion,
            dropout, device):
        super(DecoderBlock, self).__init__()
        self.attention = SelfAttention(embed_size, heads)
        self.norm = nn.LayerNorm(embed_size)
        self.transformer_block = TransformerBlock(
            embed_size, heads, dropout, forward_expansion
        )
        self.dropout = nn.Dropout(dropout)
```

```
def forward(self, x, value, key, src_mask, trg_mask):
    # we need to pad the inputs to equal length, src_mask is
    # to avoid computation on padded values. optional.

    attention = self.attention(x, x, x, trg_mask)  # <- target mask.
    query = self.dropout(self.norm(attention + x))
    out = self.transformer_block(value, key, query, src_mask)
    return out


class Decoder(nn.Module):

    def __init__(self, trg_vocab_size, embed_size, num_layers,
            heads, forward_expansion, dropout, device, max_length
    ):

        super(Decoder, self).__init__()
        self.device = device
        self.word_embedding = nn.Embedding(trg_vocab_size, embed_size)
        self.position_embedding = nn.Embedding(max_length, embed_size)
```

```
self.layers = nn.ModuleList(
    [
      DecoderBlock(embed_size, heads, forward_expansion,
          dropout, device)
      for _ in range(num_layers)
    ]
)

self.fc_out = nn.Linear(embed_size, trg_vocab_size)

self.dropout = nn.Dropout(dropout).


def forward(self, x, enc_out, src_mask, trg_mask):
    N, seq_length = x.shape.

    positions = torch.arange(0, seq_length).expand(N, seq_length).
        to(self.device)

    x = self.dropout((self.word_embedding(x) +
            self.position_embedding(positions)))
```

```
    for layer in self.layers:
        x = layer(x, enc_out, src_mask, trg_mask):

    out = self.fc_out(x)
    return out

class Transformer(nn.Module):
    def __init__(self, scr_vocab_size, trg_vocab_size,
            src_pad_idx, trg_pad_idx, embed_size=256,
            num_layers=6, forward_expansion=4, heads=8,
            dropout=0, device="cuda", max_length=100
    ):

    super(Transformer, self).__init__()
    self.encoder = Encoder(
            src_vocab_size, embed_size, num_layers, heads, device,
            forward_expansion, dropout, max_length,
    )
```

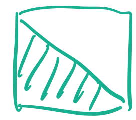
```
self.decoder = Decoder(
        trg_vocab_size, embed_size, num_layers, heads,
        forward_expansion, dropout, device, max_length
)

self.src_pad_idx = src_pad_idx
self.trg_pad_idx = trg_pad_idx
self.device = device

def make_src_mask(self, src):
    src_mask = (src != self.src_pad_idx).unsqueeze(1).unsqueeze(2).
    shape is (N, 1, 1, src_len)
    return src_mask.to(self.device)

def make_trg_mask(self, trg):
    N, trg-len = trg.shape
```

```
trg_mask = torch.tril(torch.ones((trg_len, trg_len))).expand(
    N, 1, trg_len, trg_len
)
return trg_mask.to(self.device)
```



lower triangular matrix.

```
def forword(self, src, trg):
    src_mask = self.make_src_mask(src)
    trg_mask = self.make_trg_mask(trg)
    enc_src = self.encoder(src, src_mask)
    out = self.decoder(trg, enc_src, src_mask, trg_mask)
    return out
```