Another annotated transformer

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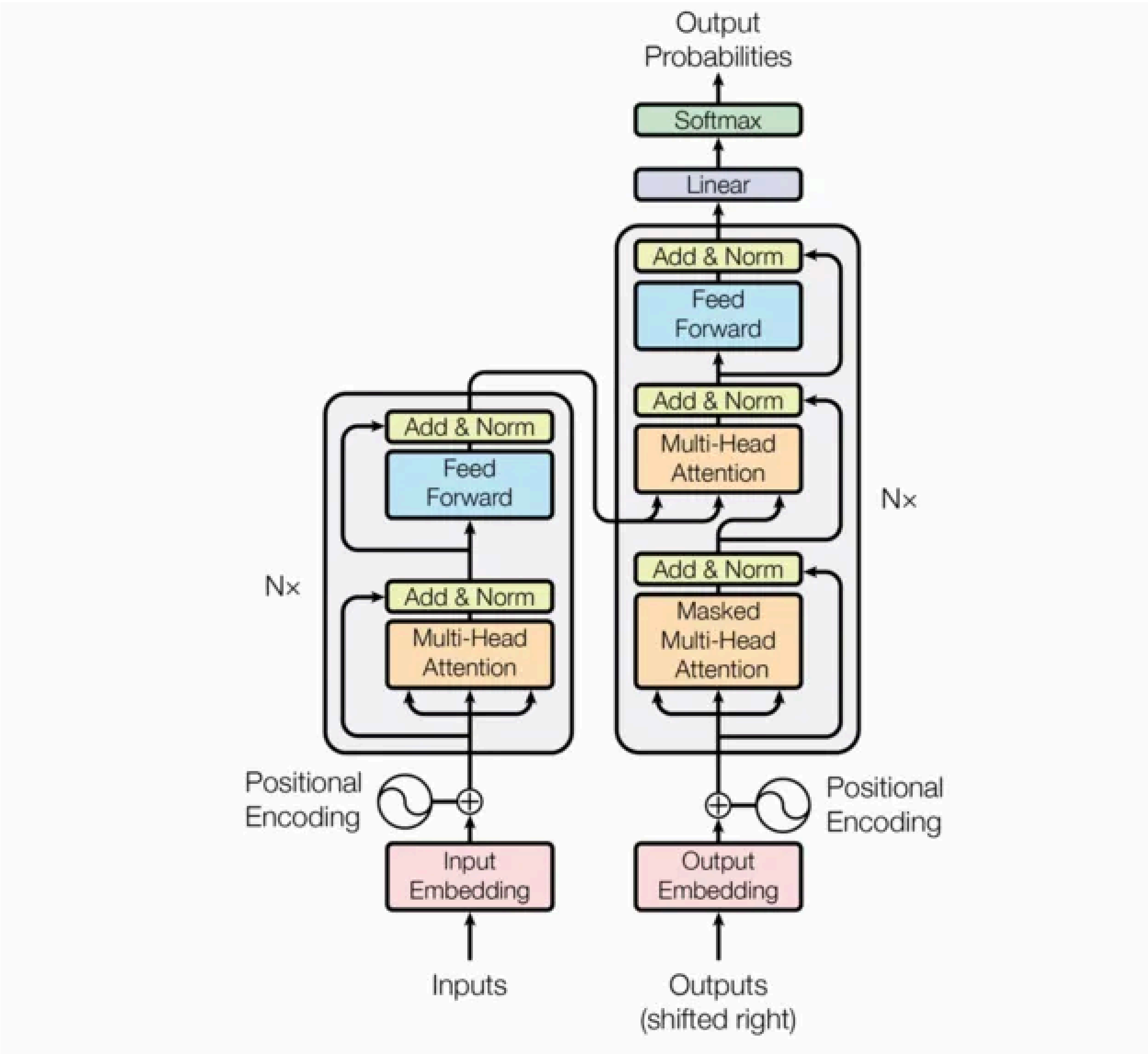


If you're anything like me, while trying to implement transformers, you've read the original attention is all you need paper, the annotated transformer, the updated version, d2l.ai, and had to cobble them all together to get something going. This post is an attempt to make that proccess easier for people like me in a short and to-the-point style. You can think of this as a bare-bones implementation with a whole lot of documentation.

Notes:

1. this post is about *how* transformers are implemented, not *why* they're implemented the way they are.
2. This post assumes the reader understands what is meant by **training** a model, **parameters** and **hyperparameters**, **dense layers**, and so on.
3. We'll be using jax and flax for this implementation.
4. Some of the math is hard to read on here so the original post is available on aaron.niskin.org.

Overview

The following is the transformer architecture diagram taken from the original paper. We'll be referring back to it often in this post.

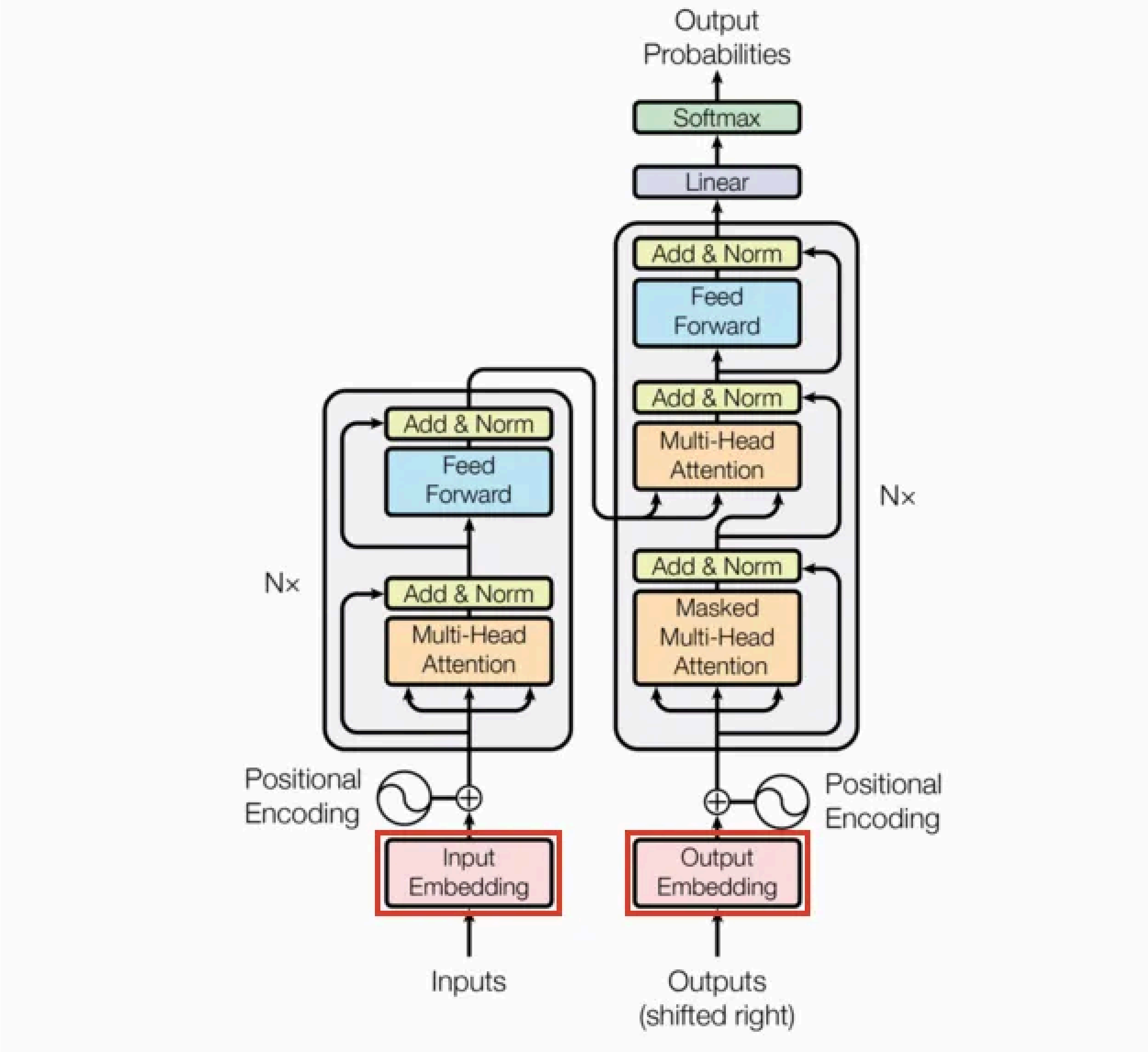
At a high level, the transformer is an encoder-decoder model; it takes a **sequence** of **tokens** from a source (e.g. English words) and learns to translate that into a destination sequence (e.g. French words). There are three flavors of transformers: *encoder/decoder*, *encoder-only*, and *decoder-only*. This post will focus on *encoder/decoder* transformers.

```
from typing import Callable, Sequence

import chex
import jax.numpy as jnp
import jax.random as jran
import jax.tree_util
import optax
from flax import linen as nn
from IPython.display import display
from tqdm.auto import tqdm

key = jran.PRNGKey(0)
```

Input (output) embeddings



As we said before, the transformer model is a sequence to sequence model. Natural language lends itself to many possible sequence definitions (words, characters, bigrams, etc.), so strictly speaking we need to define a **tokenizer** before we even get to the Embeddings.

Tokenization

The tokenizer takes something like natural language and returns a sequence (typically of unique natural numbers — IDs). We'll tokenize each character `"a"` through `"z"` along with the requisite **start** and **pad** tokens (represented by `"<start>"` and `"<pad>"` respectively -- to be explained later). So our tokens are `["a", "b", "c", ..., "z", "<start>", "<pad>"]`, and our tokenizer maps those to `[0, 1, 2, ..., 25, 26, 27]`.

```
vocab = {chr(97 + i): i for i in range(26)}
vocab['<start>'] = len(vocab)
```

```
vocab['<pad>'] = len(vocab)
```

One reason transformers really took off (in their early days) was that you could easily train them in batches without the recurrence required of something like RNNs. In order to do that, we need to arrange our sequences into a batch. But what if the sequences are of different lengths? For that we use numpy's pad function: we fill in the empty spots at the end of the shorter sequences with our `'<pad>'` token so that we can ignore these in our loss.

```
def str2ids(txt, vocab=vocab):
    return jnp.array([vocab[x] for x in txt])

def strs2ids(*txts, vocab=vocab):
    ids = [str2ids(x, vocab=vocab) for x in txts]
    maxlen = max([len(x) for x in ids])
    return jnp.stack([jnp.pad(jnp.array(x), pad_width=(0, maxlen - len(x)),
                              mode='constant', constant_values=vocab['<pad>'])
                      for x in ids])

def ids2str(ids, vocab=vocab):
    x = [list(vocab)[x] for x in ids]
    x = [y if y != '<pad>' else '~' for y in x]
    return ''.join(x).rstrip('~')

def ids2strs(ids, vocab=vocab):
    return [ids2str(x, vocab=vocab) for x in ids]

seq = ['hey', 'there', 'ma', 'dood']
assert ids2strs(strs2ids(*seq)) == seq
display(strs2ids(*seq))
del seq
```

```
Array([[ 7,  4, 24, 27, 27],
       [19,  7,  4, 17,  4],
       [12,  0, 27, 27, 27],
       [ 3, 14, 14,  3, 27]], dtype=int32)
```

Notice how `27` appears in that matrix -- `27` is our `"<pad>"` token.

Embedding

After tokenization, the **Input Embedding** is the start of the data flow. An embedding is a mapping from a discrete set with cardinality N to a subset of Rd where d≪N. This is generally done in such a way that a the topology is preserved. It can be broken down into two parts:

1. An N×d parameter matrix (also called a rank-2 tensor).
2. An association between each element of our discrete set and a row in that matrix.

The second part comes naturally from our vocabulary definition (we can map each token to the integer the vocabulary maps it to).

The first part is already implemented in `flax`. We instantiate an example `nn.Embed` layer below with N=28 and d=2 (using the notation above). You can see that the embedding layer only has one parameter, `'embedding'`, which is a N×dmatrix. d is called the **embedding dimension**.

```
model = nn.Embed(len(vocab), 2)
params = model.init(key, jnp.array([1]))
jax.tree_util.tree_map(jnp.shape, params)
```

```
{'params': {'embedding': (28, 2)}}
```

If we get some embeddings, we see that the model is doing exactly what we said it would do (it's just grabbing the ith row of the matrix).

```
model.apply(params, str2ids('abc'))
```

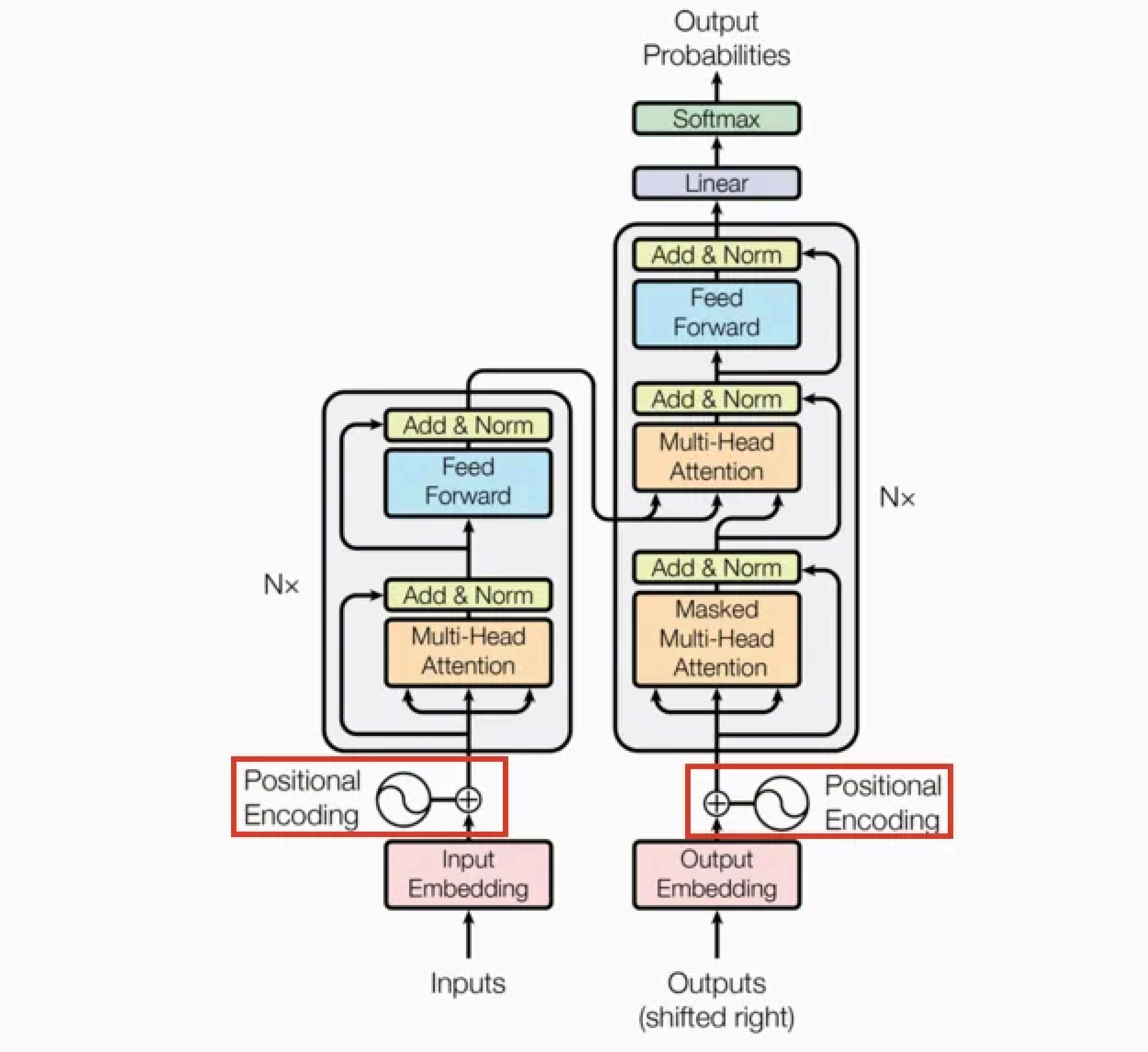
```
Array([[ 0.35985   , -0.75417924],
       [-1.206328  ,  0.7793859 ],
       [ 0.11096746, -1.0079818 ]], dtype=float32)
```

```
params['params']['embedding'][0:3]
```

```
Array([[ 0.35985   , -0.75417924],
       [-1.206328  ,  0.7793859 ],
       [ 0.11096746, -1.0079818 ]], dtype=float32)
```

These weights get tuned thereby "learning" an d-dimensional embedding for each token.

Positional encoding



The positional encoding is the same size as a single observation fed to the model and added to each observation in the batch. We use the same function as they used in the original paper. Let $X \in R^{s \times d}$ where s is the max sequence length, and d is the embedding dimension.

$$f(X_{i,j}) = \begin{cases} \sin(i/(10000^{j/d})) & \text{if } j \equiv 0 \pmod 2 \\ \cos(i/(10000^{(j-1)/d})) & \text{if } j \equiv 1 \pmod 2 \end{cases}$$

```
def sin_pos_enc(sequence_length, embed_dim):
    """create sin/cos positional encodings

    Paramters
    =========
    sequence_length : int
        The max length of the input sequences for this model
    embed_dim : int
        the embedding dimension
    Returns
    =======
    a matrix of shape: (sequence_length, embed_dim)
    """
    chex.assert_is_divisible(embed_dim, 2)
    X = jnp.expand_dims(jnp.arange(sequence_length), 1) / \
        jnp.power(10000, jnp.arange(embed_dim, step=2) / embed_dim)
    out = jnp.empty((sequence_length, embed_dim))
    out = out.at[:, 0::2].set(jnp.sin(X))
    out = out.at[:, 1::2].set(jnp.cos(X))
    return out
sin_pos_enc(5, 2)
```

```
Array([[ 0.        ,  1.        ],
       [ 0.841471  ,  0.5403023 ],
       [ 0.9092974 , -0.41614684],
       [ 0.14112002, -0.9899925 ],
       [-0.7568025 , -0.6536436 ]], dtype=float32)
```

We'll come back to this later.

Multi-Head Attention

Transformers are built around the **Multi-Head Attention** you see in the picture, but MHA is itself built on **attention.** Attention is just a function that takes 3 matrix arguments (**query**, **key**, and **value**) and aggregates them to a vector. There are a few forms of attention but we'll focus on the one used in the seminal paper: **scaled dot product** attention.

Scaled dot product attention

Let $Q \in \mathbb{R}^{n \times d}, K \in \mathbb{R}^{m \times d}, V \in \mathbb{R}^{m \times v}$ be the **query**, **key**, and **value**. Basically we just need the shapes to be fit for the matrix multiplication below. A good reference for this is d2l.ai.

$$\mathrm{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)V \in \mathbb{R}^{n \times v}$$

The $\mathrm{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)$ part is called the **attention weights**.

It's worthwhile to note that there are no learnable weights in this formula.

This formula is deceptive in 2 ways:

1. The softmax is often masked
2. There's generally some dropout on the attention weights

Masked softmax

Let $X \in \mathbb{R}^k$ a vector, then $\mathrm{softmax}(X) \in \mathbb{R}^k$.

$$\mathrm{softmax}(X)_i = \frac{e^{X_i}}{\sum_{j=0}^{k-1} e^{X_j}}$$

It's just normalization with a monotonic function applied, meaning the relative ranking of the elements of X aren't changed. For more on this, see this post.

For masked softmax, we'll be taking the approximate approach. Because of the sum in the denominator and the exponentiation, it's unwise to mask with 0 ($e^0=1$). Instead we'll mask with a very large negative number before we exponentiate so that the result is close to 0 ($e^{-\infty} \approx 0$).

```
def masked_softmax(args, mask):
    if mask is not None:
        args = args + (mask.astype(args.dtype) * -10_000.0)
    return nn.softmax(args)

def dot_prod_attn(q, k, v, dropout=lambda x: x, mask=None):
    # NxD @ DxM => NxM
    # (B[, H], N, M)
    attn_scores = q @ k.swapaxes(-2, -1) / jnp.sqrt(q.shape[-1])
    attn_weights = masked_softmax(attn_scores, mask)
    # (B[, H], N, D)
    out = dropout(attn_weights) @ v
    return out, attn_weights
```

```
# these are 13 batches of Q, K, V matrices arranged into rank 3 tensors
Q = jran.normal(jran.fold_in(key, 0), (13, 3, 7))
K = jran.normal(jran.fold_in(key, 1), (13, 5, 7))
V = jran.normal(jran.fold_in(key, 2), (13, 5, 11))
print(jax.tree_map(jnp.shape, dot_prod_attn(Q, K, V)))
del Q, K, V
```

```
((13, 3, 11), (13, 3, 5))
```

Multihead Attention

Multi-head attention involves stacking a collection of attention "heads" and adding some learned weights in the mix. As such, we'll start with attention heads and progress to multi-head attention.

At a high level, mutli-head attention is a bunch of stacked attention layers. But given that there are no learnable weights in the attention heads (they query, key, and values are all arguments), each would yield the same result — not so useful. So instead, we train a linear layer per attention head, and then concatenate the results.

One linear vs stacked linears

Many implementations use one linear layer and reshape the output rather than storing a collection of linear models. At first this might not seem kosher, but it is. The picture below shows how 2 attention heads (red and blue) can be trained with one linear model.

```
class MultiHeadAttention(nn.Module):
    n_heads: int
    size_per_head: int
    attn_dropout: float
    fc_dropout: float
    attn_fn: Callable = dot_prod_attn

    @nn.compact
    def __call__(self, q, k, v, mask=None, *, training=False):
        "expected shape: Batch, [N|M], Dim"
        B, N, D = q.shape
        _, M, _ = k.shape

        def qkv_layer(x, name):
            x = nn.Dense(self.n_heads * self.size_per_head, name=name)(x)
```

```
            x = x.reshape((B, -1, self.n_heads, self.size_per_head)).swapaxes(1
            return x
        # BxNxD => BxHxNxP
        q = qkv_layer(q, 'query_linear')
        # BxMxD => BxHxMxP
        k = qkv_layer(k, 'key_linear')
        # BxMxD => BxHxMxP
        v = qkv_layer(v, 'value_linear')
        if mask is not None:
            # accounting for reshape in qkv_layer
            # B[xN]xN    => Bx1[xN]xN
            mask = jnp.expand_dims(mask, 1)
            if mask.ndim < q.ndim:
                # softmax is applied to dim -1
                # Bx1xN => Bx1x1xN
                mask = jnp.expand_dims(mask, -2)
        attn_do = nn.Dropout(self.attn_dropout, deterministic=not training, nam
        out, attn_weights = self.attn_fn(q, k, v, attn_do, mask=mask)
        # uncomment to keep attention weights in state
        # self.sow('intermediates', 'weights', attn_weights)
        out = out.swapaxes(1, 2).reshape((B, N, -1))
        out = nn.Dense(D, name='output_linear')(out)
        out = nn.Dropout(self.fc_dropout, deterministic=not training, name='fc_
        return out
```

As we all know at this point, these models can get quite big. It turns out, transformers are just naturally large models. Below we show that even a pathalogically simple `MultiHeadAttention` layer has 63 parameters!

```
batch_size = 2
sequence_length = 5
embed_dim = 3
n_heads = 2
size_per_head = 2

X = jnp.arange(batch_size * sequence_length * embed_dim)
X = X.reshape((batch_size, sequence_length, embed_dim))

mdl = MultiHeadAttention(n_heads, size_per_head, attn_dropout=0.2, fc_dropout=0
params = mdl.init(key, X, X, X, mask=(jnp.max(X, axis=-1) < 0.8).astype(jnp.flo

nn.tabulate(mdl, key, console_kwargs={'force_jupyter': True})(X, X, X)
del batch_size, sequence_length, embed_dim, n_heads, size_per_head, X, mdl
```

MultiHeadAttention Summary

path	module	inputs	outputs	pa
	MultiHeadAttention	- int32[2,5,3] - int32[2,5,3] - int32[2,5,3]	float32[2,5,3]	
query_linear	Dense	int32[2,5,3]	float32[2,5,4]	bi ke 16
key_linear	Dense	int32[2,5,3]	float32[2,5,4]	bi ke 16
value_linear	Dense	int32[2,5,3]	float32[2,5,4]	bi ke 16
attn_dropout	Dropout	float32[2,2,5,5]	float32[2,2,5,5]	
output_linear	Dense	float32[2,5,4]	float32[2,5,3]	bi ke 15
fc_dropout	Dropout	float32[2,5,3]	float32[2,5,3]	
			Total	63

Total Parameters: 63 (252 B)

We're going to want to see keep track of how many parameters we have as we go, and looking at a giant table is just not very efficient. To that end, let's write a little function to do this:

```
def num_params(params):
    param_sizes = jax.tree_map(lambda x: jnp.prod(jnp.array(jnp.shape(x))), par
    param_size_leafs, _ = jax.tree_util.tree_flatten(param_sizes)
    return jnp.sum(jnp.array(param_size_leafs)).item()
```

```
    print(f'{num_params(params) = }')
    del params
```

```
num_params(params) = 63
```

Feed Forward and Add & Norm

The `AddAndNorm` and `FeedForward` layers are so simple that many implementations don't implement them explicitly. We'll implement them just so our code looks like the diagram.

```
class AddAndNorm(nn.Module):
    """The add and norm."""

    @nn.compact
    def __call__(self, X, X_out):
        return nn.LayerNorm()(X + X_out)

class FeedForward(nn.Module):
    """a 2-layer feed-forward network."""
    hidden_dim: int

    @nn.compact
    def __call__(self, X):
        D = X.shape[-1]
        X = nn.Dense(self.hidden_dim)(X)
        X = nn.relu(X)
        X = nn.Dense(D)(X)
        return X
```

Encoder

The encoder takes a sequence of tokens as input, and outputs a sequence of *contextual embeddings*. This means the embeddings for "light" in the sequence "light bulb" will be different from the one in "light weight", a major improvement over non-contextual embeddings like word2vec.

EncoderLayer

The `Encoder` is a combination of the various layers we've already built up along with several `EncoderLayer` s (which are themselves just combinations of previously defined layers). This section is going to be short.

Note the `EncoderLayer` takes one argument (neglecting the mask) and feeds that one argument as the `query`, `key`, and `value` in the `Multi-Head Attention` layer. This can be seen by following the arrows in the diagram.

```
class EncoderLayer(nn.Module):
    hidden_dim: int
    n_heads: int
    size_per_head: int
    attn_dropout: float
    fc_dropout: float

    def setup(self):
        self.attn = MultiHeadAttention(n_heads=self.n_heads,
                                       size_per_head=self.size_per_head,
                                       attn_dropout=self.attn_dropout,
                                       fc_dropout=self.fc_dropout)
        self.aan_0 = AddAndNorm()
        self.ff = FeedForward(hidden_dim=self.hidden_dim)
        self.aan_1 = AddAndNorm()

    def __call__(self, X, mask=None, *, training=False):
        X1 = self.attn(X, X, X, mask=mask, training=training)
        X = self.aan_0(X, X1)
        X1 = self.ff(X)
        X = self.aan_1(X, X1)
        return X
```

Encoder

```
class Encoder(nn.Module):
    pos_encoding: Callable[[int, int], jnp.array]
    vocab_size: int
    embed_dim: int
    layers: Sequence[EncoderLayer]

    @nn.compact
    def __call__(self, X, mask=None, *, training=False):
        B, N = X.shape
        if mask is not None:
            chex.assert_shape(mask, (B, N))
        X = nn.Embed(self.vocab_size, self.embed_dim, name='embed')(X)
        X = X * jnp.sqrt(self.embed_dim)
        # X.shape[-2] is the sequence length
```

```
        X = X + self.pos_encoding(X.shape[-2], self.embed_dim)
        for layer in self.layers:
            X = layer(X, mask=mask, training=training)
        return X
```

There are quite a few parameters, but with some still pathologically small numbers, we get an astronomical 47,670 parameters!

```
def layer_fn():
    return EncoderLayer(hidden_dim=13,
                        attn_dropout=0.1,
                        fc_dropout=0.1,
                        n_heads=7,
                        size_per_head=17)
mdl = Encoder(pos_encoding=sin_pos_enc, vocab_size=len(vocab),
              embed_dim=2 * 3 * 5,
              layers=[layer_fn() for _ in range(3)])
batch = strs2ids('hey', 'there', 'ma', 'dood')
mask = (batch == vocab['<pad>'])
params = mdl.init(key, batch)
num_params(params['params'])
```

```
47670
```

Decoder

The decoder generates new sequences given some input state sequence (maybe the output of the `Encoder`). You build up a sequence by iteratively asking the model for the next token until either some stop criteria or you get a token signifying the end of the sequence (we're using `"<pad>"` for this). This iterative approach cannot be parallelized efficiently.

Causal masking

Transformers can train on full sequences without the recursion, but it requires the clever so called, **causal masking.** When computing gradients, it's important that output token i cannot attend to any later output token i+k as they won't be available in production.

```
def causal_mask(shape):
    return jnp.triu(jnp.ones(shape, dtype=jnp.bool_), k=1)
causal_mask((1, 5, 5))
```

```
Array([[[False,  True,  True,  True,  True],
        [False, False,  True,  True,  True],
        [False, False, False,  True,  True],
        [False, False, False, False,  True],
        [False, False, False, False, False]]], dtype=bool)
```

DecoderLayer

One thing to note: decoder only transformer layers remove the cross attention layer (the middle attention).

```
class DecoderLayer(nn.Module):
    hidden_dim: int
    n_heads: int
    size_per_head: int
    attn_dropout: float
    fc_dropout: float

    @nn.compact
    def __call__(self, X_enc, X_dec, enc_mask, dec_mask, *, training=False):
        def attn(q, kv, mask, training, name):
            mdl = MultiHeadAttention(n_heads=self.n_heads,
                                     size_per_head=self.size_per_head,
                                     attn_dropout=self.attn_dropout,
                                     fc_dropout=self.fc_dropout,
                                     name=f'{name}_attn')
            out = mdl(q, kv, kv, mask=mask, training=training)
            aan = AddAndNorm(name=f'{name}_addnorm')
            return aan(q, out)
        X_dec = attn(X_dec, X_dec, dec_mask, training, 'self')
        X_dec = attn(X_dec, X_enc, enc_mask, training, 'src')
        X1 = FeedForward(hidden_dim=self.hidden_dim)(X_dec)
        X_dec = AddAndNorm()(X_dec, X1)
        return X_dec

class Decoder(nn.Module):
    pos_encoding: Callable[[int, int], jnp.array]
    vocab_size: int
    embed_dim: int
    layers: Sequence[DecoderLayer]
```

```
    @nn.compact
    def __call__(self, X_enc, X_dec, enc_mask, *, training=False):
        B, N = X_dec.shape[:2]
        dec_mask = causal_mask((1, N, N))
        X_dec = nn.Embed(self.vocab_size, self.embed_dim, name='embed')(X_dec)
        X_dec = X_dec * jnp.sqrt(self.embed_dim)
        # X.shape[-2] is the sequence length
        X_dec = X_dec + self.pos_encoding(X_dec.shape[-2], self.embed_dim)
        for layer in self.layers:
            X_dec = layer(X_enc, X_dec, enc_mask, dec_mask, training=training)
        X_dec = nn.Dense(self.vocab_size, name='final')(X_dec)
        return X_dec
```

Checking the size of these models using the same hyperparameters as we did with the `Encoder` … 91 thousand parameters!

```
def layer_fn():
    return DecoderLayer(hidden_dim=13,
                        attn_dropout=0.1,
                        fc_dropout=0.1,
                        n_heads=7,
                        size_per_head=17)
mdl = Decoder(pos_encoding=sin_pos_enc,
              vocab_size=len(vocab),
              embed_dim=2 * 3 * 5,
              layers=[layer_fn() for _ in range(3)])
batch = strs2ids('hey', 'there', 'ma', 'dood')
kv = strs2ids('i', 'really', 'enjoy', 'algorithms')
enc_mask = (kv == vocab['<pad>'])
kv = nn.one_hot(kv, len(vocab))
params = mdl.init(key, kv, batch, enc_mask)
print(f'{num_params(params) = }')
del layer_fn, mdl, batch, kv, enc_mask, params
```

```
num_params(params) = 91291
```

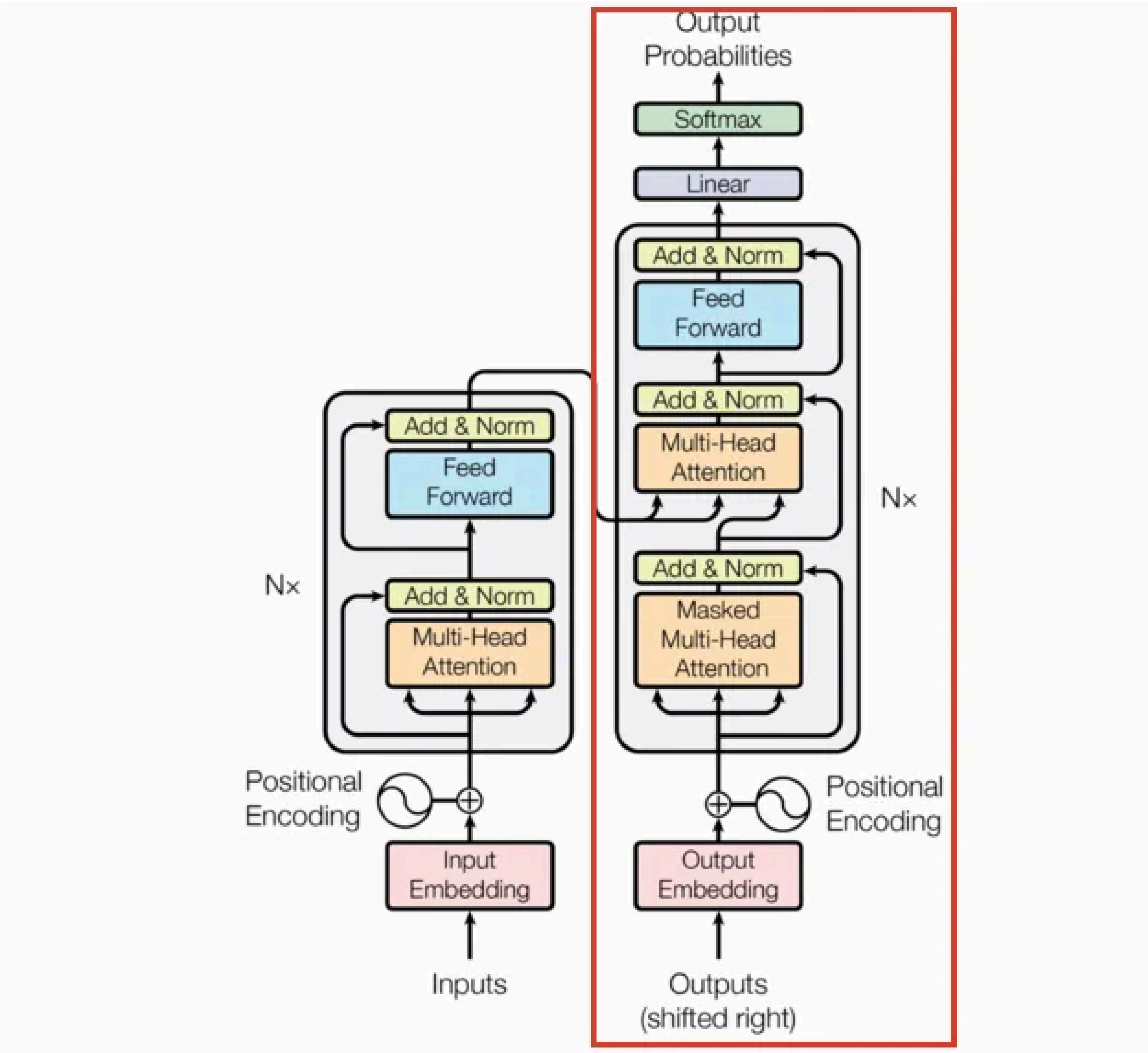
Flavors

Transformers come in three main flavors.

Encoder-only

- These take in a sequence and output state features.
- It's mostly useful for tasks like text classification, sentiment analysis, stuff like that.
- One notable example is Google's bert).

Decoder-only



Decoder only transformers remove the middle multi-head attention (the cross-attention) layer as there is nothing to cross with.

- These are called generative models.
- They take a static state and generate a sequence iteratively.
- Mostly useful for text (media) generation, although this is becoming outdated quickly.

- One notable example: GPT.

Encoder-decoder

- These models are officially just this diagram.
- They're of a class of models called seq2seq models.
- They take sequence inputs, generate some state features (via the encoder), and generate a sequence output (via the decoder).
- As such, they're typically used as translation models.

And as we'll see in a minute, they can be used to compute rot13 encryption!

```
class EncoderDecoderTransformer(nn.Module):
    pos_encoding: Callable[[int, int], jnp.array]
    in_vocab_size: int
    out_vocab_size: int
    embed_dim: int
    n_layers: int
    hidden_dim: int
    attn_dropout: float
    fc_dropout: float
    n_heads: int
    size_per_head: int

    def setup(self):
        self.encoder = Encoder(
            pos_encoding=self.pos_encoding,
            vocab_size=self.in_vocab_size,
            embed_dim=self.embed_dim,
            layers=[EncoderLayer(hidden_dim=self.hidden_dim,
                                 attn_dropout=self.attn_dropout,
                                 fc_dropout=self.fc_dropout,
                                 n_heads=self.n_heads,
                                 size_per_head=self.size_per_head,
                                 name=f'encoder_{i}')
                    for i in range(self.n_layers)])
        self.decoder = Decoder(
            pos_encoding=self.pos_encoding,
            vocab_size=self.out_vocab_size,
            embed_dim=self.embed_dim,
            layers=[DecoderLayer(hidden_dim=self.hidden_dim,
                                 attn_dropout=self.attn_dropout,
                                 fc_dropout=self.fc_dropout,
                                 n_heads=self.n_heads,
                                 size_per_head=self.size_per_head,
                                 name=f'decoder_{i}')
```

```
                    for i in range(self.n_layers)])

    def __call__(self, X, Y, source_mask, *, training=False):
        # required for dot product attention
        chex.assert_equal(self.encoder.embed_dim, self.decoder.embed_dim)
        encodings = self.encoder(X, source_mask, training=training)
        self.sow('intermediates', 'encodings', encodings)
        return self.decoder(encodings, Y, source_mask, training=training)
```

A tiny `EncoderDecoder` model has over 140 thousand parameters. And we're not even trying yet.

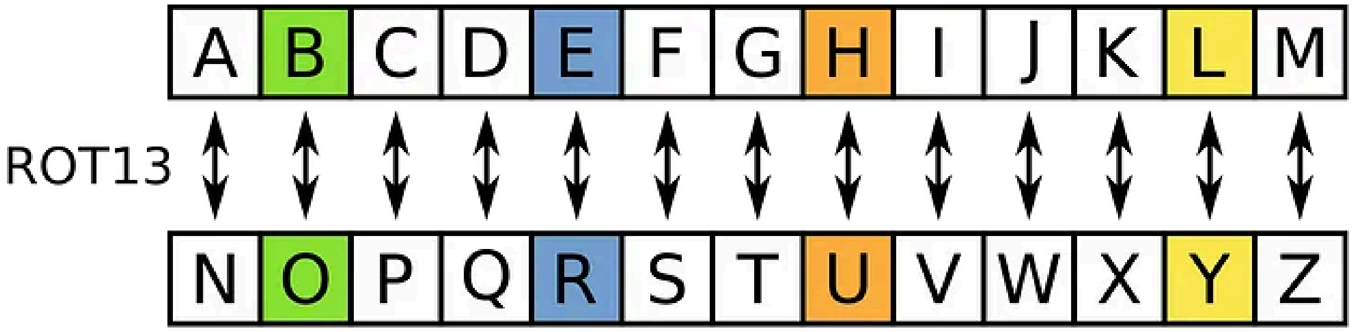
```
mdl = EncoderDecoderTransformer(
    pos_encoding=sin_pos_enc,
    in_vocab_size=len(vocab),
    out_vocab_size=len(vocab),
    embed_dim=2 * 3 * 5,
    n_layers=3,
    hidden_dim=13,
    attn_dropout=0.1,
    fc_dropout=0.1,
    n_heads=7,
    size_per_head=3
)
X = strs2ids('hey', 'there', 'ma', 'dood')
y = strs2ids('i', 'really', 'enjoy', 'algorithms')
mask = (X == vocab['<pad>'])
params = mdl.init(key, X, y, mask)
print(f'{num_params(params) = }')
del mdl, X, y, mask, params
```

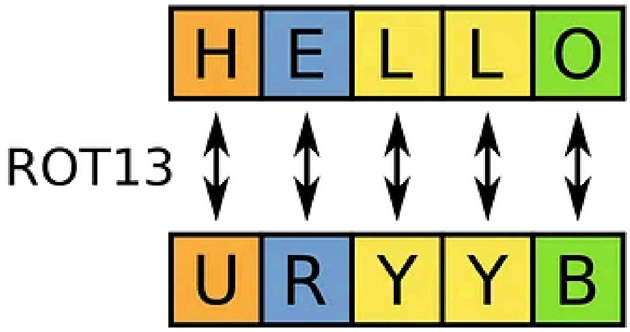
```
num_params(params) = 31903
```

Example

Rot13

We're going to train our transformer to encrypt words via rot13. Rot13 is an old-school encryption algorithm where each character is shifted by 13 characters (see below).





Training a transformer to do rot13 is a bit like using a chainsaw to give an injection but it's simple so it's well suited to purpose.

Since there are 26 letters in the English alphabet, rot13 is its own inverse! That means if you encode a message with rot13 twice, you get back the original message.

```
def rot13(input_string):
    return ''.join([chr(((vocab[x] + 13) % 26) + 97) for x in input_string])
a = 'asdfqwerz'
print(a, '=>', rot13(a), '=>', rot13(rot13(a)))
del a
```

```
asdfqwerz => nfqsdjrem => asdfqwerz
```

Let's write our data generator.

```
def get_data(key):
    k0, k1 = jran.split(key, 2)
    max_len = 15
```

```
        X = jran.randint(k0, (50, max_len), 0, len(vocab) - 2)
        mask = jnp.stack([jnp.arange(max_len) >= i for i in jran.randint(k1, (50,),
        X = X * (1 - mask) + (mask * vocab['<pad>'])
        Y = ((X + 13) % (len(vocab) - 2))  # cheap version of rot13 at the encoded
        Y = (1 - mask) * Y + mask * vocab['<pad>']
        Ys = (
            jnp.ones_like(Y, dtype=jnp.int32)
            .at[:, 1:].set(Y[:, :-1])
            .at[:, 0].set(vocab['<start>'])
        )
        return (X, Ys, mask.astype(jnp.float32)), Y
    mdl = EncoderDecoderTransformer(pos_encoding=sin_pos_enc,
                                    in_vocab_size=len(vocab),
                                    out_vocab_size=len(vocab),
                                    embed_dim=8,
                                    n_layers=1,
                                    hidden_dim=5,
                                    attn_dropout=0.0,
                                    fc_dropout=0.0,
                                    n_heads=7,
                                    size_per_head=5)
    opt = optax.chain(
        optax.clip_by_global_norm(1),
        optax.sgd(
            learning_rate=optax.warmup_exponential_decay_schedule(
                init_value=0.5, peak_value=0.8, warmup_steps=100,
                transition_steps=200, decay_rate=0.5,
                transition_begin=100, staircase=False, end_value=1e-3
            )
        )
    )
```

```
params = mdl.init(key, *get_data(key)[0])
print('num_params: ', num_params(params))
opt_state = opt.init(params)
```

```
num_params:  4665
```

One nice thing about jax is that you don't compile a model, you compile the whole training loop (which, in our case includes data generation).

```
@jax.jit
def train_step(params, opt_state, step, key):
```

```
    """Train for a single step."""
    k0, k1 = jran.split(jran.fold_in(key, step))
    args, y = get_data(k0)

    @jax.grad
    def grad_fn(params):
        logits = mdl.apply(params, *args,
                           training=True, rngs={'dropout': k1})
        loss = optax.softmax_cross_entropy_with_integer_labels(
            logits, y
        ).mean()
        return loss
    grads = grad_fn(params)
    updates, opt_state = opt.update(
        grads, opt_state, params)
    params = optax.apply_updates(params, updates)
    return params, opt_state
```

We'll the 10,000 train steps (which takes about 3 minutes on my laptop)…

```
for step in tqdm(range(10_000)):
    params, opt_params = train_step(params, opt_state, step, key)
```

Now let's run the test.

```
X = strs2ids('hey', 'there', 'ma', 'dood')
start = jnp.array([[vocab['<start>']]] * X.shape[0], dtype=jnp.int32)
Y = start
while (Y[:, -1] != vocab['<pad>']).any():
    Y = jnp.argmax(mdl.apply(params, X, jnp.concatenate([start, Y], axis=-1), X
ids2strs(list(Y))
```

```
['url', 'gurer', 'zn', 'qbbq']
```

```
[rot13(x) for x in ids2strs(list(Y))]
```

```
['hey', 'there', 'ma', 'dood']
```

And that's all folks! You can now transform with the best of 'em!

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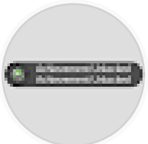

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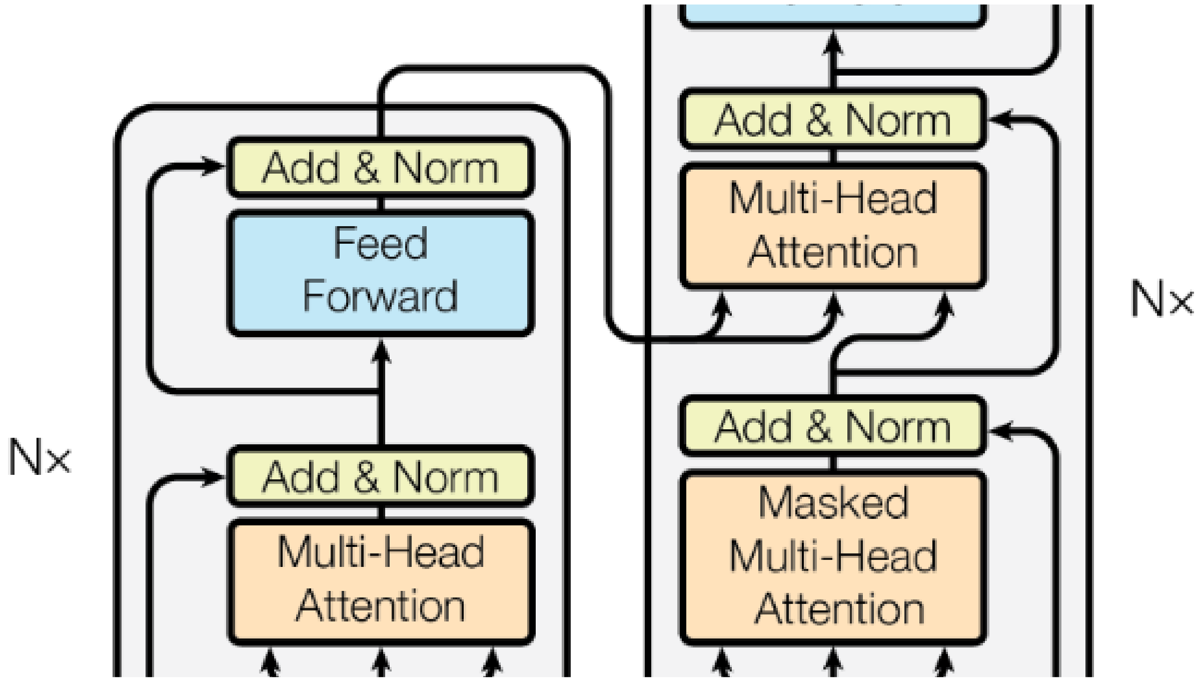

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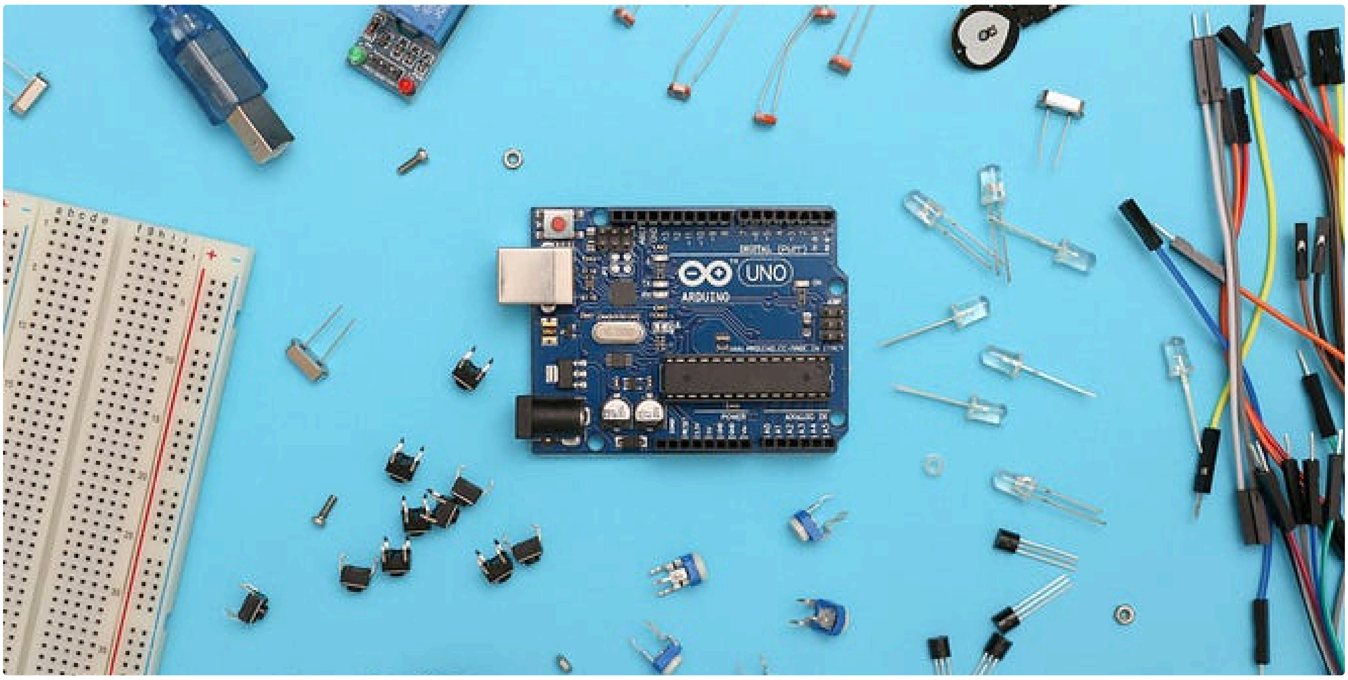

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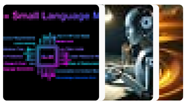

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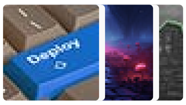

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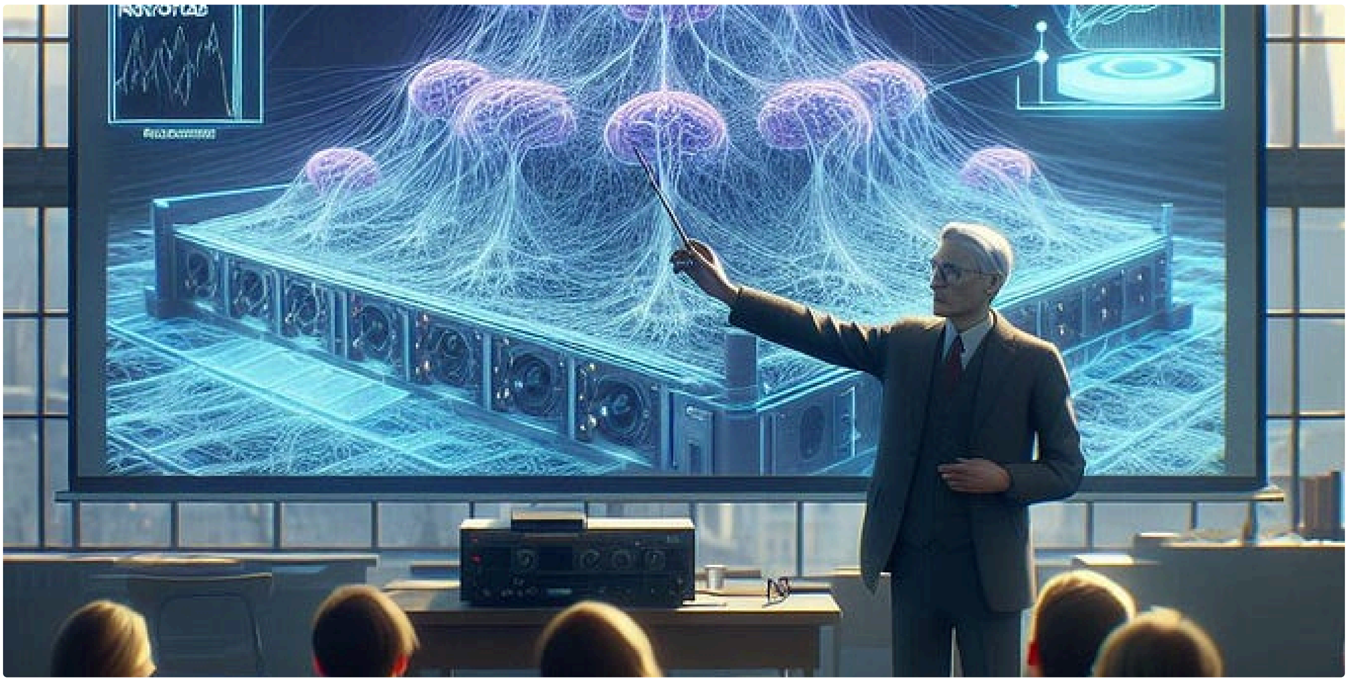

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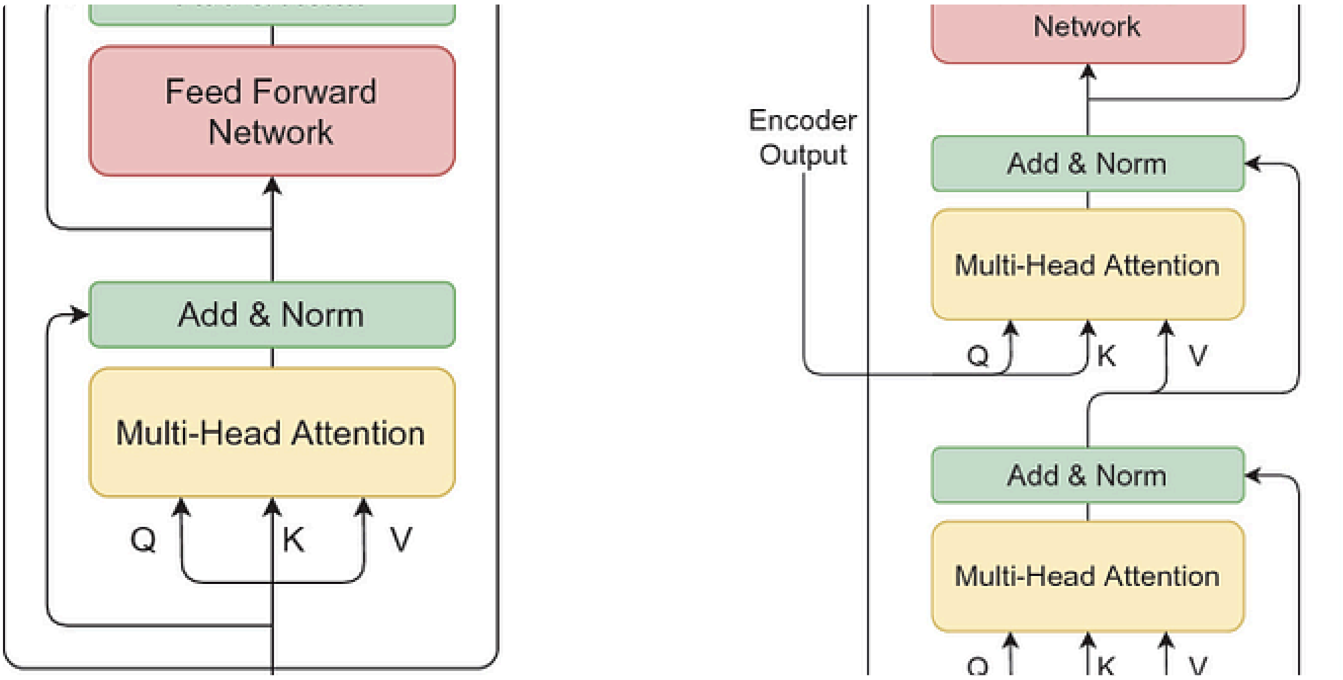

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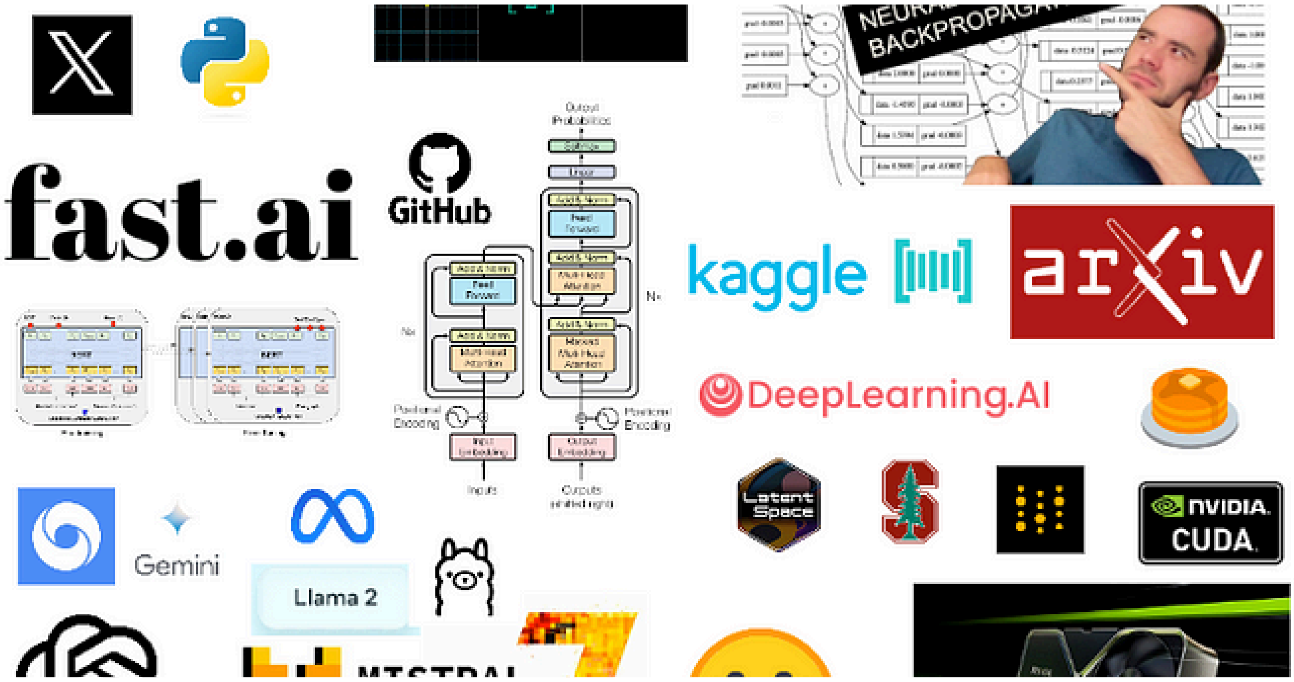

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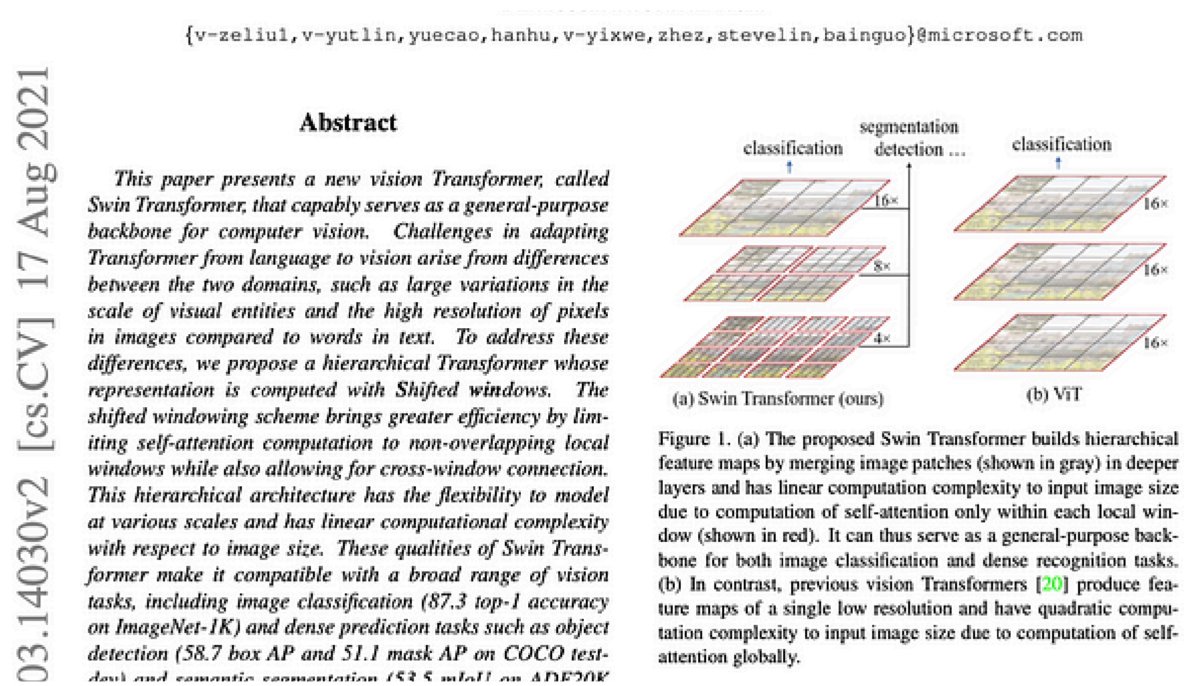

{v-zeliu1,v-yutlin,yuecao,hanhu,v-yixwe,zhez,stevelin,bainguo}@microsoft.com

arXiv:2103.14030v2 [cs.CV] 17 Aug 2021

Abstract

This paper presents a new vision Transformer, called Swin Transformer, that capably serves as a general-purpose backbone for computer vision. Challenges in adapting Transformer from language to vision arise from differences between the two domains, such as large variations in the scale of visual entities and the high resolution of pixels in images compared to words in text. To address these differences, we propose a hierarchical Transformer whose representation is computed with Shifted windows. The shifted windowing scheme brings greater efficiency by limiting self-attention computation to non-overlapping local windows while also allowing for cross-window connection. This hierarchical architecture has the flexibility to model at various scales and has linear computational complexity with respect to image size. These qualities of Swin Transformer make it compatible with a broad range of vision tasks, including image classification (87.3 top-1 accuracy on ImageNet-1K) and dense prediction tasks such as object detection (58.7 box AP and 51.1 mask AP on COCO test-dev) and semantic segmentation (53.5 mIoU on ADE20K

classification | segmentation detection … | classification | 16× | 8× | 4× | 16× | 16× | 16×

(a) Swin Transformer (ours) (b) ViT

Figure 1. (a) The proposed Swin Transformer builds hierarchical feature maps by merging image patches (shown in gray) in deeper layers and has linear computation complexity to input image size due to computation of self-attention only within each local window (shown in red). It can thus serve as a general-purpose backbone for both image classification and dense recognition tasks. (b) In contrast, previous vision Transformers [20] produce feature maps of a single low resolution and have quadratic computation complexity to input image size due to computation of self-attention globally.

Christian Lin

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