ECE 1786 Lecture #5

Work-in-Flight: Assignment 3 - Training & Using Transformer, due Mon Oct 23

- Assignment 2 Due Today at 9pm
- Team forming due today - form https://forms.office.com/r/jx0KmWDTed

Last Day: Intro to Language Models & Transformers; Project Structure/Scope

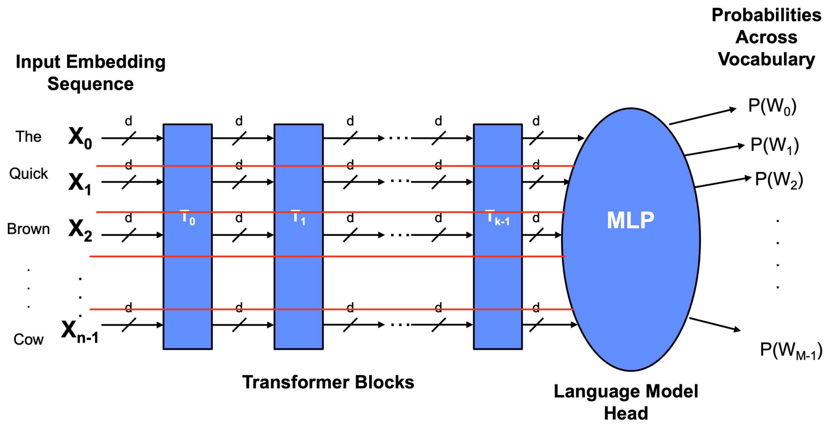
- suggest waiting until after seeing A3 (&A4) to choose topic

Today: The Core Mechanisms of Transformers & Assignment 3

Recall: When training a Transformer from scratch we train it to be a language model: given a sequence of n words, predict the probability that each word in the vocabulary is the next (n+1)st word.
Using sentences that have been written and are coherent/relevant/grammatical: e.g "The smooth blue lake became choppy in the wind" gives rise to training examples:

Training Example 4: The smooth blue ______
Training Example 5: The smooth blue lake _____
Training Example 6: The smooth blue lake became ______

- Lots of training data! Everything ever written!
- Here is the global structure of a transformer, reprised:

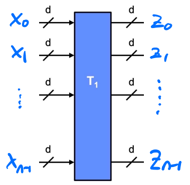


M = size of Vocabulary.

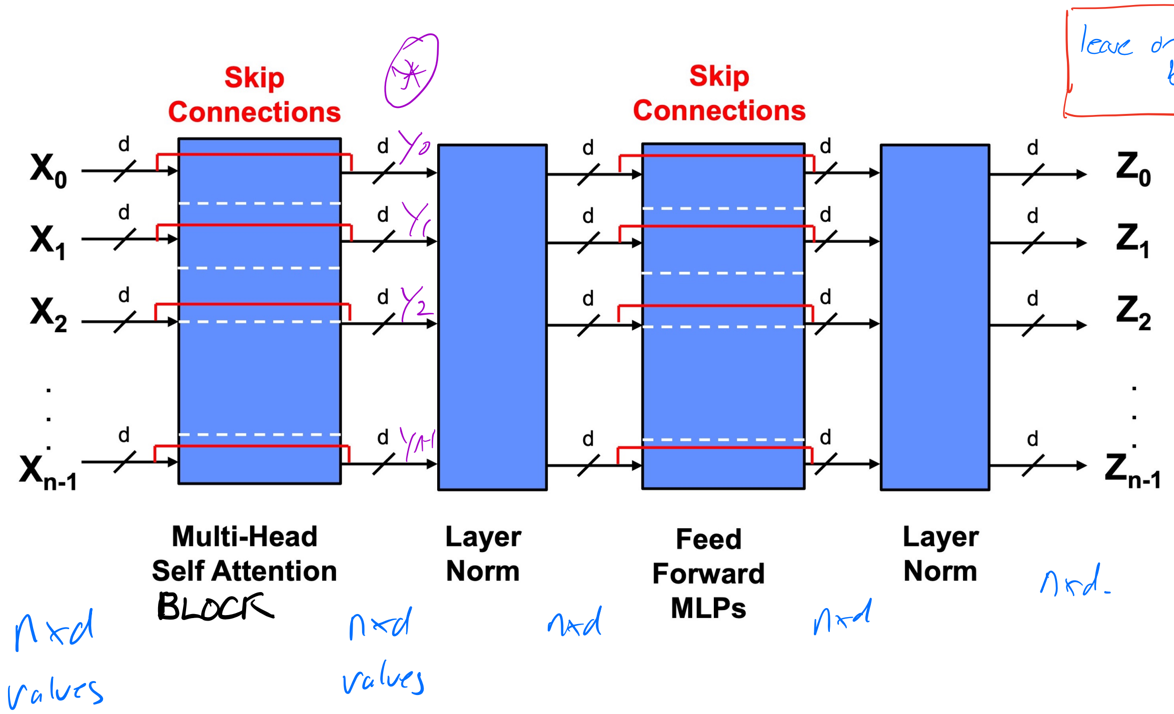
- Even though n tokens always go in, may use fewer than n, as in above example.
- Important: in a single inference the final MLP just takes in d inputs (not n x d)
  - Which d inputs? The d inputs corresponding to the last input token
  - (Which could be n-1, or n-2, n-3, however long the actual input is)

Now, here is what is in each transformer block Ti:

- Recall it has the same number of numbers in and out



Here is the structure of one such Transformer Block:



leave on board.

Multi-Head Self Attention:

The intuition of the Transformer self-attention block is said to be doing:

- The input word embeddings are transformed from their initial, very general meanings (across all uses/contexts of the words) to something more specific to the context - i.e. the other words in the sequence

- e.g. the embedding for "bank" would become different in these contexts:
  - She sat on the river bank …
  - He emptied his bank account …
  - They should not bank on the result …

- From * in above picture consider how to compute the outputs Yi from the inputs Xi (ignoring skip connections for now)

e.g. X0 X1 X2 $\boxed{\text{X3}}$ X4
He emptied his $\boxed{\text{bank}}$ account

- Self attention asks the question: how similar is each word to all the preceding words and itself? [See Jurafsky Section 9.8 and 10.1]

e.g. how similar is X3 (bank) to X0(He)?
  - how similar is X3 (bank) to X1(emptied)?
  - how similar is X3 (bank) to X2(his)?
  - how similar is X3 (bank) to X3(bank)?

How have we computed a single number that says how similar/related two words are?
=> use the dot product of the word embeddings - bigger means more similar

i.e. compute:

$$X_3 \cdot X_0$$

$$X_3 \cdot X_1$$

$$X_3 \cdot X_2$$

$$X_3 \cdot X_3$$

Define $score(X_i, X_j) = X_i \cdot X_j$

We will need to normalize across these scores when use it to compute combination:

So define $\alpha_{ij} = softmax(score\,(x_i, x_j))\forall j \leq i$

I.e.

$$\alpha_{ij} = \frac{\exp\left(score\left(x_i, x_j\right)\right)}{\sum_{k=0}^{i} \exp\left(scae\left(x_i, x_k\right)\right)} \forall j \underset{\uparrow}{\leq} i$$

only previous & current word.

This score, α_{ij} gives the relative importance of Xj to Xi, and we use it to compute a <u>new</u> embedding, Yi that combines different proportions of the Xj, like so:

$$y_i = \sum_{j \leq i} \alpha_{ij} \overset{**}{x_j}$$

- So, we are adding a fraction of the meaning of those other words into the original embedding; the fraction depends on how similar the words are.
- This is how "bank" gets more "river" into it
- The literature refers to these as 'contextual embeddings', as does the Jurafsky text

- Compute the Yi from i = 0 up to n-1 (if all occupied with embeddings)
    - Notice that Yi is only allowed to be a function of the input words that came before it, in what is callled a 'causal' model

Now, notice that there are <u>no learned parameters</u> so far. Gotta have those! (I.e. the weights/biases/parameters of the model)

- Will use an ML 'trick' to insert learning, as follows:

Notice that the Xi get used in three ways:

1. as the focus Xi in score(Xi, Xj) - we'll refer to this as the "query" (perhaps the word that is asking "who am I really in this context?")
2. As the 'searched' Xj in score(Xi,Xj) - call this the "key"
3. To compute the Yi in ** above - we'll call this the "value"

- In all three cases we will transform the input Xi by multiplying it times (three different) matrices consisting of learned parameters.

- The matrices will be a size that leaves the size of the output the same as the Xi input, hence just transformed.

- e.g. for the query, call it q and compute:

$$q_i = W^Q X_i$$

$$\text{where } W^Q = \begin{bmatrix} w_{00} & \cdots & w_{0,d-1} \\ \vdots & & \vdots \\ w_{d-1,0} & \cdots & w_{d-1,d-1} \end{bmatrix} \overset{\overset{x_i}{\downarrow}}{\begin{bmatrix} x_0^0 \\ \\ x_{d-1}^0 \end{bmatrix}}$$

  - Think of WQ as a bit like a CNN kernel
  - If you multiply this out you'll see that qi has the same size as Xi
  - but it has been projected/transformed by WQ
    - The elements of W are learned parameters, learned through gradient descent

- Similarly there are two other learned W matrices, for the key and the value:

$$k_i = W^K X_i$$

$$v_i = W^V X_i$$

- Together, qi, ki and vi "look" for patterns in the input and express the output based on these, like a CNN kernel

- So the overall computation becomes:

For each input embedding, Xi, compute:

$$\alpha_{ij} = softmax(score\,(x_i, x_j)) \quad \forall j \leq i$$

$$= softmax(\frac{q_i \cdot k_j}{\sqrt{d}}) \quad \forall j \leq i$$

→ scaled to keep sizes under control

$$y_i = \sum_{j \leq i} \alpha_{ij} v_j$$

→ the value.

↳ the output embedding corresponding to x_i

- Note that the <u>same</u> learned $W^Q, W^K, and\ W^V$ matrices are applied across every input Xi "row" in the transformer
- I find it difficult to have strong intuition on what these W are learning; even so it is thought that there are different sets of things to learn, just like there are different kernels learned and use successfully in CNNs
- So, that brings us to "Multi-Head Self-Attention"
  - There are several versions ('heads') of these weights so get:

$$W_i^Q, W_i^K, and\ W_i^V \quad 1 \leqq i \leqq h$$

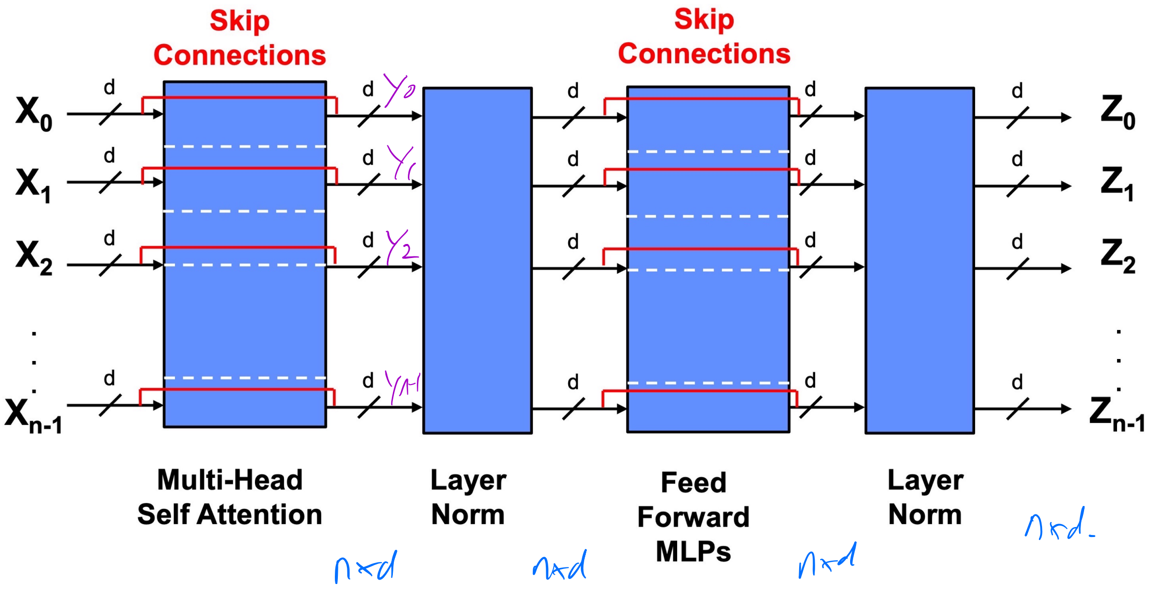
where h is the number of heads.

- To keep the number of parameters reasonable, some versions of the transformer make each head produce only a part of the output embedding size by dividing d/h and producing that many numbers in the embedding.

- Can also use different sizes for the heads of the transformers, and reduce it back to the desired size (d) by using a learned transformation matrix called

$$W^O \qquad (hd_v \times d)$$

Now, return to the specific Transformer block above:



- The other parts of the above transformer block are more common

1. Skip connections (red lines) - are an insurance policy against failed optimization - essentially 'skips' the block if nothing useful happening, but keeps the information passing through the block
2. Layer Normalization, Dropout and Weight Decay also used

- Very important: the computation in between the dashed lines are all independent! Yi is a function of some or all of the Xi, but can all be done in paralllel! This speed-up was crucial to the ability to train against huge amounts of training data - trillions of tokens.

- Also, the Feed-forward MLPs are isolated - i.e. there are n separated MLPs, not one big one, and their parameters are all the same

- Think of the transform block as a set independently computed "rows", where there is one "row" per input token/embedding.
  - Each "row" has the same trained parameters in it, including the layer norm
  - Similar to a CNN's kernels - like how the kernel is used all over the image, t attention, MLP, norm are applied the same on different input token rows

- Now, I mentioned that attention is "said" to be working as described, but to me this only really makes sense on the very first transformer block T0, and even there, just a the beginning attention
- Everything after that is the typical black-box of neural networks - the feed forward MLP for example
- THEN, the next transformer block mixes up all the input embeddings again, through a different set of learned Matrices on that layer, then MLP and so on through all layers.
- To me the key to the transformer is really how wide it is - it keeps the information flowing from the input embeddings flowing all the way to the end, versus RNNs which "pinched" that information after every word input

Notes on Assignment 3

- Code for Transformer is too complex to write from scratch
- So, A3 gives you Karpathy's mingpt - a well written, simpler GPT style transformer
- You'll have to read code and try to understand it
- we will use mingpt "nano" which has these parameters:
  - # Transformer blocks = 3 = n_layer
  - # Heads, h = 3 = n_head
  - Embedding dimension, d = 48 = n_embed

- The assignment is to train this transformer on a small, then large corpus (same as ones from A1)
- Re-use the language model as a sentiment classifier, after fine-tuning it
- Learn to use the Huggingface model hub/code to fine-tune GPT-2

- Missing from this lecture: Positional Embeddings - the answer to the question "how does the transformer know the order of the input words?"