FEED FORWARD THAT PRODUCES SHAKESPEARE...

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ABSTRACT

When we use a Feed Forward in General Purpose Transformer neural network, it is the last dimension's vector that participates in the vector and weight matrix multiplication (parallel to Time domain). Hence, the Feed Forward neural network calculates different interconnections between Embedding nodes, but the Time domain is left untouched. But if you transpose input between Time domain and Embedding domain, now the Time domain nodes participate in interconnection computation. We only needed to shut down the future nodes...

***K*eywords** Self-Attention · General Purpose Transformer · Natural Language Processing

Methods and Materials

"All Shakespeare" dataset, data type - float16-mix, token size – 3 symbols, vocabulary size – 8507 tokens, token embedding – 800, number of heads – 20 (head size – 40), layers – 20, time intervals (context block) - 300, number of parameters 41.75M, optimizer - Adam, learning rate – 3e-5, dropout – 0.1, batch size – 64, pytorch library, videocard - NVidia GPU 3060 RTX

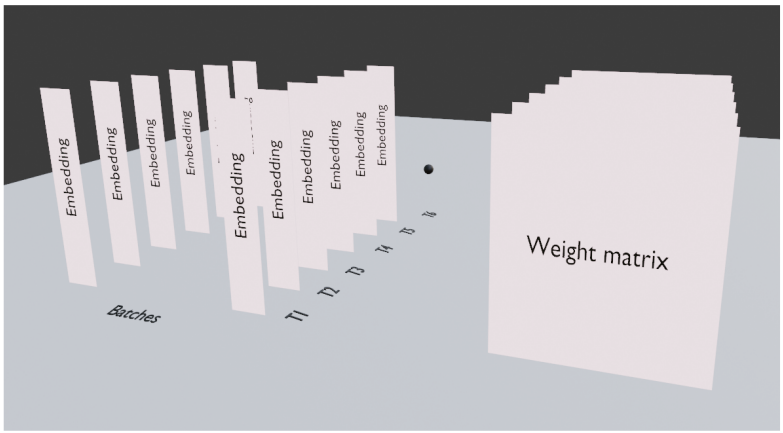
1 Introduction

This work is a pure showcase and no comparison with state-of-the-art was made due to computational limitations. It is based on the recent achievements of the simplification of Self-Attention[1] mechanism[2][3][4]. Though we started our research independently, the closer alternatives are work by [2] applied for the speech recognition task, unpublished work of Abdulrahman, H [5] where the author passed the united token and position embedding values through 2 weight matrices independently and used masked second output as an attention for the first output and pNLP-Mixer[6] , the project based on MLP-Mixer[7] which studied the replacement of Convolution[8] and Self-Attention with Multilayer Perceptron[9] with Channel and Spatial resolutions mixing. They use different tools, e.g. minimum hash fingertip in non-trainable projection layer to enhance MLP-Mixer, and the work can be considered as more advanced step in comparison to ours achieving 99.4% performance of mBERT on MTOP with less parameters involved. Our work is a simple showcase that it is possible to use Feed Forward layer instead of Self-Attention in Language Model[10] to generate a reasonable text as an output, we only need to suppress nodes that are responsible for future tokens in computational communication. This results in only one triangular linear layer for each head. We were able to put 20 heads and 20 layers inside single NVidia 3060 RTX with 12GB memory.

2 Feed Forward network that produces Shakespeare

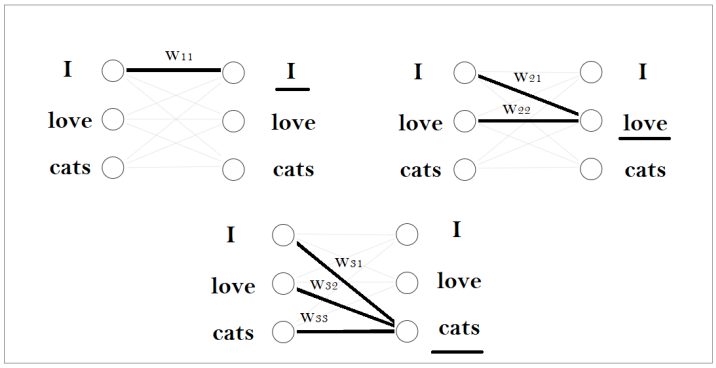
When you have "3D" Tensor consisting of: Batch, Time, Embedding (which in general case can be thought as a description of each time series), Linear Layer just uses the last "1D" vector "Embedding"[1] and multiplies it by "2D" weight matrix producing "1D" vector output, but does it for all "Time" series.

[1] "1D" vector is an abstraction for separate processing of Embedding columns for each Time Series row in the input matrix



Embedding domain. Conventional computation

Time domain with Lower Triangular mask applied to Weight Matrix



Resultant operation in Time domain

Figure 1: Separate processing of Embedding and Time Series Vectors [2]

Hence, TIME does not participate in the linear layer. So, there is no interconnection between tokens or words in the sentence. But what Linear Layer does, it learns interconnection (through weights) between each embedding value or node in the embedding vector to better suit the target.

Though we encounter limitations because we do not consider TIME domain. Let us transpose the (Batch, Time, Embedding) into (Batch, Embedding, Time). In this way Time series will participate in computation. What is still missing is the idea that the current Word (Embedding) cannot talk to the future Words (Embeddings). We can apply lower triangular matrix with distributed values as the mask to the weights as in Fig.1.

[2]for illustration purposes only, vectors and weight matrix should be transposed in the real $x \cdot W^T$ calculation

Averaging weights in this manner helps the neural network to adjust faster in the beginning, but weights are still learned, not to mention, that with a lower triangular matrix we do not consider future words (and we do not use bias that can distort interconnections between tokens). Instead of 1.0, one can also use the decreasing discount factor with an initial value of $\gamma = 0.9999$, to make the latest words more important, but 1.0 works perfectly fine and faster.

Positional Encoding can be seen as extra information if you process Time domain directly. This resembles the Attention mechanism with straightforward simplifications.

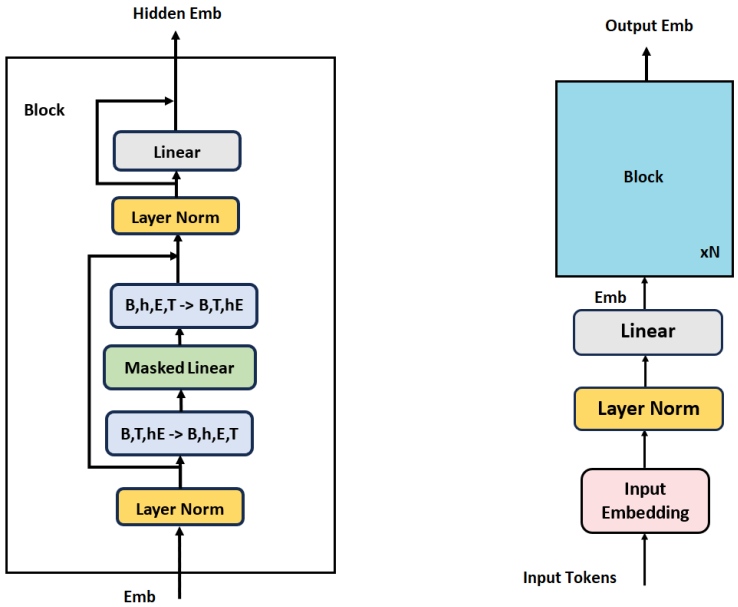


Figure 2: Feed Forward Transformer Architecture

3 An experiment and preliminary conclusion

We tested our algorithm on the "All Shakespeare" Dataset. The model had only 41.75M parameters, with context size of 300 tokens of size-1. (Activation Function used in Conventional Linear Layers was Leaky Relu, with input 0.07). It started producing meaningful words at 1000 iteration, after 2000 - some phrases, after 10000 iterations it started producing small sentences without particular meaning, and after 70000-80000 iterations it produced sentences with an understanding of the past context:

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FLORIZEL: Fortune speed us! Thus we set on, Camillo, to the sea-side.
CAMILLO: The swifter speed the better.
AUTOLYCUS: I understand the business, I hear it: to have an open ear, a quick eye,
 and a nimble hand, is necessary for a cut-purse; a good nose is requisite also, t
o smell out work for the other senses. I see this is the time that the unjust man
doth thrive. What an exchange had this been without boot! What a boot is here with
 this exchange! Sure the gods do this year connive at us, and we may do any thing
extempore. The prince himself is about a piece of iniquity, stealing away from his
 father with his clog at his heels: if I thought it were a piece of honesty to acq
uaint the king withal, I would not do't: I hold it the more knavery to conceal it;
 and therein am I constant to my profession. Aside, aside; here is more matter for
 a hot brain: every lane's end, every shop, church, session, hanging, yields a car
eful man work.
Clown: See, see; what a man you are now! There is no other way but to tell the kin
g she's a changeling and none of your flesh and blood.
Shepherd: Nay, but hear me.
Clown: Nay, but hear me.
Shepherd: Go to, then.
Clown: She being none of your flesh and blood, your flesh and blood has not offend
ed the king; and so your flesh and blood is not to be punished by him. Show those
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Figure 3: Word completion

We believe it can be further improved with a Large Language model and/or with Reinforcement Learning. While the Embedding size was 800 and the output of the model was 8507 to suit token numbers in vocabulary, there is a high necessity to increase embedding size to 2000-4000 (head size, 100-200) to better suit the output's dimension. To increase number of time series are important as well. There is one unsolved drawback however: with a single embedding vector we need to re-think the cross-attention mechanism.

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