Introduction to the Transformer Model

Hello everyone. In this video, I will introduce and explain the concepts and features of the Transformer, an AI model that has revolutionized not only the field of Natural Language Processing (NLP) but the entire world of artificial intelligence.

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The Transformer model was introduced in the paper titled "Attention Is All You Need," authored by Vaswani and colleagues in 2017, under the work at Google Brain and Google Research.

Why is this publication considered a game-changer? The reason is that it addressed longstanding challenges in NLP up until 2017, paving the way for advanced AI models capable of understanding and generating human-like text.

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Let's first examine which models were predominant in NLP before the advent of the Transformer.

Up until 2017, Recurrent Neural Networks (RNNs) and their variations, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU), were the primary architectures for NLP tasks.

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RNNs offer several advantages, including, but not limited to:

* Efficient management of sequential data types, including text, speech, and time series.
* The capability to handle inputs of varying lengths, a feature absent in feedforward neural networks.
* Improved training efficiency through the sharing of weights across different time steps.

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Now, let's explore some of the major limitations of RNNs.

Consider the task of language modeling as an example. Given the beginning of a sentence, such as "She stands up and opens the...", the model's objective is to predict the next word.

RNNs process words one at a time, generating a hidden state for each timestep that feeds into the computation of the next state.

This sequential processing limits opportunities for parallel computation, resulting in longer computation times for longer sequences.

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Furthermore, due to the sequential nature of computing these hidden states, the influence of early states or information on the final state or prediction diminishes for contexts involving long sequences.

This leads to a loss of information for long-range dependencies.

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Another significant limitation of RNNs is their susceptibility to vanishing or exploding gradients. RNNs update their weights using Backpropagation Through Time.

For instance, to compute the gradient of the loss function L with respect to the network's weights, the chain rule is applied across timesteps to calculate the product of gradients.

If the gradients are less than 1, their magnitude decreases with each multiplication. Over many timesteps, the gradient can diminish to zero, rendering the weight updates during optimization negligible. This hampers the learning process, particularly for long sequences or deep architectures.

On the other hand, the exploding gradient problem arises when gradients at each timestep exceed 1, causing the gradients to exponentially increase as they are propagated backward in time. This can lead to extremely large gradient values, causing instability during optimization and resulting in weight updates that either oscillate or diverge, thereby destabilizing the training process.

Both vanishing and exploding gradients significantly complicate the training of RNNs, impairing their ability to capture long-term dependencies in sequential data. These challenges render the training of RNNs unstable and exceedingly difficult.

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To summarize, RNNs face several significant disadvantages:

* Sequential computation makes parallel processing with GPUs challenging.
* They often lose information pertaining to long-term dependencies.
* They are prone to vanishing or exploding gradient issues.

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And then, the arrival of the Transformer model in 2017, as proposed in the paper "Attention Is All You Need," marked a significant advancement.

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This paper introduced the Transformer architecture, initially for the task of machine translation, such as translating from one language to another, for instance, from English to French. At a high-level overview, its architecture comprises an encoder and a decoder. In this video, we will delve into the two main components of the Transformer.

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What set the Transformer apart as a groundbreaking innovation at the time? The Transformer employs self-attention mechanisms, enabling parallel computation, which allows for the use of GPUs to expedite the training process significantly.

Moreover, it can effectively capture long-range dependencies.

Importantly, its architecture makes the model less susceptible to the problems of vanishing or exploding gradients.

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Following the success of the Transformer, from 2018 onwards, there has been a trend in NLP towards developing pre-trained language models based on the Transformer architecture. Examples of these include BERT, GPT, T5, Llama, Mistral, Phi, Falcon, and OLMo.

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Let's dive deep into the transformer. Here is our plan of attack. I will explain to you:

The text data at the input and output of the model, and how the model understands the text data.

Then, I will walk you through the transformer block by block. I will discuss the input, output, and process of each block. Furthermore, we will delve into its significance.

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First of all, I am going to discuss the Input/Output blocks in the transformer architecture.

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In the case of the Transformer, the model is often used for machine translation tasks. Therefore, the Inputs will be in the source language, and the Outputs will be in the target language. For example, we have a pair of source-target texts, like in English: "I am fine." In French: "Je vais bien." Or in English: "Thank you very much," in French: "Merci beaucoup." This means that the Inputs/Outputs of the models are text data.

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There are three points we need to consider:

1. It is important to understand that the model only comprehends numerical values. Therefore, we need to transform text into a numerical representation.
2. The source and target texts may have different lengths, but the model requires a fixed length for the sequence.
3. The model needs to know when to start and end the prediction. So, we need to find ways to indicate to the model when to begin and end a sequence.

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To address these concerns, we can:

* Choose a fixed length for the sequences.
* Add special values to indicate the start and end of a sentence, as well as to represent padding for instances where the sentence length is shorter than the chosen fixed length.
* Utilize a tokenizer to convert text into numerical representation, effectively dealing with the translation from textual to numerical data.

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Let's dive deep into Tokenizers.

What is a tokenizer?

A tokenizer possesses a large vocabulary and enables the transformation of text into numerical representations.

A token can represent a word or a character.

Additionally, it defines special tokens, for example: UNK for Unknown; PAD for padding; SOS for Start of Sentence; and EOS for End of Sentence.

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Let's explore the two main processes in a tokenizer:

The first is encoding, which means transforming text tokens into numerical representations.

The second is decoding, which means converting numerical representations back into text tokens.

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Now, let's put it all together.

First, let's prepare the inputs for the source language. For example, we have a batch of 3 English sentences: "I am fine," "Thank you very much," and "I cook French cuisine."

* These 3 English sentences have a maximum length of 4, so for simplicity, let's choose a fixed length of 7.
* Then, we add the special tokens SOS (Start of Sentence), EOS (End of Sentence), and PAD (Padding) to achieve a fixed sequence length for all sentences.
* Using the encode method of the English tokenizer, we obtain the final inputs for the encoder part.

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Similarly, we follow the same process for preparing the outputs for the decoder part. The difference is that we only use the SOS (Start of Sentence) and PAD (Padding) tokens, and do not use the EOS (End of Sentence) token. With the SOS token, it signals the model to start the prediction. Additionally, we use the target tokenizer for the French language to encode the tokens.

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Finally, the third use case of the encoding process is to prepare the target for loss calculation.

In this case, we only use two special tokens: EOS (End of Sentence) and PAD (Padding). The idea is to optimize the model so that it knows when to stop the prediction.

In this case, we also use the target tokenizer for the French language to encode the tokens.

Next, I'll walk you through all the building blocks of the Transformer architecture, including Encoder Input, Decoder Input, Encoder, Decoder, Projection, and Transformer Output. Let's dive in.

Now, I am going to discuss the Encoder Input and Decoder Input. As they share the same structure and building blocks—Input Embedding and Positional Encoding—we only need to discuss one of them.

For instance, in the case of the Encoder Input, there are two main components: Input Embedding and Positional Encoding. They utilize the numerical representation of text data as inputs to generate a tensor of dimension (batch, seq, d\_model). Then, their results are combined to obtain the encoder input. Now, we will discuss more in detail the functions of each component.

Input Embedding takes inputs of dimension (batch, seq) and generates a tensor of dimension (batch, seq, d\_model), meaning it transforms each token into a feature vector of length d\_model for that token.

Positional Encoding transforms the input tensor of dimension (batch, seq) into a tensor of dimension (batch, seq, d\_model). Its function depends solely on the position of the token in the sequence, assigning each position index in the sequence a unique feature vector of size d\_model. It conveys the positional information within a sequence.

To put it all together, for example, if we have a batch size of 2, a sequence length of 7, and a d\_model of 512, by applying Input Embedding and Positional Encoding to the inputs of (batch, seq), we obtain two tensors with dimensions of (batch, seq, d\_model). These tensors are then added together to form the Encoder Input.

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Now, I am going to explain the Encoder block. The input to the Encoder block is the Encoder Input that we have previously discussed. It consists of four layers: multi-head attention (which includes the self-attention mechanism), layer normalization, feedforward network, and residual connection.

First, let's discuss Multi-Head Attention and its self-attention mechanisms. The input to this block is the Encoder Inputs, a batch of tensors that represent the semantic meaning and the positional feature of each word or token. This input is duplicated into three identical tensors, named Q (Query), K (Key), and V (Value). Let's examine what happens inside the Multi-Head Attention block.

Before defining what multi-head attention is, let's consider a simpler case: a single-head attention layer. In a single-head attention layer, it calculates Attention, which is formulated as follows: The component with the Softmax function is called the Self-Attention mechanism. Let's examine a concrete example to understand why it's called Self-Attention. For instance, with a batch size of 1, a sequence length of 3, and d\_model equals d\_k equal to 512, applying this function will yield a matrix of dimension 3 by 3. This matrix represents the correlation of each word to the others, with the Softmax function normalizing the values of each row to range between 0 and 1, while ensuring the sum of all values in each row equals 1. This matrix, representing the correlation between words in a sequence, is why it's referred to as Self-Attention.

Afterward, the result of the Self-Attention is multiplied by V to obtain the output of the single-head Attention. The Self-Attention mechanism highlights the correlation between words in a sentence, while V encapsulates both word meaning and positional features. Consequently, the final attention tensor represents a synthesis of these elements. Having understood the concept of self-attention for a single-head attention, let's extend this understanding to multi-head attention.

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For multi-head attention, there are four main steps to realize this process:

1. Firstly, we split the encoder inputs, Q, K, and V, into ℎ*h* heads for each input by applying linear layers. This step allows for the parallel processing of information, which enhances the model's ability to focus on different parts of the input sequence.
2. Secondly, we calculate attention for each head, similar to how we calculate for a single-head attention. This involves computing the attention scores and applying the Softmax function to obtain the weighted sum of values for each head.
3. Next, we concatenate the attention tensors from each head. This step combines the independently computed attention outputs into a single tensor, preserving the information captured by each head.
4. Finally, we apply another linear layer to obtain the final multi-head attention tensor of dimension (batch, seq, d\_model). This linear layer transforms the concatenated tensor back into the original dimensionality, ready for subsequent processing.

Now that we have covered multi-head attention, let's continue with Layer Normalization.

When discussing Layer Normalization, we're focusing on the normalization of a feature vector of a token, which has a length of *dmodel*​. The process involves:

* First, calculating the mean value of the feature vector. This step involves averaging the values across the *dmodel*​ dimensions.
* Then, calculating the variance from the mean value. The variance measures the dispersion of the feature vector values around the mean.
* Finally, obtaining the normalized vector using the formula for layer normalization. This formula adjusts each feature vector by subtracting the mean and dividing by the square root of the variance, followed by scaling and shifting. This normalization ensures that the activations across the features have a mean of 0 and a standard deviation of 1, improving the stability and performance of the neural network.

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Putting it all together: Given a tensor with the dimensions of (batch, seq, d\_model), layer normalization normalizes the values within this tensor, resulting in an output tensor with the same dimensions but with normalized values.

Next, we'll discuss the feedforward layer: Given an input tensor *x* with dimensions (seq, d\_model), the original Transformer architecture proposed the application of two linear layers to *x*:

* With the first linear layer, we multiply *x* by a weight matrix of dimensions (d\_model, d\_ff) and then add a bias.
* We then apply the ReLU function to the result of the first linear layer, followed by the application of the second linear layer to the resulting tensor, with a weight matrix 2*W*2​ of dimensions (d\_ff, d\_model) and a bias 2*b*2​.
* The output tensor retains the dimension (seq, d\_model).

Next, I am going to talk about the residual connection: Given an input tensor *x*, a sublayer (which can be either a feedforward layer or multi-head attention), and a residual connection, we can obtain the resulting tensor *x*′ using the formula, effectively adding *x* and the output of the sublayer applied to *x*.

We have now gone through all the building blocks of the encoder part, including multi-head attention with self-attention mechanism, layer normalization, feedforward layer, and residual connection. In the Transformer architecture, it uses six identical encoder layers.

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Next, I'm going to tell you about the Decoder part.

For the Decoder part, most blocks are the same as those in the Encoder part, except there are some differences in Multi-Head Attention and the inclusion of Masked Multi-Head Attention.

* In Multi-Head Attention within the Decoder, the Key and Value tensors come from the Encoder output, while the Query tensor comes from the previous block in the Decoder part.
* Another important block is the Masked Multi-Head Attention. It functions similarly to Multi-Head Attention, except that a mask is applied during the calculation of the Self-Attention score to prevent future tokens from influencing the prediction of the current token. We will discuss this in more detail soon.
* Finally, regarding the sequence length in the Decoder part: For training, the sequence length of the Decoder is equal to the sequence length of the Encoder. However, during inference, the sequence length of the Decoder can vary from 1 to the sequence length of the Encoder.

Now, let's dive deeper into Masked Multi-Head Attention: The major difference in the calculation of Self-Attention within this context is the addition of a mask (set to -infinity) to the values above the diagonal line of the Self-Attention matrix. Applying the softmax function then ensures that positions with the mask are assigned a value of 0. The objective is to force each word in the target language to correlate only with the preceding words in that sentence, not the following words. This is crucial for ensuring the model generates text in a left-to-right manner, preserving the sequential nature of language.

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Next, I am going to talk about the Multi-Head Attention in the Decoder.

The first point to note is that the Key and Value tensors are derived from the Encoder output, while the Query tensor comes from the preceding block of the Decoder. Consequently, the shape of Q dictates the shape of the outputs of Multi-Head Attention in the Decoder.

Regarding sequence lengths (*seq*−*de*): For training, the sequence length of the Decoder is equal to the sequence length of the Encoder. However, during inference, the sequence length of the Decoder can vary from 1 up to the sequence length of the Encoder.

Having covered all the building blocks and the important differences of the Decoder compared to the Encoder, we can proceed to construct the Decoder block. In the original Transformer paper, the authors proposed applying six identical Decoder blocks to form the final Decoder layer part.

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Finally, we will discuss the two last layers used to generate the Transformer output: Projection with a linear layer and Softmax.

Here we go:

To derive the Transformer's predictions, we start with a Decoder output *x* with the shape (batch, *seqde*​, *dmodel*​).

* First, we apply a linear layer to project *x* to ′*x*′. This transformation maps the sequence feature of length *seq\_de*​ to the vocabulary size (*vocab*\_*size*).
* Then we apply the Softmax function to normalize the feature vector of size *vocab*\_*size* to a range between 0 and 1, with the sum of the probabilities equaling 1. By identifying the index corresponding to the maximum value, we can pinpoint the token with the highest probability of occurrence. Taking its index, we then use the decode method for the tokenizer of the target language to convert this index back into the corresponding word. As a result, we obtain the predicted word.

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Congratulations! You have done it! Now take a bow. We have gone through all the building blocks of the Transformer. Such an achievement! Now, we can build the Transformer model. Let's see how the model is trained and performs inference.

Let's examine what happens during the training of a Transformer: at each time step, it processes the entire text batch simultaneously in a parallel manner. For example, in this demonstration, the batch size is equal to 1. After calculating the loss, it updates the model parameters. For the next time step, the process repeats.

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For inference, there are several steps to obtain the final predictions. For example, let's say we want to translate the English sentence "I am fine" into French.

1. At the first step, the English sequence is fed into the encoder, while only the special token SOS – Start of Sentence is processed by the decoder. This special token allows the decoder to predict the first word: "Je".
2. The model is auto-regressive, meaning it consumes the previously generated symbol as additional input when generating the next. So, at the second step, the word "Je" is concatenated back to the existing input of the decoder, resulting in the decoder input as "SOS Je". In the encoder, we don't need to recompute the processing; we just need to use the encoder output. As a result, the decoder predicts the next word "vais".
3. For the third step, the process repeats, and the word "vais" is added to the existing decoder input, resulting in "SOS Je vais". The encoder output is reused for the computation in the decoder. As a result, the decoder predicts the word "bien".
4. At the fourth step, the process repeats, and finally, we obtain the special token EOS, which indicates that the model's prediction has reached its end. At that point, we obtain the final prediction in French: "Je vais bien."

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Well, thank you so much for bearing with me until the end of this long journey. I hope you now have a good understanding of the Transformer.

If there are any points you don't understand, please let me know in the comments, and I will try to answer them. Or if you find any mistakes, please let me know so I can correct them and improve for next time. Finally, if you like my video, you can encourage me by subscribing to my channel, liking, and sharing my video with your friends or on your social networks. That will motivate me greatly for the upcoming videos. Let's learn and grow together. Thank you. Bye-bye.